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

Ke Bi†

Leonidas G. Barbopoulos‡

Yue Liu §

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†University of Edinburgh Business School, The University of Edinburgh, 29 Buccleuch Place, Edinburgh, EH8 9JS, UK. Email: k.bi-1@sms.ed.ac.uk.

‡University of Edinburgh Business School, The University of Edinburgh, 29 Buccleuch Place, Edinburgh, EH8 9JS, UK. Email: leonidas.barbopoulos@ed.ac.uk. Tel: +44 131 650 8344. Corresponding author.

§University of Edinburgh Business School, The University of Edinburgh, 29 Buccleuch Place, Edinburgh, EH8 9JS, UK. Email: Yue.Liu@ed.ac.uk.

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Abstract

What is the role of different types of information in the target share price on the effect of 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, the punishment to the bidder for paying the target relying on the target 52-week high price disappears after considering the noise in the target share price. This suggests that bidders' reliance on the target's 52-week high price may not always be irrational. Moreover, the increased likelihood of deal success by paying over the target 52-week high price is reduced in the presence of increased noise in the target's share price. This indicates that target shareholders might not be that satisfied with receiving a noisy reference price. Further results confirm that the percentage of noise, indicating undervalued targets to bidders with information advantages, drives the offer price's reliance on the target's 52-week high. In summary, the target reference point effect does not work uniformly but depends crucially on the underlying percentage of noise in the target share price and the reliance on the target 52-week price might not always be irrational.

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

JEL Classification Codes: G14; G34; G41.

1. Introduction

Valuing a target in merger and acquisitions (M&A) is complex, particularly in projecting future cash flows under different ownership and management contexts. It is common to reference a recent peak price to simplify intricate valuation processes, especially the past 52-week high price (e.g., Baker et al., 2012; Della Vedova et al., 2022; George and Hwang, 2004)[1]. In the context of M&A, 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.

Existing literature on the reference point effect typically attributes it to anchoring bias, considered irrational and detrimental to the affected party (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, challenging the assumption of significant sway of anchoring biases in decision-making processes. Particularly, 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 behaviours. Psychological studies by 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 sizes, lower institutional ownership, lower analyst coverage). Therefore, it is reasonable to expect that reference-dependent behaviours diminish in a favourable information environment. Put differently, the extent of participants' reference-dependent behaviours is contingent upon the richness of information available in the environment. This suggests that decision-makers are capable of effectively processing the

[1] For more on the effect of the 52-week high price, see also Choy and Wei (2022); Della Vedova et al. (2021); George et al. (2018); Hung et al. (2022); Khasawneh et al. (2022); Lasfer and Ye (2023); Ma et al. (2019)

available information to make informed decisions rather than being unduly influenced by anchoring biases.

Noise in a company's share price, indicative of irrational investor behaviour that distorts the stock price from its information-efficient value, 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 directly becomes essential in evaluating a company's information environment through share price informativeness measures, whereas previous measures fail to do so (Brogaard et al., 2022; Chan and Hameed, 2006; Fernandes and Ferreira, 2009; Piotroski and Roulstone, 2004). 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. The measure is *noiseshare*. Brogaard et al. (2022) propose a model that decomposes return variance into components representing noise (*noiseshare*) and different types of information (*privateinfoshare*, *publicinfoshare* and *mktinfoshare*) in share prices. This method separates noise from information, providing a clearer understanding of the informativeness of share price. 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. A higher *noiseshare* suggests that the stock price will experience a greater deviation before it finally adjusts to the efficient price, as dictated by newly arrived information, without specifically indicating whether this deviation is an undervaluation or overvaluation. A higher fraction of noise in the target company's share price also compresses the fraction of other information, signalling a weaker information environment for the firm. Consequently, the offer price in mergers and acquisitions relies more heavily on the target's 52-week high price as a reference point when the target share price is more noisy (less informative). In addition, if reliance on reference points consistently signifies biased behaviour, 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.

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 extend our analysis to assess how the offer price, influenced by the interaction between the percentage of noise (various types of information) and the targets' 52-week high prices, affects the market reaction towards bidders and the overall success rate of the deals.

We document two main results. The first one, in line with the prediction, is 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 the 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 variables. 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 0.078% increase in the offer premium. This suggests 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 confirmed using the instrumental variable two-stage least square regressions. Breaking into the information in the target share price (variation other than noise), in contrast, the second finding is that 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 variables. This further emphasises the effectiveness of noise in affecting the influence of the target's 52-week high price. We promote 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[2] and arbitrage costs. The established mechanism suggests that when a target is undervalued within a challenging information environment[3], bidders with information advantages are more comfortable utilising an undervalued target's 52-week high price while still obtaining a favourable deal. In addition, two results further support 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 implies that relying on the target's 52-week high price can be a rational decision for the bidder. 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 become aware of the undervaluation of the reference price, and their satisfaction with the offered price based on this undervalued reference point is reduced.

The paper contributes to the literature in several areas. First, the paper contributes to the literature that analyses 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[4] is stronger for targets with nosier share prices. 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 biased behaviour. Second, our results highlight the necessity to separate noise from information. As our results indicate a reverse effect between the total information and noise, mixing these two together biases conclusions based on the interpretation of proxies that mix up noise and information as share price informativeness,

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

[3]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.

[4]We also find similar patterns in terms of target other weeks high price, see Appendix Table H.

e.g., return non-synchronicity and firm idiosyncratic volatility (Brogaard et al., 2022). Third, the paper contributes to the literature that analyses information's role in mitigating reference-dependent behaviour. 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 (Della Vedova et al., 2022; 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), there exists a body of literature presenting opposite findings (Hovakimian and Hu, 2020; Kumar, 2009). Distinguishing 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 behaviour. Fourth, the paper contributes to the literature by further investigating the effect of different types of information on the reliance on the reference point. The effect of different types of information in alleviating behavioural effects (e.g., the reference point effect) is still unclear in previous literature except for some rough ideas that more analyst coverage may increase the public information in share price (Kumar, 2009) and higher institutional ownership is expected to increase private information in share price (Brogaard et al., 2022). The paper fills this gap by directly and separately testing the effect of different types of information in the target share price on the reliance on the target 52-week high price. None of the private, public and market information is found effective. To the best of our knowledge, our study is the first to separately analyse the effect of noise and different types of information to the reliance 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 bidder's announcement return and deal success, respectively. Section 9 presents various robustness tests for the main results. Section 10 summarises and 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. In equity markets, significant influence has been documented (Della Vedova et al., 2022; 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., 2022; 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.

