Asymmetric Information and Asset Sales versus Mergers and Acquisitions

Abstract

We propose average absolute value of cumulative abnormal returns around earnings announcements (ACARE) as a measure of asymmetric information about a firm's value. Using panel data, we show that higher asymmetric information is associated with lower asset sales frequency but higher probability of the firm being acquired in whole. We validate these results in the context of natural disasters, which raise both asymmetric information and financing need, compared to similar but unaffected control firms. We further show that private acquirers play an important role in the market for corporate assets by acquiring firms in part or in whole when there is higher asymmetric information about their market value.

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1. Introduction

Ever since the seminal "Market for Lemons" insight of Akerlof (1970), many papers have studied the role of asymmetric information as an important friction in the market for sale and purchase of corporate assets. However, this literature predominantly focuses on asymmetric information about the acquirer's market value, the acquisition of firms in whole (i.e., mergers and acquisitions), and related wealth effects. This paper differs from this previous literature in that we study the effects of asymmetric information about the seller's market value, we examine the acquisition of firms both in part (i.e., asset sales) and in whole, and we emphasize transaction likelihood rather than wealth effects.

Our key contributions are as follows. First, we propose a new measure of asymmetric information. Second, we use this measure to document an interesting contrast, that higher asymmetric information about a firm's value decreases the likelihood of its selling parts of itself as asset sales but increases the likelihood of its being acquired in whole in a merger or acquisition.[1] We show this result using a panel dataset of firm years listed in the U.S. market during 1985 to 2022 and confirm it with another experiment of how natural disasters that increase asymmetric information about treatment firm values affect the frequency of their asset sales and acquisitions over several quarters after disasters. Third, we illustrate the positive role of private acquirers in

[1] References to existing papers that study mergers and acquisitions of whole firms, overvaluation of acquirer stock, and wealth effects of stock payment are too numerous to cite. A few existing papers do study the effects of asymmetric information about seller's value in mergers and acquisitions (Hansen 1987, Faccio and Masulis 2005, Officer, Poulsen, and Stegemoller 2009), the likelihood of making asset sales (Warusawitharana 2008, Yang 2008), their wealth effects (Lang, Poulsen, and Stulz 1995, Maksimovic and Phillips 2001, Bates 2005, Officer 2007, Edmans and Mann 2019), and the likelihood of being acquired, also known as targetiveness (Andrade, Mitchell, and Stafford 2001, Vijh and Yang 2013). This list is necessarily incomplete.

resolving the information asymmetry about the seller's market value. Overall, our comprehensive framework shows the contrasting effects of seller-side information asymmetries between asset sales and whole-firm acquisitions.

To study the role of asymmetric information about firm value in corporate events, we propose a measure that is the average absolute value of cumulative abnormal returns surrounding all available quarterly earnings announcements over a year, which we call ACARE (Absolute-CAR-Earnings). Conceptually, we need to estimate the difference between valuation-specific information possessed by a firm's insiders and outsiders. Assuming that a firm's value is determined by its earnings stream, this difference can be measured by the strength of market reaction in either direction to periodic earnings announcements.

For several reasons, we argue that the insiders of a firm possess asymmetric informational advantage relative to analysts and investors about a firm's earnings and therefore its market value. First, sometimes managers issue earnings guidance which are followed by revisions of analyst forecasts and significant market reaction (Cotter, Tuna, and Wysocki 2006, Anilowski, Feng, and Skinner 2007). Second, a large part of their informational advantage about earnings and market value remains as shown by superior profits to insider trading (Seyhun 1986, Aboody and Lev 2000). Third, and most importantly, firms' own governance practices reveal the concentration of information asymmetries around earnings announcements. To prevent insiders from exploiting the informational advantage about earnings, most firms impose blackout periods starting two to four weeks before a fiscal quarter-end and lasting until one or two days after the corresponding earnings announcements. According to a 2022 NASPP/Deloitte survey, 96% of firms restricted Section 16 executives from trading during such blackout periods surrounding earnings announcements and

76% of firms also placed these restrictions on other senior executives.[2,3] Finally, in markets where insider trading is rampant and insider information has already been revealed to market participants, Bhattacharya, Daouk, Jorgenson, and Kehr (2000) show that there is no market reaction on earnings announcement. The combined evidence suggests that we should look around earnings announcements to measure asymmetric information about a firm's market value possessed by a firm's insiders in U.S. markets.

Previous researchers have measured earnings surprise by analyst forecast error, which is the absolute difference between actual and forecast earnings divided by stock price (Krishnaswamy and Subramaniam 1999, Chemmanur, Paeglis, and Simonyan 2009, Chatterjee, John, and Yan 2012, Luypaert and Van Caneghem 2017). However, this measure assumes that the analyst consensus forecast is the market's unbiased forecast of earnings. We argue that this assumption is problematic and that the actual market's expected earnings is unknown. Keung, Lin, and Shih (2010) show that zero forecast errors are accompanied by significantly negative market reaction (a result that we replicate in our sample), confirming that market's expectations diverge systematically from analyst expectations. In addition, analyst forecast error does not adjust for the persistence and riskiness of earnings changes or other valuation-related information revealed as part of an earnings announcement. ACARE addresses these limitations by implicitly using the correct market's expectation of earnings and capturing the market value impact of comprehensive information released during an earnings announcement. Both improvements make it a superior measure of asymmetric information about firm value that matters in asset sales.

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[2] NASPP is an acronym for National Association of Stock Plan Professionals. A summary of this survey by Barbara Baksa, Executive Director, is available on https://www.naspp.com/blog/4-Trends-in-Trading-Blackout-Periods. A corresponding YouTube video is also available https://www.youtube.com/watch?v=W5t8kkHhwKc.

[3] The SEC Section 16 executives include the president, principal financial officer, principal accounting officer, any vice-president of the issuer in charge of a principal business unit, division or function (such as sales, administration, or finance), any other officer who performs a policy-making function, or any other person who performs similar policy-making functions for the issuer.

Many other measures of asymmetric information based on trading volume, stock price volatility, and components of bid-ask spread have been used in literature. However, such measures are more likely to capture asymmetric information across investors than between the sellers of assets and the rest of the world. While all measures are correlated to some extent, ACARE is more likely to capture the asymmetric information about asset values between sellers and buyers as intended by Akerlof (1970).[4]

In addition to such conceptual differences, we look at two desirable statistical properties of ACARE and other measures, which are skewness and autocorrelation. ACARE has lower skewness, not much higher than that of the right half of a normal distribution, which means that our results are not driven by a few extreme observations. In comparison, analyst forecast errors suffer from extreme skewness. ACARE also has a moderate autocorrelation compared to other measures. A very low autocorrelation raises the concern that the measure is not really a firm characteristic or that it is measured with a large error, and a very high autocorrelation raises the concern that the measure does not change significantly after events that should change the asymmetric information about the firm value. Given these desirable properties, in this paper we employ ACARE and a related measure that is its quintile rank to study the asymmetric information effects in the market for the sale of corporate assets.

Next, analyzing a comprehensive sample of firm-years from 1985 to 2022, we find that ACARE calculated during the previous year is negatively related to the likelihood of asset sales by a firm during the current year but positively related to the likelihood of its being acquired in

[4] It has sometimes been suggested that market reaction around earnings announcements also measures the uncertainty about a firm's earnings in addition to asymmetric information between insiders and outsiders. While true, we argue that the informational advantage possessed by insiders arises due to uncertainty about a firm's prospects. If there were no uncertainty, it is difficult to imagine that there would be asymmetric information. Thus, all measures of asymmetric information between sellers and buyers capture uncertainty about firm's value to some extent.

whole (which is also known as targetiveness). This result seems anomalous at first given that both asset sales and mergers and acquisitions involve sales of corporate assets, but it is consistent with differences in adverse selection and a few other reasons. Asymmetric information should matter more when a firm chooses and sells a part of its assets, which increases the possibility of adverse selection (or lemons). There is no such choice or incremental adverse selection with whole-firm acquisitions, although some of the firms that agree to be acquired will turn out to be lemons.

