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Market Reaction to Synergy Disclosure in M&A

From a management perspective: How should the disclosure of projected synergies be approached in M&A announcements?

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Abstract

We use a sample of U.S. public deals from 2012-2021 and examine the short-term market reaction to synergy disclosure in M&A announcements. We do not find that synergy disclosure per se impacts acquirer returns. The lack of impact is attributable to the manner by which forecasted synergies are presented. By performing textual analysis on investor presentations, we construct measures of synergy emphasis, sentiment, and readability. We find that managements disclosing synergies with a highly positive tone outperform those with a neutral or negative tone.

Acknowledgement

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The literature explaining acquirer returns is divided and often inconsistent within mergers and acquisitions. We find this, in addition to our growing interest in the topic, to be sources of excitement and motivation for our thesis. It has been rewarding, challenging, and comprehensive at times. However, we are left with good experiences and knowledge of the topics of M&A and synergy disclosure.

We would like to thank those that have supported us during our project. We especially want to thank our supervisor, Associate Professor Kyeong Hun Lee, for his guidance, constructive feedback, and discussions throughout the project. We are very grateful.

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I. Introduction

The "variety of intentions behind conduction and justifying M&A is captured by the umbrella term synergy" (Bauer et al., 2022, p. 2). The estimation of these synergies, however, is a complex endeavour and not commonly understood. Even though synergy estimates are subject to uncertainty, there is a growing tendency by acquires to disclose their forecasts. In this context, our thesis examines how the market reacts to the disclosure of synergies and how the reaction depends on the acquiring management´s disclosure approach in investor presentations (IP).

A well-established concern by shareholders is that management pursues other objectives than maximizing shareholder wealth. An article by Dutordoir et al. (2014) addresses this concern arguing that the decision to disclose synergies is in line with the signalling hypothesis; shareholders´ concern about overpayment for the target. If investors perceive the estimated synergies to be credible, the disclosure should positively affect the market reaction. Alternatively, if the estimates are discerned as not credible and a management´s way to mitigate shareholder concerns, the disclosure is hypothesised to have no or even a negative effect on acquirer returns. We examine the impact of synergy disclosure by using a sample of U.S. public M&A deals between 2012 and 2021. Our regression results do not show any statistically significant difference in bidder returns between disclosing and non-disclosing deals.

However, shareholders´ incorporation of management forecasted synergies into their valuations is hypothesised to be impacted by the disclosure approach. Therefore, how the estimates are presented can explain the insignificant differences in acquirer returns between disclosing and non-disclosing deals. Furthermore, as the disclosure of synergy estimates is voluntary, the disclosure itself may take different forms depending on the nature of the deal. In our thesis, we analyse investor presentations as we assume this is a natural medium for management to present their forecasts. This assumption is supported by the fact that 97% of disclosing deals in our sample mention synergies in their presentations. Additionally, the average rate of mentioning synergies is much higher in disclosing deals than in non-disclosing deals. To the best of our knowledge, there is also a lack of literature on investor presentations, which provides additional incentive for our research.

We examine the disclosure decision with three moderation variables based on the textual analysis of investor presentations. The moderation entails looking at the IP emphasis on synergies, underlying tone, and readability. We do not find any evidence supporting that increased synergy emphasis nor readability has any statistically significant additional effect on acquirer returns. However, the interaction term between *Net Tone and Synergy Disclosure* is statistically significant, implying that the disclosure of synergies effect on acquirer returns depends on the level of tone in investor presentations.

This thesis contributes to the existing literature for mainly two reasons. First, our paper relates to the relatively limited literature on synergy forecast disclosure. To our knowledge, only one paper has examined the relationship between synergy disclosure and bidder returns. Using a sample of U.S. public acquisitions between 1995 to 2008, Dutordoir et al. (2014) find that the disclosure of synergies provides a positive market reaction for bidders in deals that would otherwise yield high negative announcement returns. Furthermore, when controlling for endogeneity, the authors find that the decision to disclose estimated synergies is associated with almost 5% higher acquirer returns. Our thesis complements the existing literature by applying more recent data and by examining the disclosure approach.

Second, in analysing investor presentations, our thesis supplements the small but growing literature of textual analysis on M&A disclosure. Dasgupta et al. (2020) and Hu et al. (2021) applied, respectively, a topic probabilistic modelling approach and sentimental analysis on M&A conference calls and examined the impact on acquirer returns. In both articles, the authors find that textual analysis in M&A is significantly and economically vital in explaining variation in acquirer returns. Our thesis differs from these studies by analysing the content of investor presentations disclosing synergies rather than the conference call transcript.

The remainder of the thesis proceeds as follows. Section II reviews existing literature regarding determinants of acquirer returns, voluntary disclosures, and textual analysis. Section III presents the hypothesises tested and their reasoning. Section IV describes the data, sample selection and the variables tested. Section V inspects the synergy forecasted deal characteristics. Section VI examines the impact of synergy disclosure on acquirer returns. Section VII analyses the moderated effect of synergy disclosure on acquirer returns. Section VIII concludes.

II. Literature review

II.1 Determinants of acquirer returns

Determinants of abnormal returns within mergers and acquisitions is a long-discussed topic, whereas earlier research often provides ambiguous results. In the article *Explaining M&A performance: a review of empirical research*, Das and Kapil (2012) structured an assessment of the past literature providing an extensive list of variables explaining M&A firm performance, both in the short- and long-term. However, this section examines primarily common short-term determinants of acquirer cumulative abnormal returns (CAR).

It is well-established in the M&A industry that the payment method is a significant predictor of abnormal returns. According to Myers & Maljuf (1984), the payment method reflects how the bidder management perceives their market valuation. Payment by cash gives the impression that the management perceives their stock as undervalued, while financing by equity implies the opposite. An early cornerstone article illustrating this is Travlos (1987), who concluded that all-stock transactions overall had negative abnormal returns, all-cash deals had "normal" returns, and the difference between the mean of the groups was significant. Similarly, Servaes (1991) finds that firms paying completely by cash increase the acquirer abnormal returns by 11%. On the other hand, Eckbo et al. (1990) argue that a mix of stock and cash payment outperforms either all-cash or all-stock bids in terms of abnormal returns.

A determinant of returns with more contradictory literature is relative deal size. For example, Asquith et al. (1983) find that the relative deal value is statistically significant and positively related to cumulative excess returns. In contrast, Travlos (1987) observe that relative size is negatively correlated with CAR over a two-day event window, even though not statistically significant. However, Moeller et al. (2004) report that the sign of the coefficient differs between the size of bidders where the relative deal size is statistically significant and negative (positive) for large (small) firms.

Unlike relative deal size, there is a consensus in the past literature that acquirer size is negatively correlated with cumulative abnormal returns (i.e., Golubov et al. (2015), Masulis et al. (2007), and Moeller et al. (2004)). The latter argues that this is related to the managerial hubris hypothesis (Roll, 1986), stating that, on average, large firms tend to overpay for their targets.

The public/private status of the target firm has been shown through previous literature to have an explanatory effect on CAR. For instance, Fuller et al. (2002) find that bidders experience significantly negative abnormal returns when the target firm is public and significantly positive returns acquiring private companies or subsidiaries. Furthermore, looking at domestic and cross-border acquisitions in the UK, Conn et al. (2005) find that the acquisitions of public companies, respectively, result in negative and zero announcement returns. Similar results also appear in Moeller et al. (2004) and Masulis et al. (2007), finding that large firms gain negative returns acquiring public companies, holding the payment method constant.

Considering industry-specific determinants of abnormal returns, merger-relatedness and high-tech industries are commonly studied in previous research. A well-cited article by Barney (1988) argues that firm relatedness between the bidder and target, per se, does not gain abnormal returns for the acquirer shareholders. Referring to Lubatkin (1987) and Singh and Montgomery (1987), there is no statistically significant evidence of excess returns for the acquiring firm shareholders in strategically related mergers. However, looking at M&As in the 1980s, Morck et al. (1990) found lower abnormal returns for the acquiring firm shareholders in diversified acquisitions. This is supported by Masulis et al. (2007), who also found that acquirer returns are lower, even though insignificantly, for unrelated acquisitions. Thus, prior literature is somewhat inconsistent.

