The Noise Share of the 52-Week Price-Peak Effect on Mergers and Acquisitions[*]

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Abstract

What is the role of different types of information in the target share price on the effect of the 52-week high on takeover premia? We find that a higher fraction of noise in the target share price amplifies the reliance on the target's 52-week high price in determining the offer price in corporate takeovers. Conversely, none of the separate private, public and market information plays a significant role in this context. Interestingly, both the penalty to bidders and the higher deal success rate from paying over the target's 52-week high price diminishes with increased target price noise, suggesting that neither bidders nor targets are consistently influenced by reference prices. Further results confirm that the percentage of noise, indicating an undervalued target to the bidder, drives the offer price's reliance on the target's 52-week high. Overall, the target reference point effect does not work uniformly but depends on the underlying percentage of noise in the target share price, and the reliance on the target 52-week price might not always be value-destroying.

Keywords: Mergers; Acquisitions; Offer price; Reference point; 52-week high; Information environment; Noise; Behavioral corporate finance

JEL Classification Codes: G14; G34; G41.

1. Introduction

It is common to reference a recent peak price (e.g., the 52-week high price) to simplify intricate valuation processes, for example, valuing a target company in mergers and acquisitions (M&A).[1] Baker et al. (2012) and Ma et al. (2019) have identified strong evidence indicating that targets' 52-week high prices significantly influence the offer price paid to publicly traded targets. However, evidence suggests that the extent of decision-makers' reliance on reference points depends crucially on the information environment, challenging the assumption of significant sway of reference prices in decision-making processes. In this paper, we explore how the information environment (different types of information) of the target company shapes the effectiveness of targets' peak prices in M&A transactions.

Existing literature on the reference point effect typically attributes it to anchoring bias (Baker et al., 2012; Li et al., 2023). Anchoring bias is a cognitive shortcut where individuals start with a salient but possibly irrelevant value and inadequately adjust from it to form a final estimate, which is biased toward the initial value (Tversky and Kahneman, 1974). However, evidence suggests that the extent of decision-makers' susceptibility to anchoring biases varies depending on the information environment. In particular, decision-making becomes more complex and uncertain in limited or challenging information contexts, highlighting a negative correlation between the quality of the information environment and the prevalence of reference-dependent behaviors. Psychological studies, such as Mussweiler and Strack (2000) and Wilson et al. (1996), illustrate that anchoring effects depend on judges' knowledge about the question. Ma et al. (2019) demonstrate that the influence of the bidder's 52-week high price on decision-making is magnified when information about the target is scarce (private target). Huang et al. (2021) find that the explanatory power of the 52-week high price to the return predictability of economically linked firms is stronger for firms under a worse information environment (smaller firm size, lower institutional ownership, lower analyst coverage). Therefore, it is reasonable to expect the extent of participants' reference-dependent behaviors to be contingent upon the richness of information available, with diminished reference-dependent be-

[1] For more on the effect of the 52-week high price, see also Choy and Wei (2022); Della Vedova et al. (2021); George and Hwang (2004); George et al. (2018); Hung et al. (2022); Khasawneh et al. (2023); Lasfer and Ye (2024).

haviors in a favorable information environment. This suggests that decision-makers are capable of effectively processing information, when available, to make informed decisions rather than being unduly influenced by anchoring biases.

Noise in a company's share price, indicative of irrational investor behavior that distorts the stock price from its information-efficient value upon information arrivals, measures the quality of the information environment through share price informativeness (Brogaard et al., 2022). A higher percentage of noise in the target's share price, implying a less informative environment about the target to the market, can complicate the valuation process. Thus, distinguishing the impact of noise from that of information becomes essential in evaluating a company's information environment through share price informativeness measures. However, previous measures fail to do so. Share price informativeness measures using price non-synchronicity can behave like noise rather than information (Brogaard et al., 2022). In addition, a higher analyst coverage can also lead to a reduced amount of firm-specific information reflected in stock prices (e.g., Chan and Hameed, 2006; Easley et al., 1998; Piotroski and Roulstone, 2004) although it is often expected to represent a better information environment (e.g., Schutte and Unlu, 2009).

Recent advancements in share price informativeness research allow for the differentiation of noise from various types of information in share prices, allowing a more nuanced analysis of potential heterogeneities in the impact of different information types on the reliance of the reference point. Brogaard et al. (2022) propose a model to decompose return variance into components representing noise (*noiseshare*) and different types of information (*privateinfoshare*, *publicinfoshare* and *mktinfoshare*) in share prices. Separating noise from information provides a clearer understanding of the informativeness of share prices. In this context, "noise" refers to the actions of irrational investors who frequently misinterpret various forms of information, thereby diverting the stock price from its true (information-efficient) level upon the arrival of new information. A higher *noiseshare* suggests that the stock price is more likely to have a greater deviation before it finally adjusts to the efficient price, as dictated by newly arrived information. A higher fraction of noise in the target company's share price also compresses the fraction of other information, signaling a weaker information environment for the firm.

Consequently, we expect the offer price in mergers and acquisitions to rely more heavily on the target's 52-week high price as a reference point when the target share price is noisier (less informative). In addition, if reliance on reference points consistently signifies overpayment, the adverse market reaction to the bidder (and the higher deal success rate) from the reference-dependent offer price should be exacerbated by a higher fraction of noise in the target's share price.[2]

In this paper, we start by examining how a higher proportion of noise in the targets' share prices affects the reliance on targets' 52-week high prices in M&A transactions. We then explore how different types of information (private, public and market) play a role in this dependence. We also extend our analysis to assess how noise affects the impact of targets' 52-week high prices on bidders' market reaction and the deal success rate.

We document two main results. Firstly, and in line with the prediction, we find that the offer premium is more affected by the target 52-week high when there is a higher percentage of noise in the target share price. A 1% (one standard deviation, around 20%) increase in noise amplifies the influence of a 1% increase in the target 52-week high on the offer premium by around 0.003% (0.05%) while controlling for several of the deal, target, and bidder characteristics. This amplification effect of noise is economically large as the influence of the target 52-week high on the offer premium before adding its interactive terms with *noiseshare* is that a 1% increase in the 52-week high is associated with a 0.076% increase in the offer premium. Under a high-dimensional fixed effects model, a 1% (one standard deviation) increase in noise amplifies the influence of a 1% increase in the target 52-week high on the offer premium by 0.005% (0.09%), compared to the baseline effect of 0.151% before adding interaction terms with *noiseshare*. These results suggest that participants are more likely to use the straightforward reference point, 52-week high price, to value a company with a noisy information environment. The causal relationship is validated using a combination of econometric methods, including instrumental variable two-stage least squares regressions, propensity score matching regressions, and shock-based difference or difference-in-differences estimators.

[2]An alternative explanation, though uncommon in the context of using CAR to assess the overpayment, is plausible within this paper's framework. In a high *noiseshare* information environment, shareholder behavior may become irrational, making their reactions unreliable for assessing overpayment. We rule out this alternative explanation by showing that investors' non-value-destroying reaction in the short term (CAR) remains persistent and does not reverse over the long horizon (using buy-and-hold abnormal returns in one, two, three, and four years after the announcement).

Furthermore, sub-period analyses indicate that reliance on reference prices and the impact of noise are concentrated in periods with lower levels of noise, whether assessed across the entire market or within our target company sample.

Looking further into the information in the target share price, and in particular in the variation in the other components of information other than noise, in contrast, the second main finding is that the three types of information (private, public and market) do not independently affect the reliance on the target's 52-week high price when determining the offer price while controlling for several of the deal, target, and bidder characteristics. This further emphasizes the role of noise in affecting the influence of the target's 52-week high price.

We explore four potential mechanisms through which the noise in the target share price can affect the reliance of the offer price on the target share price: information environment, uncertainty, absolute mispricing[3] and arbitrage costs. The established mechanism suggests that when a target is undervalued within a challenging information environment,[4] bidders with information advantages are more comfortable utilizing an undervalued target's 52-week high price while still obtaining a favorable deal. In addition, two results further indicate that *noiseshare* is working through representing the undervaluation of target share price under a worse information environment. First, while the market punishes the bidder for the reliance on the target 52-week high price in determining the offer price, this penalty is not applied when the noise in the target's share price is accounted for. This suggests that relying on the target's 52-week high price does not necessarily reflect a value-destroying decision for the bidder.[5] Second, while offering above the target's 52-week high usually enhances the likelihood of deal success, this impact is lessened when the target's share price exhibits a greater proportion of noise. In such cases, the target shareholders may become aware of the undervaluation of the reference price, and their satisfaction with the offered price based on this undervalued reference point is reduced.

[3]Here, "absolute mispricing" means the absolute deviation from the efficient share price, matching the definition of *noiseshare* which does not emphasize the direction of deviation.

[4]Here, "undervalued" means the share price is lower than the efficient level as the results of the corresponding company's worse information environment, which is different from the definition of absolute mispricing defined above.

[5]Note that not being value-destroying does not necessarily imply rational decision-making. Reliance on reference points (e.g., the 52-week high price) represents biased behavior because such widely available public information should already be incorporated in the stock price under rational expectations. Therefore, any influence of reference points on share valuation is inherently a biased behavior, unrelated to whether it is value-destroying or not.

The paper contributes to the literature in several areas. First, the paper contributes to the literature that analyzes the role of target reference points in the takeover market. Previous papers find that target reference points play a role in the takeover market (e.g., higher reference prices lead to higher offer premiums and worse bidders' market reaction) (Baker et al., 2012; Ma et al., 2019). This paper fits this research area by adding that the target 52-week high price as a reference point does not work uniformly. Instead, the reliance of the offer price on the target reference prices[6] is stronger for targets with nosier share prices. Sub-period analyses reveal that such reference price reliance and the influence of noise are clustered in periods characterized by lower noise levels, whether measured across the entire market or only within our sample of target companies. Both results imply that the role of target reference points becomes stronger under noisy information environments. In addition, the results of both bidders' announcement return and deal success indicate that the reliance of the offer price on the target 52-week high price, considering the noise in the target share price, may not always be a value-destroying behavior.

Second, our results highlight the necessity to separate noise from information. As our results indicate a reverse effect between noise and the total information (1-*noiseshare*), mixing these two together biases conclusions based on the interpretation of proxies that mix up noise and information as share price informativeness, e.g., return non-synchronicity and firm idiosyncratic volatility (Brogaard et al., 2022).

Third, the paper contributes to the literature that analyzes information's role in mitigating reference-dependent behavior. There remains an ongoing debate regarding the information environment and the reliance on referent points. While most previous literature does indicate that a better information environment mitigates the reference point effect,[7] there exists a body of literature presenting opposite findings but using noisy information measures (e.g., firm size and firm age) (Hovakimian and Hu, 2020; Kumar, 2009). Applying the method to distinguish noise from information in the target share price, this paper supports the former by showing that a better information environment (lower *noiseshare*) does mitigate the reference-dependent behavior.

[6] We also find similar patterns in terms of other weeks of high target firm's prices, see Appendix Table A9.

[7] See, Della Vedova et al. (2023); Dougal et al. (2015); George et al. (2014); Giacoletti and Parsons (2023); Huang et al. (2021); Hur and Singh (2019); Li et al. (2021); Malhotra et al. (2015).

Fourth, this paper contributes to the literature by further examining the impact of different types of information on reliance on reference points. The role of various types of information in mitigating behavioral biases (e.g., the reference point effect) remains unclear in prior research, beyond general notions that greater analyst coverage may increase public information in share prices (Kumar, 2009) and higher institutional ownership is expected to enhance private information in share prices (Brogaard et al., 2022). While the literature generally anticipates that both types of information can alleviate certain behavioral effects, empirical findings are mixed. Kumar (2009) show that analyst coverage does mitigate investor overconfidence but is positively associated with the disposition effect. Similarly, Li et al. (2023) find that analyst coverage weakens the impact of CEO anchoring on the reference point effect, whereas institutional ownership only weakly mitigates this effect. A clear separation of how different types of (de-noised) information influence behavioral biases, particularly the reference point effect, remains largely unexplored in prior literature. This paper fills this gap by directly and separately testing the impact of different types of de-noised information embedded in the target share price on the reliance on the target's 52-week high price. The results indicate that none of the private, public, or market information significantly influences this reliance. To the best of our knowledge, this study is the first to analyze separately the effects of noise and distinct types of information on the reference point effect.

Section 2 proposes the hypothesis based on the reference point effect and share price informativeness. Section 3 reviews the basic data. Sections 4 report how noise combined with reference points affect offer prices. Section 5 reports the identification results. Section 6 presents various tests of potential reasons for the main results. Sections 7 and 8 report how noise combined with reference points affect the bidder's announcement return and deal success, respectively. Section 9 presents various robustness tests for the main results. Section 10 concludes.

2. Hypothesis development

The reliance on a reference point to simplify complex valuation tasks is often referred to as the reference point effect or the anchoring effect. These are two closely related yet distinct phenomena. The reference point effect, stemming from prospect theory (Kahneman and Tversky, 1979), involves individuals assessing gains or losses relative to a specific reference point. The concept of anchoring and adjustment, introduced by Tversky and Kahneman (1974), describes a cognitive bias where individuals base their judgment on an initial, often irrelevant value (the anchor) and then make insufficient adjustments, leading to biased final valuations. These effects have demonstrated significant influence across various financial sectors.[8]

In the context of M&A, Baker et al. (2012) have identified strong evidence indicating that targets' 52-week high prices significantly influence the offer price paid to publicly traded targets. Ma et al. (2019) further verified the effectiveness of the target's 52-week high price in determining the offer price. Existing literature on the reference point effect typically attributes it to anchoring bias, which is considered irrational and detrimental to the affected party. Anchoring bias is a cognitive shortcut where individuals start with a salient but possibly irrelevant value and inadequately adjust from it to form a final estimate, which is biased toward the initial value (Tversky and Kahneman, 1974). Baker et al. (2012) contend that relying on the target 52-week high price when setting the offer price constitutes biased behavior by showing that the market dislikes this reliance (negative market reactions towards bidders) and biased target shareholders are satisfied in selling their shares at a price above the 52-week high price (higher deal success rate). Li et al. (2023), extending the findings of Baker et al. (2012), pinpoint that this reliance can stem from the anchoring biases of CEOs within either the bidder or target companies. Li et al. observe that the resultant negative announcement returns for bidders and the heightened deal success rate are more pronounced when the CEOs exhibit anchoring biases. Li et al. (2021) claim that analysts' tendencies to downgrade stocks as prices approach the 52-week high constitute anchoring behaviors rather than information-driven decisions, supported by showing that such downgrades are associated with less negative future returns and earnings forecast revisions compared to other downgrades.

Although widespread, the influence of reference points is not uniform across scenarios. In the

[8]In equity markets, significant influence has been documented (Della Vedova et al., 2023; George et al., 2014; Huang et al., 2021; Kumar, 2009; Li et al., 2021), as well as in the loan industry (Dougal et al., 2015), corporate finance (Graffin et al., 2013; Hovakimian and Hu, 2020; Li et al., 2023), mergers and acquisitions (M&A) (Baker et al., 2012; Li et al., 2023; Malhotra et al., 2015; Ma et al., 2019), and the real estate sector (Giacoletti and Parsons, 2023). The impact of these cognitive biases is not limited to specific sectors but extends to a wide range of subject groups. Retail equity investors (Della Vedova et al., 2023; George et al., 2014; Kumar, 2009), equity market analysts (Li et al., 2021), macroeconomic forecasters (Campbell and Sharpe, 2009), and participants in the corporate loan industry (Dougal et al., 2015) have all been demonstrated to be susceptible to the anchoring effect.

context of psychological experiments, studies suggest that psychological biases (e.g., anchoring) are intensified under conditions of higher uncertainty, less information, and tighter time constraints (Epley, 2004; Hirshleifer, 2001; Jacowitz and Kahneman, 1995; Strack and Mussweiler, 1997). Wilson et al. (1996) and Mussweiler and Strack (2000) have shown that the strength of anchoring effects varies with judges' knowledge of the subject. Behavioral finance research indicates that reliance on reference points intensifies in situations characterized by high uncertainty, limited information, and time constraints (Della Vedova et al., 2023; Dougal et al., 2015; George et al., 2014; Giacoletti and Parsons, 2023; Hur and Singh, 2019). Malhotra et al. (2015) find that in mergers and acquisitions (M&A), offer prices for a particular deal tend to be anchored to the prices of other transactions, especially when the deal is international. Ma et al. (2019) indicate that the impact of a bidder's 52-week high price on decision-making intensifies in the context of limited information about the target. Research by Huang et al. (2021) and Li et al. (2021) further reveals that the influence of 52-week high prices is more pronounced in stocks with fewer analysts, lower institutional ownership, and those that are smaller and younger. Li et al. (2023) observe that CEOs who demonstrate anchoring bias in personal stock selling near 52-week highs also exhibit this bias in doing secondary equity offerings (SEO) and M&A activities. However, this increased reliance is mitigated in a better-informed environment for target companies, indicated by higher analyst coverage and institutional ownership. In essence, the tendency to rely on reference points is expected to decrease when the parties involved are in a better information environment, characterized by being more informed and experienced, facing lower uncertainty, and evaluating stocks that are easier to value.