Adverse selection can be reduced with regular audits that are required for publicly traded firms (Jansen 2020). Due diligence and scrutiny of audited statements by investment bankers as part of ascertaining the target value can reduce asymmetric information, but it is less effective for subsidiaries than for whole firms given the nexus of intra-firm sales and purchases and the possibility of opportunistic transfer pricing for such transactions. Further, it does not help that the decision to make asset sales rests entirely with the managers of the seller and buyer firms without involvement of their shareholders. In comparison, whole-firm acquisitions are subject to more intense scrutiny by capital markets, including shareholder approval on both sides of the transaction. The shareholders exercise their own judgment and may vote down an acquisition, thereby introducing an additional layer of market discipline that reduces the adverse selection problem. These differences can further explain why asset sales may be more susceptible to adverse selection problems arising from information asymmetries about firm values.

Among other reasons, firms characterized by higher asymmetric information about their assets value are often growth firms with unique technologies that can be valuable in whole to the right buyer, but not as valuable if sold piecemeal without the remaining infrastructure of the parent firm. Finally, the compensation structure of management in these firms introduces another factor. Managers of growth firms with relatively opaque assets often hold large amounts of illiquid stock

and options, creating strong incentives to pursue whole-firm acquisitions that enable immediate liquidation of their holdings, which is not possible with asset sales (Cai and Vijh 2007). Consequently, some of the firms facing higher asymmetric information may withdraw from the market for asset sales and opt for whole-firm acquisitions.

To address potential identification concerns, we exploit exogenous variation in asymmetric information arising from natural disasters. Specifically, we implement a quasi-natural experiment design that examines changes in asset sales and mergers and acquisitions among affected firms. Events such as thunderstorms, hurricanes, floods, wildfires, and tornados and perils such as flash floods and heavy rainfall cause damages whose repair costs and the effects on business activity are unknown to markets. This uncertainty temporarily increases asymmetric information between firms and market participants, while being exogenous to affected firms.

Using a comprehensive sample of firms affected by natural disasters retrieved from the Sheldus^{TM} database (Spatial Hazard Events and Losses Database for the United States) during the same period of 1985 to 2022 as our primary tests, we show that treated firms that suffer from natural disasters have increased asymmetric information compared to control firms over a period of up to eight quarters after disasters than before disasters. Natural disasters increase the need for external finance, which firms obtain from both traditional and nontraditional sources (Baltas, Fiordelisi, and Mare 2022, Wang 2023). Therefore, one would expect more frequent asset sales after natural disasters. However, we find the opposite – a significant decrease in the frequency of asset sales for treatment firms relative to that for the same firms before disasters as well as unaffected control firms after disasters. Our difference-in-difference analysis shows that this decrease in asset sales for treatment firms is partially explained by the increased asymmetric

information following natural disasters. In addition, we find a simultaneous increase in mergers and acquisitions for treatment firms compared to control firms.

We last examine the relation between asymmetric information about target value and acquirer type, which broadly consists of two categories: public firms and private firms. For both asset sales and mergers and acquisitions separately, we find that the proportion of all acquirers that are private firms increases steadily from the lowest to the highest ACARE quintile. The evidence remains significant in the presence of control variables. It supports the predictions of Nary and Kaul (2023). They argue theoretically that one type of private firms, namely the private equity firms, have an advantage in undertaking long term strategic investments whose unique, specialized, and uncertain nature (thus, facing higher asymmetric information) makes it challenging for public equity markets to value them correctly. We further argue that all private firms have a certain advantage that they operate outside the focus and limelight that public markets put on public firms and their quarterly performance. So private firms in general are better suited for long-term, strategic projects with high information asymmetry whose prospects are less clear and whose profitability can take time to reveal itself, provided they can muster enough resources to invest in such projects.

Section 2 describes our measure of asymmetric information, and Section 3 describes our main results about the relation between asymmetric information and the frequency of asset sales vs. mergers and acquisitions using a panel dataset of firm years. Section 4 describes our alternate experiment to test the same effects around natural disasters, and Section 5 describes the roles of private vs. public acquirers in the market for sale of corporate assets in the presence of asymmetric information. Section 6 reports a few robustness tests, and Section 8 concludes.

2. Measures of asymmetric information

2.1. Previous measures

Several measures of asymmetric information between different market participants have been proposed in the finance literature. A partial list includes: 1. Volatility calculated by the annualized standard deviation of raw stock returns. 2. Idiosyncratic Volatility calculated by the annualized standard deviation of residuals from a one-factor market model or a multi-factor Fama-French model of stock returns. 3. Analyst Forecast Error (AFE) calculated by the absolute difference between actual earnings and analyst consensus forecast scaled by the stock price, averaged over all quarters in the last year. 4. Analyst Forecast Dispersion (AFD) calculated by the standard deviation of analyst forecasts of earnings scaled by the stock price. 5. Number of Analysts tracking the firm. 6. Probability of Informed Trading (PIN) proposed by Easley, Hvidkjaer, and O'Hara (2002). 7. Abnormal Idiosyncratic Volatility before earnings announcements (AIV) proposed by Yang, Zhang, and Zhang (2020).[5]

Some of these measures capture asymmetric information between informed and uninformed traders, which includes volatility, idiosyncratic volatility, PIN, and AIV, while others capture asymmetric information between a firm and the analysts, or across analysts, which includes AFE, AFD, and the number of analysts. One might think that in most situations the asymmetric information across different market participants is about the firm value, so all measures should be correlated and useful to some extent. However, the correlation is often quite low. We require a measure of asymmetric information between a firm that may sell its assets, in part or in whole, and the potential buyers and their advisors, which is broadly speaking the entire market. We propose

[5] Appendix 1 defines these measures in greater detail. PIN requires transactions data and is not explored in this paper.

such a measure below after discussing the potential limitations of analyst forecast based measures of asymmetric information.

2.2. Analyst forecast based measures and our proposed measure

Analyst forecast error, AFE, is a popular measure of information asymmetry in literature (Krishnaswamy and Subramaniam 1999, Chemmanur, Paeglis, and Simonyan 2009, Chatterjee, John, and Yan 2012, Luypaert and Van Caneghem 2017). However, based on a large accounting literature, there are some problems with this measure. Cohen and Lys (2003) show that, relative to a normal distribution, the distribution of signed forecast errors is characterized by a significant over-representation of very negative forecast errors, a significant under-representation of forecast errors just below zero, and a significant over-representation of small forecast errors just above zero. The first result can be attributed to a tendency by firms to sometimes take a 'big bath' in earnings whereby they clean house and set the stage for future over-performance (Kirschenheiter and Melumad 2002), and the second and third results can be attributed to a tendency by firms to avoid reporting small negative earnings surprises (Degeorge, Patel, and Zeckhauser 1999, Burgstahler and Eames 2006). The combined effect of such earnings management is to make analyst forecast errors a biased and highly skewed measure of asymmetric information between firms and analysts. This concern is exacerbated by another observation that zero forecast errors do not convey zero valuation surprises. Keung, Lin, and Shih (2010) show that zero forecast errors are accompanied by a mean three-day announcement excess return of -0.58% during 1992-2006, which they term as the growing investor skepticism toward zero and small positive earnings surprises.[6] Finally, we are interested in asymmetric information as it relates to firm value, but

[6] We find the same result with 40,537 cases of zero forecast errors during 1984-2021 in our sample for which we observe a mean three-day market-adjusted announcement excess return of -0.55% (*t*-statistic -14.07). Popular press is full of anecdotal evidence to support the claim that analyst estimates are not the same as market's expectations. For one example, consider that Nvidia Corp. announced strong quarterly results on August 28, 2024, that handily beat the

analyst forecast error misses out on important information related to firm valuation such as the risk and the persistence of earnings surprise and other items such as revenue surprise and future outlook in the same announcement that jointly determine the firm value.

Analyst forecast dispersion, AFD, shares some of the criticism applicable to analyst forecast errors. Besides, it primarily captures the information asymmetry among individual analysts rather than the information asymmetry between the firm and the consensus of outside market participants, which we want to measure. The number of analysts is a crude proxy for asymmetric information that is highly related to firm size and suffers from endogeneity and extreme stability despite changing firm circumstances as we document below.

We propose that the average absolute market-adjusted cumulative abnormal return measured over a five-day period centered on the earnings announcement date, ACARE, measures what we want to measure, which is asymmetric information about firm value between the firm and the outside world, and it does not suffer so much from the problems listed above. It is a measure of firm value and not just related to firm value, it partly corrects for earnings management that investors can recognize, and it includes all hard and soft information released during earnings announcements such as revenue surprise, future earnings forecasts, and the tone and content of management discussion as well as analyst questions raised during earnings calls. In fact, an alternate terminology for ACARE could be Market Value Forecast Error, or MVFE, with the added qualification that is the forecast error concerning a firm's market value between the firm and the market (not analysts). In the main experiment, we measure ACARE by averaging over the four

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analyst estimates (60+ analysts) of second quarter's earnings and revenues and improved on their revenue forecasts for the third quarter. Yet, the stock declined by 6.4% on the following day while the broad market increased slightly. https://www.barrons.com/livecoverage/nvidia-earnings-stock-price-today/card/nvidia-reports-strong-earnings-the-stock-is-down--9hq3dUwNVYGfUrfNJwro?siteid=yhoof2 .

earnings announcements during a calendar year (fewer if necessary), and in the natural disasters experiment we measure it by just the current quarter's abnormal return.