Nevertheless, in the context of high-technology industries, Johnson et al. (2000) and Field et al. (2005) report that firms operating in these industries are associated with more uncertainty due to litigation risk. However, Kohers & Kohers (2001) examined the acquisitions of technology firms finding that bidder shareholders respond favourably to high-tech announcements with an initial average abnormal return of 0.92%, statistically significant at a 99% confidence level. This effect contrasts with what Masulis et al. (2007) found a few years later, where the coefficient was negative, albeit insignificant, in deals where both firms were categorized as high-tech.

Another firm-specific way of controlling for variations in acquirer returns is to use accounting measures. For example, the free cash flow hypothesis proposed by Jensen (1986) suggests that Tobin´s Q, leverage, and free cash flow (FCF) can be applied to predict takeover performance. Jensen (1986) argues that firms with ample free cash flows and unused borrowing power are likelier to attend low-benefit mergers. This is supported by Lang et al. (1991) finding that bidder returns are negatively related with FCF, and by Masulis et al. (2007) and Golubov et al.

(2015) finding that leverage has a positive effect on CARs. However, examining the relationship between Tobin´s Q and acquirer returns, the literature is ambiguous. While for instance, Servaes (1991) and Blose et al. (1997) find a significant positive relationship between the two, Golubov et al. (2015) report a significant negative impact of Tobin´s Q on bidder CAR in corporate takeovers.

II.2 Voluntary disclosure and M&A

A merger or acquisition is often a significant event for a corporation. Thus, the acquiring shareholders often expect to receive information from management about the deal´s risk level and related impact (Ott, 2020). A tool to mitigate information asymmetry and address shareholder demands can be engaging in voluntary disclosures. This way, management could impact how investors perceive the deal.

In the existing literature, voluntary disclosure is one of two main areas of literature on disclosure, the other being positive account theory. Healy et al. (2001) highlight six motives for a management´s voluntary disclosure, including capital market transactions, corporate control contests, stock compensation, litigations, proprietary costs, and management talent signalling. However, in broader terms, Kim et al. (2021) differentiate between two features: adverse selection and disclosure costs.

Prior literature in M&A has examined the relationship between voluntary disclosures and specific deal- and firm characteristics. For example, Kimbrough and Louis (2011) and Fraunhoffer et al. (2018) found that the probability of holding a deal-related conference call depends on the deal value and payment method. After controlling for endogeneity, the authors further find that a management´s decision to hold conference calls positively relates to the market reaction. Similar results are reported by Dutordoir et al. (2014), finding that companies use synergy disclosure to mitigate stock reaction in deals that otherwise would yield highly negative bidder returns. Hence, it appears from existing research that management actively employs voluntary disclosures as a means of action to mitigate adverse announcement responses.

However, the extent of the mitigation of market reactions depends on the credibility of the disclosure (Healy et al., 2001). Prior research reports that positive forecasts are less credible compared to lousy news projections and that the market reacts accordingly (Rogers & Stocken, 2005; Hutton et al. 2003). For example, Houston et al. (2001) found when examining synergies in bank mergers that the market tends to discount management projections and that the estimates disclosed were typically overly optimistic. Similar results are reported by Ng et al. (2013), finding that investors discount less credible management forecasts. Thus, the market reaction reflects the reliability of voluntary disclosures.

II.3 Textual analysis

In accounting and finance, textual analysis is an emerging area and a part of the broader literature on qualitative information (Loughran & McDonald, 2011). The concept is to rightfully reduce a large amount of qualitative data into numeric, quantitative information. Over the years, several different methods and models have been applied, all well summarized by Li (2010), Das (2014), Kearney & Liu (2014), and Loughran & McDonald (2016). However, the most frequent methods are categorized under topic modelling, document similarity, document readability, and sentiment analysis.

Common ways of measuring readability are often based on a text´s number of complex words and sentences (Das, 2014, p. 66). One of the most traditional measures used in financial research is the Fog Index, measuring readability as a function of average words per sentence and the percentage of complex words (words with more than two syllables). However, pioneers in textual analysis, Loughran and McDonald (2014), report that traditional readability instruments (i.e. Fog Index and the Flesch Indexes) are poor measures in the context of financial disclosures[1]. Using 10-K filings, they argue that file size can be a better alternative. Applying the size of "complete submission text file" from SEC Edgar as a proxy for readability, the authors found a significant positive relationship with post-filing date abnormal return volatility.

In behavioural finance, mainly investor and textual sentiment have been studied. The former identifies investor beliefs and behavioural characteristics towards a stock´s or a market´s future beyond the facts. Textual sentiment, however, in addition to capturing investor judgements, also includes more objective reflections (Kearney & Liu, 2014). Textual sentiment and tone are often used interchangeably and refer to a text´s positive/negative linguistic tone. However, in broad terms, the term sentiment may also include other word classifications like uncertainty, litigious and strong modal words (Loughran & McDonald, 2011).

[1] Loughran and McDonald (2014) argue that financial texts have a high percentage of complex words defined by the Fog Index that, however, are well understood (i.e., management, corporation, and agreement). They further conclude that sentence length as a measure of readability is less precise in financial disclosures than in other texts.

In textual sentiment analysis, the two most common methods applied in earlier literature are the dictionary approach and machine learning. The dictionary approach is based on pre-defined word lists, where a mapping algorithm is used to classify the different components of a text within the chosen glossaries (Li, 2010, p. 146). Commonly used dictionaries in financial research are the Harvard General Inquirer, Diction and L&M (Kearney & Liu, 2014). The machine learning method, however, is based on a statistical approach using a part of the corpus as a "training set". The words in the training set are each manually categorized within a dimension of sentiment (i.e., positive and negative) and learned using algorithms. Consequently, the trained algorithms are applied to the whole corpus to identify the textual sentiment.

Both the concept of readability and sentiment analysis are well applied in prior event studies. In the context of readability, previous literature in finance and accounting has mainly investigated the comprehensibility of annual reports (i.e., Guay et al., (2016), Loughran & McDonald (2014), Lawrence (2013), Lehavy et al. (2011) and Miller (2010)). However, an exception is De Franco et al. (2013), who found a statistically significant positive relationship between analyst reports` readability and abnormal trading volumes/returns over a three-day event window centred on report dates. In contrast to readability, sentiment analysis is well used across different types of corporate disclosures, summarized by Kearney and Liu (2014). For example, using short event windows (-1, +1), Davis et al. (2012), Feldman et al. (2010), and Price et al. (2012) find that the linguistic tone in, respectively, earnings press releases, MD&A sections[2], and conference calls, is significantly related with abnormal returns.

III. Hypothesis development

According to Verrecchia (1990, p. 375), "information of higher quality implies a lower threshold of disclosure and a greater probability of disclosure". Therefore, following Verrecchia´s information quality rationale, it is expected that management would not disclose low-quality synergy estimates considering the disclosures are voluntary and not obligatory. This is also supported by Dutordoir et al. (2014), whose findings indicate that the chance of disclosing synergies increases significantly with the confidence of the management estimates.

[2] MD&A is an abbreviation for Management Discussion and Analysis. Feldman et al. (2010) studied the MD&A sections in 10-K and 10-Q fillings.

Furthermore, as stated in Rule 10b-5 of the U.S. Securities Exchange Act 1934, "it is illegal for any person to defraud or deceive someone, including through the misrepresentation of material information, with respect to the sale or purchase of a security". Legal ramifications introduce litigation risk to the acquirer management, considering the potential lawsuits of disclosing estimated synergies with low quality. Following this reasoning, one might think managements only choose to disclose when considering the projected synergies as reliable. Because of the arguments made surrounding Verrecchia´s statement and rule 10b-5, investors are likely to react positively to the disclosure of estimated synergies. Therefore, the first hypothesis is as follows:

Hypothesis 1: *Disclosure of estimated synergies positively affects the market reaction.*

An expression says: "If people are told something often enough, they will believe it". Even though the intuition behind the proverb is about repeating a lie until people accept it as the truth, the theory of the illusory truth effect (Hasher & Goldstein, 1977), is an interesting theory to examine. In the article *Frequency and the conference of referential validity*, Hasher & Goldstein (1977) present an experiment finding a relationship between the repetition of plausible statements and a person´s belief in their validity. Although it is unlikely that managements explicitly lie about their projected synergies, the rationale of repeating the synergy effects could potentially affect shareholders´ incorporation of synergies in their valuations. Consequently, the second hypothesis is:

Hypothesis 2: *More frequent repetition of "synergies" in synergy-related investor presentations positively affects the market reaction.*