Share price informativeness serves as a direct metric for evaluating the information environment, quantifying the extent of information reflected in the share price. However, most existing measures, often presumed to indicate a superior information environment, may not always accurately represent the quality of that environment. For instance, Brogaard et al. (2022) identify that the degree of price non-synchronicity[9] conflates noise and firm-specific information within the share price, and fluctuates with noise rather than firm-specific information. In addition, while analyst coverage is generally expected to signal a better-informed environment, studies such as those by Chan and Hameed (2006)

[9] Originally proposed by Roll (1988) and widely applied in subsequent studies (e.g., Adra and Barbopoulos, 2023; Chen et al., 2007; Durnev et al., 2003, 2004).

and Piotroski and Roulstone (2004) have identified a paradoxical relationship where increased analyst coverage correlates with a decrease in firm-specific information manifested in stock prices. Recent advancements in the study of share price informativeness, particularly by Brogaard et al. (2022),[10] have furthered our understanding by allowing the distinction between various types of information and noise in share prices. This development paves the way for a more detailed examination of how different types of information may influence reliance on reference points differently, offering insights into potential heterogeneities in this effect.

As a result, the target's 52-week high price is expected to affect more offer pricing when the target's share price contains a greater percentage of noise. Furthermore, following the spirit of Baker et al. (2012), if the use of reference points consistently reflects value-destroying decision-making, a noisier target share price is likely to amplify both the negative market reaction faced by the bidder and the increased likelihood of deal completion associated with reference-dependent pricing.

3. Sample, data and variable construction

3.1. Merger and acquisition sample

The Securities Data Corporation (SDC) Mergers and Acquisitions database is the source of the M&A deals. The deals are announced from 1 Jan 1984 to 31 Dec 2022; the targets are publicly traded firms, and both the target and the bidder have stock price data from the Center for Research in Security Prices (CRSP) and accounting data from Compustat.[11] Following Baker et al. (2012), we require the offer price to be non-missing, and the bidder starts with less than 50% of the target firm shares outstanding and, if completed, ends with 100% or else the percentage acquired is unknown. Our sample also includes withdrawn deals. We exclude deals classified as recapitalization, repurchases, rumors, or target solicitations. Following Baker et al. (2012), *offer_premium* represents the offer price expressed as a log difference from the target stock price 30 calendar days before the announcement, and *target52WH* denotes the target's 52-week high stock price over the 365 calendar days ending 30 days before the announcement, expressed as a log difference from the target stock price 30 calendar

[10]See Section *3.2* for the construction of share price informativeness measures as in Brogaard et al. (2022).

[11]We adhere to the commonly accepted practice of maintaining a minimum six-month gap between the fiscal year-end data from Compustat and the share data from CRSP to ensure the financial report data are publicly known (see e.g., Alford et al., 1994; Fama and French, 1992).

days before the announcement.[12] As in Baker et al. (2012), both variables are scaled by the 30-day lagged price to mitigate heteroskedasticity and attenuate any upward rumors or new information effects on the offer premium.[13] The offer premium is truncated to the range of (0, 200) as in Officer (2003),[14] leaving us with a final sample of 9,264 deals. See Appendix Table A1 for complete variable definitions.

Table **1** presents the sample of deals. SDC provides information on whether the offer is tender, hostile, and diversified. SDC also gives information on the payment method (full cash or full stock), relative size, number of bidders, and toeholds. Out of 9,264 deals, there are 2,118 tender offers, 4,816 deals paid fully in cash, 2,047 deals paid fully in stock, 430 hostile deals, 7,260 completed deals and 1,868 withdrawn deals.

3.2. Measuring share price informativeness

Share price informativeness captures the extent to which equity prices aggregate and transmit heterogeneous information, serving as a critical proxy for evaluating the quality of a firm's information environment where higher informativeness indicates a richer information set integrated in the share price and enhanced price discovery efficiency (Morck et al., 2000; Roll, 1988). The key proxy for this is *noiseshare*. Brogaard et al. (2022) introduce a vector-autoregression (VAR) model that dissects return variance into components representing noise and information in share prices. By analyzing daily stock returns, trading volumes, and market returns, the model categorizes the short-term re-

[12]The main results still hold using other weeks (13, 26, 65, 78, 91, 104) high price, see Appendix Table A9.

[13]The main results hold using other calendar days (20, 60, 90), see Appendix Table A10.

[14]Our results hold only if this approach is followed. Observations with an offer premium exceeding 200% account for less than 0.73% of the total sample (74 out of 10,137 deals). The upper limit of 200% follows the arbitrary bound of Officer (2003) but is not a strict cutoff. Our results hold when applying higher limits (e.g., 250%), which affects an even smaller proportion of the sample (less than 0.35%). However, the lower bound of 0% should be strictly enforced, as it is the economically meaningful bound (Officer, 2003). Firstly and intuitively, offering target shareholders, especially those of public targets, a price below the market price (or even below the price net of information leakage, e.g., the price 30 days before the announcement date) is generally unreasonable, as shareholders could instead sell on the open market. Secondly, reference points (e.g., the target's 52-week high price) provide bargaining leverage for target shareholders to demand a higher price. Bidders who propose such an unreasonably low price relative to the current market price are less likely to consider the target's past peak prices, which are even higher than the current market price. In scenarios where bids are justifiably below market value (e.g., for distressed targets), target shareholders are in a significantly weaker bargaining position, losing their ability to influence the deal price through reference points. The above arguments are empirically supported by the finding that *target52WH* significantly increases *offer_premium* only after excluding observations with negative *offer_premium*. Observations with a negative offer premium account for less than 7.70% of the total sample (780 out of 10,137 deals). Moreover, replacing negative offer premiums with zero or winsorizing premiums has no effect, further highlighting the distinctive nature of negative premium deals.

action of stock returns to shocks in these variables as noise. In contrast, the stable alterations in stock returns due to these shocks are identified as various types of information (market information, trading-based private information and disclosure-based public information, respectively). Conceptually, the short-term over- or under-reaction of firm returns to shocks epitomizes traders' noise. In contrast, the final stable response of firm returns to shocks in market returns, share trading order flow, and the firm's returns symbolize market information, trading-based private information, and disclosure-based public information, respectively. This methodology is distinct from previous share price informativeness studies due to its 1) effectiveness in disentangling noise from information (noise), thus clarifying the share prices' informativeness. 2) The information component is further divided into three categories: market-wide information, firm-specific information unveiled through private information trading (private information), and firm-specific information disclosed publicly (public information). This differentiation gives the possibility to analyze the roles of these different parts of information. In our M&A setting, the noise and other information of the target share price are calculated over the 365 calendar days ending 30 days before the announcement. In this framework, "noise" pertains to the behaviors of irrational investors who often misinterpret various information types, leading share prices astray from their true or efficient levels. Therefore, it is logical to infer that a higher proportion of noise in a target company's share price indicates a less robust information environment. As a result, we predict that in the context of mergers and acquisitions, the offer price is likely more reliant on the target's 52-week high price as a reference point when the target's share price is noisier (less informative).

A higher *noiseshare* may indicate greater volatility in the target stock price, increasing the likelihood of reaching a higher 52-week high price. This raises concern that the positive link between *target52WH* and *offer_premium* could stem from volatility effects rather than the direct influence of *noiseshare* itself. To address this concern and following Baker et al. (2012), *Target volatility %* is included as a control variable.

3.3. Summary statistics and Correlation matrix

Table **2** presents summary statistics and the correlation matrix. Panel A presents means, standard deviations, medians, and extreme values for the variables used. The median offer premium is 32.29%, the median *target52WH* is 18.23%, and the median *noiseshare* of the target is 0.18. The median bidder 3-day announcement abnormal return is -0.94%, and about 80% of the offers are completed. All continuous variables are winsorized at the 1% and 99% level except for the offer premium, which is already truncated to control for outliers. After considering the target and bidder characteristics, we have financial ratios of the target for 6,955 deals and of the bidder for 3,166 deals. Panel B presents the correlation matrix of key variables. The *offer_premium* is positively correlated with both *target52WH* and *noiseshare*. In addition, *noiseshare* is negatively correlated with other information in the target share price (*privateinfoshare*, *publicinfoshare* and *mktinfoshare*).

4. Offer prices

4.1. Noise in the target share price

Figure 1 plots the density of offer prices minus the target 52-week high price in the lowest and highest *noiseshare* groups. The plots show that the offer price is increasingly higher relative to the target 52-week high price from the lowest to the highest *noiseshare* groups. This pattern becomes increasingly evident as the number of groups classified by *noiseshare* rises from 3 to 10 groups.

To test the impact of *noiseshare* on the reliance of offer price on the target 52-week high price, we initially run the following logistic regression:[15,16]

$$offer\_big\_52WH = \beta_0 + \beta_1 noiseshare + \beta_2 \text{Other\_information\_variables} + \beta_3 Controls + e \qquad (1)$$

where the *offer_big_52WH* is a dummy variable that equals one if the offer price exceeds the target 52-week high price and zero otherwise. Table **3** presents the marginal effects. The results demonstrate that *noiseshare* is the key driver in pushing the offer price above the target's 52-week high, as shown in Column (1). The coefficients of *noiseshare* are all significantly positive at a 1% significance level

[15] Employing probit regression yields similar results.

[16] Table **3** encompass comprehensive control variables and include time and target industry fixed effects. Results are robust to gradually adding control variables (inverse price, deal characteristics, firm characteristics) and fixed effects.

with values around 0.350. A 1% (one standard deviation, approximately 20%) increase in noise increases the probability of the offer price being higher than the target 52-week high price by around 0.350% (7%).[17] In addition, the horse race between *noiseshare* and the three types of information shares confirms that *noiseshare* plays a dominant role in driving the offer price above the target's 52-week high, surpassing the influence of other information shares. While *publicinfoshare* exhibits a significantly negative effect in Column (3) and all three information shares are significantly negative in Column (5), their effects lose significance when included in the same regression alongside *noiseshare*, as shown in Columns (6) to (8).[18]

After establishing the initial logistic results, we further examine the impact of *noiseshare* on the reliance of the offer price on the target's 52-week high price using a continuous outcome regression. Building upon the approach of Baker et al. (2012), we estimate the following regression:[19]

$$offer\_premium = \beta_0 + \beta_1(noiseshare \times target52WH) + \beta_2 Controls + e \tag{2}$$

Results in Table 4 demonstrate the effectiveness of *noiseshare* in enhancing the dependence of the offer premium on the target's 52-week high price. A 1% (one standard deviation, approximately 20%) increase in noise amplifies the influence of a 1% increase in the target 52-week high on the offer premium by around 0.003% (0.05%) after controlling for various deal, target, and bidder characteristics in Column (8). This amplification effect of *noiseshare* is economically significant, as the baseline effect of a 1% increase in the 52-week high on the offer premium, before including interaction terms with *noiseshare*, is a 0.076% increase.[20] The coefficients of *target52WH* and *noiseshare* are insignificant after adding the interaction term and control variables in Columns (5) to (8). This result indicates that *target52WH* has an insignificant impact on *offer_premium* when the target's *noiseshare* is 0%. Additionally, significant control variables generally exhibit coefficient directions

[17] The sample size with all control variables is approximately 3,100 as adding target and bidder control variables restricts the sample to public-to-public deals. However, the results hold even without these control variables, with a sample size of 10,119. These results are unreported and will be available upon request.

[18] In Columns (5) to (8), one of the full parts (noise and three other information variables) is excluded to prevent perfect multicollinearity, given that the sum of all four variables equals one.

[19] Table 4 encompass comprehensive control variables and include time and target industry fixed effects. Results are robust to gradually adding control variables (inverse price, deal characteristics, firm characteristics) and fixed effects.

[20] Again, the sample size with all control variables is approximately 2,800 as adding target and bidder control variables restricts the sample to public-to-public deals. However, the results hold even without these control variables, with a sample size of 9,200.

consistent with previous literature.[21]

To address the possible high-dimensional fixed effects, we run the baseline regression Equation 2 under a high-dimensional fixed effects model. Table **5** presents the results that confirm the baseline effects with even larger effects. A 1% (one standard deviation, approximately 20%) increase in noise amplifies the influence of a 1% increase in the target 52-week high on the offer premium by 0.005% (0.09%), compared to the baseline effect of 0.151% before adding interaction terms with *noiseshare*.

4.2. Other information shares in the target share price

After confirming the impact of noise, we examine whether different types of information in the target's share price can mitigate the reference point effect. Previous literature generally expects all types of information, particularly public and private information, to reduce reference point reliance. However, empirical findings provide mixed evidence, showing both mitigating and reinforcing effects (Kumar, 2009; Li et al., 2023). Prior studies often use analyst coverage and institutional ownership as proxies for public and private information, respectively. However, these proxies may contain noise which may contaminate the results. Brogaard et al. (2022) introduce de-noised information measures that separately capture public, private, and market information, allowing for more nuanced analyses. We run the following regression:

$$offer\_premium = \beta_0 + \beta_1(Otherinfoshare \times target52WH) + \beta_2 Controls + e \tag{3}$$

Results in Table **6** show the ineffectiveness of other information in affecting the effectiveness of the target 52-week high price in the M&A offer pricing. Columns (1) to (3) show that other information (*privateinfoshare*, *publicinfoshare* and *mktinfoshare*) has insignificant coefficients, indicating that other information in the target share price does not affect the M&A offer pricing. Columns (4) to (6) show that the interactive terms between other information and *target52WH* have insignificant coefficients. In conjunction with the ineffectiveness of other information in Table **3**, results indicate that different types of information in the target share price do not affect the effectiveness of the reliance of the target 52-week high price on the offer price.

[21]Specifically, *Target Runup*, *Financial Buyer*, and *log(Target MktCap)* negatively affect *offer_premium*, while *Hostile*, *Tender*, *log(Bidder MktCap)*, and *Bidder Runup* have positive effects, in line with Baker et al. (2012) and Li et al. (2023).

5. Endogeneity and identification

It is crucial to consider the potential unobservable factors that may correlate with the target share price *noiseshare* and have the capacity to influence the dependence of the offer price on the target's 52-week high. This raises the concern that the impact of share price *noiseshare* might inadvertently encompass the effects of these variables. A notable example of such a factor is the unobservable business potential of the target company. Companies with higher unobservable business potential pose a greater challenge in valuation, as investors may hold divergent opinions regarding their worth, resulting in a departure from efficient valuation (leading to higher share price *noiseshare*). Furthermore, a target company with substantial unobservable business potential may elicit more lucrative offers relative to its 52-week high, signifying a higher degree of dependence. Buyers may be inclined to expedite the deal's progress with a target boasting significant business potential by offering prices relative to the target's 52-week high price. Consequently, greater unobservable business potential may correspond to increased *noiseshare* and reliance. Neglecting to account for the target company's unobservable business potential may inflate the observed positive impact of share price *noiseshare* on the offer price's dependence on the target's 52-week high, thereby overestimating the influence of *noiseshare*.

We address potential endogeneity using three approaches: 1) matched sample analysis; 2) shock-based difference-in-differences (DiD) estimators; and 3) instrumental variable two-stage least squares (IV-2SLS) regressions.