We point out a few other attractions of ACARE as a measure of asymmetric information relative to analyst forecast based measures. First, ACARE only requires the returns data from CRSP and the quarterly earnings announcement dates from Compustat whereas the analyst forecast based measures require more complex I/B/E/S (Institutional Brokers' Estimate System) database. Second, the I/B/E/S coverage is scarce for small firms, which may impart a size bias to the analysis of corporate events that are related to firm size. For example, AFE is available for only 29% of observations in the bottom market value decile of the dataset analyzed in our Table 1 (below) and AFD is available for only 14% of observations (as it requires at least two analyst estimates). Third, in many cases there are only one or two analyst estimates. In comparison, ACARE is based on the consensus estimate of the entire market. We now turn to a quantitative assessment of a few attributes of ACARE relative to other measures.

2.3. Statistical properties of different measures of asymmetric information

Panel A of Table 1 shows the summary statistics of seven different measures of asymmetric information including ACARE. We use a sample of 149,764 firm years during 1984-2021 (year *t*-1) for which the year-end stock price is at least $5 and the relevant data to calculate the primary measure ACARE are available. This period precedes the sample period of asset sales and mergers and acquisitions analyzed in this paper, which covers 1985-2022 (year *t*), by one year. ACARE, AFE, AFD, ANALYSTS, Volatility, and Idiosyncratic Volatility have zero or positive value in all cases, but AIV can have positive or negative value (depending on whether idiosyncratic volatility preceding earnings announcements is greater than or less than at other times). ACARE has mean and median values of 5.45% and 4.41% and a standard deviation of 3.91%. The corresponding

statistics for other measures are shown in the table. We turn our attention to skewness and autocorrelation, which are important properties of the measures of asymmetric information.

ACARE has a skewness value of 1.52. For comparison, the distribution of the absolute value of a normal random variable with zero mean (also known as the folded normal distribution) has a skewness of 0.99527.[7] Table 1 further shows that ANALYSTS, volatility, and idiosyncratic volatility have comparable skewness of 1.50, 1.29, and 1.31, and the two-sided AIV has a skewness of -0.10. However, AFE and AFD have skewness values of 10.56 and 8.48 despite our winsorization of their right-tail values at the 1% level.[8] Such extreme skewness values of AFE and AFD are a matter of concern because in any experiment the results can be driven by a few observations in the tails of their distribution.

The last column of Panel A in Table 1 reports the first-order autocorrelations of all measures. AIV exhibits the lowest autocorrelation of 0.06, compared to the autocorrelations of all other measures which range between 0.48 and 0.94.[9] On the one hand, a very low autocorrelation raises the concern that the measure does not capture an enduring and consistent firm characteristic. On the other hand, a very high autocorrelation raises the concern that the measure does not change sufficiently when there are events in a firm's life that should change the asymmetric information about its market value. Although the optimal range of autocorrelations is an open question, the autocorrelations of AFD (0.72), ANALYSTS (0.94), volatility (0.74), and idiosyncratic volatility (0.80) seem to be problematic for studying temporal variations in firm behavior around firm

[7] Open source LibreTexts Statistics online, Section 5.13, authored by Kyle Siegrist.

[8] Skewness can take values over the entire range from $-\infty$ to $+\infty$. For example, the skewness of a binomial distribution equals $(1-2p)/\sqrt{np(1-p)}$, which goes to $-\infty$ as $p \to 1$ and to $+\infty$ as $p \to 0$ (Box, Hunter, and Hunter 1978). Here, n and p refer to sample size and probability of the event. Luypaert and Van Caneghem (2017) report a more acute skewness of AFE calculated using annual earnings announcements, indicated by mean and median values of 2.24% and 0.07% for acquirers and 1.52% and 0.25% for targets in their sample of mergers and acquisitions.

[9] Using a different sample and a 12-month rolling window methodology, Yang et al (2020) document an autocorrelation of 0.067.

events. The autocorrelations of 0.48 and 0.65 for ACARE and AFE are comparatively moderate and seem to be more suitable for such time-series analysis. Overall, based on the combined evidence on skewness and autocorrelations, we believe ACARE is more appropriate than other measures of asymmetric information about a firm's value. That is, of course, in addition to its intuitive appeal and ease of calculation that were argued before.

Panel B of Table 1 shows the correlations between different measures of asymmetric information. ACARE has relatively high correlations with volatility (0.60) and idiosyncratic volatility (0.59) and low correlations with AFE (0.11) and AFD (0.12), which may be due to skewness of the latter two measures. It further has a correlation of -0.03 with ANALYSTS, perhaps due to the latter measure's stop-clock like autocorrelation of 0.94, and 0.10 with AIV, which represents incremental idiosyncratic volatility before earnings announcements rather than the idiosyncratic volatility.

Table 2 examines the relation between ACARE and a few firm characteristics. We arrange all firm years into five quintiles based on ACARE, which has mean values of 1.59%, 2.99%, 4.43%, 6.48%, and 11.77% across quintiles. Firms with higher ACARE values tend to be smaller in market value and size rank (by year). Higher ACARE firms also tend to be higher growth firms as shown by lower book-to-market and earnings-to-price ratios and higher betas. In addition, higher ACARE firms tend to have lower net leverage and higher capital expenditure, thus likely to be in the growth phase of their life. The relationships between ACARE and these firm characteristics demonstrate reasonably monotonic patterns across quintiles, which suggests robust correlations between information asymmetry and firm attributes. These correlations are not surprising because small firms, growth firms, and other firms in the growth phase of their life typically face higher asymmetric information about their market value. Furthermore, the

correlations underscore the importance of controlling for these firm characteristics in the later multivariate tests to examine the impact of information asymmetry.

3. Asymmetric information and asset sales vs. mergers and acquisitions – primary tests

3.1. Motives, sample description, and summary statistics

3.1.1. Asset sales

An asset sale occurs when a seller firm transfers ownership of a part, but not all, of its assets to an acquiring firm for a price. Previous literature offers many motivations for asset sales, such as: 1. Increasing the operating efficiency of sold assets under new ownership (Hite, Owers, and Rogers 1987, Maksimovic and Phillips 2001, Warusawitharana 2008, Yang 2008); 2. increasing the operating efficiency of remaining assets by improving focus of the seller/parent firm (John and Ofek 1995, Berger and Ofek 1999); 3. cashing in on a liquid and attractive market for sold assets (Schlingemann, Stulz, and Walkling 2002); and 4. meeting the financing needs of the seller firm (Shleifer and Vishny 1992, Lang, Poulsen, and Stulz 1995, Edmans and Mann 2019). We examine how asymmetric information affects the likelihood of publicly-traded firms doing asset sales for any of these reasons by using a comprehensive sample of firm years.

We identify a sample of 19,321 asset sales during 1985-2022 using the following criteria: 1. The divestiture dummy is coded yes. 2. The target type is subsidiary. 3. The target's Cusip is not the same as the target's ultimate parent's Cusip. 4. The merger form is acquisition of certain assets or acquisition of assets. 5. The acquisition status is completed. 6. The acquirer owns greater than 99% of target after the acquisition is completed. 7. The asymmetric information measure ACARE for the target's ultimate parent is available for the previous year using the database described in Table 1 (which implicitly requires that the parent firm that sells the assets is publicly traded, available on CRSP and Compustat, and has a stock price at last year-end of at least $5). Our sample

begins in 1985 because the Thomson-Refinitiv Mergers and Acquisitions (previously SDC, or Securities Data Company) database has thin coverage of asset sales before 1985.