Several studies have applied textual analysis to different management disclosures and their effect on stock returns. For example, Loughran & McDonald (2011) found, using 10-Ks, that a higher proportion of negative words is associated with lower excess returns. On the other hand, Hu et al. (2021) applied sentimental analysis to M&A conference calls finding that a net positive tone has a statistically and economically significant negative relationship with abnormal bidder returns. They further found that information asymmetry mitigates the negative market reaction using public/private status for the target firm, the Herfindahl-Hirschman index, and information intensity as proxies for information asymmetry. Our data sample consists of only public targets; thus, the information asymmetry should be low, considering that investors have more access to information. Hence, shareholders can more easily tell whether managements are too optimistic in disclosing projected synergies. However, due to the ambiguous literature, the following hypotheses will be tested:

Hypothesis 3a*: Higher net tone in synergy-related investor presentations negatively affects the market reaction.*

Hypothesis 3b*: Higher net tone in synergy-related investor presentations positively affects the market reaction.*

An alternative way to analyse the approach of disclosing synergies is readability, whose concept and definition depend critically on the context of the text. We base our definition of readability on Loughran and McDonald (2014, p. 11) as the ability of individual investors and analysts to assimilate valuation-relevant information from investor presentations. Previous literature shows a connection between readability in annual/quarterly reports and firm financial performance/stock volatility. For instance, Li (2008) found a negative relationship between annual reports that are harder to read and firm earnings. Similar results are also presented by Loughran & McDonald (2010), who found that improved readability in 10-K fillings positively impacts absolute abnormal returns. Comparable tendencies are hypothesised to be observed in the disclosure of estimated synergies. If shareholders have difficulties understanding the content disclosed, our rationale is that they also pay less attention to the incorporation of projected synergies. Consequently, the fourth hypothesis is:

Hypothesis 4: *Higher readability in synergy-related investor presentations positively affects the market reaction*

IV. Data and methodology

This section covers the sample construction and the variables analysed throughout the paper. All variables can be found in greater detail in Appendix I. Following the significant number of computations involved in generating our variables, measurement errors might occur. Therefore, all continuous variables are winsorized at the 1st and 99th percentile.

IV.1 Data sample

IV.1.1 Sample selection

Our sample consists of completed mergers and acquisitions between publicly listed U.S. companies announced between January 1st, 2012, and December 31st, 2021, retrieved from

SDC Platinum. In line with Masulis et al. (2007) and Golubov et al. (2015), we have excluded deals with a transaction value of less than \$1 million and less than 1% of the bidder´s market capitalisation 11 days prior to the announcement. Furthermore, leveraged buyouts, spinoffs, recapitalisations, self-tenders, exchange offers, repurchases, minority stake repurchases, acquisitions of remaining interest, and privatisations are screened per Huang et al. (2016). We also require the bidder to own 100% of the target shares after the transaction. Additionally, following extant literature (e.g., Fuller et al. (2002) and Lee et al. (2018)), as well as the argument of Fama & French (1992), firms within the financial industry are removed. Lastly, deals with no available data from CRSP (within 210 trading days prior to announcements) or Compustat are also excluded. Consequently, after applying these filters, our dataset consists of 501 unique deals.

Table I: Sample selection

The table lists the criteria for admittance in the final sample in the first column and the number of deals remaining after each criterion in the second column. The selection is based primarily on data from SDC Platinum, with CRSP and Compustat being integral supplementary databases.

Selection criteria	No. of deals after screening
2012-2021 completed SDC deals between U.S public listed firms	2 257
Deal size \$1 million ≤	2 123
Exclusion of special deal types following Huang et al. (2016)	1 219
Acquirers own ≥ 100% of shares after transaction	1 191
Exclusion of deals from financial industries	678
Deal size ≥ 1% of bidder´s market capitalization	640
Available data in CRSP/Compustat	501
Final Sample	**501**

IV.1.2 Sample summary

Table II provides an overview of the deal distribution of our sample spanning from 2012-2021. The 501 observations are separated into two groups: *Disclosing and Non-Disclosing deals*. The two groups have respectively 191 and 310 observations.

The total amount of M&A deals differs substantially between the years, with the lowest number of deals in 2020 and 2021. Furthermore, the variation in the disclosure rate is considerable, ranging from approximately 26% in 2014 to 59% in 2017. In total, 38% of the deal announcements are accompanied by synergy estimates, significantly higher than the average of

17% in the Dutordoir et al. (2014) sample between 1995-2008. Overall, the disclosure of synergies has increased over time. Of the total sample 501 deals, 43% are accompanied by investor presentations. The percentage of deals with IP has shown a distinct upward trend, increasing from 26% in 2012 to 71% in 2021.

Table II: Yearly distributions of deals

This table displays the number and the relative size of the deals that disclose synergies and investor presentations per year. Deals are categorized as "Disclosing" if synergy estimates are attached to the deal in SDC. Investor presentations are retrieved from 8-K relevant M&A announcements in SEC EDGAR.

Year	Total Deals	Disclosing deals relative to whole sample	Deals with IPs relative to total deals
2012	50	30.00%	28.00%
2013	45	26.67%	31.11%
2014	57	26.32%	35.09%
2015	72	33.33%	36.11%
2016	64	46.88%	42.19%
2017	46	58.70%	43.48%
2018	60	35.00%	56.67%
2019	43	53.49%	48.84%
2020	30	43.33%	53.33%
2021	34	32.35%	70.59%
Total	**501**	**38.12%**	**43.11%**

IV.2 Investor presentations

Investor presentations are often provided as exhibits of M&A-related 8-K filings[3]. For each of the 501 deals in our final sample, we have searched manually through SEC EDGAR for 8-Ks. By law, the 8-K form must be filed within four days of an event (U.S. Securities and Exchange Commission, 2004). However, considering we operate with a five-day event window (-2, +2), we require the 8-Ks to be released within this period. Finally, available deal-related investor presentations are collected through the relevant 8-K filings.

[3] A form 8-K is a report a company is required to file to the SEC to inform shareholders about major events.

The format of the investor presentations downloaded from SEC EDGAR makes it challenging to gather textual information. Standard text extraction methods like PDF-converters do not work well, as extracting text directly from investor presentations often yields inconsistencies in the output quality (i.e., missing words or spaces). These inconsistencies are further aggravated by slides being uploaded as images. Consequently, optical character recognition (OCR) technology is identified as the most optimal solution because of its ability to extract text from images. The OCR from Google Vision AI is applied due to its accuracy and compatibility with programming languages.

However, a challenge in applying the OCR-approach to investor presentations is that it extracts irrelevant information from purely decorative content. For example, number plates on images of cars or warning signs on images of building sites are instances where the textual information is clearly immaterial to the objective of investor presentations. Consequently, each investor presentation is individually censored to resolve this concern.

Several variables presented in section IV.4 are based on the word count and the number of slides in investor presentations. In that regard, to avoid measurement error, we have provided a set of screening guidelines to be able to compare the presentations. The following are removed:

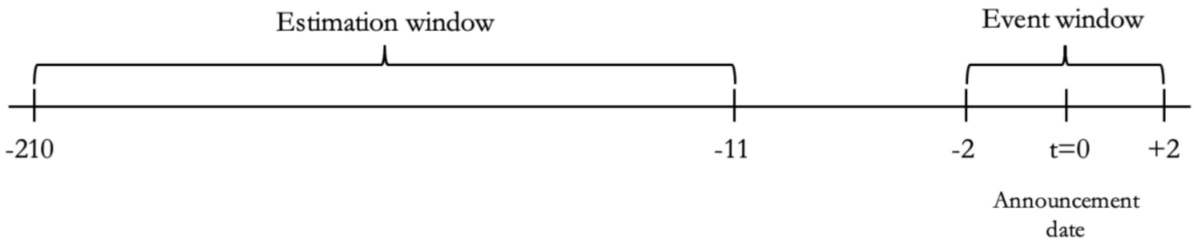
1. **Headline and agenda slides.** The number of these slides relative to total slides differs substantially between companies and does not contain any significant information to investors.
2. **Slides regarding disclaimers, Non-GAAP measures and reconsolidations**. Disclaimers are generally standardized and a formality full of legal jargon attempting to mitigate potential litigation risk, while Non-GAAP measures and reconciliations are specialized information, including adjusted accounting information and its explanation. The information on these slides is either not the objective of the investor presentation or very numeric and would therefore create unnecessary noise to our textual analysis.
3. **Repeated company catchphrases, watermarks, and copyrights stamps**. These are all removed due to their lack of deal-relevant information.