5.1. Matched sample analysis

We firstly address the potential endogeneity concern firstly by using the propensity score matching approach (e.g. Lawrence et al., 2024; Rosenbaum and Rubin, 1983).[22] After obtaining the matched and balanced sample,[23] we run the following regression:

$$offer\_premium = \beta_0 + \beta_1(Treated \times target52WH) + \beta_2 Controls + e \tag{4}$$

[22] We use the 1:2 nearest neighbor matching approach with a caliper of 0.002. The balance between treated and control groups depends on the choice of PSM specifications, but the results remain generally robust across different matching approaches.

[23] The balancing results are untabulated but will be available upon request. The same goes for all the following PSM-related regressions.

The results are in Appendix Table A2. *Treated* in Panel A and B are *noi_2* and *noi_3*, respectively. *noi_2* is a dummy variable that takes the value of one if *noiseshare* is in its high half (above the sample median) and zero otherwise. *noi_3* is a dummy variable that takes the value of one if *noiseshare* is in its highest tertile group and zero in its lowest tertile group. All the results indicate a significantly higher effect of the *target52WH* with the increase of *noiseshare*.

5.2. Shocks-based difference-in-differences estimators

We then use two exogenous shocks to address endogeneity and identify the causal relationship. The brokerage house closures and mergers and the ticker size reduction.

5.2.1. Brokerage house closures and mergers

Exogenous shocks to analyst coverage provide a natural experiment that changes the information environment for individual stocks. According to Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012), when brokerage houses merge, they often choose one analyst to continue covering a stock, discontinuing the coverage of the other if both were following the same stock before the merger. This provides an exogenous variation of analyst coverage. Brogaard et al. (2022) find this reduction to increase the *noiseshare*. Therefore, we perform a PSM-DiD analysis following Brogaard et al. (2022) and Cortes and Marcet (2023).[24] *Treated* is a dummy variable that takes the value of one if the number of analysts of the target company is reduced during the 3-year period prior to the announcement due to the closure of brokerage houses and zero otherwise.[25] The positive coefficients in Appendix Table A3 confirm that an increase in *noiseshare* by the shock intensifies the effectiveness of *target52WH* with magnitudes similar to the baseline effects.

5.2.2. Ticker size reduction

Following Brogaard et al. (2022), we use the reduction in tick sizes in the U.S. markets from eighths of a dollar to sixteenths of a dollar on 24 June 1997, as a natural experiment for the PSM-DiD

[24] We use a 1:2 nearest neighbor matching approach with a caliper of 0.001. The balance between treated and control groups depends on the choice of PSM specifications, but the results remain generally robust across different matching approaches.

[25] We thank Marcin Kacperczyk for providing data on companies affected by these shocks, available on his website. The data covers the period from 1984 to 2005.

analysis.[26] Brogaard et al. (2022) find that the ticker size reduction causes a reduction in *noiseshare*, and this reduction is higher for shares with lower share prices. Follwoing Brogaard et al. (2022), *Treated* is a dummy variable that takes the value of one if the target company's share price 30 days before the announcement is not in its highest quartile (low share price) and zero otherwise (high share price). *Post* is a dummy variable that takes the value of one after the effective date (24 June 1997) and zero otherwise in the period from 1996 to 1998. The negative coefficients in Appendix Table A4 confirm that a reduction in *noiseshare* by the shock in the treated group decreases the effectiveness of *target52WH*.

5.3. Instrumental variable two-stage least squares regressions

We use two instrumental variables to identify the causal relationship: 1) *trading_turnover* and 2) *CoverageShock*.

The first instrumental variable, *trading_turnover*, is the average daily trading turnover of the target company over the past year window, where the trading turnover is the daily trading volume divided by the company's outstanding share at the end of the trading day. Trading turnover can influence the noise component in share price. On the one hand, elevated trading turnover may stem from substantial noise trading, which is largely irrelevant to fundamentals, leading to an increased noise share (Bergers and Blomkvist, 2024; Black, 1986; Karpoff, 1987). Such trading activities often encapsulate speculative transactions that do not reflect the stock's underlying value. On the other hand, higher trading turnover can facilitate the incorporation of information by informed traders (Dávila and Parlatore, 2018), leading to greater information share (i.e., lower *noiseshare*). Furthermore, the direct linkage between an offer price's reliance on a target's 52-week high and the target's trading turnover is arguably tenuous, particularly when considering the *noiseshare* aspect. For example, trading turnover is less likely to be directly associated with unobservable business potential. High trading turnover may not necessarily reflect the firm's long-term growth prospects or innovative capabilities, but rather, it might indicate market sentiment or trading trends.

[26] We use a 1:3 nearest neighbor matching approach with a caliper of 0.008. The balance between treated and control groups depends on the choice of PSM specifications, but the results remain generally robust across different matching approaches.

The second instrumental variable, *CoverageShock*, captures exogenous shocks to analyst coverage that alter the information environment of individual stocks. *CoverageShock* is a dummy variable, set to one if the target company's analyst coverage has been impacted by mergers or closures of brokerage houses within the three years preceding the announcement date.[27,28] Brogaard et al. (2022) demonstrated that such shocks lead to an increase in the *noiseshare* of the affected companies. The decrease in analyst coverage, due to its exogenous origin, is unlikely to be directly related to the fundamentals of the companies involved (Hong and Kacperczyk, 2010).

Table 7 presents the 2SLS results using the *trading_turnover* and *CoverageShock* as the instrumental variables to identify the causal interpretation of *noiseshare*:[29]

$$\mathit{offer\_premium} = \beta_0 + \beta_1(\widehat{\mathit{noiseshare}} \times \mathit{target52WH}) + \beta_2 \mathit{Controls} + e \tag{5}$$

Columns (1) and (2) in Panel A are regressions with and without fixed effects (industry and time), respectively. The instrumented $\widehat{\mathit{noiseshare}}$s still positively and significantly influence the reliance of the offer premium on the *target52WH* with stronger significance. The results support the causal influence of *noiseshare* and past three identification tests (under-identification, over-identification and weak-identification). Kleibergen-Paap-LM-statistics reject the null hypothesis of under-identification at 1% level. Sargan–Hansen-J-statistics fail to reject the null hypothesis of over-identification at 10% level. Kleibergen-Paap-F-statistics are 23.968 and 20.082 for regressions with and without fixed effects, supporting strong instrumental variables (the corresponding critical values are 11.04 for 5% maximal relative bias and 16.87 for 10% maximal IV size). Overall, the results support the causal relationship.

[27]We thank Marcin Kacperczyk for providing data on companies affected by these shocks, available on his website. The data covers the period from 1984 to 2005.

[28]According to Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012), when brokerage houses merge, they often choose one analyst to continue covering a stock, discontinuing the coverage of the other if both were following the same stock before the merger.

[29]In untabulated results, the $\widehat{\mathit{noiseshare}}$ remains significantly positive in driving the influence of *target52WH* when separately instrumented by either *trading_turnover* or *CoverageShock*. Results also reject under-identification tests, and the first-stage F-statistics (around 20) confirm instrument strength.

6. Mechanism

Drawing on Brogaard et al. (2022) and other preceding literature, particularly those focusing on stock market microstructure, we delineate four potential factors influencing the noise fraction in the share price. We test whether these factors serve as potential mechanisms through which noise in the target share price influences the reliance of offer premium on the target's 52-week high price. These include 1) the value of information acquisition and resultant undervaluation; 2) uncertainty; 3) mispricing, characterized by absolute deviations from fundamental values; and 4) arbitrage costs.

The first potential mechanism is identified as the primary mechanism. Other potential mechanisms either fail to provide robust theoretical predictions as to why a higher *noiseshare* intensifies the reliance of the offer price on the target 52-week high price or are disproven by empirical evidence.

6.1. The value of information acquisition and resultant undervaluation

In the context of the value of information acquisition mechanism, target companies are perceived as more valuable to bidders than to the market. From the target's perspective, the market would heavily discount targets in the presence of a poor information environment (Cheng et al., 2016; Dow et al., 2024; Kelly and Ljungqvist, 2012). This discount reflects the market's limited ability to accurately assess the target's intrinsic value due to informational asymmetries, leading to under-buying and suppressed valuations (Hauser and Lauterbach, 2003; Merton, 1987). Conversely, from the bidder's perspective, target companies hold greater perceived value. It is primarily because bidders typically possess informational advantages regarding the target firms' valuation under their management, surpassing what is available in the market and these advantages often stem from due diligence processes and/or acquiring confidential information during negotiations (Edmans et al., 2012; Li and Tong, 2018; Raman et al., 2013). Therefore, bidders with such informational edges are inclined to propose a higher premium (Croci et al., 2012). Consequently, targets embedded in such an environment are deemed even more valuable to bidders, resulting in a greater offer premium and/or a better bidder announcement return (Chatterjee et al., 2012; Cheng et al., 2016; Dong et al., 2006; Officer et al., 2009).[30]

Building on the above arguments, we expect to observe that the bidder's information advantages are more valuable where: 1) the information asymmetry between the target company and the market is greater, and 2) the target company is more undervalued. In addition, the target's 52-week high price, as set by the market, can also represent an undervaluation from the perspective of a bidder with informational advantages, especially in a poor information environment. Hence, if this is the true mechanism of *noiseshare*, we will observe that the impact of *noiseshare* on the reliance on the target's 52-week high price is more pronounced for targets: 1) operating in a poor information environment, and 2) being undervalued.

We use institutional ownership and analyst coverage to measure the target information environment and use *firm_error* and *misprice_score* to measure the target firm misvaluation. The first misprice measure *firm_error* is following Rhodes–Kropf et al. (2005) to decompose the market-to-book ratio firm-specific error, time-series sector error, and long-run market value to book value. The firm-specific error is used as the misvaluation measure. The second misprice measure *misprice_score* is from Stambaugh et al. (2012) to capturing the mispricing of stock by averaging its ranking percentile for each of the 11 anomalies.[31]

Results confirm that these predictions, the effect of *noiseshare* is lower (or insignificant) if the target has higher institutional ownership and analyst coverage (Column (1) to (4) Panel B in Appendix Table A5). More importantly, the effect of *noiseshare* is only significant when the target is undervalued (Column (1) to (4) Panel A in Appendix Table A5), further confirming the theoretical predictions of the information mechanism. In addition, by substituting *noiseshare* with *noiseshare* instrumented by target valuation measures (*firm_error* and *misprice_score*) and analyst coverage (Appendix Table A6), the positive and significant coefficients[32] validate that the variation in *noiseshare* attributable to target undervaluation significantly heightens the reliance on *target52WH*.[33]

[30]E.g., Cheng et al. (2016) find that target with information asymmetry will receive higher offer premium as the target is underpriced and the bidder pay high to grasp the opportunity. In addition, the bidder's shareholders positively react to this decision. We find similar results.

[31]We thank Robert F. Stambaugh for providing this measure on his website.

[32]The coefficient of institutional ownership instrumented *noiseshare* interact with *target52WH* is still positive but insignificant. Analyst coverage seems to generate stronger results than institutional ownership

[33]Similar patterns are found by direct interact potential mechanism measures with *target52WH* (Appendix Table

Therefore, the value of the information acquisition mechanism, which bidders value targets higher than the market by possessing informational advantages, is affirmed.

6.2. Uncertainty

Extensive literature posits and demonstrates that the reference point effect intensifies under heightened uncertainty. Yet, in the domain of takeovers, there are counterarguments suggesting that anticipated future uncertainty may lead to a reduced offer premium to account for the interim risk that is asymmetrically borne by the bidder (Bhagwat et al., 2016). Additionally, bidders might seek discounts in the offer price from targets with greater uncertainty. Theoretically, increased uncertainty typically results in lower prices, implying that targets under higher uncertainty are likely to be valued lower. However, determining whether this low valuation constitutes undervaluation becomes challenging, particularly under the aggregate market risk aversion assumption. This challenge remains unless we consider the information mechanism. Bidders give a higher valuation to targets with higher uncertainty than the market as the targets' valuation uncertainty is (partly) resolved by the bidder's information advantages (Charoenwong et al., 2024; Veldkamp, 2023).[34] Furthermore, Ma et al. (2019) observe that the target 52-week high (target52WH) significantly impacts the offer premium only in lower bidder return uncertainty scenarios. Consequently, the theoretical clarity regarding the influence of *target52WH* as a reference point on the offer premium under increased uncertainty remains elusive in takeover contexts.

To measure the different levels of uncertainty, we use relative size for high deal-level uncertainty, target return volatility for target-level uncertainty, and *EPU* and *Ahir_WU* for macro-level uncertainty. All four measures are positively correlated with uncertainty over different levels. The first macro-level uncertainty measure *EPU* is a country-level monthly policy uncertainty measure from Baker et al. (2016), constructed by measuring the uncertainty-related words in various policy documents. The second macro-level uncertainty measure *Ahir_WU* is an international country-level quarterly economic uncertainty measure from Ahir et al. (2022), constructed by measuring the un-

A7) and interact potential mechanism measures with *noiseshare* x *target52WH* (Appendix Table A8).

[34] Veldkamp (2023) argues that the majority value of information is from its ability to resolve uncertainty. Charoenwong et al. (2024) demonstrate that the detrimental impact of uncertainty on firm values and capital productivity can be mitigated through ex-ante information acquisition.

certainty words in the Economist country reports.[35]

The evidence is mixed. The effect of *noiseshare* in the reliance on the target 52-week high price exists only in subsamples of high deal-level uncertainty (relative size) and target-level uncertainty (target return volatility) (Column (5) to (8) Panel B Appendix Table A5) but in subsamples of low macro-level uncertainty(Column (1) to (5) Panel C Appendix Table A5). However, the variation of *noiseshare* due to all of these four uncertainty measures fails to affect the reliance of *target52WH* (Panel B Appendix Table A6).[36] Therefore, although introducing some heterogeneity into the impact of *noiseshare*, uncertainty does not serve as a direct mechanism behind it.

6.3. Absolute mispricing: absolute deviations from the fundamental values

If noise is defined as the absolute deviation from the fundamental value at a particular point in time, then the reliance of the offer price on the *target52WH* should vary in cases of more pronounced absolute mispricing (encompassing both overvaluation and undervaluation) rather than when the target is overvalued or undervalued monotonically.

To measure the absolute mispricing, we first subtract the no mispricing values (0 for *firm_error* and 50 for *misprice_score*) from each variable. We then calculate the absolute value of these differences, yielding *abs_firms_error* and *abs_misprice_score*.

The results show that the effect of *noiseshare* on the reliance on the *target52WH* is only significant in the subsample of the higher absolute value of only one of the misprice measures (*abs_firms_error* in Column (5) and (6) Panel A Appendix Table A5), this result is inconsistent by using the other misprice measure (*abs_misprice_score* in Column (7) and (8) Panel A Appendix Table A5). The variation of *noiseshare* due to absolute misprice measures significantly affects the reliance on the *target52WH* (Column (3) and (4) Panel A Appendix Table A6). However, the influence of absolute mispricing measures may stem from fluctuations in undervaluation, potentially yielding findings that are less compelling than those achieved through direct consideration of undervaluation. This is underscored by the negligible differences in coefficients across regressions segmented

[35]We thank the authors of these two papers for sharing these indexes.
[36]Similarly, the other two methods do not offer clear support to the uncertainty mechanism.

by *abs_misprice_score*. Results further confirmed this possibility that the direct interactions between these measures and *target52WH* as well as with *noiseshare* x *target52WH* (coefficient are all insignificant in Columns (3) and (4) of Panel A in Appendix Table A7 and A8), fail to affirm the impact of both the absolute value of mispricing measures on reliance upon *target52WH*. Meanwhile, the results support undervaluation measures (Columns (1) and (2) of Panel A in the same two tables).[37] Thus, the intensification of reliance on a target's 52-week high, attributed to *noiseshare*, does not emanate from a deviation from the target share's fundamental values.