Panel A of Table 3 reports the descriptive statistics of this sample. The 19,321 asset sales occur in a sample of 140,902 firm years, which implies an average 0.137 asset sale per firm year. In many firm years we observe more than one asset sale, so there are an average 1.594 asset sales each firm year during the 12,119 firm years when there is at least one asset sale. Seller firms tend to be large, with a median market value of $2,596 million (mean $18,587 million) at the end of last year. Only 46% of acquirer firms are publicly traded, and those have a median market value of $1,248 million (mean $7,559 million). The remaining 54% of acquirer firms are privately owned and we expect those to be smaller than the publicly traded acquirer firms. Thus, in departure from what is widely known for mergers and acquisitions, the acquirer firms in asset sales are generally smaller than the seller firms. However, the acquirer firms are bigger than the acquired assets, or the subsidiary firm. The sold assets have a median value of $61 million (mean $252 million) based on the 47% cases where their deal value is available. That translates into a median ratio of deal value to seller firm value of 0.033 and deal value to acquirer firm value of 0.067.

Table 3 also shows that cash payment is used in 94% of all asset sales for which payment data are available. The sold or subsidiary assets have the same industry code as the seller firm in 44% cases and the same industry code as the acquirer firm in 49% cases, suggesting only a slight improvement in firm focus upon transfer of ownership. The asset sales are beneficial for both the seller and the acquirer firms, indicated by their average market-adjusted excess returns of 0.59% and 1.13% during a three-day measurement window centered on the announcement date. Finally, we observe 4629, 4884, 4072, 3244, and 2492 asset sales in the five quintiles of firm years arranged by their ACARE rank, from lowest asymmetric information to the highest. That provides some

preliminary but univariate evidence in favor of a negative relation between asymmetric information and the likelihood of asset sales.

3.1.2. Mergers and acquisitions

Unlike an asset sale, a merger or an acquisition involves the purchase of all assets of a target firm that the acquirer firm does not already own. Previous literature offers numerous motivations for mergers and acquisitions, including: 1. Efficiency gains by replacing underperforming or shirking target managers; 2. cost cutting or other economies of scale by combining operations; 3. reducing competition; 4. complementarity of target and acquirer resources; 5. acquiring an important technology; 6. wealth transfer from target shareholders to acquirer shareholders by purchasing an undervalued target or by payment with overpriced acquirer stock; 7. personal incentives of target managers to cash out their stock and options; 8. overconfidence of acquirer managers; 9. empire building by acquirer managers; and many others. We collect a sample of mergers and acquisitions of public targets during the same 1985-2022 period that is used for asset sales to study the effect of asymmetric information about a firm's value on its merger prospects, which we also refer to as targetiveness.

We identify a sample of 5,373 mergers and acquisitions by using the following criteria: 1. The merger form is coded as merger, acquisition, acquisition of assets, or acquisition of major interest. 2. The acquisition status is completed. 3. The acquirer owns less than 50% of target shares before acquisition and greater than 99% after acquisition. 4. The asymmetric information measure ACARE for the target firm is available for the previous year using the database described in Table 1 (which requires that the target is publicly traded, available on CRSP and Compustat, and has a stock price at last year-end of at least $5).

Panel B of Table 3 provides summary statistics of the sample of mergers and acquisitions. The 5,373 completed acquisitions in a sample of 140,902 firm years represent a targetiveness of 0.038 per year for included firms. The acquirer is public in 72% cases when the public status information is available. The target firms have a median market value of $278 million (mean $1,556 million) while the acquirer firms have a median market value of $2,703 million (mean $21,400 million) when they are publicly traded. The median ratio of target to acquirer market value equals 0.155 when acquirer is public, compared to 0.067 for asset sales. Consistent with previous literature, target firms receive a large acquisition premium that has a median value of 30.8% (mean 36.4%). In contrast, the acquirers earn a mean market-adjusted excess announcement return of −1.14% (median -0.81%). Finally, we observe 950, 967, 1109, 1099, and 1248 acquisitions in the five quintiles of firm years arranged by their ACARE rank, from lowest asymmetric information to the highest. In this case, that frequency distribution provides some preliminary but univariate evidence in favor of a positive relation between asymmetric information and targetiveness.

Panel C of Table 3 shows the industry distribution of seller, subsidiary, and acquirer firms in asset sales and target and acquirer firms in mergers and acquisitions. The financials sector accounts for the largest number of deals in both categories, followed by the business equipment sector.

3.2. Control variables used in analysis of the likelihood of asset sales and targetiveness

In the following sections, we explore the effects of asymmetric information about a firm's market value on the likelihood of it doing an asset sale or the likelihood of its being targeted and acquired in whole. Since both actions involve sale of assets, they should have many common determinants. However, selling only a part of the firm vs. the whole firm can make a difference to the predicted direction or at least the strength of the effects of many determinants. Below we

present these determinants used as control variables in our analysis of asymmetric information effects. Most variables are motivated by theory models of what causes asset sales by Warusawitharana (2008), Yang (2008), and Edmans and Mann (2019). In addition, we control for a few firm characteristics correlated with asymmetric information in Table 2.

1. Firm size: This is a fundamental factor and a key determinant of many or most corporate finance effects. Warusawitharana argues that large firms can be excessively diversified and may want to sell non-core assets to improve their focus and increase their efficiency. Thus, firm size should be positively and monotonically related to the likelihood of firms doing asset sales. However, the monotonicity argument does not hold when we study targetiveness. Vijh and Yang (2013) show that firm targetiveness is higher for midsize firms than for small firms. Following their evidence, we use a quadratic function of firm size decile rank in targetiveness regressions, which is measured for any firm relative to all included firms as of the last year-end. Using firm size rank by year is also an effective approach to control for the time trend in market values of publicly-traded U.S. firms over the 38-year period of our study.
2. Book-to-market: Growth and value firms differ in many ways, so this is another fundamental factor and a significant determinant of many corporate finance effects. High book-to-market firms have low growth prospects and in extreme cases may be in financial distress. Edmans and Mann (2019) and others have argued that asset sales are an important source of financing for parent firms, so book-to-market should be related to the likelihood of their doing an asset sale. However, its effect on targetiveness is less clear. Value firms with high book-to-market and facing financial distress may often choose to be acquired, but growth firms with low book-to-market and a new technology may also attract large acquirer firms which may have greater resources but lower growth prospects of their own.

3. Return on assets: Warusawitharana (2008) argues that investment scale is related to ROA. He argues that firms with higher ROA purchase assets and firms with lower ROA sell assets. It is a measure of firm efficiency.
4. Sales: Yang (2008) argues that industry productivity is related to asset turnover (sales/assets) and shows that lower asset turnover is associated with higher asset sales.
5. Cash flow from operations: This measures the annual cash generation ability of firm and should be related to asset sales that are often motivated by the financing needs of the seller firm.
6. Net leverage: Following from the last point, debt financing is an alternative to asset sales in meeting the parent firm's financing needs, but it is limited by the firm's existing debt, or leverage. Cash on the balance sheet has the opposite effect of debt, so we use net leverage, which is the difference between debt and cash scaled by market assets. Lambrecht and Myers (2017) and Chen and Lambrecht (2021) use net leverage as a measure of firm's financing ability in their theory models. Leverage is a balance sheet variable that supplements cash flow which is a flow variable, offering a more comprehensive view of a firm's financial position and capacity to undertake strategic transactions.
7. Capital expenditure: This variable comes from Yang (2008) who argues that firms with higher capital expenditure are expanding their scale of operations and less likely to sell assets.
8. Industry and year fixed effects: An extensive literature on merger waves points to industry and time trends in the market for sale and purchase of corporate assets. So, we include industry and year fixed effects in our regressions whenever feasible. Sometimes we also include the more stringent industry*year fixed effects.

The above variables are measured as of the last fiscal year for the seller or the parent firm in asset sales regressions and for the firm under consideration in targetiveness regressions. The exact calculation of these variables is described in Appendix 1.

3.3. Regressions

Table 4 shows test results for the effect of asymmetric information on the frequency of asset sales. The starting sample in univariate regressions includes the 140,902 firm years described in Section 3.1.1. However, this sample is reduced to 118,937 firm years in multivariate regressions due to the unavailability of one or more control variables. Our dependent variable in all regressions is the number of asset sales during a firm year. Because this variable can have multiple discrete values, we use the Poisson model for limited dependent variable analysis. The key independent variable is either ACARE or its quintile rank, which we denote by ACARE_rank. We cluster standard errors by year in all regressions.