IV.3 Cumulative abnormal returns

To measure the acquirer initial announcement effects, we have used cumulative abnormal returns over a five-day event window (-2, +2) around the announcement day provided in SDC. We base our event window on a study from Fuller et al. (2002), who found that in a random sample of 500 companies, the announcement dates in SDC are correct in 92.6% of the cases. In the other instances the announcement date was within two days. In this way, we believe that an event window of (-2, +2) will capture most of the short-term acquirer initial announcement effects.

In calculating abnormal returns, the market model is employed using adjusted stock returns, as this is commonly used in event studies thoroughly explained by MacKinlay (1997) in *Event studies in Economics and Finance.* We utilize the CRSP value-weighted index as the benchmark, considering the firms incorporated in the index are all US-listed firms on either NYSE, AMEX, or NASDAQ, in line with our dataset. Following the argument of MacKinlay (1997), the estimation window is calculated over a 200-day (-210, -11) estimation period to prevent the M&A announcements from affecting the intercept and beta-coefficient in the calculation of abnormal returns.

Figure 1: Estimation period and event window



IV.4 Independent variables of interest

In our study, the main independent variable of interest is *Synergy Disclosure*. The variable is binary and takes the value one if projected synergies are disclosed and the value null otherwise. We base the classification on disclosing and non-disclosing deals on information retrieved from SDC, considering their estimates are based on "transactions disclosed as in the press or investor presentations/material" (Thomson Reuters, 2017, p. 200).

In further analysis, *Synergy Disclosure* is interacted with three moderation variables. These variables are based on the deal-related investor presentations retrieved from SEC EDGAR. The first moderator is *Synergy Emphasis* which is a measure of how often synergies are mentioned relative to the total number of words in the respective investor presentation. To capture all the variations of the word synergy, we count the stem "synerg".

The *Net Tone* of language is given by the net usage of positive words versus negative words scaled by the total amount of words in the given investor presentation. We apply the Loughran & McDonald (2011) dictionaries as these word lists are specified for financial texts and well-used in financial literature (i.e., Kostovetsky & Warner (2019), Hu et al. (2021) and Gómez-Cram & Grotteria (2022)).

The last moderator is *Readability*. By its very nature, investor presentations are usually quite figurative and contain fewer words than other types of disclosures. In addition, the text in the presentations is often provided as bullet points, making it difficult and less representative applying the Fog Index as a measure of readability. Another estimate of comprehensibility could be using the file size of the investor presentations, as Loughran and McDonald (2016) suggested when analysing 10-K fillings. However, we do not find this measure appropriate either because the non-textual material (i.e., illustrations, pictures, and graphs) that often makes the content easier to understand also increases the size of the file. Therefore, the increased file size will not necessarily mean less readability in the context of investor presentations. Consequently, the most common measures of readability within financial literature are not applicable to the nature of investor presentations.

We believe the average words per slide is a better proxy for investor presentations´ comprehensibility. Following the argument of Loughran & McDonald (2016, p. 1193), non-textual materials in document composition strengthen a reader´s ability to understand the presented material. In investor presentations, fewer words per slide mean more room for non-textual information implying a less convoluted text. To interpret the coefficient more efficiently, the words-per-slide ratio is divided by -100. Consequently, a higher *Readability* value is interpreted as a more readable investor presentation.

IV.5 Control variables

Based on previous literature regarding determinants of CAR, several control variables are included to increase the internal validity of the results. The firm-specific controls included are *Tobin´s Q*, *Free Cash Flow*, *Leverage*, *Acquirer Size* and *Litigation Risk*. The three formers are calculated using accounting data from each deal´s last ex-ante fiscal year, retrieved from Compustat. *Tobin´s Q* is originally a firm assets market value over its replacement value.

However, due to the complexity of calculating replacement value, we follow Masulis et al. (2007) and Golubov et al. (2015), using the assets´ market value over its book value as a proxy. Regarding *Free Cash Flow* and *Leverage*, the key figures are scaled by, respectively, the book and market value of assets to have the measures relative to the bidder size. Furthermore, the *Acquirer Size* is calculated as the natural logarithm of a firm´s market capitalization 11 days before the announcement date to avoid bias from market reaction to the M&A following Golubov et al. (2015). Data on *Acquirer Size* is retrieved from CRSP. Finally, we also create a binary variable, *Litigation Risk*, taking the value one if the acquirer operates in industries that, according to Johnson et al. (2001), are exposed to litigation risk.

The deal-specific variables include *Relative Size*, *Method of Payment*, *Same Industry*, and *High-Tech*. These variables are put together using data from both CRSP and SDC Platinum. *Relative Size* is calculated as the transaction value retrieved from SDC relative to the *Acquirer Size*. The *Method of Payment* is split into the two dummy variables 100%-cash and 100%-stock, which divides the set of deals into three categories; cash-deals, stock-deals, and deals with mixed or unknown methods of payment. Furthermore, controlling for horizontal mergers, the binary variable *Same Industry* is created, taking the value one if the target and acquirer share the same two-digit SIC code and null otherwise. Additionally, a *High-Tech* dummy variable is included taking on the value one if the target is categorized as in the high-tech industry and null otherwise, following categorization from Loughran & Ritter (2004).

V. Univariate analysis of disclosure decision

In Table III, we present a univariate analysis of CAR, deal- and firm-specific characteristics separated by disclosing and non-disclosing deals. The analysis is intended to illustrate the difference in characteristics of the two groups of deals.

Overall, the bidder stock return is negative for U.S. public deals, consistent with the hubris hypothesis. However, the average *CAR* for disclosing deals is 0.4% higher than for non-disclosing deals, albeit the difference is not statistically significant. The lack of significance is naturally explained by large variations in the groups´ deal- and firm-specific characteristics, indicating that the multiple regression analysis in section VI can provide better insight. The firm-specific variables in the table, *Acquirer Size, Tobin´s Q, Leverage* and *Free Cash Flow*, do not show any statistically significant differences between the two groups.

Table III: Univariate analysis for disclosing and non-disclosing deals

*This table presents an overview of the differences in means/medians of dependent and independent variables, given the two groups Disclosing and Non-Disclosing deals. The variables are divided into Dependent Variable, Firm-Specific Characteristics and Deal-Specific Characteristics. A detailed description of the variables can be found in Appendix I. In the last column, t- and z-values are reported—t-values for the continuous variables and z-values for the binary variables. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	Disclosing Deals (N=191)		Non-Disclosing Deals (N=310)		t-/z statistic for difference in means
	Mean	Median	Mean	Median	
Dependent Variable					
CAR(-2, +2)	-0.0030	-0.0061	-0.0071	-0.0044	-0.54
Firm-Specific Characteristics					
Acquirer Size	8.5491	8.4395	8.8091	8.9349	1.52
Tobin´s Q	2.0703	1.7306	2.1569	1.7193	0.71
Leverage	0.1987	0.1593	0.1977	0.1569	-0.07
Free Cash Flow	0.0347	0.0544	0.0317	0.0590	-0.28
Litigation Risk	0.1309		0.2677		3.62***
Deal-Specific Characteristics					
Relative Size	0.5219	0.4485	0.3107	0.1433	-6.00***
All Cash	0.2775		0.5096		5.11***
All Stock	0.2880		0.1677		-3.19***
Same Industry	0.7644		0.6935		-1.72*
High-Tech	0.2304		0.3548		2.93***

For the variable *Relative Size*, we observe large differences between the two groups´ median. These dissimilarities are also reflected in the differences in means, statistically significant at 1%. Intuitively, this makes sense as a larger relative size represents significant investments for the acquiring company, giving incentives for the management to "justify" the deal for the bidder firm shareholders. Furthermore, the difference in means for *Litigation Risk* is statistically significant. The difference can be explained by the additional uncertainty synergy disclosure entails for companies already subject to litigation risk (Field et al., 2005).

Moreover, we find that the payment method differs significantly between the disclosing and non-disclosing deals. In public deals, paying purely by cash may indicate that acquiring management believes their stock is undervalued, while the opposite can explain all-stock deals.

In line with the signalling hypothesis, the result supports that managements use synergy disclosure to mitigate deals that can be poorly perceived by shareholders.

Regarding *Same Industry* and *High-Tech*, the differences between the groups are, respectively, significant at 10% and 1%. Allegedly, the former can be explained by the fact that it is easier to calculate synergies in horizontal mergers, considering that the acquiring management will have more knowledge of the industry in which the target operates. The differences are in line with Verrecchia´s (1990) statement that the disclosure decision is a function of the information quality.