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, 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 the offer price on the target 52-week high price constitutes biased behaviour by showing that the market dislikes this reliance (negative market reactions towards bidders) and biased target shareholders are satisfied in selling their shares over 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 behaviours 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 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; Mussweiler and Strack, 2000; Strack and Mussweiler, 1997; Tversky and Kahneman, 1974; Wilson et al., 1996). Wilson et al. (1996) and Mussweiler and Strack (2000) have shown that the strength of anchoring effects varies with judges' knowledge of the subject. Behavioural finance research indicates that reliance on reference points intensifies in situations characterised by high uncertainty, limited information, and time constraints (Della Vedova et al., 2022; 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). 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, characterised 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 degree of price non-synchronicity[5], conflates noise and firm-specific information within the share price, fluctuates with noise rather than firm-specific information. In addition, while analyst coverage is generally expected to signal a better-informed environment, studies like those by Chan and Hameed (2006) 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)[6], 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.

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 01 January 1984 to 31 December 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[7]. We require the offer price to be non-missing, and the bidder starts with less than 50% of the target firm shares

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

[6] See Section 3 for the construction of share price informativeness measures as in Brogaard et al. (2022).

[7] 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)

outstanding and ends with 100% or else the percentage acquired is unknown. We exclude deals classified as recapitalisations, repurchases, rumours, 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[8] 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 days before the announcement. The 30-day lagged price scales both variables to mitigate heteroskedasticity and attenuate any upward rumours or new information effects on the offer premium, as in Baker et al. (2012)[9]. The offer premium is truncated to the range of (0, 200) as in Officer (2003)[10], left with a final sample of 9,264 deals. See the Appendix Table A for constructions of all variables.

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

Leveraging share data alone, share price informativeness can be constructed to assess a firm's information environment directly. A higher level of share price informativeness indicates a richer information integration in the share price, signifying a more robust information environment. The key proxy for this is *noiseshare*. Brogaard et al. (2022) introduce a model that dissects return variance into components representing noise and information in share prices. By analysing daily stock returns, trading volumes, and market returns within a vector-autoregression model, the model categorises the short-run reaction of stock returns to shocks in these variables as noise. In contrast, the long-run 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, re-

[8]The main results still exist using other weeks (13, 26, 65, 78, 91, 104) high price, see Appendix Table H.
[9]The main results still exist using other calendar days (20, 60, 90), see Appendix Table I.
[10]Our results hold only if this approach is followed.

spectively). Conceptually, the short-term over- or under-reaction of firm returns to shocks epitomises traders' noise. In contrast, the long-term response of firm returns to shocks in market returns, share trading order flow, and the firm's returns symbolise 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, thus clarifying the share prices' informativeness. Here, "noise" denotes the conduct of irrational investors who frequently underreact or overreact to different information types. 2) The information component is further divided into three categories: market-wide information, firm-specific information unveiled through private information trading, and firm-specific information disclosed publicly. This differentiation gives the possibility to analyse the roles of these different information. 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 behaviours of irrational investors who often misinterpret various information types, leading share prices astray from their true, efficient values. 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).

3.3. Summary statistics and Correlation matrix

Table 2 presents Summary statistics and Correlation matrix. Panel A presents means, standard deviations, medians, and extreme values for used variables. 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 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 only 6,955 deals and the bidder for only 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. Table **3** presents the marginal effects of the following logistic regression[11]:

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

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. The results show the effectiveness of *noiseshare* in driving the offer price above the target's 52-week high price. In addition, none of the other information variables (*privateinfoshare*, *publicinfoshare*, and *mktinfoshare*)[12] demonstrate effectiveness in this regard. Table **4**[13] presents the outcomes of the following regression:

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

The results demonstrate the effectiveness of *noiseshare* in enhancing the dependence of the offer premium on the target's 52-week high price. Figure 2 visualises the marginal effect of the *target52WH* on the *offer_premium*, conditioned on the *noiseshare*. As expected, the impact of *target52WH* intensifies with an increase in *noiseshare*.

4.2. Other information shares in the target share price

Table **5** presents the outcomes of the following regression:

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

[11] Employing probit regression yields similar results.

[12] In each regression analysis, one of the three other information variables is excluded to prevent perfect multicollinearity, given that the sum of all four variables equals one.

[13] Table **4** 's results encompass comprehensive control variables and include time and target industry fixed effects. The robustness of these results is confirmed by gradually adding control variables (inverse price, deal characteristics, firm characteristics) and fixed effects separately.

It shows the results of 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 the other information have insignificant coefficients. In conjunction with the ineffectiveness of other information in Table 3, the results indicate that other information in the target share price does not affect the effectiveness of the reliance of the target 52-week high price on the offer price.

5. Endogeneity and Identification

Our results are subject to Omitted variable bias. 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 corresponds 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*.

5.1. Shocks and matched sample analysis

5.1.1. Matched sample analysis by *noiseshare*

We address the potential endogeneity concern firstly by using the propensity score matching approach (e.g. Lawrence et al., 2024; Rosenbaum and Rubin, 1983)[14]. After obtaining the matched sample, we run the regression:

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

The results are in Appendix Table L. *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 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*.

5.1.2. Regulation FD

Our results suggest that a better information environment can alleviate the effect of the reference point (*target52WH*). The introduction of Regulation FD is generally found to improve the information environment (e.g. Gintschel and Markov, 2004; Petacchi, 2015). This regulation has been effective since 2000-10-23. Therefore, we replace the *noiseshare* with *Post* or *Post_ex* to interact with *target52WH* in the baseline regression as in the Equation 2. *Post* is a dummy variable that takes the value of one after the effective date 2000-10-23 and zero otherwise in the period from 1999 to 2001. *Post_ex* is a dummy variable that takes the value of one before the date 1999-10-01 and zero after the date 1999-10-31 in the period from 1999 to 2001 (Remove a 1-year window before and after the shock)[15]. Consistent with the interpretation that a better information environment reduced the effect of reference points, the effect of *target52WH* is reduced past the shock of Regulation FD in Appendix Table M.

[14] We use the 1:2 nearest neighbour matching approach with a caliper of 0.002.

[15] PSM matched sample analysis are also performed for the *Post*, whereas there is not enough sample size to do PSM for *Post_ex* (N=177 before match). We use the 1:1 nearest neighbour matching approach without a caliper.

5.1.3. Regulation SHO

In the two years between 2005 and 2007, the SEC suspended short-sale price restrictions for a randomly selected group of stocks. Generally, this shock leads to higher short-selling pressure by allowing more aggressive short-selling (Alexander and Peterson, 2008; Diether et al., 2009). Di Maggio et al. (2021) find that the introduction of Regulation SHO causes a detrimental effect on the price efficiency of treated shares compared with the control shares[16]. We perform Difference-in-difference analysis under a matched sample (PSM-DiD)[17]:

$$offer\_premium = \beta_0 + \beta_1(Post \times Treated \times target52WH) + \beta_2 Controls + e \tag{5}$$

Post is a dummy variable that takes the value of one after the effective date 2005-05-02 and zero otherwise in the period from 2003 to 2007 (the pilot program ends on the date 2007-08-06). *Treated* is a dummy variable that takes the value of one if the target company is affected by the pilot program and zero otherwise. Consistent with the baseline idea, results in Appendix Table N show that the effect of *target52WH* is intensified in the treated group by shock compared with the control group.