Models (4.1) and (4.2) report univariate results (but with the inclusion of industry and year fixed effects) for ACARE and ACARE_rank. Either measure of asymmetric information is negative and highly significant by itself at the 1% level, with *t*-statistics of -8.53 and -8.77. Models (4.3) and (4.4) next include the control variables described above. Most, but not all, control variables have the predicted sign. Size rank (by year) is highly significant, followed by net leverage and book-to-market. It is no surprise that larger firms do more asset sales. Financing needs or constraints of seller firm are an important consideration, shown by the positive coefficient of net leverage and negative coefficient of return on assets, both highly significant. However, the coefficient of cash flow is positive and marginally significant, opposite to that predicted by the financing reason for asset sales. Seller firms are likely to be value firms past their growth phase as shown by the significantly positive coefficient of book-to-market and significantly negative

coefficient of capital expenditure. The coefficient of sales (i.e., asset turnover) is significantly positive, contrary to our prediction that asset sales are done more often by less productive firms.

Next, we present the evidence on our newly proposed measures of asymmetric information. The coefficients of ACARE and ACARE_rank are both negative and significant at the 5% and 1% levels in Models (4.3) and (4.4), with *t*-statistics of -2.45 and -3.33. This evidence is consistent with the market-for-lemons theory of Akerlof (1970). Higher asymmetric information about the market value of a seller's assets decreases the frequency of asset sales after controlling for the other known determinants of asset sales. Finally, for robustness, Models (4.5) and (4.6) reported in the last two columns of Table 4 include the more stringent industry*year fixed effects. This does not much alter the evidence on the key variables or the control variables. Asymmetric information measures ACARE and ACARE_rank remain significant at the 5% and 1% levels.

Table 5 shows the evidence on the relation between asymmetric information and targetiveness using the Logit model, since the dependent variable of whether a firm year had an acquisition offer that was later completed is binary. It takes the value of one if it did receive an offer, and zero if it did not receive an offer. The coefficients of control variables in Models (5.3) to (5.6) have sometimes the same sign as in the asset sales regression and sometimes different. The coefficient of size rank is positive and that of size rank squared is negative, both highly significant. Consistent with the results of Vijh and Yang (2013), it suggests that targetiveness is maximized for midsize firms in the fourth or fifth decile of firm value, although our sample is quite different from their sample.[10] The negative coefficient of return on assets, the positive coefficient of cash flow, and the insignificant coefficient of net leverage provide mixed evidence on the financing needs of targeted firms. The coefficients of book-to-market and capital expenditure are both significantly

[10] Taking partial derivatives of regression model in Table 5 with respect to size rank and equating to zero, the targetiveness is maximized for decile rank value of 0.167/(2×0.020), or 4.35.

positive, which also provides mixed evidence on whether value firms or growth firms are more likely to be targeted. These seemingly contradictory findings reflect the complex nature of acquisitions. Consistent with an extensive literature on mergers and acquisitions, we find that firms of many different characteristics can be targeted for many different reasons.

That brings us to the coefficients of the key asymmetric information variables in the targetiveness regressions. Models (5.1) and (5.2) in Table 5 show univariate evidence that the coefficients of ACARE and ACARE_rank are positive and highly significant. Models (5.3) and (5.4) show that this evidence remains unchanged in the presence of control variables, and Models (5.5) and (5.6) show that the interactive industry*year fixed effects do not change the results.

The combined evidence of Tables 4 and 5 shows that, after accounting for the effects of all other determinants, higher asymmetric information about the seller's asset value decreases the likelihood of their making an asset sale but increases the likelihood of their being targeted and acquired in whole. This contrast is surprising, and to the best of our knowledge, it has not been documented before. The evidence on asset sales is consistent with the market-for-lemons theory, but the evidence on targetiveness is inconsistent with that theory. Below, we conjecture several reasons for this difference in evidence on the role of asymmetric information in asset sales and mergers and acquisitions.

We posit that information availability exhibits systematic differences between whole firms and parts of a firm. For the whole firm, analysts and investors can access and analyze comprehensive historical financial performance data, which enables them to predict the future performance with some uncertainty captured by the asymmetric information measure. However, they would be unable to do so with the same degree of accuracy for parts of a firm for which

separate financial information is not available. Even when that information is available, it may be less reliable than for the whole firm.

Auditors play an important role in authenticating financial information. Audited information may be available for parts of the firm that are organized as a subsidiary before their sale. However, the auditors can only certify the performance of the concerned subsidiary or division as a part of the parent firm and not as an independent firm subject to the competition of the marketplace. This past financial performance may depend on transfer pricing of inputs from and outputs to other parts of the parent firm. Transfer pricing can be subjective, and the subsidiary or division may be catering to a largely captive market. These difficulties would constrain the investment bankers and analysts hired by a potential acquirer to value the sold assets. The situation is made more complex by the fact that the parent firm in an asset sale can often choose which of its units to sell, and any such choice would increase the adverse selection from the point of view of the buyer. To summarize, all the factors that increase the asymmetric information of a multi-divisional firm are also the reasons that make it difficult to value individual divisions and reduce their attractiveness in the market for the sale of corporate assets.

The positive association between information asymmetry and acquisition probability of a whole firm (or targetiveness) presents a more complex puzzle. We conjecture a few explanations to resolve this puzzle. First, we acknowledge that for most firms making an asset sale or being acquired in full are not likely to be substitute decisions. That is because the median firm doing an asset sale is much bigger than the median firm being acquired in full as shown in Table 3 and it is usually selling only a small part of its total assets that it selects. But for some firms, such possibility may exist. For such firms, facing financial constraints but unable to sell parts of their assets in view of higher asymmetric information, being acquired in full may be an option. This substitution

effect can explain some of the positive relation between a firm's asymmetric information and targetiveness. Second, some parent firms may have higher asymmetric information about their asset value because they possess unique technologies, which can make their divisions less attractive to potential acquirers without the support network of the parent firm and force them to be acquired in full.

Third, in similar spirit to the last reason, firms facing higher asymmetric information are likely to be complex and more volatile firms. The managers of such firms are often substantially compensated with stock and options of their firms and may want to cash out of their holdings for diversification purpose. Cai and Vijh (2007) show that managers often face a variety of restrictions on selling their company-specific holdings, but in most cases an acquisition leads to removal of those restrictions. For example, stock options usually vest immediately upon a change in control. Removal of restrictions usually does not occur on selling one part of the firm. This reason also suggests a positive relation between asymmetric information of firms and the likelihood of their being acquired in full. In summary, this positive relation between asymmetric information and mergers and acquisitions can be explained, although it remains inconsistent with the market for lemons theory and anomalous to some extent.

4. Asymmetric information and asset sales vs. mergers and acquisitions after natural disasters

While panel data regressions in Section 3 provide first evidence, they may be subject to endogeneities and concerns about the specification of control variables. We therefore conduct another experiment in which asymmetric information changes exogenously for a set of treatment firms affected by natural disasters. Events such as hurricanes, floods, wildfires, tornados, thunderstorms, and heavy rainfall can leave a trail of destruction whose direct costs of repairs and

restoration and indirect costs of business shutdown or slowdown are not obvious to outsiders. It creates significant information asymmetries between firm insiders and outsiders. In the meanwhile, these events generate acute financing needs in affected firms.

Baltas, Fiordelisi, and Mare (2022) show that firms hit by natural disasters turn to alternative financing sources such as private equity, crowdfunding, and venture capital, and Wang (2023) shows that natural disaster affected firms increase their lease financing. Asset sales could be an important financing source for such times, which would predict an increase in their frequency after natural disasters. However, the increased asymmetric information for those firms would predict the opposite. We therefore examine, first, whether asymmetric information increases after natural disasters using our ACARE measure, and second, whether these firms experience decreased frequency of asset sales and increased frequency of mergers and acquisitions as predicted.

4.1. Sample of firms affected by natural disasters

Our treatment sample is constructed using the Sheldus database, which provides county-level natural disaster data. We include all publicly-listed firms that were headquartered in counties that incurred a damage of at least $1 billion in 2022 dollars and which had a stock price of at least $5 as of the month before the natural disaster. We choose control firms from a sample of firms that were never hit by a billion-dollar natural disaster. For each treatment firm, we choose five control firms with replacement in the same Fama-French 12-industry classification that were the closest in market value and had a stock price of at least $5 as of the month before the natural disasters. We find a sample of 1,104 treatment firms and 5,505 control firms in the quarters of natural disaster using this procedure.

We expect the increase in asymmetric information after natural disasters to be relatively short lived. Thus, we cannot calculate measures of it over a generous one-year period as in the last experiment. We measure ACARE over only the current quarter's earnings announcement. We label the quarter during which a natural disaster occurs as quarter 0, and we conduct our investigation over quarters -8 to +8.