6.4. Arbitrage costs

If the arbitrage mechanism works behind the *noiseshare*, the *noiseshare* should be higher for shares under higher arbitrage cost or risk (Brogaard et al., 2022; Lam and Wei, 2011; Li, 2020).[38] Higher arbitrage costs or risks lead to overvaluation as the existence of arbitrage asymmetry that shorting overvalued stocks is harder than longing undervalued stocks (Stambaugh et al., 2012), leading to lower targets' bargaining power. Similarly, illiquid (higher arbitrage costs) targets are generally associated with lower bargaining power (Adra and Barbopoulos, 2019; Fuller et al., 2002; Massa and Xu, 2013).[39] If the arbitrage mechanism works behind the *noiseshare*, 1) overvalued targets should have a higher offer premium reliance on the *target52WH*. In addition and 2) the effect of *noiseshare* should be stronger under higher arbitrage costs.

To measure the arbitrage costs, *illiq_Amihud* and *trade_dollar_volume* are employed. The former is a widely adopted illiquidity measure from Amihud (2002), which positively correlated with arbitrage cost. The latter is the daily share trading volume multiplied by the closing price, averaged over the 365 calendar days ending 30 days before the announcement date, which are negatively correlated with arbitrage cost.

The first prediction is rejected by the results that overvalued targets have a lower reliance on *target52WH*, as discussed in the value of information acquisition mechanism analysis. More importantly, the variation of *noiseshare* due to arbitrage costs measures insignificantly affect the reliance

[37]The coefficient of *firms_error* x *noiseshare* x *target52WH* is also negative but insignificant in Columns (1) Panel A Appendix Table A8.

[38]See also, Miller (1977); Sadka and Scherbina (2007); Shleifer (2000)

[39]See also, Officer (2007) and Roosenboom et al. (2014)

on *target52WH* (Column (5) and (6) Panel B Appendix Table A6). In addition, illiquidity measures fail to affect the effectiveness of *noiseshare* in affecting the reliance on *target52WH* (subsample analysis in Column (5) to (8) Panel C Appendix Table A5 and direct triple interactive terms in Column (6) and (7) Panel B Appendix Table A8). Therefore, although increasing the reliance of *target52WH*(Column (5) and (6) Panel B Appendix Table A7), arbitrage costs measures do not work behind the *noiseshare* as a potential mechanism to affect the reliance on the *target52WH*.

7. Bidders' announcement returns

We next investigate how the noise in the target share price affects the bidder's shareholders' reaction to the offer premium news, particularly the offer premium component that reflects the target's 52-week high. If a high offer premium largely indicates an overpayment, we would expect a negative market response. Otherwise, the market should respond neutrally or even positively. We use the instrumented offer premium estimated through the below two equations as the first stage regressions, following the approach used by Baker et al. (2012) and Li et al. (2023).

$$offer\_premium = \beta_0 + \beta_1 noiseshare + \beta_2 target52WH + \beta_3 Controls + e \tag{6}$$

$$offer\_premium = \beta_0 + \beta_1 (noiseshare \times target52WH) + \beta_2 Controls + e \tag{7}$$

In the second-stage regression, we regress the bidders' abnormal returns on the instrumented offer premium using the following specification:

$$CAR = \beta_0 + \beta_1 (\widehat{offer\_premium}) + \beta_2 Controls + e \tag{8}$$

where the dependent variable *CAR* represents the 3-day market-adjusted abnormal returns of the bidder around the announcement date.

Table 8 reports the corresponding results. Columns (1) and (2) in Panel A confirm that the market negatively reacts to the announcement of higher *offer_premium*, and the coefficients of *offer_premium* are significantly negative. Consistent with Baker et al. (2012), Columns (3) and (4) in Panel A confirm that the market reacts much more negatively to the component of *offer_premium* instrumented by the *target52WH*, the coefficients of $\widehat{offer\_premium}$ are significantly negative with a higher magnitude than the coefficients in Columns (1) and (2) in Panel A. Therefore, the market punishes the higher offer premium itself and the component of the offer premium due to the reliance on the target 52-week high price. Interestingly, the coefficients of $\widehat{offer\_premium}$ (instrumented by the interactive term *noiseshare* x *target52WH*) in Columns (5) and (6) are insignificant with only marginally higher magnitude than coefficients of *offer_premium* in Column (1) and (2) Panel A. Hence, the market does not punish the component of the offer premium due to the reliance on the target 52-week high price when this decision is made with consideration of the noise fraction in the target's share price.

These results suggest that the decision to rely the offer price on the target 52-week high price, considering the target share price noise, is not detrimental for the bidder. Therefore, reference-dependent decisions might not always be value-destroying[40] and harmful to the involved party (in this case, the bidder).[41]

Other information (private, public and market) in the target share price seems to amplify the market punishment of the offer premium due to the target 52-week high price. All coefficients of $\widehat{offer\_premium}$ in Panel B are negative and significant with much higher magnitude than the coefficient of *offer_premium* in Column (1) and (2) Panel A.

Overall, the results highlight the significant economic implications of noise fraction in the target share price relative to other informational components, offering valuable insights for both investors and firms.

[40] Again, not being value-destroying does not necessarily imply rational decision-making.

[41] A potential concern with the above results is that, while uncommon in assessing overpayment using CAR, shareholder behavior in a high *noiseshare* environment may become irrational, making their reactions unreliable for evaluating overpayment. Following the spirit of Ma et al. (2019), we analyze long-horizon returns to distinguish between a non-value-destroying effect and the alternative explanation that irrational shareholders temporarily inflate short-term returns. If irrational behavior drives the above results, we expect it to correct over the long term, leading to a negative relation between long-horizon bidder returns and $\widehat{offer\_premium}$ (instrumented by *noiseshare* $\times$ *target52WH*). Conversely, if the above results reflect a true non-value-destroying effect, the short-term return pattern should persist, and we should observe an insignificant relation. To test this, we replace *CAR* with *BHAR* (the bidder's buy-and-hold abnormal return over one, two, three, or four years post-announcement windows). Untabulated results show that the coefficient of $\widehat{offer\_premium}$ (instrumented by *noiseshare* $\times$ *target52WH*) remains insignificant, indicating that the short-term effect does not reverse over time. Results support that reference-dependent decisions may not always be harmful to bidders .

8. Deal success

In this section, we investigate the impact of noise in the target 52-week high price on the "real" economic effects via capital reallocation (deal success). We estimate probit regressions about the deal success rate, following the approach used by Baker et al. (2012) and Li et al. (2023):[42]

$$success = \beta_0 + \beta_1(noiseshare \times Offer\_big\_52WH) + \beta_2 offer\_premium(s) + \beta_3 Controls + e \quad (9)$$

where the dependent variable *success* equals one if the deal is completed and zero if it is withdrawn. Following the approach of Baker et al. (2012), we include *offer_premium(s)* as up to fourth-order polynomial of *offer_premium* to count for its potential discontinuity.

The results in Table 9 show a notable decrease in the deal success probability when the target share price contains higher noise and makes an offer price above the target 52-week high price while offering higher than the target 52-week high price increases the success probability.

The above result indicates while the target company and shareholders are satisfied when they receive an offer higher than the target 52-week high price, they are less satisfied with this offer when the target share contains higher noise. This finding is consistent with the notion that the decision to rely the offer price on the target 52-week high price, considering the target share price noise, seems not to be value-destroying to the bidder. More importantly, the target can identify and is less satisfied with this non-value-destroying decision of the bidder.[43]

Other information in the target share price seems ineffective in affecting the target's satisfaction about an offer with higher than the target 52-week high price, except that the market information has a marginal significance at 10% level in only one of its regressions in Column (6) Panel B but not in Column (5).

Overall, results highlight that the interplay between offer prices above the target's 52-week high and the noise in the target's share price reveals a nuanced impact on deal success probability and

[42] Employing logistic regression yields similar results.

[43] To rule out the irrational target shareholder explanation, we test whether the effect varies with the target's analyst coverage and institutional ownership by interacting them with the key interaction term. If shareholder biases drive the effect, we expect the triple interaction terms to be significantly positive, as higher coverage and ownership should reduce irrational behavior. Conversely, insignificant or negatively significant coefficients would support the non-value-destroying argument. Untabulated results show that the triple interaction terms remain insignificant, rejecting the irrational shareholder behavior explanation.

target satisfaction and other information components having minimal or no significant influence in this context.

9. Robust checks, sub-periods and other subsamples

9.1. The effectiveness of other weeks' high prices of the target

Following the Baker et al. (2012), the highest prices over other weeks windows (13, 26, 39, 65, 78, 91 and 104) are also tested. Appendix Table A9 shows the results of the effectiveness of the target other weeks' high prices. The results show that *noiseshare* can amplify the reliance of offer price on the target 52-week high prices calculated over all of these weeks except the 39-week high price in Column (3).

9.2. The effectiveness of other pre-announcement event days

We change the pre-announcement event days from 30 days to 20, 60 and 90 days to calculate *offer_premium*, *target52WH*, *noiseshare*, and other measures (market capitalization, runup, and volatility). Appendix Table A10 shows the results that *noiseshare* can intensify the reliance of offer price on the target 52-week high prices calculated over all of these pre-announcement event days except the 60 days with both time and industry fixed effects in Column (3).[44]

9.3. The effectiveness of other possible noise measures

We replace *noiseshare* with other potential noise measures. As proxies specifically representing the noise of share prices are scarce, we adopt two share price informativeness measures that prior literature has shown to capture extensive noise rather than information.

The first proxy is price non-synchronicity (*1-R2*) at the daily frequency, introduced by Roll (1988) and widely utilized in the literature. Brogaard et al. (2022) demonstrate that this proxy, at the daily frequency, co-varies with noise rather than the firm-specific information. Accordingly, we calculate the daily frequency price non-synchronicity of the target company over the past year window ending 30 days before the deal announcement date to replace *noiseshare*. The second proxy is

[44] It has a t-statistics 1.63 (slightly smaller than 1.65, the 10% significance critical value)

the Probability of Informed Trading (*PIN*), proposed by Easley et al. (1997) and estimated by Brown and Hillegeist (2007). Duarte et al. (2020) find this measure ineffectively capturing the behavior of private information traders, instead reflecting the actions of noise traders.[45] Therefore, we use the *PIN* of the target company at the most recent quarter[46] before the deal announcement date, to replace *noiseshare*.

Appendix Table A11 presents the results of replacing *noiseshare* in Table **3** (Table **4**) to test whether alternative noise proxies affect deal pricing. Specifically, Panel A examines whether other noise proxies increase the probability of offering a price above the target's past 52-week high price, while Panel B assesses whether other noise proxies amplify the reliance of the offer price on the target's 52-week high price. The results indicate that both proxies generally reinforce the reliance of the offer price on the target's 52-week high price.

9.4. The effectiveness of *CAR* using various event windows and factor models

We use different event windows (([-1, +1] and [-2, +2]) and different ways to adjust returns (market return and returns predicted by Fama French 3-factor model and Fama French 5-factor model) to calculate *CAR*. Appendix Table A12 shows the results, where Panel A reports the results based on *offer_premium* instrumented by *target52WH* and Panel B reports the results based on *offer_premium* instrumented by the interactive terms between *noiseshare* and *target52WH*. Consistent with the results in Table **8**, the negative and significant coefficients in Panel A uniformly indicate that bidders' shareholders disapprove of the *offer_premium* 's dependence on *target52WH*. Similarly, the uniformly insignificant coefficients in Panel B convey that such reliance, when accounting for the noise percentage in the target's share price, does not incur penalization from the bidders' shareholders.

9.5. Sub-periods analyses and long-term implications

Results of Equation 2 across sub-periods are reported in Table A13. During the sample period (1984–2022), *noiseshare* is relatively high until 2001 or 2005 in the CRSP company sample, as shown in Figure 3 of Brogaard et al. (2022). In our M&A target sample, *noiseshare* remains high until 2003

[45] We thank Stephen Brown for providing quarterly frequency *PIN* data from 1993 to 2010

[46] Results are robust to use *PIN* at the year frequency.

or 2009, which aligns closely with the years observed in the CRSP sample.[47] We, therefore, conduct sub-period analyses based on these four break-point years. Intuitively, the effect of target52WH and the influence of *noiseshare* are primarily evident during periods of higher *noiseshare* level. These results suggest that reference-dependent behavior, at least in the context of the offer premium, tends to cluster during periods of noisy share prices. Therefore, such behavior may diminish as the stock market becomes increasingly efficient, characterized by lower *noiseshare*.

9.6. **Other subsamples**

Results of Equation 2 for a variety of subsamples are in Table A14. The influence of *noiseshare* is only apparent when both the target and bidder exhibit high leverage, alongside the bidder having high return volatility and market size. This suggests that *noiseshare* 's effects are predominantly present under conditions of elevated risk. Subgroup analyses of deal characteristics support this finding, showing that *noiseshare* impacts deals primarily when they involve not full cash payments and diversification strategies.[48]

10. Conclusion

We have explored the intricate dynamics of valuing target companies, emphasizing how noise within the target's share price impacts the role of the target's 52-week high price as a reference point. Our investigation reveals that the reference point effect in the M&A valuation process is significantly influenced by the target company's share price informativeness, with a particular emphasis on the impact of noise versus different types of information (private, public, and market information). Specifically, we document that an increment in noise amplifies the influence of the target's 52-week high on the offer premium, while other forms of information are ineffective in this context. This behavior is rationalized by the notion that bidders with informational advantages view targets' reference prices as undervalued prices due to these targets' noisy information environment. Consequently, these bidders are inclined to pursue acquisitions based on these undervalued reference prices.

[47] Untabulated results, available upon request.

[48] The effect becomes negative and insignificant in the presence of toeholds, implying that prior holdings in the target may provide the bidder with sufficient information to mitigate the influence of *noiseshare*. Notably, the sample size for non-zero toehold transactions is small (243 samples), which may limit the robustness of this observation.

Contrary to our expectations regarding the mitigating role of specific information types on the reliance of the reference point, our analysis indicates that private, public, and market information do not independently alter the impact of the target's 52-week high price on offer pricing decisions. This observation points to the unique and dominant effect of noise in shaping valuation behaviors in M&A contexts, overshadowing different information types in influencing reference point reliance. Interestingly, the data on bidders' market reactions further highlight the non-value-destroying basis of the reference points effect. While the bidders' shareholders punish the decision to rely the offer price on the target 52-week high price, this reliance is mitigated when the target share price contains a high fraction of noise. Moreover, the implications for deal success, representing a tangible impact on the allocation of capital among investment opportunities (Baker et al., 2012), affirm the non-value-destroying basis of the reference points effect. Although receiving offers above reference prices please target shareholders, their satisfaction diminishes when these reference prices are influenced by a higher percentage of noise, indicating that target shareholders recognize and unmask the bidders' non-value-destroying decision-making.

Overall, our paper highlights the importance of distinguishing between noise and information in share price informativeness for a more accurate understanding of valuation practices in M&As. The target reference point effect does not work uniformly but depends on the level of noise in the target share price, and the reliance on the target 52-week price might not always be value-destroying. Our study contributes to the broader discourse on reference points in the takeover market, behavioral finance, and the nuanced role of information in financial decision-making. By demonstrating that the reliance on a simplistic reference point like the target's 52-week high price is not merely a biased behavior but a pragmatic approach under specific conditions, our research offers new insights into the adaptive strategies employed by market participants in complex valuation scenarios. Our results underscore the need for future research to further dissect the interplay between information quality, market behaviors, and valuation methodologies in the dynamic landscape of corporate finance. As we advance our knowledge on these fronts, it becomes increasingly clear that the contexts in which financial decisions are made, marked by varying degrees of information asymmetry and psychological biases, profoundly influence the strategies and heuristics employed by practitioners in the field.