5.1.4. 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 June 24, 1997, as a natural experiment for the PSM-DiD analysis[18]. 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. Therefore, *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 1997-06-24 and zero otherwise in the period from 1996 to 1998. The negative coefficients in Appendix Table O confirm that a reduction in *noiseshare* by the shock in the treated group decreases the effectiveness of *target52WH*.

[16] Some paper also finds SHO does not improve market quality and price efficiency too much by using various proxies (e.g. Alexander and Peterson, 2008; Diether et al., 2009). In untabulated statistics using all CRSP shares, we find that SHO increases the *noiseshare* significantly

[17] We use a 1:1 nearest neighbour matching approach with a caliper of 0.01.

[18] We use a 1:3 nearest neighbour matching approach with a caliper of 0.008.

5.1.5. 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); Cortes and Marcet (2023)[19]. *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[20]. The positive coefficients in Appendix Table P confirm that an increase in *noiseshare* by the shock intensifies the effectiveness of *target52WH*.

5.2. 2SLS

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, 2023; 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 po-

[19] We use a 1:2 nearest neighbour matching approach with a caliper of 0.001.

[20] 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.

tential. 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. 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[21,22]. 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 **6** presents the 2SLS results using the *trading_turnover* as the instrumental variable to identify the causal interpretation of *noiseshare*:

$$offer\_premium = \beta_0 + \beta_1(noiseshare(instrumented) \times target52WH) + \beta_2 Controls + e \qquad (6)$$

Columns (1) and (2) in Panel A are regressions with and without fixed effects (industry and time), respectively. The instrumented *noiseshare*s are still positively significant, affecting the reliance of the offer premium on the *target52WH* with stronger significance. The two identification tests (under-identification and weak-identification) of the 2SLS support a causal interpretation. First, Kleibergen-Paap-LM-statistics reject the null hypothesis of under-identification at 1% level. Second, the Kleibergen-Paap-F-statistics are 30.602 and 23.287 for regressions with and without fixed effects, indicating strong and unbiased instruments (the corresponding critical value is 7.03 for 10% maximal IV size). The first stage results in Panel B also support the strength of the instrumental variables as the t-statistics of *trading_turnover* are -8.29 and -7.41 with and without fixed effects. As the second instrument is only up to 2005, we add it to the 2SLS in the Appendix Table B. The results adding the second instrumental variable *attention* past all tests but are relatively weak in terms of IV size out of two weak instrument tests (bias and size, respectively). The instrumented *noiseshare* are also positively significant. Three identification tests (under-identification, over-identification and weak-identification) of the 2SLS generally support causal interpretation. Results reject under-identification

[21] 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.

[22] 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.

at 1% level and fail to reject the over-identification null hypothesis. The weak-identification statistics, Kleibergen-Paap-F-statistics, are 20.101 and 15.729 for regressions with and without fixed effects. The corresponding critical values are 11.04 for 5% maximal relative bias and 16.87 for 10% maximal IV size. The Kleibergen-Paap-F-statistic of the regression without fixed effects (20.101) are over both thresholds (11.04 and 16.87). However, the Kleibergen-Paap F-statistic of the regression with fixed effects is 15.729, although exceeding the 5% bias critical value of 11.04, remains below the 10% maximal IV size critical value of 16.87 and is only higher than the 15% maximal IV size critical value of 9.93. Overall, results generally support the causal relationship.

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, characterised 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 value of information acquisition mechanism context, target companies are perceived as more valuable to bidders than to the market. This is largely because bidders typically possess informational advantages regarding the target firms' valuation under their management, surpassing what is available in the market (Edmans et al., 2012; Li and Tong, 2018; Raman et al., 2013). These advantages often stem from due diligence processes and/or acquiring confidential information during negotiations. Bidders with such informational edges are inclined to propose a higher premium. The market would heavily discount targets in the presence of a poor information environment (Cheng et al., 2016; Kelly and Ljungqvist, 2012; Li and Tong, 2018; Raman et al., 2013). 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; Li and Tong, 2018; Officer et al., 2009; Raman et al., 2013)[23] Thus, 1) the greater the information asymmetry between the target company and the market and 2) the more undervalued the target company is, the more valuable the bidder's information acquisition becomes. 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 should observe that the impact of *noiseshare* on the reliance on the target's 52-week high price will be more pronounced 1) in the presence of a poor information environment for targets and 2) if targets are 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. (2015) to capturing the mispricing of a stock by averaging its ranking percentile for each of the 11 anomalies[24]. 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 C). More importantly, the effect of *noiseshare* is only significant when the target is undervalued (Column (1) to (4) Panel A in Appendix Table C), 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 D), the positive and significant coefficients[25] validate that the variation in *noiseshare* attributable to target undervaluation significantly heightens

[23] 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.

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

[25] 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

the reliance on *target52WH*[26]. Therefore, the value of the information acquisition mechanism that 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)[27]. 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

[26]Similar patterns are found by direct interact potential mechanism measures with *target52WH* (Appendix Table E) and interact potential mechanism measures with *noiseshare* x *target52WH* (Appendix Table F).

[27]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.

quarterly economic uncertainty measure from Ahir et al. (2022), constructed by measuring the uncertainty words in the Economist country reports.[28] 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 C) but in subsamples of low macro-level uncertainty(Column (1) to (5) Panel C Appendix Table C). However, the variation of *noiseshare* due to all of these four uncertainty measures fails to affect the reliance of *target52WH* (Panel B Appendix Table D)[29]. 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 initially subtract the no mispricing values (0 for *firm_error* and 50 for *misprice_score*) from each. 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 C), this result is inconsistent by using the other misprice measure (*abs_misprice_score* in Column (7) and (8) Panel A Appendix Table C). The variation of *noiseshare* due to absolute misprice measures significantly affects the reliance on the *target52WH* (Column (3) and (4) Panel A Appendix Table D). 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 by *abs_misprice_score*. Results further confirmed this possibility

[28]We thank the authors of these two papers for sharing these indexes.

[29]Similarly, the other two methods do not offer clear support to the uncertainty mechanism.

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 E and F), 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)[30]. 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; Miller, 1977; Sadka and Scherbina, 2007; Shleifer, 2000). 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., 2015), 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; Officer, 2007; Roosenboom et al., 2014). 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 are insignificantly affect the reliance on *target52WH* (Column (5) and (6) Panel B Appendix Table D).