Table 6 reports the changes in mean ACARE values surrounding natural disasters. We report two sets of statistics: Unadjusted values that do not correct for survivorship bias, and adjusted values that correct for this bias. *Unadjusted* mean ACARE values for treatment firms go up significantly for a few quarters after natural disasters. Comparing windows from -4 to -1 quarters and from 1 to 4 quarters, the unadjusted mean ACARE increases from 6.14% for 4,336 firm-quarters before to 6.76% for 4,338 firm-quarters after natural disasters. Thus, ACARE increases by 0.62% for treatment firms, which is significant at 1% level with a *t*-statistic of 4.03. The corresponding increase for control firms is 0.09%, which is insignificant with five times as many observations. The increase in asymmetric information is short-lived. Over two-year windows from -8 to -1 quarters and from 1 to 8 quarters, ACARE values increase by 0.25% for treatment firms, which is significant at 5% level, and an insignificant 0.06% for control firms.

Table 6 shows that, out of 1,104 treatment firms in quarter 0, only 989 survive by quarter 8. The corresponding decay rate of 10.4% for treatment firms is somewhat higher than 8.6% for control firms (p-value of difference equals 0.06 using a χ_1^2-statistic.) If some of the treatment firms decay because they were severely affected by natural disasters, then it may induce a subtle survivorship bias because such firms may have experienced higher asymmetric information before decay. To account for such survivorship bias, we forward-fill the ACARE values of disappearing firms during quarters 1 to 8 using the last available values before they disappear.

We find that for treatment firms, *adjusted* mean ACARE calculated this way increases by 0.60% over a four-quarter window and by 0.31% over an eight-quarter window from before to after natural disaster, significant in each case at 1% level. For control firms, the corresponding numbers are 0.09% and 0.08%, insignificant in the first case and marginally significant at 10% level in the second case. The overall evidence suggests that treatment firms experience a significant increase in asymmetric information after natural disasters that lasts for about one year whereas control firms experience no significant increase. A small increase for control firms may not be totally unexpected given the spillover effects from treatment firms to control firms in the same industry due to possible competitive effects and supply-chain effects.

4.2. Matched-pairs tests of changes in asset sales frequency and targetiveness after natural disasters

4.2.1. Univariate evidence

Table 7 compares raw frequencies of asset sales and mergers and acquisitions by treatment firms and control firms before and after natural disasters. The control firms are matched on industry and size. Over four-quarter windows, Panel A shows that there are 3.62 asset sales per 100 firm quarters before disasters and 3.20 asset sales per 100 firm quarters after disasters for treatment firms. The corresponding numbers for control firms are 3.90 and 4.05 asset sales per 100 firm quarters. The pre-disaster difference in asset sales frequency between treatment and control firms of -0.27 per 100 firm quarters is insignificant, but the post-disaster difference of -0.85 per 100 firm quarters is significant at 1% level using a χ_1^2-statistic.

The evidence is somewhat stronger if we look at eight-quarter windows. There are 3.81 assets sales per 100 firm quarters before disasters and 3.54 asset sales per 100 firm quarters after disasters. The corresponding numbers for control firms are 3.72 and 4.28 asset sales per 100 firm

quarters. Once again, the pre-disaster difference in asset sales frequency between treatment and control firms of 0.09 per 100 firm quarters is insignificant, but the post-disaster difference of -0.73 per 100 firm quarters is significant at 1% level. This evidence shows that natural disasters decrease frequency of asset sales for treatment firms relative to matched control firms, which we attribute to an increase in asymmetric information for the treatment firms. That decrease in asset sales frequency occurs despite the increased need for financing in the aftermath of natural disasters as shown by the previous literature.

Panel B of Table 7 shows the corresponding evidence for acquisition announcements. The time scale here goes only from quarter 0 to +8. Unlike in the case of asset sales, one cannot examine the evidence on acquisition announcements (which is also referred to as targetiveness at various places in this paper) going back to quarter -8. That is because a firm continues to exist after an asset sale but may die any time after a successful acquisition announcement. So, firms that make it to quarter 0 are mostly the firms that did not have a successful acquisition announcement in preceding quarters. The bottom rows of Panel B show that, over a four-quarter window after the quarter of natural disaster, treatment firms are targeted at a rate of 0.76 per 100 firm quarters whereas control firms are targeted at a rate of 0.63 per 100 firm quarters. The difference in these two frequencies equals 0.13 per 100 firm quarters, but it is statistically insignificant. That could be due to smaller samples of acquisition announcements relative to asset sales.

Over a longer eight-quarter window after disasters, however, the two frequencies equal 0.83 and 0.61 per 100 firm quarters and the difference of 0.22 per 100 firm quarters is significant at 5% level using a χ_1^2-statistic. This panel shows that, contrary to the evidence for asset sales, after natural disasters the targetiveness measured by the number of acquisition announcements that are later completed is higher for treatment firms compared to control firms. This is despite very

few acquisition announcements in quarters 0, 1, and 2 for treatment firms which may be occupied with immediate assessment and rescue efforts.

4.2.2. Multivariate difference-in-difference analysis

Table 8 reports a multivariate difference-in-difference analysis of changes in asset sales frequency from before to after natural disasters. The sample of firm quarters is the same as in Table 7, consisting of treatment and control firms spanning over 17 quarters, from quarter -8 to quarter +8 relative to the quarter of natural disaster. The dependent variable is the number of assets sales during a firm quarter. We employ the Poisson model as in Table 4, because there may be more than one asset sale in some of the firm quarters. Besides ACARE, the key independent variable are a Post ND dummy, which takes the value one for quarters 1 to 8 and zero otherwise, a Treatment dummy, which takes the value one for treatment firms and zero for control firms, and an interaction term between these two dummies. We include the same control variables as in Table 4. However, size rank and industry fixed effects are omitted from the specification due to the matching procedure employed in sample construction, which explicitly accounts for these characteristics. We include quarter fixed effects and cluster standard errors by quarter as well.

Model (8.1) in Table 8 starts with the baseline difference-in-difference model. Treatment dummy is always insignificant in this and all other models of this table, which shows that treatment firms and control firms have the same asset sales frequency before natural disasters. Post ND dummy is positive, corresponding to the evidence in Table 7 that the more numerous control firms do more asset sales per firm quarter after disasters. The interaction term is negative and significant at 5% level, which shows that post natural disasters the treatment firms do fewer asset sales.

Model (8.2) includes ACARE in addition to the previous three difference-in-difference variables. The coefficient of ACARE is negative and statistically significant at 1% level,

suggesting that firms do fewer asset sales when they suffer from higher asymmetric information about their market value. The significance levels of the coefficients of Post ND dummy and the interaction term decrease with the inclusion of ACARE. Model (8.3) further adds the control variables to the list of key independent variables. ACARE remains negative and significant, while all three difference-in-difference variables become insignificant. This model highlights the role of asymmetric information in explaining the significant decline in raw asset sales frequency of treatment firms after natural disasters first shown in Table 7. Models (8.4) and (8.5) test the same specifications of independent variables as in Models (8.2) and (8.3) but replace ACARE by ACARE_rank. The results remain qualitatively similar.

The results of Tables 6, 7, and 8 show that natural disasters increase asymmetric information for treatment firms while simultaneously reducing their asset sales frequency. There seems to be a causal relationship between these two phenomena. These results corroborate our panel data evidence from Section 3.3. We also confirm the opposite result for targetiveness. Thus, the frequency of successful acquisition offers for treatment firms post natural disasters is higher than the frequency of successful acquisition offers for control firms. However, our analysis of acquisition patterns is limited to post-disaster comparisons between treatment and control groups. The methodological constraints discussed in Section 4.2.1 prevent extending the acquisition analysis to pre-disaster periods. Despite this limitation, the cross-sectional comparison between disaster-affected and unaffected firms provides valuable evidence supporting our hypotheses about the relationship between information asymmetries and corporate asset sales market.

5. Asymmetric information and acquirer type

Having established the relationship between information asymmetry and asset sale decisions, we now extend our analysis to the differential effects of information asymmetry on

acquirer type selection. Specifically, we examine systematic variation in public versus private acquirer participation based on the degree of information asymmetry surrounding seller assets. The existing literature documents many differences in the roles and performance of public vs. private acquirers that motivate our investigation of this issue. For example, Bargeron et al (2008) find that private equity firms pay a smaller acquisition premium than public firms, which they attribute to lower agency costs in private equity firms whose managers are not afraid of deal failure. Dittmar, Li, and Nain (2012) find that public acquirers realize higher long-term returns when they acquire targets for which they face competing bids by private equity firms than when they acquire targets for which they face competing bids by other public firms. They attribute this difference in returns to the superior valuation ability of public equity firms in picking their target firms.