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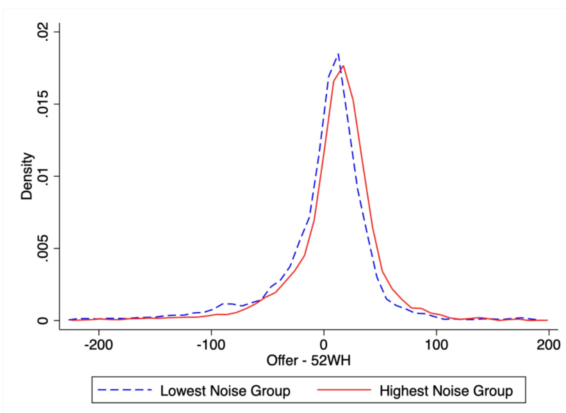
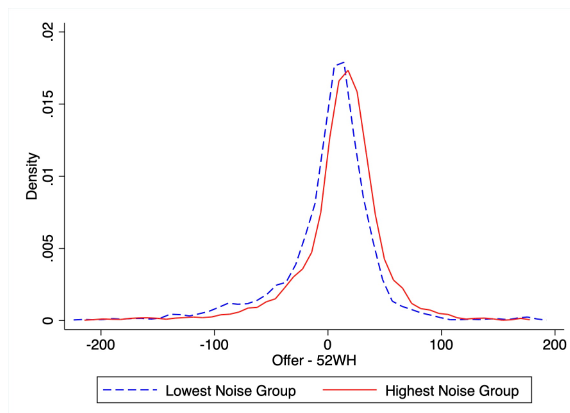
Figure 1: Offer price density by *noiseshare*.

Histograms of the log percentage difference between the offer price and the target's 52-week high price in the lowest and highest *noiseshare* subgroups: (a) 3 subgroups by *noiseshare*, (b) 4 subgroups by *noiseshare*, (c) 5 subgroups by *noiseshare*, (d) 10 subgroups by *noiseshare*.

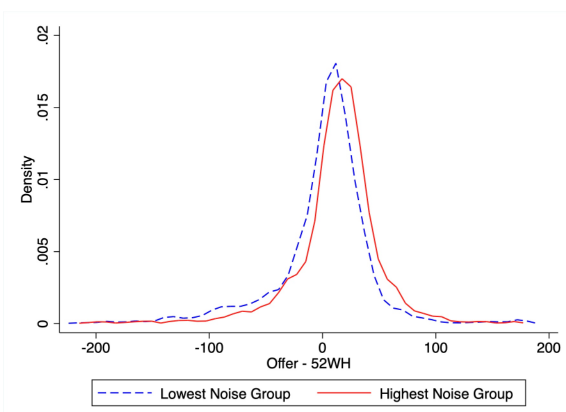
(a) noiseshare 3 groups



(b) noiseshare 4 groups



(c) noiseshare 5 groups



(d) noiseshare 10 groups

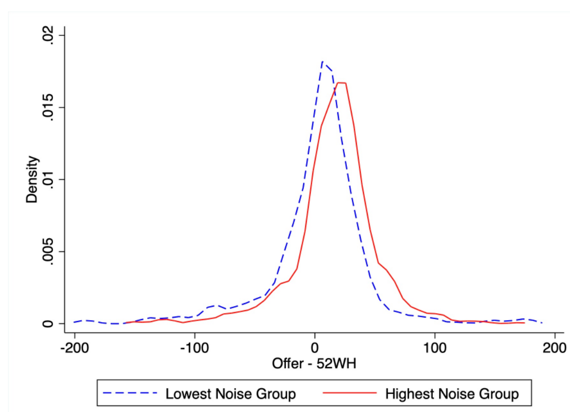


Table 1: M&A Sample distribution

The sample consists of merger or acquisition announcements from Thomson Financial, announced between 1 Jan 1984 and 31 Dec 2022, where the target is a public company, where the offer price is not missing, and where the bidder starts with less than 50% of the target firm shares outstanding and ends with 100% or else the percentage acquired is unknown, or the bid is withdrawn. Of these, we were able to compute 52-week high prices from CRSP for a sample of 10,137. The offer premium is truncated to the range of (0, 200) as in Officer (2003), leaving us with a final sample of 9,264 deals. For all deals, we have information on whether the offer is a tender offer, whether the bidder and the target are in Thomson's financial industry, and whether the form of payment is fully in cash, fully in stock, or other. For only a subset of deals, we have information on whether the deal is completed or withdrawn and whether the bidder's attitude is hostile, friendly, or neutral.

Year	Total Deals	Offer Premium %	Tender	Cash	Stock	Other	Friendly	Hostile	Completed	Withdrawn	?	LBO
1984	236	43.12	63	39	18	26	209	22	130	97	9	53
1985	242	33.00	67	126	42	22	208	33	147	80	15	45
1986	310	39.96	128	187	39	17	265	38	210	91	9	40
1987	319	39.09	108	168	37	33	235	45	202	111	5	65
1988	442	48.25	174	274	37	27	333	59	252	174	15	104
1989	303	41.89	103	171	50	18	253	25	175	113	15	41
1990	142	47.17	35	71	33	9	115	10	97	43	2	10
1991	114	51.15	11	23	47	7	100	5	84	28	1	5
1992	114	45.42	6	35	54	4	103	5	88	23	0	5
1993	178	38.53	20	56	66	9	161	5	139	33	0	4
1994	276	40.41	53	98	115	6	245	20	212	63	1	8
1995	343	36.89	67	131	147	6	296	33	270	69	4	11
1996	363	33.83	62	125	138	4	330	26	301	56	3	11
1997	466	33.47	108	164	183	7	437	16	396	66	0	16
1998	487	38.56	105	187	189	14	460	9	416	71	0	24
1999	592	40.58	154	268	189	10	547	17	494	95	0	40
2000	497	42.03	135	240	147	7	464	8	408	82	0	45
2001	319	44.80	71	151	83	2	303	4	278	40	0	20
2002	191	41.98	44	117	28	2	169	4	155	36	0	22
2003	242	35.30	37	132	31	12	218	8	203	36	0	15
2004	201	27.55	20	98	35	8	178	5	170	30	0	14
2005	249	26.02	30	164	24	5	224	3	210	36	0	37
2006	290	28.48	27	214	23	6	271	5	244	43	0	55
2007	295	28.13	48	214	20	2	281	2	247	48	0	52
2008	194	39.31	46	140	14	4	163	4	145	46	1	17
2009	130	48.57	39	74	24	0	118	1	105	25	0	15
2010	185	36.90	42	144	13	1	170	4	159	26	0	31
2011	164	34.44	43	116	15	0	143	7	135	29	0	24
2012	178	34.15	43	129	15	5	161	2	154	24	0	30
2013	136	30.97	30	98	9	1	125	0	115	21	0	24
2014	135	31.40	31	80	25	1	120	2	117	18	0	10
2015	154	33.54	36	78	26	4	132	1	130	24	0	15
2016	132	35.42	25	92	13	6	118	0	116	14	0	19
2017	131	31.05	28	76	31	2	118	0	115	16	0	12
2018	104	26.65	15	63	20	1	97	0	93	10	0	10
2019	102	34.46	18	66	20	4	96	1	92	10	0	10
2020	75	42.26	18	53	11	3	69	0	62	12	0	10
2021	123	31.76	12	72	23	2	116	0	105	16	0	18
2022	110	45.76	16	82	13	9	98	1	89	13	0	18
Total	**9264**	**37.49**	**2118**	**4816**	**2047**	**306**	**8249**	**430**	**7260**	**1868**	**80**	**1005**

Table 2: Summary statistics and correlation matrix

This table presents variables' summary statistics (*N*, *mean*, *standard deviation*, *10th percentile*, *25th percentile*, *median*, *75th percentile*, and *99th percentile*) in Panel A and the correlation matrix of key variables in Panel B. All variables are defined in the Appendix Table A1. To mitigate the effect of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. The offer premium is truncated to the range of (0, 200) as Officer (2003).

Panel A: Summary statistics

VarName	N	Mean	SD	P1	Q1	Median	Q3	P99	Winsorized
offer_premium %	9264	37.74	26.49	2.00	20.30	32.29	48.23	135.96	No
target52WH %	10137	33.53	41.53	0.00	6.45	18.69	43.69	225.13	Yes
noiseshare	10119	0.25	0.19	0.04	0.12	0.18	0.32	0.86	Yes
privateinfoshare	10119	0.26	0.17	0.00	0.12	0.24	0.38	0.67	Yes
publicinfoshare	10119	0.38	0.17	0.04	0.25	0.37	0.50	0.79	Yes
mktinfoshare	10119	0.11	0.12	0.00	0.02	0.07	0.17	0.52	Yes
success	9957	0.78	0.41	0.00	1.00	1.00	1.00	1.00	No
CAR %	5493	-1.33	7.22	-26.07	-4.48	-0.91	2.05	21.71	Yes
firm_error	4871	-0.07	0.36	-1.07	-0.28	-0.06	0.14	0.90	Yes
misprice-score	6916	51.05	12.12	24.18	42.60	50.57	59.03	81.52	Yes
Institutional ownership %	4058	56.84	31.98	0.01	29.84	59.50	84.23	117.38	Yes
log(1+analyst)	8760	1.02	1.00	0.00	0.00	0.69	1.79	3.26	Yes
EPU	9840	103.54	31.38	61.16	78.98	95.86	122.04	207.91	Yes
Ahir_WU	10137	0.13	0.13	0.00	0.03	0.10	0.19	0.50	Yes
illiq_Amihud	10137	-2.12	3.07	-8.83	-4.45	-2.01	0.25	4.35	Yes
trade_dollar_volume	10137	13.16	2.31	8.62	11.34	12.97	14.83	18.58	Yes
Cash	10137	0.50	0.50	0.00	0.00	1.00	1.00	1.00	No
Stock	10137	0.23	0.42	0.00	0.00	0.00	0.00	1.00	No
Hostile	10137	0.10	0.31	0.00	0.00	0.00	0.00	1.00	No
Tender	10137	0.22	0.42	0.00	0.00	0.00	0.00	1.00	No
Financial buyer	10137	0.40	0.49	0.00	0.00	0.00	1.00	1.00	No
Financial seller	10137	0.21	0.41	0.00	0.00	0.00	0.00	1.00	No
Diversified	10137	0.47	0.50	0.00	0.00	0.00	1.00	1.00	No
Rel_size	5304	0.56	1.34	0.00	0.04	0.16	0.52	10.32	Yes
# bidder	10137	1.14	0.41	1.00	1.00	1.00	1.00	3.00	Yes
Toehold	9982	1.94	6.98	0.00	0.00	0.00	0.00	41.80	Yes
Target ROA %	8171	-0.02	0.18	-0.95	-0.03	0.02	0.06	0.24	Yes
Target M/B	7627	2.30	3.28	-9.23	0.95	1.57	2.71	20.61	Yes
log(Target mktcap)	10137	11.84	1.76	8.17	10.54	11.71	13.05	16.21	Yes
Target Leverage	9158	0.22	0.21	0.00	0.03	0.17	0.34	0.88	Yes
Target Runup	10120	-0.02	0.53	-2.07	-0.24	0.05	0.29	1.14	Yes
Target volatility %	10120	3.53	1.95	0.98	2.14	3.04	4.32	10.77	Yes
Bidder ROA %	4130	0.00	0.24	-1.77	0.01	0.04	0.07	0.24	Yes
Bidder M/B	3495	3.35	4.97	-9.14	1.23	2.16	3.66	34.99	Yes
log(Bidder mktcap)	5481	13.93	2.12	8.84	12.50	13.92	15.29	18.96	Yes
Bidder Leverage	5131	0.23	0.18	0.00	0.10	0.20	0.33	0.79	Yes
Bidder Runup	5481	0.13	0.39	-1.16	-0.06	0.14	0.34	1.27	Yes

Panel B: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)
(1) offer_premium %	1.000					
(2) target52WH %	0.300***	1.000				
(3) noiseshare	0.070***	-0.070***	1.000			
(4) privateinfoshare	-0.060***	0.010	-0.500***	1.000		
(5) publicinfoshare	-0.020	0.040***	-0.440***	-0.320***	1.000	
(6) mktinfoshare	0.000	0.040***	-0.230***	-0.130***	-0.310***	1.000

Table 3: Offer above target 52-Week High price: Effects of target's noise

This table shows the marginal effect of the noise in the target share price in driving the offer price over the target 52-week high price using the following logit model:

$$offer\_big\_52WH = \beta_0 + \beta_1 noiseshare + \beta_2 \text{infoshares} + \beta_3 Controls + e$$

offer_big_52WH equals one if the offer price is higher than the target 52-week high price. infoshares can be any two of *privateinfoshare*, *publicinfoshare* & *mktinfoshare*. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
noiseshare	0.330***					0.348***	0.345***	0.309***
	(6.12)					(3.77)	(5.69)	(4.83)
privateinfoshare		-0.083			-0.307***	0.039	0.037	
		(-1.58)			(-4.77)	(0.48)	(0.59)	
publicinfoshare			-0.162***		-0.342***	0.003		-0.036
			(-3.27)		(-5.65)	(0.04)		(-0.58)
mktinfoshare				-0.035	-0.344***		-0.001	-0.037
				(-0.46)	(-3.71)		(-0.01)	(-0.45)
inverseprice	0.099***	0.101***	0.102***	0.100***	0.099***	0.099***	0.099***	0.099***
	(4.83)	(4.70)	(4.79)	(4.65)	(4.83)	(4.84)	(4.84)	(4.84)
Target Runup	0.325***	0.337***	0.341***	0.338***	0.326***	0.325***	0.325***	0.325***
	(18.18)	(18.45)	(18.82)	(18.58)	(17.87)	(17.85)	(17.87)	(17.86)
Cash	0.005	0.003	0.003	0.003	0.005	0.005	0.005	0.005
	(0.26)	(0.16)	(0.17)	(0.16)	(0.24)	(0.26)	(0.26)	(0.26)
Stock	-0.012	-0.018	-0.017	-0.018	-0.011	-0.011	-0.011	-0.011
	(-0.53)	(-0.82)	(-0.77)	(-0.81)	(-0.52)	(-0.52)	(-0.52)	(-0.52)
Hostile	0.030	0.028	0.026	0.028	0.030	0.030	0.030	0.030
	(1.09)	(1.01)	(0.95)	(1.02)	(1.09)	(1.09)	(1.09)	(1.09)
Tender	0.005	0.002	0.003	0.001	0.005	0.005	0.005	0.005
	(0.28)	(0.08)	(0.15)	(0.04)	(0.29)	(0.28)	(0.28)	(0.28)
Financial buyer	-0.113*	-0.106*	-0.111*	-0.106*	-0.113*	-0.113*	-0.113*	-0.113*
	(-1.93)	(-1.83)	(-1.90)	(-1.82)	(-1.92)	(-1.93)	(-1.93)	(-1.93)
Financial seller	0.026	0.042	0.043	0.046	0.027	0.027	0.027	0.027
	(0.40)	(0.66)	(0.68)	(0.72)	(0.42)	(0.41)	(0.41)	(0.41)
Rel_size	-0.002	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
	(-0.31)	(-0.16)	(-0.15)	(-0.10)	(-0.30)	(-0.29)	(-0.29)	(-0.30)
# bidder	0.008	0.010	0.007	0.009	0.008	0.007	0.007	0.007
	(0.39)	(0.51)	(0.37)	(0.47)	(0.38)	(0.36)	(0.36)	(0.37)
Diversified	-0.010	-0.008	-0.008	-0.008	-0.010	-0.010	-0.010	-0.010
	(-0.69)	(-0.57)	(-0.55)	(-0.52)	(-0.69)	(-0.68)	(-0.68)	(-0.68)
Toehold	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
	(-1.21)	(-1.10)	(-1.04)	(-1.08)	(-1.20)	(-1.21)	(-1.21)	(-1.21)
Target ROA	-0.085*	-0.056	-0.070	-0.054	-0.086*	-0.086*	-0.086*	-0.086*
	(-1.88)	(-1.25)	(-1.56)	(-1.21)	(-1.91)	(-1.90)	(-1.90)	(-1.90)
Target M/B	-0.003	-0.003	-0.004	-0.004	-0.003	-0.003	-0.003	-0.003
	(-1.35)	(-1.40)	(-1.53)	(-1.46)	(-1.37)	(-1.37)	(-1.37)	(-1.37)
log(Target mktcap)	0.017**	0.009	0.003	0.008	0.017*	0.017*	0.017*	0.017*
	(2.10)	(1.12)	(0.41)	(0.96)	(1.92)	(1.95)	(1.94)	(1.94)
Target Leverage	0.048	0.053	0.052	0.053	0.048	0.048	0.048	0.048
	(1.19)	(1.32)	(1.27)	(1.32)	(1.19)	(1.18)	(1.18)	(1.18)
Target volatility %	-0.050***	-0.044***	-0.047***	-0.044***	-0.050***	-0.050***	-0.050***	-0.050***
	(-7.43)	(-6.68)	(-7.06)	(-6.61)	(-7.44)	(-7.44)	(-7.45)	(-7.45)
Bidder ROA	-0.099**	-0.092**	-0.085**	-0.089**	-0.098**	-0.098**	-0.098**	-0.098**
	(-2.38)	(-2.17)	(-2.02)	(-2.09)	(-2.34)	(-2.35)	(-2.35)	(-2.35)
Bidder M/B	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000
	(0.16)	(0.04)	(0.00)	(-0.03)	(0.13)	(0.14)	(0.14)	(0.14)
log(Bidder mktcap)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.17)	(0.12)	(0.10)	(0.10)	(0.16)	(0.16)	(0.16)	(0.16)
Bidder Leverage	0.013	0.012	0.014	0.012	0.014	0.013	0.013	0.013
	(0.31)	(0.28)	(0.32)	(0.29)	(0.34)	(0.31)	(0.31)	(0.31)
Bidder Runup	-0.041**	-0.045**	-0.045**	-0.046**	-0.041**	-0.041**	-0.041**	-0.041**
	(-1.99)	(-2.12)	(-2.16)	(-2.20)	(-2.01)	(-2.00)	(-2.00)	(-2.00)
Industry Effect	Y	Y	Y	Y	Y	Y	Y	Y
Time Effect	Y	Y	Y	Y	Y	Y	Y	Y
N	3089	3089	3089	3089	3089	3089	3089	3089
Pseudo-R2	0.250	0.241	0.243	0.240	0.250	0.250	0.250	0.250