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

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 C and direct triple interactive terms in Column (6) and (7) Panel B Appendix Table F). Therefore, although increasing the reliance of *target52WH*(Column (5) and (6) Panel B Appendix Table E), 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. Conversely, if the premium reflects synergies, the market should respond neutrally or 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).

$$offer\_premium = \beta_0 + \beta_1 noiseshare + \beta_2 target52WH + \beta_3 Controls + e \tag{7}$$

$$offer\_premium = \beta_0 + \beta_1 (noiseshare \times target52WH) + \beta_2 Controls + e \tag{8}$$

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

$$CAR = \beta_0 + \beta_1 (offer\_\hat{p}remium) + \beta_2 Controls + e \tag{9}$$

where the dependent variable *CAR* represents the 3-day market-adjusted abnormal returns of the bidder around the announcement date. Table **7** 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 $offer\_\hat{p}remium$ 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 $\widehat{\textit{offer\_premium}}$ (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. The results in Panel C confirm this interpretation. Panel C regressions are based on Column (4) but adding dummy variables indicating *noiseshare* groups to test whether the market punishment on higher *offer_premium* due to the reliance of *target52WH* works differently over different *noiseshare* groups (2, 3, 4, 5, and 10). All coefficients of the interactive terms are insignificant, indicating that there are no different market reactions on the component of offer premium due to the reliance on the target 52-week high price over groups with different *noiseshare* levels. 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 but advantageous for the bidder. Therefore, reference-dependent decisions might not always be irrational and harmful to the involved party (in this case, the bidder). In other words, it might be a rational strategy for the bidder to rely on the reference price to capture benefits or mitigate negative market responses. In addition, 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 $\widehat{\textit{offer\_premium}}$ 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.

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[31] regressions about the

[31] Employing logistic regression yields similar results.

deal success rate:

$$success = \beta_0 + \beta_1(noiseshare \times \mathit{Offer\_big\_52WH}) + \beta_2 \mathit{offer\_premium(s)} + \beta_3 Controls + e \tag{10}$$

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 8 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. This 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 to be rational to the bidder. More importantly, the target can identify and is less satisfied with this rational decision of the bidder. In addition, 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 target satisfaction and other information components having minimal or no significant influence in this context.

9. Robust checks and other subsamples

9.1. The effectiveness of ***target52WH*** over ***noiseshare*** sub-groups

Appendix Table G shows the results of the difference in the effectiveness of the *target52WH* across different *noiseshare* sub-groups (2 or 3). Columns (1), (2), (5), and (6) show that the *target52WH* is more pronounced in the highest *noiseshare* groups. In contrast, columns (3), (4) and (8) show that the *target52WH* is less pronounced in the lowest *noiseshare* groups, except for Column (7) with negative but insignificant coefficients.

9.2. 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, 104) are also tested. Appendix Table H shows the results of the effectiveness of the target other weeks' high prices. The results show that *noiseshare* can intensify the reliance of offer price on the target high prices calculated over all of these weeks except the 39-week high price in Column (3).

9.3. 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 capitalisation, runup, and volatility). Appendix Table I shows the results that *noiseshare* can intensify the reliance of offer price on the target 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)[32].

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 J 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 **7**, 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 penalisation from the bidders' shareholders.

9.5. Other subsamples

Results of Equation 2 for a variety of subsamples are in Table K. The influence of *noiseshare* is only apparent when both the target and bidder exhibit high leverage, alongside the bidder having

[32] it has a t-statistics 1.63 (1.65 is the 10% significance critical value)

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[33].

10. Conclusion

We have explored the intricate dynamics of valuing target companies, emphasising 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 behaviour is rationalised 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. 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 behaviours in M&A contexts, overshadowing different information types in influencing reference point reliance. Interestingly, the data on bidders' market reactions further highlight the rational 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. This demonstrates the rational calculus behind the bidders' reliance on reference prices. Moreover, the implications for deal success, representing a tangible impact on the allocation of capital among

[33]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.

investment opportunities (Baker et al., 2012), affirm the rational 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 recognise and unmask the bidders' rational 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 irrational. Our study contributes to the broader discourse on reference points in the takeover market, behavioural 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 behaviour 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 behaviours, 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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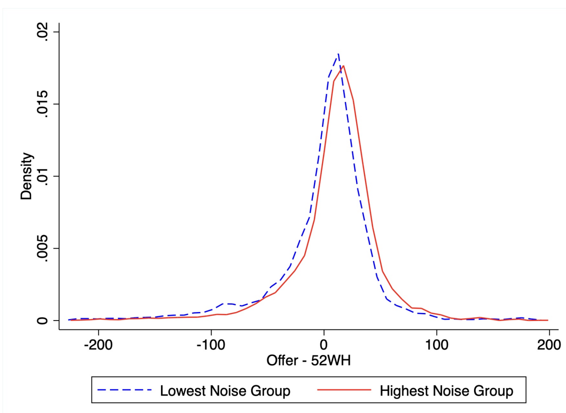
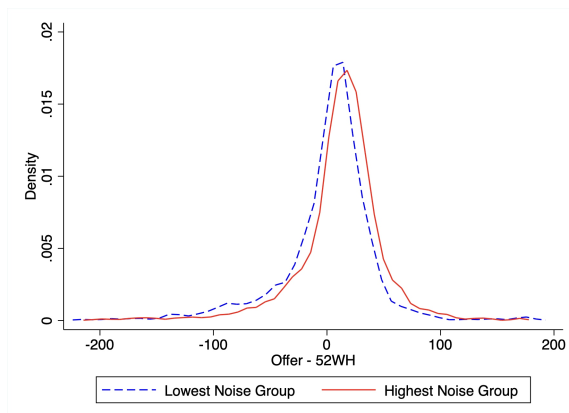
Figure 1: Offer price density by *noiseshare*.

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*.