More recently, Nary and Kaul (2023) survey a large literature and build a strong case that private equity firms play a positive role in acquiring targets that suffer from higher asymmetric information about their business activities and are therefore hard to value. They argue that private equity firms possess three advantages in acquiring other firms: A valuation advantage, which is the ability to assess the intrinsic value of a business when it is bought; a governance advantage, which is the ability to offer high-powered incentives to key personnel who increase the value of acquired assets; and a timing advantage, which is the ability to wait to sell the business until the best potential corporate buyer comes up with an offer. In this paper, we focus on the valuation advantage.

Nary and Kaul cite several reasons for why private equity firms have a valuation advantage. For example, a seller may share more information with a private equity investor that it does not want to make public, confident in the knowledge that the private equity investor has an incentive to honor the nondisclosure agreement, if only to maintain its reputation. Successful private equity

firms also have many valuation experts who specialize in valuing parts of a complex business as standalone entities. Using such arguments, Nary and Kaul (2023) state as their Proposition 1a that the more inscrutable a business (i.e., the greater the asymmetric information or the uncertainty about its market value), the greater the likelihood that it will be acquired by a private equity firm. However, they do not provide empirical evidence in support of this proposition. That is a gap we fill with our measure of asymmetric information in the following analysis.

Private equity acquirers are not rare, instead they are a large and growing presence in the market for the sale of corporate assets. Bargeron et al. (2008) document that 27% of public targets in their sample were acquired by private firms of which 48% were private operating firms and 52% were private equity firms. Since then, there seems to have been a considerable increase in the acquisition activity of private equity firms. According to a 2020 report by McKinsey & Company, private equity firms grew their assets by eight times over the period from 2000 to 2019 and at a rate that was three times faster than the rate at which public firms grew their assets over the same period. This evidence highlights the importance of private equity players in the acquisitions by private firms in our sample. Besides, as pointed out in the introduction, even private firms that are not specifically private equity firms, have an advantage relative to public firms in acquiring assets that suffer from greater information asymmetry. All types of private firms escape the constant scrutiny of public markets while they wait for such uncertain investments to pay off.

Table 9 shows univariate tests of the relation between asymmetric information and acquirer type. We classify an acquirer as a public acquirer when it or its ultimate parent firm is included in the CRSP database. Otherwise, we classify it as a private acquirer. Panel A of Table 9 shows that 54.1% of all 16,921 asset sales are made to private acquirers, which is a higher proportion than the 27.6% of all 4,863 target firms in Panel B that sell themselves in whole to private acquirers. That

result is consistent with Nary and Kaul's Proposition 1b, which predicts that private equity acquirers will be more active in the market for subsidiary assets that are more inscrutable than the assets of entire firms.

Looking across ACARE quintiles, we find that 50.9%, 53.3%, 55.4%, 55.3%, and 58.4% of acquirers in asset sales across the five partitions formed by lowest to highest asymmetric information are private firms. Clearly, there is an increasing trend in the proportion of subsidiary targets that are acquired by private firms across ACARE quintiles. A χ_4^2-statistic with four degrees of freedom rejects the equality of these five proportions at 1% significance level. Panel B shows similar evidence for mergers and acquisitions of entire firms. We find that 21.6%, 25.7%, 28.2%, 29.0%, and 32.0% of target firms in this case are acquired by private firms. The associated χ_4^2-statistic again rejects the equality of all five proportions at 1% significance level.

Table 10 presents multivariate tests of the relation between asymmetric information and acquirer type. Bargeron et al (2008) study the differences between firm characteristics and find that targets of private firms are characterized by smaller size, lower growth, and higher debt relative to targets of public firms. We therefore include firm size rank, book-to-market, and net leverage of target firms as control variables in the mergers and acquisitions of entire firms. Unfortunately, this is not possible with the sample of asset sales due to unavailability of corresponding data in most cases. Book-to-market and net leverage for subsidiary assets are less meaningful and almost never available. Deal value is available in about 46% cases, so we report multivariate results for acquirer type in asset sales with only deal value rank for part of the sample. Besides, we always include year fixed effects and cluster standard errors by year. The dependent variable in all regressions is a public acquirer dummy that equals one for public acquirers and zero for private acquirers. The key independent variables remain ACARE and ACARE_rank as before.

For each of asset sales and mergers and acquisitions of whole firms, Table 10 shows the results of four Logit regressions. Those regressions include permutations of univariate and multivariate specifications with ACARE and ACARE_rank as the key independent variables. To summarize findings, the asymmetric information variables ACARE and ACARE_rank are always negative and statistically significant at 1% level. The multivariate results are slightly stronger than univariate results. Overall, these results show that firms facing greater asymmetric information about their asset values, whether for partial asset sales or whole-firm acquisitions, have a higher probability of being acquired by private firms. Our evidence lends strong support to the predictions of Nary and Kaul (2023) and offers new insights into the roles of private equity firms in the market for sale and control of corporate assets.

6. Robustness tests

We have argued that our measure ACARE captures asymmetric information about a firm's market value between the firm and all other market participants including potential buyers and their advisors better than alternate measures discussed in Section 2. However, for robustness, in an Internet Appendix we replicate our key results in Tables 4, 5, and 8 with two alternate measures, which are the total return volatility and the idiosyncratic volatility calculated over the same period as ACARE. These alternate measures are chosen because they do not have significant conceptual problems and are available whenever ACARE is available. Our results with these alternate measures are qualitatively similar to those reported in the main body of the paper with the ACARE measure of asymmetric information.

7. Conclusion

Asymmetric information has been recognized as an important factor in corporate decisions, yet its effect on the *likelihood* of a firm selling its assets in part or in whole has received limited

attention. We analyze this effect using a new measure of asymmetric information that we name ACARE, the average absolute value of cumulative abnormal returns around earnings announcements during a year. We argue that this is a better measure of asymmetric information between a firm and the outside world concerning the market value of its assets than many alternative measures. Using this measure, we document a contrasting result in the market for sale of corporate assets. On the one hand, higher asymmetric information reduces the likelihood of a firm selling a part of its assets (i.e., a subsidiary sale). On the other hand, higher asymmetric information increases the likelihood of a firm selling all its assets (i.e., being targeted in a merger or an acquisition). We first document this result using a panel dataset of firm years. We then confirm it using an experiment where we examine the changes in frequency of asset sales and whole-firm acquisitions after natural disasters that increase the asymmetric information about assets value of treatment firms relative to control firms.

We offer several explanations for this result that appears anomalous at first sight: Picking and selling one part of a portfolio of assets exacerbates adverse selection, buyers are less able to assess a subsidiary's value as an independent firm separated from its parent firm, and asset sales are almost done deals when announced and escape the scrutiny of capital markets. Besides, firms suffering from higher asymmetric information are complex operations that are more attractive in whole than in part, and they are more likely to compensate their managers with illiquid stock and options. Being acquired in whole allows managers to cash out of their holdings, something that they cannot do after partial asset sales.

We also shed some new light on the positive role of private acquirers in resolving asymmetric information in the market for sale of corporate assets. In both partial asset sales and whole-firm acquisitions, the proportion of private acquirers increases significantly with an increase

in asymmetric information about the firm value. This paper contributes to the literature in three ways: by introducing a novel measure of firm-level information asymmetry, by documenting contrasting transaction patterns in corporate asset markets, and by highlighting how private acquirers facilitate market functioning when information frictions are most severe. These findings enhance understanding of how information asymmetries shape corporate asset allocation and the mechanisms markets develop to address these frictions.