VI. Synergy disclosures effect on acquirer returns

The disclosure of synergies` effect on bidder stock returns is examined through OLS regressions provided in Table IV. Common for all our models throughout the paper is that variables are observed in different time periods and across different industries. Hence, all regressions are controlled for the year- and industry-fixed effects. To control for the latter, we use macro industries retrieved from SDC to avoid overfitting our models rather than the Fama-French 48 industry groupings and acquirer two-digit SIC[4]. Furthermore, the model statistics are based on robust clustered standard errors allowing for correlation between observations within the macro industries.

From Model 1, the sign of the coefficient on *Disclosing Synergies* is in line with H1, suggesting that disclosing deals are associated with 0.8% higher abnormal returns over a five-day event window. However, the coefficient is not statistically significant, preventing us from rejecting H0. Allegedly, a primary concern with our model is omitted variable bias where other firm- and deal-specific characteristics not included in the model are both correlated with acquirer returns and the decision to disclose synergies. This way, the model will suffer from endogeneity. Interestingly, *All Cash* and *Same Industry* are statistically significant at 5%. The former suggests that in public deals, payment exclusively in cash yields, on average, 2.7% higher stock returns relative to a payment consisting of a mix of cash and stock. This is consistent with the argument of Myers & Maljuf (1984). In turn, *Same Industry* can be interpreted as the market reacting positively, with about 1.7%, to horizontal M&As.

[4] Employing the two-digit SIC provides 51 different industries in our data sample and yields some industry groupings with very few observations.

To control for the endogeneity issue in Model 1, we apply the Heckman (1979) two-stage treatment effect model. We use this model rather than the Heckman (1979) sample selection model because we have outcome observations (*CAR*) for both the disclosing and non-disclosing deals. The first stage of the treatment model is a probit analysis of the decision to disclose synergies, provided in Appendix II. From this model, the *Inverse Mills Ratio* is calculated for each deal. The ratio is the probability of the management deciding to disclose synergies over the cumulative probability of a management decision to disclose. It is used in Model 2, which is similar to the original regression (Model 1) but controlled for endogeneity. From Model 2, the inclusion of the *Inverse Mills Ratio* does not have any apparent effect on the variable of interest. Reportedly, the ratio is statistically insignificant, suggesting that endogeneity is not a problem in our models. Therefore, the regression results align with the univariate analysis in Table III, implying that the disclosure of synergies is not statistically significantly associated with acquirer returns[5].

We notice that the regression results differ substantially, both statistically and economically, from Dutordoir et al. (2014), whose findings suggest that the disclosure of synergies is associated with approximately 5% higher abnormal returns. From a research design perspective, the difference can be elucidated by our different sample sizes, criteria and models. Alternatively, it can be explained by increased voluntary disclosures and online availability in the last decade, reducing the information asymmetry between investors and shareholders. This way, shareholders are more informed and can more easily tell the difference between inflated and realistic estimates.

There might be underlying nuances in the disclosure itself due to the uncertainty surrounding the estimation of synergies. We expect the market reaction to not only reflect management´s decision to disclose synergies but also incorporate how the estimates are disclosed. Therefore, examining only the impact of *Synergy Disclosure* on bidder returns in isolation can prove too simple and be the source of the insignificant results in Model 1 and Model 2. The disclosure approach consequently motivates our analyses in the forthcoming section.

[5] As a test of robustness, we tested CAR with event windows of (-1, +1) and (-3, +3) on models 1 and 2, which yielded the same lack of results. Regressions are listed in Appendix III.

Table IV: Regression on CAR (-2, +2)

*This table presents regression results on CAR in the event window -2, +2 around the announcement date. The market model is employed using the CRSP value-weighted market index as a benchmark. Robust standard errors clustered around SDC macro industries are used to calculate the t-values denoted in parenthesizes. The variable of interest is Synergy Disclosure, taking a value of one if a deal announcement is accompanied by a synergy estimate and zero otherwise. The Inverse Mills Ratio in Model 2 is included to control for endogeneity in the regression and is based on the probit analysis in Appendix II. Firm- and deal-specific control variables, as well as year- and industry-fixed effects, are included in both models. In Appendix I, a description of the variables can be found. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	**Model (1)**	**Model (2)**
Synergy Disclosure	0.0075	0.0076
	(0.50)	(0.50)
Acquirer Size	-0.0014	-0.0004
	(-0.62)	(-0.12)
Tobin´s Q	-0.0055	-0.0064
	(-1.39)	(-1.40)
Leverage	0.0313	0.0175
	(0.90)	(0.41)
Free Cash Flow	0.0068	0.0116
	(0.20)	(0.39)
Litigation Risk	-0.0979	-0.0182
	(-0.61)	(-1.07)
Relative Size	0.0085	0.0193
	(0.35)	(0.68)
All Cash	0.0273**	0.0209
	(2.75)	(1.12)
All Stock	-0.0059	-0.0018
	(-0.38)	(-0.16)
Same Industry	0.0168**	0.0219
	(2.47)	(1.63)
High-Tech	-0.0059	-0.0151
	(-0.70)	(-0.85)
Inverse Mills Ratio		0.0204
		(0.55)
_cons	-0.0094	-0.0417
	(-0.28)	(-0.58)
Year Fixed Effects	Yes	Yes
Macro Industry Fixed Effects	Yes	Yes
N	501	501
R-sq	0.15	0.15
Adj. R-sq	0.095	0.094

VII. The composition of investor presentations and their impact on acquirer returns

VII.1 Univariate analysis

To answer how the market reaction varies in line with the voluntary synergy disclosure approach, we have employed three variables capturing the investor presentations synergy emphasis, tone, and comprehensibility. A univariate analysis of the variables is presented in Table V.

Table V: Univariate analysis of textual components

*This table presents an overview of the differences in means of the three moderators of H2-H4, given the two groups Disclosing and Non-Disclosing deals. In the last column, the t-statistics are reported. Medians accompany the variables' mean to get further insight into the variations. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	Disclosing Deals (N=115)		Non-Disclosing Deals (N=101)		t-statistic for difference in means
	Mean	Median	Mean	Median	
Synergy Emphasis	0.582%	0.498%	0.215%	0.061%	-7.90***
Net Tone	2.018%	1.912%	1.444%	1.418%	-3.93***
Readability	-1.218	-1.172	-1.271	-1.224	-0.97

The difference in means of *Synergy Emphasis* (capturing how often the word synergy is mentioned in IPs) between disclosing and non-disclosing deals is highly statistically significant. This aligns with our expectations and intuitively makes sense, as acquirers voluntarily disclosing synergies naturally will mention synergies more in deal-related investor presentations. Interestingly, the median and mean for non-disclosing deals differ from zero, indicating that deals defined as non-disclosing also comment on synergies. However, rather than disclosing quantitative estimates, these deals mention the source of-, the role of- or the importance of the synergies and is therefore not categorized as disclosing deals.

Furthermore, the table illustrates that, on average deal-related investor presentations have a positive *Net Tone*. In both groups, the median follows the mean closely, indicating that the mean is a representable basis for comparison. Notably, the difference between the two groups differs significantly, with 0.58% higher net tone, in favour of disclosing deals. Hence, on average, managers tend to use a more positive tone when voluntarily disclosing synergies. Based on these results, expectations are attached to the multivariate analysis of *Net Tone's* effect on *CAR,* as the variation between the groups is of such magnitude.

Finally, the proxy variable for IP-readability is presented. The closely following mean and medians are both marginally higher for disclosing deals, suggesting that these deals are slightly more readable. The difference, however, is not statistically significant. Nevertheless, it still might prove significant when included in a regression on abnormal returns.

VII.2 Regression analysis

We examine the three moderator variables in three separate regressions in Table VI. Each moderator, along with the synergy disclosure variable and an interaction term between the two, are included. Doing this separates the individual effect of the moderator from the additive effect it has on the disclosing deals.

There are a lot of contradictory approaches to interpreting main effects and interaction variables. As the three variables we want to test in this section function as moderators, and the fact that the main effects intuitively are hard to interpret by themselves when including an interaction term, we use an Extended Simple Slopes Analysis[6], as advised by Busenbark et al. (2022). This analysis examines the first derivative of the regression model with respect to *Synergy Disclosure*. Using this analysis, we examine the relationship of X (*Synergy Disclosure*) on Y (*CAR*), given different values of Z (the moderator variable) (Busenbark et al., 2022). The first-order regression will be as follows:

$$\frac{\delta Y}{\delta X} = \beta_1 + \beta_3 Z \qquad (1)$$

with β_1 being the regressions coefficient for *Synergy Disclosure* and β_3 being the coefficient of the interaction term. The value and confidence interval of the *Synergy Disclosure*'s impact on *CAR* will consequently be dependent on the value of β_1, β_3 and Z.