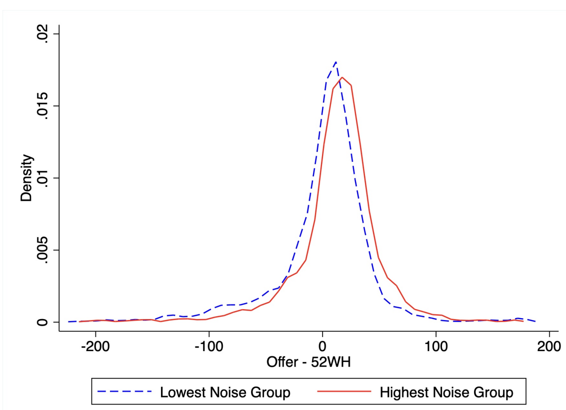
(a) noiseshare 3 groups



(b) noiseshare 4 groups



(c) noiseshare 5 groups



(d) noiseshare 10 groups

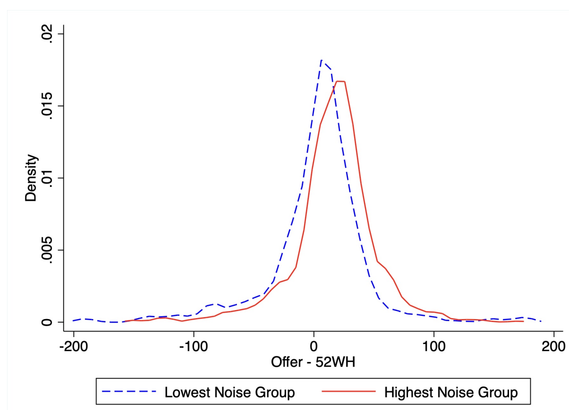
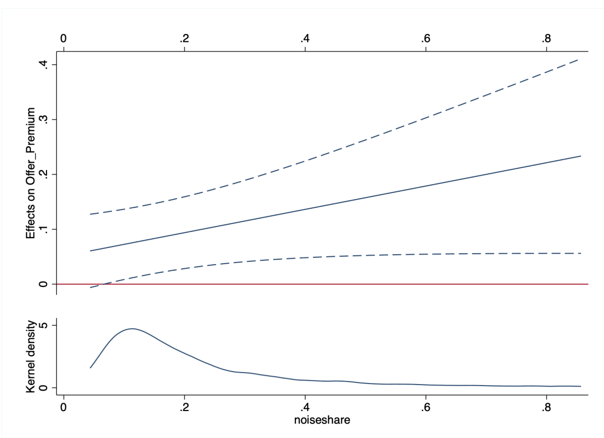


Figure 2: The conditional marginal effect of *target52WH* by *noiseshare*

This figure shows the conditional marginal effect of *target52WH* with 95% confidence intervals by the level of *noise-share*. the regressions (a) without fixed effects, (b) with industry and time effects.

(a) without fixed effects



(b) with both industry and time effects

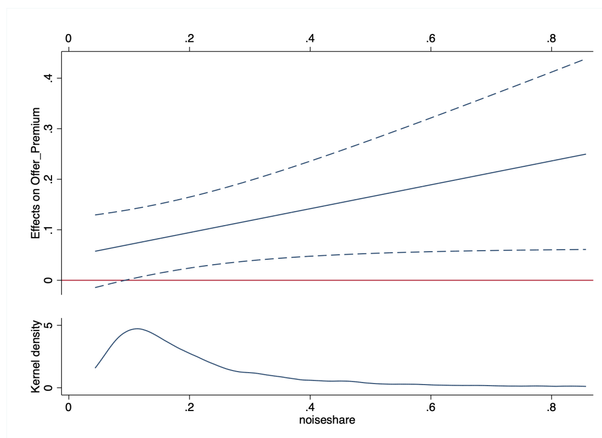


Table 1: M&A Sample distribution

The sample consists of merger or acquisition announcements. Deals from Thomson Financial, where the announcement date is between January 1, 1984, and December 31, 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. 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), left 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 cash, 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 A. 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:

$$\mathit{Pr(offer > target\ 52\text{-}week\ high)} = \beta_0 + \beta_1 \mathit{noiseshare} + \beta_2 \text{infoshares} + \beta_3 \mathit{Controls} + e$$

Pr(offer > target 52-week high) 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 A. Numbers in parentheses are 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	0.343***	0.345***	0.365***	0.376***	0.346***	0.357***	0.337***	0.328***
	(6.39)	(6.44)	(4.13)	(4.03)	(5.81)	(5.89)	(5.28)	(5.19)
privateinfoshare			0.029	0.048	0.010	0.029		
			(0.38)	(0.58)	(0.16)	(0.47)		
publicinfoshare			0.019	0.020			-0.010	-0.028
			(0.25)	(0.24)			(-0.16)	(-0.45)
mktinfoshare					-0.019	-0.017	-0.029	-0.045
					(-0.25)	(-0.20)	(-0.38)	(-0.55)
inverseprice	0.101***	0.097***	0.100***	0.097***	0.100***	0.097***	0.100***	0.097***
	(5.07)	(4.89)	(5.08)	(4.89)	(5.08)	(4.90)	(5.08)	(4.89)
Target Runup	0.332***	0.325***	0.332***	0.325***	0.332***	0.325***	0.332***	0.325***
	(18.50)	(18.16)	(18.11)	(17.78)	(18.12)	(17.80)	(18.11)	(17.79)
Cash	0.005	0.005	0.006	0.005	0.006	0.005	0.006	0.005
	(0.30)	(0.25)	(0.30)	(0.25)	(0.30)	(0.25)	(0.30)	(0.25)
Stock	-0.001	-0.012	-0.001	-0.012	-0.001	-0.012	-0.001	-0.012
	(-0.03)	(-0.56)	(-0.04)	(-0.54)	(-0.04)	(-0.54)	(-0.04)	(-0.54)
Hostile	0.030	0.032	0.031	0.032	0.031	0.032	0.031	0.032
	(1.12)	(1.18)	(1.14)	(1.19)	(1.14)	(1.19)	(1.14)	(1.19)
Tender	0.018	0.005	0.018	0.004	0.018	0.004	0.018	0.004
	(0.99)	(0.24)	(0.99)	(0.23)	(0.99)	(0.23)	(0.99)	(0.23)
Financial buyer	-0.107*	-0.110*	-0.107*	-0.110*	-0.107*	-0.110*	-0.107*	-0.110*
	(-1.75)	(-1.86)	(-1.75)	(-1.86)	(-1.75)	(-1.86)	(-1.75)	(-1.86)
Financial seller	0.029	-0.035	0.029	-0.035	0.029	-0.035	0.029	-0.035
	(0.50)	(-0.49)	(0.50)	(-0.49)	(0.50)	(-0.49)	(0.50)	(-0.49)
Rel_size	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-0.51)	(-0.45)	(-0.49)	(-0.43)	(-0.49)	(-0.43)	(-0.49)	(-0.43)
# bidder	0.017	0.006	0.017	0.006	0.017	0.006	0.017	0.006
	(0.84)	(0.32)	(0.84)	(0.30)	(0.84)	(0.30)	(0.84)	(0.31)
Diversified	-0.004	-0.009	-0.004	-0.008	-0.004	-0.008	-0.004	-0.008
	(-0.31)	(-0.56)	(-0.30)	(-0.55)	(-0.30)	(-0.55)	(-0.30)	(-0.55)
Toehold	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002
	(-0.86)	(-1.30)	(-0.85)	(-1.30)	(-0.85)	(-1.30)	(-0.85)	(-1.30)
Target ROA	-0.057	-0.087**	-0.056	-0.088**	-0.056	-0.088**	-0.056	-0.088**
	(-1.36)	(-1.98)	(-1.35)	(-1.98)	(-1.35)	(-1.98)	(-1.35)	(-1.98)
Target M/B	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(-1.45)	(-1.52)	(-1.46)	(-1.53)	(-1.46)	(-1.53)	(-1.46)	(-1.53)
log(Target mktcap)	0.018**	0.020**	0.019**	0.020**	0.019**	0.020**	0.019**	0.020**
	(2.26)	(2.37)	(2.14)	(2.27)	(2.15)	(2.26)	(2.14)	(2.26)
Target Leverage	0.047	0.052	0.047	0.052	0.047	0.052	0.047	0.052
	(1.17)	(1.27)	(1.17)	(1.26)	(1.17)	(1.26)	(1.17)	(1.26)
Target volatility %	-0.045***	-0.051***	-0.045***	-0.051***	-0.045***	-0.051***	-0.045***	-0.051***
	(-7.30)	(-7.51)	(-7.28)	(-7.50)	(-7.28)	(-7.51)	(-7.28)	(-7.50)
Bidder ROA	-0.094**	-0.100**	-0.094**	-0.099**	-0.094**	-0.099**	-0.094**	-0.099**
	(-2.16)	(-2.40)	(-2.15)	(-2.38)	(-2.15)	(-2.38)	(-2.15)	(-2.38)
Bidder M/B	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.11)	(-0.06)	(0.10)	(-0.08)	(0.10)	(-0.08)	(0.10)	(-0.08)
log(Bidder mktcap)	-0.002	-0.000	-0.002	-0.000	-0.002	-0.000	-0.002	-0.000
	(-0.34)	(-0.06)	(-0.34)	(-0.07)	(-0.34)	(-0.07)	(-0.34)	(-0.07)
Bidder Leverage	0.013	0.014	0.013	0.014	0.013	0.014	0.013	0.014
	(0.30)	(0.33)	(0.30)	(0.33)	(0.30)	(0.33)	(0.30)	(0.33)
Bidder Runup	-0.031	-0.041**	-0.032	-0.041**	-0.032	-0.041**	-0.032	-0.041**
	(-1.48)	(-2.00)	(-1.52)	(-2.02)	(-1.52)	(-2.02)	(-1.52)	(-2.02)
IndustryEffect	N	Y	N	Y	N	Y	N	Y
TimeEffect	N	Y	N	Y	N	Y	N	Y
N	3103	3089	3103	3089	3103	3089	3103	3089
Pseudo-R2	0.222	0.252	0.222	0.252	0.222	0.252	0.222	0.252