Table 4: Noise intensified reliance on the target 52-week high price

This table shows the effect of the noise in the target share price on the reliance of the offer price on the target 52-week high price using the following model:

$$offer\_premium = \beta_0 + \beta_1(noiseshare \times target52WH) + \beta_2 Controls + e$$

See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
target52WH	0.156***	0.076**	0.161***	0.093***	0.152***	0.136***	0.071***	0.045
	(13.39)	(2.21)	(13.83)	(2.60)	(9.50)	(8.60)	(2.62)	(1.17)
noiseshare			9.511***	7.735*	6.685***	6.129***	7.247***	-0.922
			(5.54)	(1.78)	(3.23)	(2.97)	(2.72)	(-0.17)
noiseshare × target52WH					0.146**	0.121**	0.178**	0.254**
					(2.57)	(2.11)	(2.11)	(2.02)
inverseprice	4.599***	5.029*	3.973***	4.877*		3.751***	4.570**	3.675
	(5.13)	(1.77)	(4.44)	(1.73)		(4.06)	(2.32)	(1.36)
Target Runup		-4.912**		-4.357*			-2.749*	-4.262*
		(-2.21)		(-1.95)			(-1.66)	(-1.92)
Cash		-2.457		-2.402			-0.331	-2.454
		(-1.61)		(-1.58)			(-0.34)	(-1.61)
Stock		-3.044**		-2.926**			-2.527***	-2.849*
		(-2.06)		(-1.98)			(-2.70)	(-1.93)
Hostile		6.953***		6.876***			7.374***	6.997***
		(2.70)		(2.67)			(3.74)	(2.72)
Tender		1.939		2.029			1.780	2.026
		(1.31)		(1.37)			(1.50)	(1.36)
Financial buyer		-9.303**		-9.331**			-3.052	-9.065**
		(-2.40)		(-2.40)			(-1.14)	(-2.34)
Financial seller		6.184		5.701			0.206	5.656
		(1.19)		(1.09)			(0.07)	(1.09)
Rel_size		2.714***		2.697***			0.476	2.715***
		(3.78)		(3.74)			(1.01)	(3.77)
# bidder		0.695		0.649			-0.368	0.771
		(0.46)		(0.44)			(-0.32)	(0.52)
Diversified		-0.534		-0.622			0.110	-0.802
		(-0.43)		(-0.50)			(0.13)	(-0.65)
Toehold		-0.008		-0.014			-0.157**	-0.016
		(-0.08)		(-0.13)			(-2.15)	(-0.15)
Target ROA		6.114		5.530				5.149
		(1.57)		(1.42)				(1.31)
Target M/B		-0.152		-0.156				-0.143
		(-0.88)		(-0.91)				(-0.83)
log(Target mktcap)		-4.076***		-3.832***				-3.981***
		(-7.12)		(-6.46)				(-6.61)
log(Target mktcap)		-4.076***		-3.832***				-3.981***
		(-7.12)		(-6.46)				(-6.61)
Target Leverage		-0.660		-0.889				-0.919
		(-0.19)		(-0.26)				(-0.27)
Target volatility %		-0.318		-0.570				-0.653
		(-0.57)		(-0.98)				(-1.11)
Bidder ROA		-1.622		-1.617				-1.600
		(-0.52)		(-0.51)				(-0.51)
Bidder M/B		0.165		0.171				0.169
		(1.31)		(1.35)				(1.34)
log(Bidder mktcap)		2.862***		2.869***				2.910***
		(6.35)		(6.38)				(6.45)
Bidder Leverage		4.569		4.578				4.261
		(1.28)		(1.29)				(1.22)
Bidder Runup		5.178***		5.266***				5.230***
		(2.97)		(3.03)				(3.02)
IndustryEffect	Y	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y	Y
N	9250	2824	9249	2824	9249	9249	4794	2824
AdjustedR2	0.193	0.335	0.197	0.336	0.195	0.198	0.253	0.339

Table 5: High-dimensional fixed effects model

This table shows the effect of the noise in the target share price on the reliance of the offer price on the target 52-week high price using the following high-dimensional fixed effects model:

$$offer\_premium = \beta_0 + \beta_1(noiseshare \times target52WH) + \beta_2 Controls + e$$

See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)
target52WH	0.151***	0.083
	(3.14)	(1.50)
noiseshare × target52WH		0.458***
		(2.71)
FullControls	Y	Y
Industry × Time Effect	Y	Y
N	1425	1425
AdjustedR2	0.510	0.516

Table 6: Other information and the reliance on the target 52-week high price

This table shows the effect of otherinfoshare (*privateinfoshare*, *publicinfoshare* or *mktinfoshare*) in the target share price on the reliance of the offer price on the target 52-week high price. Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(\text{otherinfoshare} \times target52WH) + \beta_2 Controls + e$$

See the variable definitions in the Appendix Table A1. All regressions include full control variables as in Table 4. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
target52WH	0.075**	0.078**	0.077**	0.113**	0.089*	0.083**
	(2.16)	(2.25)	(2.22)	(2.45)	(1.75)	(2.12)
privateinfoshare	-0.940			3.943		
	(-0.25)			(0.81)		
publicinfoshare		-2.965			-1.863	
		(-0.94)			(-0.45)	
mktinfoshare			-5.701			-3.934
			(-0.96)			(-0.54)
privateinfoshare × target52WH				-0.134		
				(-1.33)		
publicinfoshare × target52WH					-0.028	
					(-0.34)	
mktinfoshare × target52WH						-0.046
						(-0.38)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	2824	2824	2824	2824	2824	2824
AdjustedR2	0.183	0.184	0.184	0.184	0.183	0.183

Table 7: Instrumental variable two-stage least squares regressions

This table reports the 2SLS results of how *trading_turnover* and *CoverageShock* as instrumental variables of *noiseshare* affect the effectiveness of the target 52-week high price. Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(\widehat{noiseshare} \times target52WH) + \beta_2 Controls + e$$

The first stage is *noiseshare* on the instrument(s) and other control variables and corresponding fixed effects (if adopted):

$$noiseshare = \beta_0 + \beta_1 Instrument\ variable(s) + \beta_2 target52WH + \beta_3 Controls + e$$

See the variable definitions in the Appendix Table A1. All regressions include full control variables as in Table 4. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Panel A: The second-stage results		
	(1)	(2)
$\widehat{\text{noiseshare}}$ × target52WH	1.456***	1.448***
	(3.87)	(3.74)
FullControls	Y	Y
IndustryEffect	N	Y
TimeEffect	N	Y
N	2126	2126
Kleibergen-Paap-LM-statistic	66.396	61.473
Kleibergen-Paap-LM-p	0.000	0.000
Sargan–Hansen-J-statistic	3.907	3.733
Sargan–Hansen-J-p	0.142	0.155
Kleibergen-Paap-F-statistic	23.968	20.082
Panel B: The first-stage results		
	(1)	(2)
trading_turnover	-0.004***	-0.003***
	(-8.03)	(-7.28)
CoverageShock	0.028**	0.033***
	(2.54)	(2.71)
FullControls	Y	Y
IndustryEffect	N	Y
TimeEffect	N	Y
N	3103	3103
F-statistic	29.594	26.075

Table 8: Market reaction

This table reports the ordinary and two-stage least-squares regressions of the 3-day cumulative abnormal return of the bidder on the offer premium (or instrumented). Our regressions are as follows:

$$CAR = \beta_0 + \beta_1(\mathit{offer\_premium}\ /\ \widehat{\mathit{offer\_premium}}) + \beta_2 \mathit{Controls} + e$$

Panel A Columns (1) and (2) use ordinary least squares. All other Columns in all Panels are 2SLS. Panel A Columns (3) and (4) use 2SLS, where the offer_premium is instrumented by the *target52WH*. Panel A Columns (5) and (6) use 2SLS, where the offer_premium is instrumented by the interactive term *noise-share* x *target52WH*. Panel B uses 2SLS, where the offer_premium is instrumented by the interactive term between other information shares in the target share price and *target52WH*. The first stage is regressing *offer_premium* on the instrumental variable(s), other control variables and corresponding fixed effect (if adopted). See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: OLS and 2SLS regressions; Dependent variable CAR					
	(1) OLS	(2) OLS	(3) IV-52WH	(4) IV-52WH	(5) IV-NoiInter	(6) IV-NoiInter
offer_premium	-0.015**	-0.015**				
	(-2.27)	(-2.16)				
$\widehat{\text{offer\_premium}}$			-0.388***	-0.291**	-0.086	-0.089
			(-3.01)	(-2.44)	(-1.16)	(-1.13)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y	N	Y
TimeEffect	N	Y	N	Y	N	Y
N	2823	2823	2823	2823	2823	2823
AdjustedR2	0.074	0.097	0.076	0.098	0.072	0.095
1st stage F statistics	-	-	19.117	14.890	17.771	13.574
	Panel B: Other 2SLS regressions; Dependent variable CAR					
	(1) IV-PriInter	(2) IV-PriInter	(3) IV-PubInter	(4) IV-PubInter	(5) IV-MktInter	(6) IV-MktInter
$\widehat{\text{offer\_premium}}$	-0.206**	-0.192*	-0.298***	-0.261**	-0.382***	-0.239**
	(-1.97)	(-1.94)	(-2.66)	(-2.32)	(-3.02)	(-2.20)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y	N	Y
TimeEffect	N	Y	N	Y	N	Y
N	2823	2823	2823	2823	2823	2823
AdjustedR2	0.074	0.097	0.075	0.097	0.076	0.097
1st stage F statistics	17.560	13.605	17.704	13.743	17.615	13.829

Table 9: Deal success

This table reports the probit regressions where the deal success is the dependent variable. Our probit regressions are as follows:

$$success = \beta_0 + \beta_1(noiseshare \times offer\_big\_52WH) + \beta_2 offer\_premium(s) + \beta_4 Controls + e$$

We limit the sample only to those deals that Thomson identifies as completed or withdrawn. We use polynomial terms of offer_premium to capture potential non-linearity as in Baker et al. (2012). The coefficients reports are not marginal effects, as the interpretation of the marginal effects of interactive terms in non-linear models can be challenging (Li et al., 2023). Panel A Columns (1) and (2) are the baseline regressions without interactive terms and Other columns are regressions with interactive terms. Columns (3) and (4) add interactive terms between *noiseshare* and *offer_big_52WH* to baseline regressions. Columns (5) and (6) add interactive terms between *noiseshare* 2-subgroup dummy variable and *offer_big_52WH* to baseline regressions. Panel B adds interactive terms between other information in the target share price and *offer_big_52WH* to baseline regressions. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: Baseline and noiseshare					
	(1)	(2)	(3)	(4)	(5)	(6)
noiseshare × offer_big_52WH			-1.443**	-1.405**		
			(-2.32)	(-2.23)		
noi_2 × offer_big_52WH					-0.416*	-0.436**
					(-1.92)	(-2.01)
offer_big_52WH	0.271**	0.253*	0.643***	0.616***	0.470***	0.457***
	(2.01)	(1.81)	(3.29)	(3.08)	(2.78)	(2.65)
offer_premium	-0.008***	-0.000	-0.008***	0.000	-0.008***	0.001
	(-3.44)	(-0.02)	(-3.45)	(0.02)	(-3.41)	(0.03)
offer_premium^2		0.000		0.000		0.000
		(0.26)		(0.20)		(0.23)
offer_premium^3		-0.000		-0.000		-0.000
		(-0.81)		(-0.74)		(-0.80)
offer_premium^4		0.000		0.000		0.000
		(1.22)		(1.13)		(1.20)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	2095	2095	2095	2095	2095	2095
PseudoR2	0.477	0.482	0.481	0.485	0.479	0.484
	Panel B: Other information shares					
	(1)	(2)	(3)	(4)	(5)	(6)
privateinfoshare × offer_big_52WH	0.581	0.513				
	(0.89)	(0.79)				
publicinfoshare × offer_big_52WH			0.529	0.471		
			(0.82)	(0.73)		
mktinfoshare × offer_big_52WH					1.481	1.625*
					(1.59)	(1.75)
offer_big_52WH	0.099	0.101	0.080	0.083	0.135	0.101
	(0.42)	(0.42)	(0.29)	(0.30)	(0.82)	(0.60)
offer_premium	-0.008***	-0.002	-0.008***	-0.001	-0.008***	-0.000
	(-3.47)	(-0.08)	(-3.49)	(-0.04)	(-3.35)	(-0.03)
offer_premium^2		0.000		0.000		0.000
		(0.31)		(0.27)		(0.28)
offer_premium^3		-0.000		-0.000		-0.000
		(-0.84)		(-0.82)		(-0.84)
offer_premium^4		0.000		0.000		0.000
		(1.24)		(1.22)		(1.24)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	2095	2095	2095	2095	2095	2095
PseudoR2	0.478	0.483	0.478	0.483	0.481	0.486

Appendix Table A1: Variables, Definitions, and Sources

Variable	Definition	Source
offer_premium	The logarithmic percentage difference between the offer price from SDC and the target's price (adjusted for stock splits and stock dividends) 30 days before the announcement.	SDC & CRSP
target52WH	The logarithmic percentage difference obtained by scaling the 52-week high stock price over the window from 365 calendar days ending 30 days before the announcement date (1 calendar year window) by the target price (adjusted for stock splits and dividends) 30 days before the announcement date.	CRSP & Authors' Estimations
noiseshare	Using a VAR model to incorporate three variables - log market return, signed dollar trading volume of stocks, and log stock return over the window from 365 calendar days ending 30 days before the announcement date. The noise captures the aggregate short-term share return response to shocks originating from log market return, trading dollar volume, and log share return. In this context, the short term is defined as 15 days, given that the share return stabilizes within 15 days after information shocks in the VAR model (Brogaard et al., 2022) (verified by authors). The short-term return is calculated as the difference between the initial share return response and the stable long-term response after 15 days.	CRSP & Authors' Estimations
privateinfoshare	Utilizing a VAR model to fit three variables: log market return, stock signed dollar trading volume, and log stock return over the window from 365 calendar days ending 30 days before the announcement date. The long-term stable share return response to shocks from trade dollar volume is attributed to private information. The long-term response is the share return response after 15 days, as the share return is stable 15 days after information shocks in the VAR model (Brogaard et al., 2022) (verified by authors).	CRSP & Authors' Estimations
publicinfoshare	Utilizing a VAR model to fit three variables: log market return, stock signed dollar trading volume, and log stock return over the window from 365 calendar days ending 30 days before the announcement date. The long-term stable share return response to shocks from log share return is attributed to public information. The long-term response is the share return response after 15 days, as the share return is stable 15 days after information shocks in the VAR model (Brogaard et al., 2022) (verified by authors).	CRSP & Authors' Estimations
mktinfoshare	Utilizing a VAR model to fit three variables: log market return, stock signed dollar trading volume, and log stock return over the window from 365 calendar days ending 30 days before the announcement date. The long-term stable share return response to shocks from log market return is attributed to market information. The long-term response is the share return response after 15 days, as the share return is stable 15 days after information shocks in the VAR model (Brogaard et al., 2022) (verified by authors).	CRSP & Authors' Estimations
offer_big_52WH	Dummy equals one if the offer price is higher than the target 52-week high price.	SDC & CRSP
success	Dummy equals one if the deal is completed and zero if withdrawn.	SDC
CAR	Market-adjusted return of the bidder for the 3-day centered on the announcement date.	CRSP & Authors' Estimations
BHAR	Bidder's buy-and-hold-abnormal-return in the one-year window after the announcement	WRDS
firm_error	The misprice measure of Rhodes–Kropf et al. (2005) decomposes the logarithm of the market-to-book ratio into firm-specific error, time-series sector error, and long-run market value to book value. We use the firm-specific error as the misvaluation measure, which is positively related to overvaluation.	CRSP & Compustat & Authors' Estimations