[6] The Extended Simple Slopes Analysis is not used a lot in management literature, though it is on the rise (Busenbark et al., 2022). Only 7% of a sample of 151 articles from three different journals used this approach.

Table VI: Regression on CAR (-2, +2) including interaction terms

*This table presents regression results on CAR in the window -2, +2 around the announcement date. The calculation of abnormal returns is based on the market model employing CRSP value-weighted market index. Models (3), (4) and (5) test respectively hypotheses 2, 3 and 4. Robust standard errors clustered around SDC macro industries are used to calculate the t-values denoted in parenthesizes. Inverse Mills Ratio is included in all regressions to control for endogeneity and is based on the probit analysis in Appendix II. Additional controls and year- and industry-fixed effects are controlled for in all models. The additional controls are the firm- and deal-specific characteristics described in Appendix I. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	**Model (3)**	**Model (4)**	**Model (5)**
Synergy Disclosure	-0.0056	-0.0349	-0.0597
	(-0.03)	(-1.41)	(-0.98)
Synergy Emphasis	-1.3679		
	(-0.27)		
Synergy Disclosure * Synergy Emphasis	0.4473		
	(0.11)		
Net tone		-1.1806	
		(-1.44)	
Synergy Disclosure * Net tone		1.9754**	
		(2.31)	
Readability			-0.0053
			(0.22)
Synergy Disclosure * Readability			-0.0458
			(1.08)
Inverse Mills Ratio	0.1240**	0.1118**	0.1077*
	(2.47)	(2.58)	(2.33)
_cons	-0.1900*	-0.1545	-0.1711
	(-1.87)	(-1.64)	(-1.68)
Additional controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Macro Industry Fixed Effects	Yes	Yes	Yes
N	216	216	216
R-sq	0.253	0.263	0.267
Adj. R-sq	0.117	0.129	0.134

Model 3 tests H2, examining the illusory truth effect in disclosing deals and its impact on acquirer returns. We interpret this theory as that an increase in synergy emphasis and repetition will lead to more believable synergy estimations. However, *Synergy Disclosure*, *Synergy Emphasis,* and the interaction between them are statistically insignificant. Following the illusory truth effect, we assumed that at least some synergy estimates are conceived initially to be improbable or uncertain. The lack of significance can be due to projected synergy estimates mostly being convincing without extra emphasis, underpinned by Verrecchia´s information quality rationale. If the effect was working, but only a tiny portion of the deals lacked validity, the estimated regression would struggle to capture the significance of the effect due to the amount of variation.

The regression results in Model 4 attempt to answer how the *Net Tone* of synergy disclosure affects bidder stock returns. The coefficient of the interaction term is statistically significant; however, the main effects are not. The insignificance of the main effects is inconsequential as the variables cannot be interpreted individually, coinciding with the *Principle of Marginality* (Nelder, 1977)[7]. We observe a cross-over interaction illustrated in Figure II, where a higher net tone in investor presentations has opposite effects depending on whether the management voluntarily discloses synergies or not. Visually, the difference between disclosing and non-disclosing deals seems substantial depending on the level of net tone used in the investor presentation. The slopes cross at a *Net Tone* of 1.77%, indicating that for presentations with levels of tone above (below) this threshold, the decision to disclose (not to disclose) is the most beneficial concerning *CAR*. This analysis, however, is not considering the variance of the variables.

[7] The Principle of Marginality was described by Nelder (1977) in "A Reformulation of Linear Models". The principle limits the ability of interpreting individual effects, by claiming the main effects and interaction term have to be explained in relation to each other at all times to provide an effective interpretation.

Figure 2: Interaction plot

The figure displays the effect of the difference in change in net tone in the total regression equation, between disclosing and non-disclosing deals. The x-axis is Net Tone, while the Y-axis is relative CAR. The dashed line depicts the slope of Net Tone given Synergy Disclosure = 0, while the full line depicts the slope of Net Tone given Synergy Disclosure = 1.

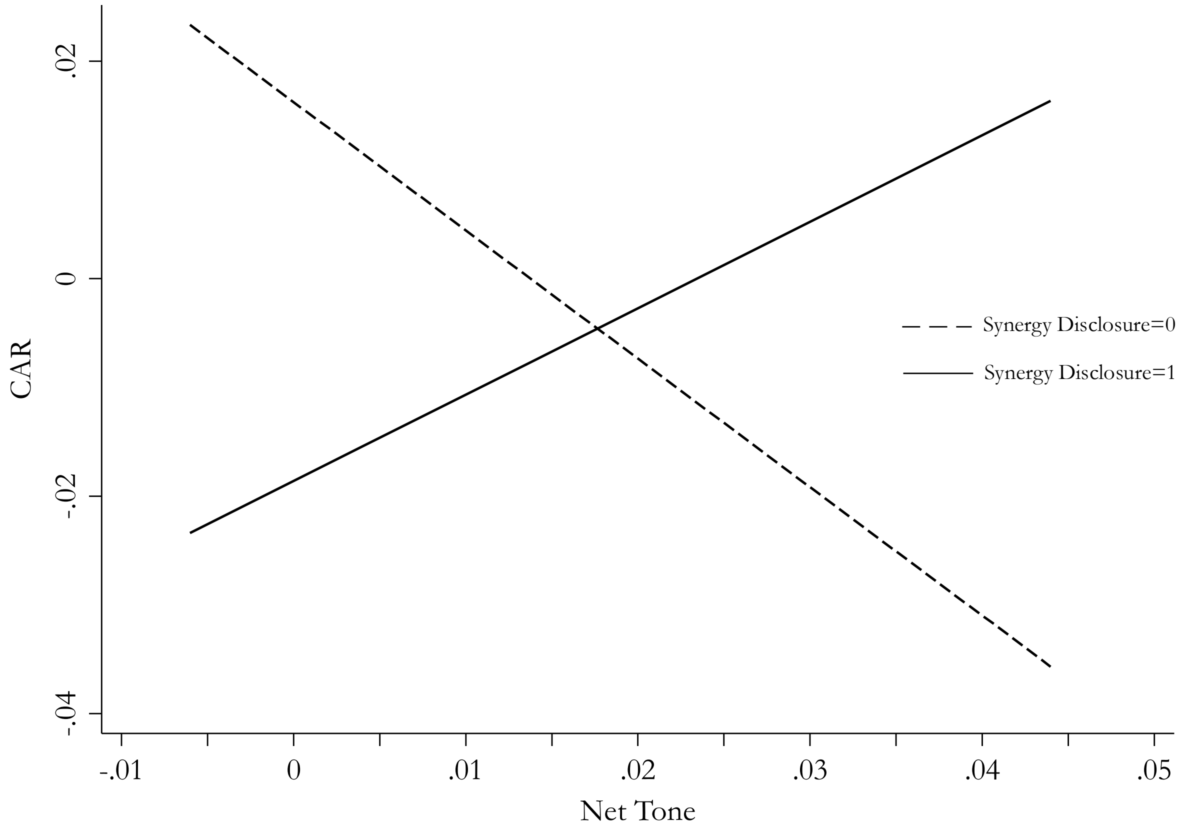
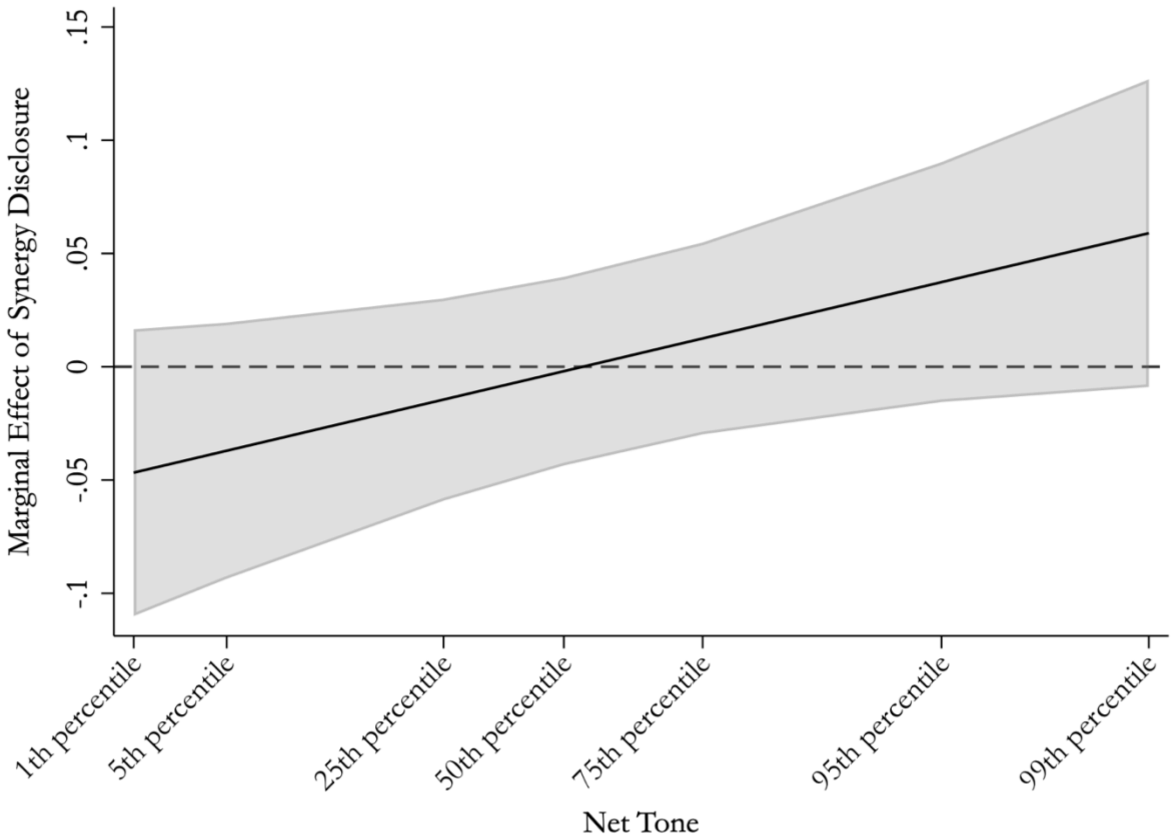