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 A. Numbers in parentheses are robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
target52WH	0.074**	0.078**	0.094***	0.095***	0.053	0.046
	(2.31)	(2.25)	(2.81)	(2.65)	(1.45)	(1.19)
noiseshare			9.660**	7.758*	2.012	-1.064
			(2.51)	(1.78)	(0.39)	(-0.19)
noiseshare x target52WH					0.219*	0.260**
					(1.89)	(2.07)
inverseprice	1.508	5.113*	1.300	4.962*	0.168	3.750
	(0.71)	(1.80)	(0.61)	(1.76)	(0.08)	(1.39)
Target Runup	-6.554***	-4.917**	-5.837***	-4.351*	-5.810***	-4.253*
	(-3.35)	(-2.21)	(-2.94)	(-1.95)	(-2.95)	(-1.92)
Cash	-1.953	-2.431	-1.840	-2.376	-1.920	-2.432
	(-1.54)	(-1.60)	(-1.45)	(-1.56)	(-1.51)	(-1.59)
Stock	-1.017	-3.052**	-0.958	-2.935**	-0.959	-2.855*
	(-0.79)	(-2.06)	(-0.74)	(-1.98)	(-0.74)	(-1.93)
Hostile	8.310***	6.884***	8.266***	6.808***	8.266***	6.930***
	(3.82)	(2.67)	(3.80)	(2.64)	(3.80)	(2.69)
Tender	4.407***	1.932	4.497***	2.021	4.503***	2.019
	(3.58)	(1.30)	(3.66)	(1.36)	(3.67)	(1.36)
Financial buyer	-7.723***	-9.063**	-7.896***	-9.095**	-7.826***	-8.825**
	(-2.84)	(-2.33)	(-2.90)	(-2.32)	(-2.90)	(-2.26)
Financial seller	8.455**	6.044	7.912**	5.560	7.985**	5.507
	(2.39)	(1.16)	(2.26)	(1.07)	(2.32)	(1.06)
Rel_size	3.177***	3.022***	3.151***	3.001***	3.171***	3.022***
	(4.98)	(4.04)	(4.92)	(4.00)	(4.96)	(4.04)
# bidder	1.488	0.662	1.410	0.616	1.492	0.740
	(1.05)	(0.44)	(1.00)	(0.42)	(1.05)	(0.50)
Diversified	-1.192	-0.535	-1.218	-0.623	-1.316	-0.806
	(-1.20)	(-0.43)	(-1.23)	(-0.50)	(-1.34)	(-0.65)
Toehold	-0.050	-0.009	-0.056	-0.015	-0.061	-0.017
	(-0.54)	(-0.08)	(-0.62)	(-0.14)	(-0.66)	(-0.16)
Target ROA	5.873*	6.181	5.031	5.590	4.657	5.213
	(1.80)	(1.57)	(1.54)	(1.41)	(1.42)	(1.31)
Target M/B	-0.122	-0.157	-0.122	-0.161	-0.121	-0.148
	(-0.85)	(-0.91)	(-0.85)	(-0.94)	(-0.84)	(-0.86)
log(Target mktcap)	-4.721***	-4.128***	-4.410***	-3.882***	-4.505***	-4.032***
	(-10.08)	(-7.21)	(-8.93)	(-6.54)	(-9.05)	(-6.70)
Target Leverage	0.992	-0.677	0.688	-0.907	0.702	-0.946
	(0.36)	(-0.20)	(0.25)	(-0.27)	(0.26)	(-0.28)
Target volatility %	0.341	-0.341	0.057	-0.597	0.021	-0.680
	(0.79)	(-0.61)	(0.13)	(-1.03)	(0.05)	(-1.15)
Bidder ROA	-0.105	-1.638	-0.295	-1.637	-0.316	-1.622
	(-0.04)	(-0.52)	(-0.11)	(-0.52)	(-0.12)	(-0.51)
Bidder M/B	0.182	0.165	0.191*	0.171	0.192*	0.170
	(1.60)	(1.31)	(1.67)	(1.35)	(1.67)	(1.34)
log(Bidder mktcap)	2.890***	2.934***	2.904***	2.940***	2.932***	2.982***
	(7.16)	(6.50)	(7.19)	(6.52)	(7.23)	(6.60)
Bidder Leverage	4.055	4.452	4.023	4.460	3.614	4.146
	(1.35)	(1.25)	(1.35)	(1.26)	(1.24)	(1.18)
Bidder Runup	4.871***	5.198***	5.107***	5.289***	5.087***	5.249***
	(3.27)	(2.98)	(3.42)	(3.04)	(3.42)	(3.03)
IndustryEffect	N	Y	N	Y	N	Y
TimeEffect	N	Y	N	Y	N	Y
N	2824	2824	2824	2824	2824	2824
AdjustedR2	0.152	0.336	0.155	0.337	0.157	0.340