Table Continued

Appendix Table A1: Variables, Definitions, and Sources (Continued)

Variable	Definition	Source
abs_firm_error	The absolute value of *firm_error*. A *firm_error* of 0 signifies the absence of mispricing, making *abs_firm_error* a gauge for the deviation from efficient pricing.	CRSP & Compustat & Authors' Estimations
misprice_score	The misprice measure of Stambaugh et al. (2012), capturing the mispricing of stock by averaging its ranking percentile for each of the 11 anomalies, consisting of net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment to assets, financial distress, O-score, momentum, gross profitability, and return on assets. This rank variable is ranging from 1 to 100, positively related to overvaluation	Robert F. Stambaugh's Website
abs_misprice_score	subtracting 50 from the *misprice_score* and then taking the absolute value. Since a *misprice_score* of 50 indicates no mispricing, *abs_misprice_score* quantifies the deviation from efficient market prices.	Robert F. Stambaugh's Website & Authors' Estimations
institutional ownership %	The percentage of shares held by institutions to the total number of shares outstanding before the announcement.	Thomson Reuters Institutional (13f) Holdings database.
log(1+analyst)	log(1+analyst) where analyst is the number of analysts following the firm in the past year.	I/B/E/S
EPU	A country-level monthly policy uncertainty measure from Baker et al. (2016). The weighted average of four components related to news, tax code changes, and dispersion in forecasts of monetary and fiscal policies.	Economic Policy Uncertainty Website
Ahir_WU	A country-level quarterly economic uncertainty measure from Ahir et al. (2022) by counting the frequency of the word "uncertainty" in the quarterly Economist Intelligence Unit country reports.	World Uncertainty Index Website
illiq_Amihud	The Amihud (2002) measure. The absolute daily returns divided by daily dollar trading volume, averaging over the 365 calendar days ending 30 days before the announcement date.	CRSP & Authors' Estimations
trade_dollar_volume	Daily share trading volume multiplied by the closing price. Using the average of over the 365 calendar days ending 30 days before the announcement date.	CRSP & Authors' Estimations
Cash	A dummy equals one if the deal is 100% paid by cash.	SDC
Stock	A dummy equals one if the deal is 100% paid by stock	SDC
Hostile	A dummy equals one if the bidder's attitude is hostile.	SDC
Tender	A dummy equals one if the deal is a tender offer.	SDC
Financial buyer	A dummy equals one if the bidder is in the financial industry.	SDC
Financial seller	A dummy equals one if the target is in the financial industry.	SDC
Rel_size	The deal value divided by the acquirer's pre-acquisition market value.	SDC
# bidder	The number of bidders bidding for the target.	SDC
Cross border	A dummy equals one if the acquirer and target come from different countries.	SDC
Diversified	A dummy equals one if the acquirer and the target have different two-digit SIC codes and zero otherwise.	SDC
Toehold	The percentage of the target shares held by the acquirer six months before the acquisition.	SDC
ROA%	The return on assets (for bidder or target) is defined as net income (NI) divided by total assets (Compustat:AT) in a percentage term.	Compustat
M/B%	The market-to-book ratio (for bidder or target) is the market equity divided by book equity. Market equity is the shares outstanding (CRSP:SHROUT) multiplied by price (CRSP:PRC) at the fiscal year's end. The book equity is total shareholders' equity (Compustat:SEQ) plus deferred taxes and investment tax credit (Compustat:TXDITC) minus the redemption value of preferred stock (Compustat:PSRKRV).	CRSP & Compustat
log(mktcap)	The market capitalization (for bidder or target) is equal to price times shares outstanding from CRSP at t-30 calendar day.	CRSP

Table Continued

Appendix Table A1: Variables, Definitions, and Sources (Continued)

Variable	Definition	Source
Leverage	Total debt (Compustat: DLTT+DLC) divided by total assets (Compustat: AT).	Compustat
target volatility%	The target's volatility is the standard deviation of daily returns over the window from 365 calendar days to 30 days before the announcement date.	CRSP & Authors' Estimations
inverseprice	The inverse of the target share price (adjusted for stock splits and stock dividends) lagged 30 calendar days.	CRSP
Runup	The cumulative raw log return over the window from 365 calendar days to 30 days before the announcement date, using CRSP data for both the target and the bidder.	CRSP
trading_turnover	The average daily trading turnover of the target company over the past year window, where the trading turnover is the daily trading volume divided by the company's outstanding share at the end of the trading day.	CRSP
CoverageShock	A dummy equals one if the target company's analyst coverage has been impacted by mergers or closures of brokerage houses within the two years preceding the announcement date.	Marcin Kacperczyk's Website
1-R2	ln(1-R2/R2), where the R2 is the R-square derived from a regression using the daily excess returns of a firm relative to market returns and corresponding Fama-French 48-industry returns over the window from 365 calendar days ending 30 days before the announcement date.	CRSP & Authors' Estimations
PIN	Probability of Informed Trading, the most recent value before the announcement date.	Stephen Brown's Website

Appendix Table A2: Matched sample analysis

This table shows the results of the target 52-week high reliance under the matched sample. Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(Treated \times target52WH) + \beta_2 Controls + e$$

In Panel A (Panel B), *Treated* is a dummy variable *noi_2* (*noi_3*) that takes the value of one if *noiseshare* is in its high half (highest tertile group) and zero otherwise (in its lowest tertile group). See other variables' definitions in the Appendix Table A1. All regressions include full control variables as in Table 4. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: noi_2 as *Treated*, divided by the median of *noiseshare*			
	(1)	(2)	(3)	(4)
Treated × target52WH	0.070**	0.068**	0.065**	0.064**
	(2.52)	(2.44)	(2.40)	(2.33)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	2306	2306	2306	2306
AdjustedR2	0.135	0.136	0.154	0.155
	Panel B: noi_3 as *Treated*, divided by tertiles of *noiseshare*			
	(1)	(2)	(3)	(4)
Treated × target52WH	0.097**	0.095**	0.083**	0.081**
	(2.39)	(2.35)	(2.12)	(2.09)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	1278	1278	1278	1278
AdjustedR2	0.152	0.159	0.172	0.179

Appendix Table A3: Brokerage house closures and mergers

This table shows the difference in the reliance of the offer price on the target 52-week high price between the deals that experienced a reduction in the number of shared analysts due to the closure of brokerage houses (*Treated*=1) and those not affected by the shock (*Treated*=0) as in Cortes and Marcet (2023). Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(Treated \times target52WH) + \beta_2 Controls + e$$

See other variables' definitions in the Appendix Table A1. All regressions include full control variables as in Table 4. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Treated × target52WH	0.220**	0.270**	0.219*	0.326**
	(2.19)	(2.37)	(1.67)	(2.15)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	145	145	145	145
AdjustedR2	0.400	0.638	0.524	0.723

Appendix Table A4: Ticker size reduction

This table shows results for the difference in difference analysis of the target 52-week high reliance around ticker size reduction. Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(Post \times Treated \times target52WH) + \beta_2 Controls + e$$

Post is a dummy variable that takes the value of one after the effective date 1997-06-24 and zero otherwise in the period from 1996 to 1998. *Treated* is a dummy variable that takes the value of one if the target company's share price is not in its highest quartile and zero otherwise, as the setting in Brogaard et al. (2022). The control variable *inverseprice* is removed as its collinearity with *Treated*. See other variables' definitions in the Appendix Table A1. All regressions include full control variables as in Table 4. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Post × Treated × target52WH	-0.478*	-0.581**	-0.524*	-0.639**
	(-1.86)	(-2.44)	(-1.97)	(-2.53)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	222	222	222	222
AdjustedR2	0.236	0.359	0.255	0.377

Appendix Table A5: Subsample regressions divided by mechanism measures

This table reports subsample regressions as Equation 2 in subsamples divided by potential mechanism measures (misprice, information environment, uncertainty and illiquidity). These variables are indicated under the column numbers. Error is *firm_error*; Score is *misprice_score*; Abs_Error is the *abs_firm_error*; Abs_Score is *abs_misprice_score*; Institution is *Institutional ownership %*; Analyst is *log(1+analyst)*; VOL is the *Target volatility %*; WorldU is *Ahir_WU*; Illiquidity is *illiq_Amihud*; Trade$ is *trade_dollar_volume*. The first column of one measure is the subsample regression result of the lowest level of the measure, and the second column is the subsample regression result of the highest level of the measure. Panel A presents the results of subsamples divided by misprice and absolute misprice measures. Panel B presents the results of subsamples divided by information environment measures and uncertainty measures (deal level and company level). Panel C presents the results of subsamples divided by uncertainty measures (macro level) and illiquidity measures. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: Sub-sample by misprice and absolute misprice							
	(1) Error Sub5-L	(2) Error Sub5-H	(3) Score Sub5-L	(4) Score Sub5-H	(5) Abs_Error Sub5-L	(6) Abs_Error Sub5-H	(7) Abs_Score Sub5-L	(8) Abs_Score Sub5-H
target52WH	-0.183*	-0.057	-0.145	0.163*	0.291***	-0.194***	0.161	-0.094
	(-1.86)	(-0.90)	(-1.36)	(1.82)	(2.99)	(-2.67)	(1.31)	(-1.25)
noiseshare × target52WH	0.595***	0.368	1.279***	0.067	-0.224	0.660***	0.466	0.474
	(2.78)	(1.22)	(3.17)	(0.24)	(-0.64)	(2.91)	(0.97)	(1.55)
FullControls	Y	Y	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y	Y
N	332	429	443	441	343	370	402	467
AdjustedR2	0.549	0.364	0.535	0.345	0.517	0.461	0.403	0.445
	Panel B: Sub-sample by information and uncertainty (deal & company level)							
	(1) Institution Sub5-L	(2) Institution Sub5-H	(3) Analyst Sub5-L	(4) Analyst Sub5-H	(5) Rel_size Sub5-L	(6) Rel_size Sub5-H	(7) VOL Sub5-L	(8) VOL Sub5-H
target52WH	-0.006	0.015	-0.003	0.060	-0.012	-0.003	0.718***	-0.022
	(-0.04)	(0.11)	(-0.05)	(0.50)	(-0.16)	(-0.05)	(3.25)	(-0.39)
noiseshare × target52WH	0.763*	1.105	0.424**	0.444	-0.068	0.432*	-1.702	0.275**
	(1.77)	(1.34)	(1.99)	(1.00)	(-0.38)	(1.74)	(-1.59)	(2.12)
FullControls	Y	Y	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y	Y
N	167	246	881	542	527	678	416	714
AdjustedR2	0.514	0.602	0.283	0.447	0.373	0.312	0.390	0.294
	Panel C: Sub-sample by uncertainty (macro level) and illiquidity							
	(1) EPU Sub5-L	(2) EPU Sub5-H	(3) WorldU Sub5-L	(4) WorldU Sub5-H	(5) Illiquidity Sub5-L	(6) Illiquidity Sub5-H	(7) Trade$ Sub5-L	(8) Trade$ Sub5-H
target52WH	0.032	0.092	0.059	-0.009	0.144	-0.013	0.099	0.098
	(0.75)	(0.83)	(1.24)	(-0.09)	(1.61)	(-0.12)	(0.63)	(1.14)
noiseshare × target52WH	0.321*	0.286	0.327**	0.200	-0.555	0.176	-0.232	-0.038
	(1.96)	(0.98)	(2.01)	(0.88)	(-1.24)	(1.12)	(-0.99)	(-0.13)
FullControls	Y	Y	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y	Y
N	615	469	731	543	716	442	389	705
AdjustedR2	0.293	0.354	0.269	0.325	0.322	0.311	0.399	0.298

Appendix Table A6: Mechanism variables as IV of noiseshare

This table reports the second stage of 2SLS regressions as follows:

$$offer\_premium = \beta_0 + \beta_1(\widehat{noiseshare} \times target52WH) + \beta_2 Controls + e$$

The second stage uses predicted $\widehat{noiseshare}$ from the first stage to replace *noiseshare*. The first stage is *noiseshare* on potential mechanism measures, other control variables, and corresponding fixed effects (if adopted). Error is *firm_error*; Score is *misprice_score*; Abs_Error is the *abs_firm_error*; Abs_Score is *abs_misprice_score*; Institution is *Institutional ownership %*; Analyst is *log(1+analyst)*; VOL is the *Target volatility %*; WorldU is *Ahir_WU*; Illiquidity is *illiq_Amihud*; Trade$ is *trade_dollar_volume*. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: Misprice, absolute misprice and information					
	(1) Error	(2) Score	(3) Abs_Error	(4) Abs_Score	(5) Institution	(6) Analyst
target52WH	125.763	0.133	1.021*	0.520	0.153	-0.847*
	(1.31)	(1.05)	(1.89)	(1.12)	(0.64)	(-1.92)
$\widehat{noiseshare}$ × target52WH	0.609***	0.485*	0.609***	0.469*	0.146	0.323*
	(2.80)	(1.89)	(2.80)	(1.83)	(0.29)	(1.66)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	1784	2134	1784	2134	1088	2563
AdjustedR2	0.430	0.368	0.433	0.368	0.528	0.369
	Panel B: Uncertainty and illiquidity					
	(1) Rel_Size	(2) VOL	(3) EPU	(4) WorldU	(5) Illiquidity	(6) Trade$
target52WH	-0.505	0.035	4.983	0.549**	0.183***	0.324***
	(-0.70)	(0.07)	(1.15)	(2.21)	(3.14)	(4.23)
$\widehat{noiseshare}$ × target52WH	0.215	0.217	0.204	0.209	0.204	0.164
	(1.25)	(1.26)	(1.19)	(1.21)	(1.23)	(0.99)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	2824	2824	2797	2824	2824	2824
AdjustedR2	0.336	0.336	0.336	0.337	0.341	0.344

Appendix Table A7: Mechanism variables interact with target52WH

This table reports the results of interacting mechanism measures with the *target52WH* as follows:

$$offer\_premium = \beta_0 + \beta_1(\text{mechanism measures} \times target52WH) + \beta_2 Controls + e$$