Figure III shows the marginal effect of *Synergy Disclosure* and its concomitant confidence interval for different levels of *Net Tone*. At all levels, the confidence interval overlaps with zero, preventing us from concluding anything significant at the 5% level. Though at the 10% level, the 99th percentile is significantly higher than zero. Visually, the confidence interval is notably lower at small percentiles of *Net Tone* compared to large percentiles of *Net Tone*, making the interaction significant.

An observation of interest is that the trend line may possess a predictive capability outside of our data. For example, suppose that, even though the confidence interval would expand due to fewer observations in the tail ends, the trendline was expanded beyond our data area. In that case, synergy disclosure´s effect might be significantly lower or higher than zero at a very low or a very high *Net Tone*. This supposition is valid if the claim holds that it is possible to have a net tone either lower than -0.6% or higher than 4.8%, which it is reasonable to believe it does. A more extensive or targeted sample may prove this, making it a source of interest for further research.

Figure 3: Marginal effect

This figure depicts the marginal effects of Synergy Disclosure on CAR, at different levels of Net Tone. Equation 1 depicts the line. The trend line is based on the predictive values of Synergy Disclosure at each listed percentile of Net Tone, accompanied by a concomitant 95% confidence interval.



Model 5 attends to H4, examining the effect of readability in disclosing deal investor presentations on bidder stock returns. Neither the main effects nor the interaction term is statistically significant. Even though the proxy *Readability* is intended to be a measure of the presentations´ comprehensibility, it simultaneously might be a measure of its informativeness. This will be because a higher word-per-slide ratio may induce more information in investor presentations, prompting a reduction in information asymmetry between management and shareholders. Consequently, the proxy variable might be a measure of two oppositely working forces that potentially impact *CAR*.

Another explanation for the lack of significant results might be the nature of investor presentations. If the purpose of IPs is meant to convey important information in the easiest way possible, the variance in presentations´ comprehensibility is likely to be minor. This way, a readability measure is less likely to explain the difference in acquirer returns as the content of investor presentations on most occasions are easily understood.

In Models 3 to 5, the treatment effect model is applied to the regressions, introducing a major concern for high levels of multicollinearity (Lennox et al., 2012). The multicollinearity in our case can arise in the absence of exclusion restrictions, as we have the same independent variables in the first- and second-stage models. Due to this concern, we have tested Models 3 to 5 without the Inverse Mills Ratio (see Appendix IV), which yielded the same results on all variables of interest. We have further included a correlation matrix in Appendix V. All pairwise correlations are below the "folk-lore" threshold of 0.7 (Dormann et al., 2013), with the highest being 0.48. Our concern of multicollinearity seems, therefore, to be a slight concern.

VIII. Conclusion

In this thesis, we have examined whether managements should disclose estimated synergies in M&A and how they should approach the disclosure in investor presentations. From relevant literature on disclosure and textual analysis, we derive a fitting dataset and gather appropriate measures for analysing investor presentations and market returns.

Initially, we tested the unmoderated effect of synergy disclosure with- and without controlling for endogeneity on acquirer returns and were left without any statistically significant results. Supposing that the insignificant results originated in the approach managers take to disclose the synergies, we further analysed the textual composition of the disclosure.

Three variables extracted from investor presentations´ textual composition were used to moderate the disclosure decision. The *Net Tone* of the presentations was the only moderator whose interaction term with *Synergy Disclosure* had a statistically significant impact on acquirer returns. Examining the first derivative of the regression with respect to *Synergy Disclosure*, we observe that the decision to disclose at a high positive tone has a significantly different effect on acquirer returns than at low tone levels. From an economic perspective, a disclosing deal with a higher net tone will, ceteris paribus, significantly outperform a disclosing deal with a low net tone.

The two other moderators, *Readability* and *Synergy Emphasis*, did not show any results of statistical significance. Investor presentations natural comprehensibility, along with bias in the proxy, indicated that *Readability* might lack validity and struggle to capture the sought-after effect. The lack of significance in *Synergy Emphasis* is likely due to the illusory truth effect not having the expected impact on an investor´s ability to judge synergy estimates.

Overall, we cannot differentiate the effect on short-term acquirer returns of the management decision to disclose synergies or not. However, if management chooses to disclose synergies, the estimates should be presented with a highly positive tone. Assuming there are observations of particularly positive or negative net tone, the decision to disclose synergies may have a significant impact on bidder returns.

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IX. Appendix

IX.1 Variable definitions

Variable:	Definition:
Panel A: Cumulative abnormal returns	
CAR (-2, +2)	The cumulative abnormal returns over a five-day event window around the announcement date. The market model is employed using a 200-day (-210, -11) estimation window for the parameters. The CRSP value-weighted index is used as a benchmark index. The calculation of abnormal returns using the market model is given by: $AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,i})$ Where $R_{i,t}$ is the actual adjusted stock return for a given firm *i* in event window *t*, and α and β (calculated with OLS-regression) is used in the estimation of normal return. R_m is the actual return from the CRSP value-weighted index. The calculation of cumulative abnormal return for firm *i* is given by the sum of the abnormal returns over the event window: $CAR_i(t_{-2}, t_{+2}) = \sum_{t=t_2}^{t_{-2}} AR_{i,t}$
Panel B: Independent variables of interest	
Synergy Disclosure	Binary variable taking the value one if acquiring firm have disclosed synergy estimated according to SDC, and null otherwise.
Synergy Emphasis	Number of times the stem "synerg" is used relative to total number of words in the deal-related investor presentation
Net Tone	The net tone in deal-related investor presentations using Loughran & McDonald (2011) dictionary. The net tone is given by: $\frac{Number\ of\ positive\ words - Number\ of\ negative\ words}{Total\ number\ of\ words}$
Readability	Total number of words relative to the total number of slides within the deal-related investor presentation. The ratio is multiplied by (-100) for interpretation purposes.
Panel C: Firm-specific characteristics	
Acquirer Size	The natural logarithm of market capitalization 11 days prior to M&A announcement.