Table 5: 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:

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

See the variable definitions in the Appendix Table A. All regressions include full control variables as in Table 4. Numbers in parentheses are 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 6: Instrumental Variables two-stage least square

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

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

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

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

The *noiseshare* here is centred around its mean to improve the explainability of the following results of this table. See the variable definitions in the Appendix Table A. All regressions include full control variables as in Table 4. Numbers in parentheses are 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)
noiseshare (instrumented) × target52WH	1.841***	1.842***
	(3.64)	(3.47)
FullControls	Y	Y
IndustryEffect	N	Y
TimeEffect	N	Y
N	2824	2824
AdjustedR2	0.005	0.008
Kleibergen-Paap-LM-statistic	51.579	42.632
Kleibergen-Paap-LM-p	0.000	0.000
Panel B: The first-stage results		
	(1)	(2)
trading_turnover	-0.004***	-0.003***
	(-8.29)	(-7.41)
FullControls	Y	Y
IndustryEffect	N	Y
TimeEffect	N	Y
N	3103	3103
AdjustedR2	0.295	0.316
F-statistic	30.637	17.086

Table 7: 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:

$$CAR = \beta_0 + \beta_1(\mathit{offer\_premium} \;/\; \mathit{offer\_pr\hat{e}mium}) + \beta_2 Controls + e$$

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 *noiseshare* 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*. Panel C interacts group dummy based on *noiseshare* with offer_prêmium (instrumented by *target52WH*) to test the regression in Panel A Column (4) over different *noiseshare* groups (2, 3, 4, 5 and 10 in Panel C Columns (1) to (5), respectively). 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 A. Numbers in parentheses are robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	Panel A: OLS and 2SLS regressions					
	(1) Base	(2) Base	(3) 52WH	(4) 52WH	(5) NoiseInter	(6) NoiseInter
offer_premium	-0.015**	-0.015**				
	(-2.27)	(-2.16)				
offer_prêmium			-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
	Panel B: Other 2SLS regressions					
	(1) PrivateInter	(2) PrivateInter	(3) PublicInter	(4) PublicInter	(5) MarketInter	(6) MarketInter
offer_prêmium	-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

	Panel C: *noiseshare* group variables interactive with Panel A Column (4)				
	(1) 52WH	(2) 52WH	(3) 52WH	(4) 52WH	(5) 52WH
offer_prêmium	-0.259**	-0.275**	-0.279**	-0.279**	-0.293**
	(-2.14)	(-2.24)	(-2.27)	(-2.26)	(-2.39)
noi_2_H1_O0 × offer_prêmium	-0.013				
	(-0.47)				
noi_3_H1_O0 × offer_prêmium		-0.022			
		(-0.80)			
noi_4_H1_O0 × offer_prêmium			0.011		
			(0.35)		
noi_5_H1_O0 × offer_prêmium				-0.003	
				(-0.10)	
noi_10_H1_O0 × offer_prêmium					-0.033
					(-0.72)
FullControls	Y	Y	Y	Y	Y
IndustryEffect	Y	Y	Y	Y	Y
TimeEffect	Y	Y	Y	Y	Y
N	2823	2823	2823	2823	2823
AdjustedR2	0.098	0.097	0.097	0.097	0.097

Table 8: 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 A. Numbers in parentheses are 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
Pseudo-R2	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
Pseudo-R2	0.478	0.483	0.478	0.483	0.481	0.486

Appendix Table A: 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 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 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). 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 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).	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 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).	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 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).	CRSP & Authors' Estimations
offer_big_52WH	Dummy equals one if the offer price is higher than the target 52-week high price.	SDC & Authors' Estimations
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 centred on the announcement date.	CRSP & Authors' Estimations
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
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

Table Continued

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

Variable	Definition	Source
misprice_score	The misprice measure of Stambaugh et al. (2015), capturing the mispricing of a 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 Webpage
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 Webpage & 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 Webpage
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 Webpage
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 0 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
Leverage	Total debt (Compustat: DLTT+DLC) divided by total assets (Compustat: AT).	Compustat

Table Continued

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

Variable	Definition	Source
target volatility%	The target's volatility is the standard deviation of daily returns for the 335 calendar days ending 30 days before the announcement date from CRSP.	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 raw log return over the 365 calendar days ending 30 days before the announcement date from CRSP for both target and 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 Webpage

Appendix Table B: Instrumental Variables two-stage least square

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:

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

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 A. All regressions include full control variables as in Table 4. Numbers in parentheses are 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)
noiseshare (instrumented) × target52WH	1.505***	1.451***
	(3.980)	(3.880)
FullControls	Y	Y
IndustryEffect	N	Y
TimeEffect	N	Y
N	2126	2126
AdjustedR2	0.002	0.018
Kleibergen-Paap-LM-statistic	62.124	55.538
Kleibergen-Paap-LM-p	0.000	0.000
Sargan–Hansen-J-statistic	2.716	2.353
Sargan–Hansen-J-p	0.257	0.308
Kleibergen-Paap-F-statistic	20.101	15.729
Panel B: The first-stage results		
	(1)	(2)
trading_turnover	-0.005***	-0.005***
	(-8.76)	(-7.93)
CoverageShock	0.035***	0.030**
	(2.88)	(2.31)
FullControls	Y	Y
IndustryEffect	N	Y
TimeEffect	N	Y
N	2346	2346
AdjustedR2	0.316	0.350
F-statistic	27.440	19.556

Appendix Table C: 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 A. Numbers in parentheses are 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
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)
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)
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
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)
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)
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
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)
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)
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 D: Mechanism variables as IV of noiseshare

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

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

The second stage uses predicted $\widehat{\textit{noiseshare}}$ 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 A. Numbers in parentheses are 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
$\widehat{\textit{noiseshare}}$ × 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)
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)
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$
$\widehat{\textit{noiseshare}}$ × 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)
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)
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 E: 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 A. Numbers in parentheses are 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 F: 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 A. Numbers in parentheses are 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 G: *target52WH* across 2 or 3 noiseshare groups

This table reports the results of robustness tests conducted through regressions similar to those in Table 4, but with *noiseshare* replaced by *noiseGroup* variables that divide the entire sample into subgroups based on *noiseshare* levels. Our regressions are as follows:

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

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

Panel A: Regression results

	(1) 2-Sub	(2) 2-Sub	(3) 2-Sub	(4) 2-Sub	(5) 3-Sub	(6) 3-Sub	(7) 3-Sub	(8) 3-Sub
target52WH	0.057*	0.073**	0.117***	0.116***	0.066**	0.077**	0.092***	0.097***
	(1.69)	(2.15)	(3.00)	(3.05)	(1.99)	(2.31)	(2.60)	(2.72)
noi_2_H1_O0 × target52WH	0.060**							
	(2.19)							
noi_2_Hc_O0 × target52WH		0.169**						
		(2.05)						
noi_2_L1_O0 × target52WH			-0.060**					
			(-2.19)					
noi_2_Lc_O0 × target52WH				-0.515**				
				(-2.41)				
noi_3_H1_O0 × target52WH					0.056*			
					(1.78)			
noi_3_Hc_O0 × target52WH						0.148*		
						(1.81)		
noi_3_L1_O0 × target52WH							-0.039	
							(-1.41)	
noi_3_Lc_O0 × target52WH								-0.551*
								(-1.94)
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	2824	2824	2824	2824	2824	2824	2824	2824
AdjustedR2	0.175	0.177	0.175	0.176	0.175	0.176	0.174	0.175

Panel B: Definition of above Variables

Variable	Definition
noi_2_H1_O0	Equals 1 if the observation is in the highest *noiseshare* group, 0 otherwise.
noi_2_Hc_O0	Equals *noiseshare* if the observation is in the highest *noiseshare* group, 0 otherwise.
noi_3_H1_O0	Equals 1 if the observation is in the highest *noiseshare* group, 0 otherwise.
noi_3_Hc_O0	Equals *noiseshare* if the observation is in the highest *noiseshare* group, 0 otherwise.
noi_2_L1_O0	Equals 1 if the observation is in the lowest *noiseshare* group, 0 otherwise.
noi_2_Lc_O0	Equals *noiseshare* if the observation is in the lowest *noiseshare* group, 0 otherwise.
noi_3_L1_O0	Equals 1 if the observation is in the lowest *noiseshare* group, 0 otherwise.
noi_3_Lc_O0	Equals *noiseshare* if the observation is in the lowest *noiseshare* group, 0 otherwise.

Appendix Table H: 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). These regressions include all control variables as in Column (6) Table 4. See the variable definitions in the Appendix Table A. Numbers in parentheses are 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 I: *target52WH* by other pre-announcement day windows

This table reports the regressions results of *noiseshare* in affecting 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 A. Numbers in parentheses are robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1) 20-day	(2) 20-day	(3) 60-day	(4) 60-day	(5) 90-day	(6) 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 J: *CAR* by other event windows and factor models

This table presents the outcomes of market reactions, substituting *CAR* from Table **7** with *CAR* calculated over event windows ([-1, +1] and [-2, +2]) and incorporating factor models (Fama French 3-factor and Fama French 5-factor) in addition to simply using cumulative market-adjusted returns over 3-day window [-1,+1]. 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 A. Numbers in parentheses are 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 K: 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 A. Numbers in parentheses are 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
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)
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)
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
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)
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)
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

Appendix Table L: Target 52-week high reliance and 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, *Treated* is a dummy variable (noi_2) that takes the value of one if *noiseshare* is in its high half and zero otherwise. In Panel B, *Treated* is a dummy variable (noi_3) that takes the value of one if *noiseshare* is in its highest tertile group and zero in its lowest tertile group. See other variables' definitions in the Appendix Table A. All regressions include full control variables as in Table 4. Numbers in parentheses are 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	0.072**	0.070**	0.065**	0.062*
	(2.26)	(2.16)	(1.84)	(1.90)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	2180	2180	2180	2180
AdjustedR2	0.156	0.164	0.187	0.193
Panel B: noi_3 as *Treated*, divided by tertiles of *noiseshare*				
	(1)	(2)	(3)	(4)
Treated × target52WH	0.086**	0.087**	0.070*	0.070*
	(2.12)	(2.13)	(1.73)	(1.71)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	1310	1310	1310	1310
AdjustedR2	0.164	0.174	0.207	0.219

Appendix Table M: Target 52-week high reliance and Regulation FD

This table shows the difference in the reliance of the offer price on the target 52-week high price between deals before and after the effectiveness of the Regulation of Financial Disclosure date. Our regressions are as follows:

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

Post is a dummy variable that takes the value of one after the effective date 2000-10-23 and zero otherwise in the period from 1999 to 2001. *Post_ex* is a dummy variable that takes the value of one before the date 1999-10-01 and zero after the date 1999-10-31 in the period from 1999 to 2001 (Remove a 1-year window before and after the shock). The regression results of *Post* under the subsample matched by propensity score are indicated by PSM under the column names (there is not enough sample size to do PSM for *Post_ex*, N=177 before match). See other variables' definitions in the Appendix Table A. All regressions include full control variables as in Table 4. Numbers in parentheses are robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1) Full	(2) Full	(3) Full	(4) Full	(5) PSM	(6) PSM
Post × target52WH	-0.074*	-0.077*			-0.104**	-0.102*
	(-1.84)	(-1.76)			(-2.17)	(-1.79)
Post_ex × target52WH			-0.208***	-0.254***		
			(-4.01)	(-5.00)		
FullControls	Y	Y	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y	N	Y
TimeEffect	N	Y	N	Y	N	Y
N	482	482	177	177	224	224
AdjustedR2	0.229	0.267	0.360	0.421	0.317	0.371

Appendix Table N: Target 52-week high reliance and Reg SHO

This table shows results for the difference in difference analysis of the target 52-week high reliance around Reg SHO. 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 2005-05-02 and zero otherwise in the period from 2003 to 2007 (the pilot program ends on the date 2007-08-06). *Treated* is a dummy variable that takes the value of one if the target company is affected by the pilot program and zero otherwise. See other variables' definitions in the Appendix Table A. All regressions include full control variables as in Table 4. Numbers in parentheses are robust standard errors clustered by month. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Post × Treated × target52WH	0.669	0.777*	0.828*	1.070**
	(1.63)	(1.72)	(1.76)	(2.19)
FullControls	Y	Y	Y	Y
IndustryEffect	N	Y	N	Y
TimeEffect	N	N	Y	Y
N	88	88	88	88
AdjustedR2	0.449	0.463	0.525	0.558

Appendix Table O: Target 52-week high reliance and 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 A. All regressions include full control variables as in Table 4. Numbers in parentheses are 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 P: Target 52-week high reliance and brokerage house closures

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). Our regressions are as follows:

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

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 as in Cortes and Marcet (2023). See other variables' definitions in the Appendix Table A. All regressions include full control variables as in Table 4. Numbers in parentheses are 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**	0.277*	0.219*	0.374**
	(2.19)	(2.34)	(1.67)	(2.18)
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