Error is *firm_error*; Score is *misprice_score*; Abs_Error is the *abs_firm_error*; Abs_Score is *abs_misprice_score*; Institution is *Institutional ownership %*; Analyst is *log(1+analyst)*; VOL is the *Target volatility %*; WorldU is *Ahir_WU*; Illiquidity is *illiq_Amihud*; Trade$ is *trade_dollar_volume*. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: Misprice, absolute misprice and information					
	(1) Error	(2) Score	(3) Abs_Error	(4) Abs_Score	(5) Institution	(6) Analyst
target52WH	0.085**	0.255**	0.101**	0.111*	-0.008	0.115**
	(2.27)	(2.59)	(2.16)	(1.92)	(-0.12)	(2.57)
firms_error × target52WH	-0.072*					
	(-1.68)					
misprice_score × target52WH		-0.004**				
		(-2.23)				
abs_firms_error × target52WH			-0.067			
			(-1.02)			
abs_misprice_score × target52WH				-0.003		
				(-1.03)		
Institutional ownership % × target52WH					0.001	
					(1.06)	
log(1+analyst) × target52WH						-0.019
						(-1.00)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	1784	2134	1784	2134	1088	2563
AdjustedR2	0.427	0.369	0.428	0.367	0.529	0.368
	Panel B: Uncertainty and illiquidity					
	(1) Rel_Size	(2) VOL	(3) EPU	(4) WorldU	(5) Illiquidity	(6) Trade$
target52WH	0.071*	0.192***	0.058	0.082**	0.133***	0.411***
	(1.82)	(3.87)	(0.78)	(2.27)	(3.13)	(3.21)
Rel_size × target52WH	0.011					
	(0.33)					
target volatility % × target52WH		-1.915**				
		(-2.50)				
EPU × target52WH			0.000			
			(0.30)			
Ahir_WU × target52WH				-0.038		
				(-0.25)		
illiq_Amihud × target52WH					0.011*	
					(1.71)	
trade_dollar_volume × target52WH						-0.020**
						(-2.38)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	2824	2824	2797	2824	2824	2824
AdjustedR2	0.335	0.339	0.335	0.336	0.341	0.346

Appendix Table A8: Mechanism variables interact with with noiseshare x target52WH

This table reports the results of interacting mechanism measures with *noiseshare* x *target52WH* as follows:

$$offer\_premium = \beta_0 + \beta_1(\text{mechanism measures} \times noiseshare \times target52WH) + \beta_2 Controls + e$$

Error is *firm_error*; Score is *misprice_score*; Abs_Error is the *abs_firm_error*; Abs_Score is *abs_misprice_score*; Institution is *Institutional ownership %*; Analyst is *log(1+analyst)*; VOL is the *Target volatility %*; WorldU is *Ahir_WU*; Illiquidity is *illiq_Amihud*; Trade$ is *trade_dollar_volume*. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: Misprice, absolute misprice and information					
	(1) Error	(2) Score	(3) Abs_Error	(4) Abs_Score	(5) Institution	(6) Analyst
target52WH	-0.005	-0.019	0.071	0.120*	0.021	0.013
	(-0.12)	(-0.14)	(1.28)	(1.78)	(0.25)	(0.27)
firms_error × noiseshare × target52WH	-0.067					
	(-0.23)					
misprice_score × noiseshare × target52WH		-0.029**				
		(-2.35)				
abs_firms_error × noiseshare × target52WH			0.65			
			(1.55)			
abs_misprice_score × noiseshare × target52WH				0.008		
				(0.37)		
Institutional ownership % × noiseshare × target52WH					-0.001	
					(-0.18)	
log(1+analyst) × noiseshare × target52WH						-0.259*
						(-1.69)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	1784	2134	1784	2134	1088	2563
AdjustedR2	0.25	0.233	0.255	0.224	0.31	0.228

	Panel B: Uncertainty and illiquidity					
	(1) Rel_Size	(2) VOL	(3) EPU	(4) WorldU	(5) Illiquidity	(6) Trade$
target52WH	0.092**	0.132*	0.032	0.061	0.103**	0.292*
	(2.31)	(1.90)	(0.36)	(1.42)	(2.51)	(1.85)
Rel_size × noiseshare × target52WH	0.398***					
	(3.02)					
target volatility % × noiseshare × target52WH		-4.067				
		(-0.85)				
EPU × noiseshare × target52WH			0.002			
			(0.48)			
Ahir_WU × noiseshare × target52WH				0.387		
				(0.38)		
illiq_Amihud × noiseshare × target52WH					-0.01	
					(-0.24)	
trade_dollar_volume × noiseshare × target52WH						0.008
						(0.17)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y
N	2824	2824	2797	2824	2824	2824
AdjustedR2	0.217	0.217	0.214	0.21	0.217	0.224

Appendix Table A9: Targets' other weeks high prices

This table reports the regressions results of *noiseshare* in affecting the target high price over other numbers of weeks. Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(noiseshare \times targetXWH) + \beta_2 Controls + e$$

The *targetXWH* is similar to the *target52WH* but replaces the window to calculate the highest price to other numbers of weeks (13, 26, 39, 65, 78, 91 and 104). See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noiseshare × target13WH	0.582**						
	(2.30)						
noiseshare × target26WH		0.354**					
		(2.15)					
noiseshare × target39WH			0.188				
			(1.51)				
noiseshare × target65WH				0.179*			
				(1.82)			
noiseshare × target78WH					0.166*		
					(1.93)		
noiseshare × target91WH						0.156**	
						(1.97)	
noiseshare × target104WH							0.152**
							(2.05)
FullControls	Y	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y
N	2824	2824	2824	2824	2824	2824	2824
AdjustedR2	0.188	0.183	0.179	0.175	0.176	0.175	0.175

Appendix Table A10: *target52WH* by other pre-announcement day windows

This table reports the regressions results of *noiseshare* in affecting the effect of the *target52WH* under other pre-announcement days. Our regressions are as follows:

$$offer\_premium = \beta_0 + \beta_1(noiseshare \times target52WH) + \beta_2 Controls + e$$

The *offer_premium*, *target52WH* and *noiseshare* are calculated all as before but replacing the window days from 30 to others (20, 60 and 90). These regressions include all control variables as in Column (6) Table 4. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	20-day	20-day	60-day	60-day	90-day	90-day
target52WH	0.110***	0.117***	0.130***	0.140***	0.134***	0.147***
	(4.27)	(4.54)	(4.27)	(4.68)	(3.73)	(4.10)
noiseshare x target52WH	0.254**	0.238**	0.207*	0.174	0.224**	0.198*
	(2.51)	(2.41)	(1.92)	(1.63)	(2.15)	(1.91)
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y	N	Y
TimeEffect	N	Y	N	Y	N	Y
N	2828	2828	2755	2755	2704	2704
AdjustedR2	0.149	0.172	0.152	0.175	0.157	0.177

Appendix Table A11: Other potential noise proxies

This table reports the regression results obtained by replacing *noiseshare* with two alternative noise proxies, both of which are extensively noisy price informativeness measures shown to capture noise rather than information in previous literature. These proxies are the daily frequency of price non-synchronicity ($1\text{-}R^2$) and the Probability of Informed Trading (*PIN*), which have been proved to capture noise by Brogaard et al. (2022) and Duarte et al. (2020), respectively. The results for replacing *noiseshare* in Table **3** (Table **4**) are presented in Panel A (Panel B). The dependent variables are *offer_big_52WH* in Panel A and *offer_premium* in Panel B. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Panel A: Replacing *noiseshare* in Table 3, Y is *offer_big_52WH*				
	(1) 1-R2	(2) 1-R2	(3) PIN	(4) PIN
Proxy	0.016***	0.015**	0.308***	0.312***
	(2.66)	(2.17)	(3.31)	(3.29)
Industry Effect	N	Y	N	Y
Time Effect	N	Y	N	Y
N	3103	3089	2043	2025
PseudoR2	0.213	0.242	0.220	0.248
Panel B: Replacing *noiseshare* in Table 4, Y is *offer_premium*				
	(1) 1-R2	(2) 1-R2	(3) PIN	(4) PIN
target52WH	0.090**	0.088**	0.020	0.029
	(2.54)	(2.47)	(0.44)	(0.64)
Proxy × target52WH	-0.008	-0.005	0.340**	0.340**
	(-1.09)	(-0.58)	(2.18)	(2.20)
Industry Effect	N	Y	N	Y
Time Effect	N	Y	N	Y
N	2824	2824	1855	1855
AdjustedR2	0.154	0.205	0.185	0.233

Appendix Table A12: *CAR* by other event windows and factor models

This table presents the outcomes of the market reactions regression:

$$CAR = \beta_0 + \beta_1(\widehat{offer\_premium}) + \beta_2 Controls + e$$

where *CAR* is calculated over event windows ([-1, +1] and [-2, +2]) and incorporating factor models (Fama French 3-factor and Fama French 5-factor) rather than cumulative market-adjusted returns over 3-day window [-1,+1] in Table 8. The corresponding methods are indicated under column numbers. The returns adjusted by market returns, the Fama French 3-factor model and the Fama French 5-factor model are represented by 'mkt', 'ff3' and 'ff5', respectively. The event windows [-1, +1] and [-2, +2] are represented by '3d' and '5d', respectively. Panel A reports the results based on *offer_premium* instrumented by *target52WH* and Panel B reports the results based on *offer_premium* instrumented by the interactive terms between *noiseshare* and *target52WH*. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: *offer_premium* instrumented by *target52WH*				
	(1) ff3_3d	(2) ff5_3d	(3) mkt_5d	(4) ff3_5d	(5) ff5_5d
$\widehat{\text{offer\_premium}}$	-0.219*	-0.219*	-0.265*	-0.277*	-0.277*
	(-1.81)	(-1.81)	(-1.90)	(-1.85)	(-1.85)
FullControls	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y
N	3102	3102	3102	3102	3102
AdjustedR2	0.101	0.101	0.075	0.089	0.089
	Panel B: *offer_premium* instrumented by *noiseshare* x *target52WH*				
	(1) ff3_3d	(2) ff5_3d	(3) mkt_5d	(4) ff3_5d	(5) ff5_5d
$\widehat{\text{offer\_premium}}$	-0.033	-0.033	-0.055	-0.036	-0.036
	(-0.42)	(-0.42)	(-0.62)	(-0.38)	(-0.38)
FullControls	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y
N	3102	3102	3102	3102	3102
AdjustedR2	0.100	0.100	0.074	0.088	0.088

Appendix Table A13: Sub-period based on *noiseshare* level

This table shows the effect of *target52WH* and the influence of *noiseshare* across sub-periods divided based on the level of noiseshare. During the sample period (1984–2022), *noiseshare* is relatively high until 2001 or 2005 in the CRSP sample as shown in Figure 3 of Brogaard et al. (2022) and until 2003 or 2009 in our M&A target sample. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: Sub-periods divided at 2001							
	(1) 1984-2001	(2) 2002-2022	(3) 1984-2001	(4) 2002-2022	(5) 1984-2001	(6) 2002-2022	(7) 1984-2001	(8) 2002-2022
target52WH	0.087**	0.044	0.175***	0.122	0.049	0.010	0.096	0.130
	(2.43)	(0.66)	(3.17)	(1.08)	(1.27)	(0.13)	(1.47)	(0.96)
noiseshare × target52WH					0.257**	0.359	0.486**	0.052
					(2.21)	(1.08)	(2.41)	(0.14)
Industry Effect	Y	Y	N	N	Y	Y	N	N
Time Effect	Y	Y	N	N	Y	Y	N	N
Industry × Time Effect	N	N	Y	Y	N	N	Y	Y
N	1808	963	1022	403	1808	963	1022	403
AdjustedR2	0.282	0.495	0.489	0.643	0.286	0.504	0.496	0.644
	Panel B: Sub-periods divided at 2005							
	(1) 1984-2005	(2) 2006-2022	(3) 1984-2005	(4) 2006-2022	(5) 1984-2005	(6) 2006-2022	(7) 1984-2005	(8) 2006-2022
target52WH	0.075**	0.085	0.141***	0.298*	0.050	-0.018	0.053	0.374*
	(2.25)	(1.04)	(2.69)	(1.88)	(1.36)	(-0.21)	(0.90)	(1.90)
noiseshare × target52WH					0.214**	0.661*	0.542***	-0.160
					(1.98)	(1.82)	(3.10)	(-0.39)
Industry Effect	Y	Y	N	N	Y	Y	N	N
Time Effect	Y	Y	N	N	Y	Y	N	N
Industry × Time Effect	N	N	Y	Y	N	N	Y	Y
N	2109	661	1168	257	2109	661	1168	257
AdjustedR2	0.290	0.564	0.487	0.701	0.294	0.578	0.496	0.705
	Panel C: Sub-periods divided at 2003							
	(1) 1984-2003	(2) 2004-2022	(3) 1984-2003	(4) 2004-2022	(5) 1984-2003	(6) 2004-2022	(7) 1984-2003	(8) 2004-2022
target52WH	0.080**	0.075	0.150***	0.233*	0.053	-0.009	0.062	0.246
	(2.30)	(1.07)	(2.79)	(1.68)	(1.38)	(-0.11)	(1.03)	(1.45)
noiseshare × target52WH					0.219**	0.630*	0.523***	-0.008
					(1.98)	(1.82)	(2.94)	(-0.02)
Industry Effect	Y	Y	N	N	Y	Y	N	N
Time Effect	Y	Y	N	N	Y	Y	N	N
Industry × Time Effect	N	N	Y	Y	N	N	Y	Y
N	1946	823	1090	335	1946	823	1090	335
AdjustedR2	0.283	0.530	0.484	0.673	0.286	0.543	0.491	0.674
	Panel D: Sub-periods divided at 2009							
	(1) 1984-2009	(2) 2010-2022	(3) 1984-2009	(4) 2010-2022	(5) 1984-2009	(6) 2010-2022	(7) 1984-2009	(8) 2010-2022
target52WH	0.088***	-0.012	0.146***	0.412*	0.049	0.035	0.055	0.551**
	(2.67)	(-0.12)	(2.92)	(1.89)	(1.40)	(0.23)	(1.00)	(2.02)
noiseshare × target52WH					0.284**	-0.286	0.553***	-0.712
					(2.51)	(-0.69)	(3.33)	(-0.98)
Industry Effect	Y	Y	N	N	Y	Y	N	N
Time Effect	Y	Y	N	N	Y	Y	N	N
Industry × Time Effect	N	N	Y	Y	N	N	Y	Y
N	2371	394	1285	140	2371	394	1285	140
AdjustedR2	0.309	0.611	0.499	0.738	0.315	0.611	0.507	0.743

Appendix Table A14: Subsample regressions divided by other variables

This table reports subsample regressions as Equation 2 in subsamples divided by other variables. These variables are indicated under the column numbers. The first column of one measure is the subsample regression result of the lowest level of the variable (or equal to 0 for dummy variables), and the second column is the subsample regression result of the highest level of the variable (or equal to 1 for dummy variables). Variables with "_b" are for the bidder's characteristics. See the variable definitions in the Appendix Table A1. Numbers in parentheses are t statistics based on robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Panel A: Sub-sample by target's and bidder's characteristics								
	(1) leverage Sub-L	(2) leverage Sub-H	(3) leverage_b Sub-L	(4) leverage_b Sub-H	(5) vol_b Sub-L	(6) vol_b Sub-H	(7) roa_b Sub-L	(8) roa_b Sub-H
target52WH	0.034	0.100*	0.052	0.091	0.131*	0.025	0.025	0.085
	(0.72)	(1.92)	(1.25)	(1.47)	(1.94)	(0.58)	(0.51)	(1.58)
noiseshare×target52WH	0.084	0.361***	0.022	0.401**	0.087	0.232**	0.391***	-0.197
	(0.65)	(3.00)	(0.17)	(2.58)	(0.44)	(2.05)	(3.07)	(-1.49)
FullControls	Y	Y	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y	Y
N	1412	1412	1412	1412	1401	1400	1413	1411
AdjustedR2	0.359	0.404	0.365	0.369	0.389	0.348	0.378	0.329

Panel B: Sub-sample by bidder's and deal's characteristics								
	(1) size_b Sub-L	(2) size_b Sub-H	(3) cash =0	(4) cash =1	(5) Diversified =0	(6) Diversified =1	(7) toehold =0	(8) toehold >0
target52WH	0.038	0.128**	-0.013	0.180***	0.074	0.071	0.057	0.041
	(0.81)	(2.23)	(-0.28)	(3.60)	(1.63)	(1.28)	(1.53)	(0.18)
noiseshare × target52WH	0.243**	-0.043	0.349**	-0.049	-0.051	0.348**	0.217**	-0.202
	(2.14)	(-0.23)	(2.50)	(-0.31)	(-0.44)	(2.02)	(2.06)	(-0.27)
FullControls	Y	Y	Y	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y	Y	Y	Y
N	1412	1412	1626	1198	1684	1140	2581	243
AdjustedR2	0.353	0.419	0.330	0.431	0.324	0.426	0.315	0.475