Tobin´s Q	The market value of bidder assets over the book value of bidder assets measured last fiscal year: $$\frac{Total\ assets - Common\ equity + (Common\ shares\ outstanding * Stock\ price\ )}{Total\ assets}$$
Leverage	Bidder total debt over market value of bidder assets last fiscal year: $$\frac{Long\ term\ debt + Debt\ in\ current\ liabilities}{Total\ assets - Common\ equity + (Common\ shares\ outstanding * Stock\ price\ )}$$
Free Cash Flow	Bidder free cash flow over book value of total assets last fiscal year: $$\frac{Operating\ income\ before\ depreciation - Interest\ and\ related\ expense - Income\ taxes - Capital\ expenditures}{Total\ assets}$$
Litigation Risk	Binary variable taking the value one if acquirer is according to Johnson et al. (2001) in industries that often are target to litigation risk, and null otherwise

Panel D: Deal-specific characteristics	
Relative Size	Transaction value divided by acquirer´s market value 11 days prior to the announcement
All Cash	Binary variable taking the value one if the deal is purely financed with cash, and null otherwise
All Stock	Binary variable taking the value one if the deal is purely financed with stock, and null otherwise
Same Industry	Binary variable taking the value one if acquirer and target firm share the two first SIC digits, and null otherwise
High-Tech	Binary variable taking the value one if target firm are according to Loughran & Ritter (2004) categorized as high-tech, and null otherwise

IX.2 Probit analysis on Synergy Disclosure

*This table presents a probit analysis of the decision to disclose synergies. The dependent variable Synergy Disclosure is a binary variable taking the value one if synergies estimates are attached to the deal in SDC and zero otherwise. Explanatory variables are described in Appendix I. The coefficients confidence interval at 95% are computed in the brackets. The model includes both year- and industry-fixed effects. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	**Coefficient**	**[95% conf.**	**Interval]**
Acquirer Size	0.072	[-0.020	0.164]
Tobin´s Q	-0.058	[-0.174	0.058]
Leverage	-0.969	[-2.492	0.553]
Free Cash Flow	0.433	[-0.652	1.519]
Litigation Risk	-0.578***	[-0.834	-0.321]
Relative Size	0.852***	[0.508	1.197]
All Cash	-0.452***	[-0.674	-0.230]
All Stock	0.283	[-0.068	0.635]
Same Industry	0.347**	[0.075	0.620]
High-Tech	-0.648**	[-1.265	-0.031]
_cons	-1.136**	[-2.051	-0.220]
Year Fixed Effects	Yes		
Macro Industry Fixed Effects	Yes		
N	501		
Pseudo R-sq	0.203		

IX.3 Regression with other event windows

*This table presents a robustness test for the dependent variable CAR in Models 1 and 2. Two different event windows are examined, respectively (-1, +1) and (-3, +3). The market model is employed using the CRSP value-weighted market index as a benchmark. Robust standard errors clustered around SDC macro industries are used to calculate the t-values denoted in parenthesizes. The variable of interest is Synergy Disclosure, taking a value of one if a deal announcement is accompanied by a synergy estimate and zero otherwise. The Inverse Mills Ratio in Model 2 is included to control for endogeneity in the regression and is based on the probit analysis in Appendix II. Firm- and deal-specific control variables, as well as year- and industry-fixed effects, are included in both models. In Appendix I, a description of the variables can be found. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	**CAR (-1, +1)**	**CAR (-3, +3)**	**CAR (-1, +1)**	**CAR (-3, +3)**
Synergy Disclosure	0.0079	0.0138	0.0081	0.0140
	(0.57)	(0.97)	(0.57)	(0.98)
Acquirer Size	-0.0011	-0.0036	0.0002	-0.0021
	(-0.52)	(-1.39)	(0.06)	(-0.53)
Tobin´s Q	-0.0062*	-0.0071	-0.0073*	-0.0085
	(-1.86)	(-1.43)	(-1.84)	(-1.66)
Leverage	0.0334	0.0582	0.0156	0.0372
	(0.87)	(1.53)	(0.34)	(0.90)
Free Cash Flow	0.0042	0.0427	0.0103	0.0499*
	(0.20)	(1.46)	(0.51)	(2.00)
Litigation Risk	-0.0121	0.0038	-0.0230*	-0.0090
	(-1.20)	(0.20)	(-2.17)	(-0.37)
Relative Size	0.0102	-0.0074	0.0240	0.0089
	(0.51)	(-0.32)	(1.40)	(0.28)
All Cash	0.0299**	0.0235*	0.0216	0.0136
	(2.93)	(2.09)	(1.26)	(0.74)
All Stock	-0.0048	-0.0042	0.0005	0.0020
	(-0.40)	(-0.26)	(0.05)	(0.14)
Same Industry	0.0115	0.0183*	0.0180	0.0260
	(1.67)	(2.14)	(1.69)	(1.46)
High-Tech	-0.0010	-0.0018	-0.0130	-0.0158
	(-0.15)	(-0.15)	(-1.03)	(-0.68)
Inverse Mills Ratio			0.0264	0.0311
			(1.03)	(0.73)
_cons	-0.0065	0.0080	-0.0483	-0.0411
	(-0.23)	(0.20)	(1.03)	(-0.45)
Year Fixed Effects	Yes	Yes	Yes	Yes
Macro Industry Fixed Effects	Yes	Yes	Yes	Yes
N	499	499	499	499
R-sq	0.171	0.145	0.171	0.145
Adj. R-sq	0.117	0.09	0.116	0.089

IX.4 Regressions without controlling for endogeneity

*This table presents regression results on CAR in the window -2, +2 around the announcement date. The calculation of abnormal returns is based on the market model employing CRSP value-weighted market index. Robust standard errors clustered around SDC macro industries are used to calculate the t-values denoted in parenthesizes. Additional controls, year- and industry-fixed effects are controlled for in all models. The additional controls are the firm- and deal-specific characteristics described in Appendix I. Respectively, *, **, and *** denote significance at the 10%, 5% and 1% levels.*

Variables	**Model (3)**	**Model (4)**	**Model (5)**
Synergy Disclosure	-0.0056	-0.0386	-0.0647
	(-0.27)	(-1.48)	(-1.05)
Synergy Emphasis	-1.1843		
	(-0.24)		
Synergy Disclosure * Synergy Emphasis	0.7955		
	(0.20)		
Net Tone		-1.2058	
		(-1.45)	
Synergy Disclosure * Net Tone		2.0499**	
		(2.33)	
Readability			0.0051
			(0.22)
Synergy Disclosure * Readability			0.0479
			(1.12)
_cons	0.0029	0.0213	-0.0022
	(0.05)	(0.41)	(-0.04)
Additional controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Macro Industry Fixed Effects	Yes	Yes	Yes
N	216	216	216
R-sq	0.244	0.256	0.261
Adj. R-sq	0.112	0.126	0.132

IX.5 Correlation Matrix

This table presents a correlation matrix. The Pearson´s correlations are based on the sample of 501 observations, except for Synergy Emphasis, Net Tone, and Readability, where all related correlations are based on 216 observations.

Variables	Synergy Disclosure	Acquirer Size	Tobin´s Q	Leverage	Free Cash Flow	Litigation Risk	Relative Size	All Cash	All Stock	Same Industry	High-Tech	Synergy Emphasis (N=216)	Net Tone (N=216)	Readability (N=216)
Synergy Disclosure	1.000													
Acquirer Size	-0.068	1.000												
Tobin´s Q	-0.032	0.196	1.000											
Leverage	0.003	-0.118	-0.451	1.000										
Free Cash Flow	0.012	0.372	-0.004	-0.111	1.000									
Litigation Risk	-0.162	0.240	0.287	-0.260	0.029	1.000								
Relative Size	0.259	-0.386	-0.135	0.179	-0.175	-0.233	1.000							
All Cash	-0.228	0.229	0.093	-0.230	0.284	0.251	-0.447	1.000						
All Stock	0.142	-0.260	-0.044	0.084	-0.302	-0.167	0.220	-0.445	1.000					
Same Industry	0.077	-0.016	0.043	0.094	-0.079	0.088	0.070	-0.081	0.031	1.000				
High-Tech	-0.131	0.038	0.214	-0.288	0.073	0.198	-0.144	0.247	-0.115	-0.009	1.000			
Synergy Emphasis (N=216)	0.475	-0.181	-0.080	-0.016	0.147	-0.233	0.206	-0.069	-0.062	0.022	0.012	1.000		
Net Tone (N=216)	0.260	0.065	0.005	-0.091	0.061	-0.031	0.015	0.008	-0.030	0.039	0.038	0.277	1.000	
Readability (N=216)	-0.066	-0.157	-0.206	0.410	-0.198	-0.133	0.166	-0.266	0.230	0.026	-0.266	-0.178	-0.269	1.000