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Appendix 1

Variable definitions

Variables	Definitions	Source
Information asymmetry measures		
ACARE	The average of absolute values of market-adjusted cumulative abnormal returns during the (-2, +2) window around all available earnings announcements during the last year in the main experiment using panel dataset of firm years, and only the current quarter in the natural disasters experiment. Market return throughout the paper is measured by the value-weighted return on all CRSP stocks (VWRETD).	CRSP and Compustat
ACARE_rank	Quintile rank of ACARE, 5 is for the highest values of ACARE.	CRSP and Compustat
AFE	First, we calculate the absolute difference between the median analyst forecast and actual earnings release, scaled by the stock price at the beginning of the quarter, for each quarter. Then we average over all quarters in the last year.	IBES
AFD	First, we calculate the standard deviation of analyst forecasts, scaled by the stock price at the beginning of the quarter, for each quarter. Then we average over all quarters in the last year.	IBES
ANALYSTS	First, we measure the number of analysts following a firm at the beginning of the quarter. Then we average over all quarters in the last year	IBES
Volatility	Annualized standard deviation of daily raw stock returns during the last year.	CRSP
Idiosyncratic Volatility	Annualized standard deviation of residuals from a one-factor market model of daily stock returns during the last year.	CRSP
AIV	Abnormal idiosyncratic volatility during the last year, calculated by the natural log of the ratio of idiosyncratic volatility during five-day periods before all earnings announcements divided by idiosyncratic volatility during all days of the year excluding 11-day periods from five days before to five days after all earnings announcements. See Yang, Zhang, and Zhang (2020) for further details.	CRSP and Compustat
Firm characteristics		
Market cap(italization)	Market value of the firm's equity at the beginning of the current year in the main experiment using panel dataset of firm years, or the current quarter in the natural disasters experiment, calculated in each case by multiplying stock price by the number of shares outstanding.	CRSP
Size rank	Decile rank of market cap by the year or by the quarter, 10 is for the largest market cap group.	CRSP
Book-to-market	Book value of equity to market value of equity (market cap) at the beginning of the current year or the current quarter.	Compustat

Earnings-to-price	Net income per share (ni/shares outstanding) during the last year scaled by stock price at the beginning of the current year in the main experiment. Similar calculation for the current quarter in the natural disasters experiment.	Compustat
Return on assets	Net income (ni) during the last year scaled by total assets (at) at the beginning of the current year in the main experiment. Similar calculation for the current quarter in the natural disasters experiment.	Compustat
Sales	Sales (sale) during the last year scaled by total assets (at) at the beginning of the current year in the main experiment. Similar calculation for the current quarter in the natural disasters experiment.	Compustat
Cash flow	Cash flow(ib+dp) during the last year scaled by total assets (at) at the beginning of the current year in the main experiment. Similar calculation for the current quarter in the natural disasters experiment.	Compustat
Net leverage	The difference between total debt and cash (dltt+dlc-che) scaled by the market value of assets (market value of equity+dltt+dlc) at the beginning of the year or the quarter.	Compustat
Capital expenditure	Capital expenditure (capx) during the last year scaled by total assets at the beginning of the current year in the main experiment. Similar calculation for the current quarter in the natural disasters experiment.	Compustat
Beta	Stock beta using the market model, measured using daily stock data from the previous year.	CRSP
Deal characteristics		
Deal value	Deal value as reported by the SDC.	SDC
Deal value/Seller market value	Deal value scaled by seller's market capitalization in the beginning of the deal announcement year.	SDC and CRSP
Acquirer is public	A dummy variable that equals 1 if the acquirer is available on CRSP and 0 otherwise.	SDC and CRSP
Deal value/Acquirer market value	Deal value scaled by acquirer's market capitalization in the beginning of the deal announcement year.	SDC and CRSP
Cash payment	A dummy variable that equals 1 if at least 50% paid by cash and 0 otherwise.	SDC
Seller announcement CAR	Three-day market-adjusted cumulative abnormal return in percent (CAR(-1,+1)) for the seller firm’s stock.	SDC and CRSP
Acquirer announcement CAR	Three-day market-adjusted cumulative abnormal return in percent (CAR(-1,+1)) for the acquiring firm’s stock when it is publicly traded.	SDC and CRSP
Natural disaster experiment		
Treatment dummy	A dummy variable that equals 1 for affected firms located in counties that suffered at least one billion dollars in damages in natural disasters (in 2021 dollars).	SHELDUS
Post ND dummy	A dummy variable that equals 1 in the following 8 quarters after the included billion-dollar natural disasters, and 0 in the previous 8 quarters.	SHELDUS

Table 1

Summary statistics of different measures of asymmetric information and their correlations

Panel A: Summary statistics

Measure of asymmetric information	N	Mean	Median	Std dev	Skewness	Autocorrelation
ACARE (average absolute cumulative abnormal return around earnings announcements)	149,764	5.45	4.41	3.91	1.52	0.48
AFE (analyst forecast error scaled by stock price)	114,388	0.72	0.23	2.27	10.56	0.65
AFD (analyst forecast dispersion scaled by stock price)	100,258	0.28	0.11	0.67	8.48	0.72
ANALYSTS (number of analysts)	114,808	6.41	4.50	5.76	1.50	0.94
Volatility (annualized value of daily return volatility)	149,764	0.44	0.39	0.23	1.29	0.74
Idiosyncratic Volatility (residuals from market model)	149,764	0.40	0.35	0.22	1.31	0.80
AIV (additional idiosyncratic volatility around earnings announcements)	149,760	-0.09	-0.08	0.65	-0.10	0.06

Panel B: Correlations

	ACARE	AFE	AFD	ANALYSTS	Volatility	Idiosyncratic volatility	AIV
ACARE	1.00	0.11	0.12	-0.03	0.60	0.59	0.10
AFE	0.11	1.00	0.73	-0.12	0.19	0.20	-0.03
AFD	0.12	0.73	1.00	-0.10	0.23	0.23	-0.05
ANALYSTS	-0.03	-0.12	-0.10	1.00	-0.15	-0.23	0.03
Volatility	0.60	0.19	0.23	-0.15	1.00	0.97	-0.07
Idiosyncratic volatility	0.59	0.20	0.23	-0.23	0.97	1.00	-0.07
AIV	0.10	-0.03	-0.05	0.03	-0.07	-0.07	1.00

Notes: The sample of 149,764 firm years starts with all observations from the CRSP and Compustat files during 1984-2021 (year *t*-1) for which the year-end stock price is at least $5 and the relevant data to calculate the primary asymmetric information (AI) measure ACARE are available. This period of calculating ACARE precedes the sample period of asset sales (AS) and mergers and acquisitions (MA) of 1985-2022 (year *t*) by one year. ACARE is the *average absolute value of cumulative abnormal returns* during the (-2, +2) day windows around *all available earnings announcements* during the year. We further calculate six alternate AI measures shown in this table and defined in Appendix 1. All measures except AIV and number of analysts are expressed in percent units. The calculation of forecast error, forecast dispersion, and number of analysts also requires that the analyst forecast data be available from the IBES Summary History file. All measures except AIV are bounded from below by zero, so positively skewed. For reference, note that the skewness of the right half of the standard normal distribution is 0.9953. Autocorrelation refers to the first order autocorrelation in data.

Table 2

Firm year characteristics by ACARE_rank

ACARE_rank →	1	2	3	4	5	All
N	29,953	29,954	29,954	29,952	29,951	149,764
ACARE in %	1.59 (1.65)	2.99 (2.98)	4.43 (4.41)	6.48 (6.41)	11.77 (10.64)	5.45 (4.41)
Market cap in $ million	3,947 (457)	4,163 (560)	3,369 (491)	2,432 (411)	1,437 (341)	3,069 (435)
Size rank in deciles	5.79 (6.00)	5.97 (6.00)	5.70 (6.00)	5.32 (5.00)	4.72 (5.00)	5.50 (6.00)
Book-to-market	0.64 (0.60)	0.61 (0.55)	0.58 (0.50)	0.54 (0.45)	0.51 (0.41)	0.58 (0.50)
Earnings-to-price	0.053 (0.059)	0.046 (0.055)	0.034 (0.049)	0.020 (0.041)	-0.004 (0.028)	0.030 (0.049)
Net leverage	0.17 (0.19)	0.15 (0.15)	0.12 (0.11)	0.09 (0.06)	0.05 (-0.01)	0.12 (0.10)
Capital expenditure	0.052 (0.033)	0.060 (0.037)	0.067 (0.040)	0.069 (0.041)	0.067 (0.039)	0.063 (0.038)
Beta	0.59 (0.52)	0.75 (0.71)	0.85 (0.83)	0.96 (0.94)	1.11 (1.07)	0.85 (0.81)

Notes: This table shows the firm-year characteristics by the quintile rank value of ACARE. The sample of firm years is described in Table 1 and includes 149,764 firm years during 1984-2021 for which ACARE can be calculated and the year-end stock price is at least $5. The first number in every cell shows the mean value and the second number in parentheses shows the median value of corresponding firm characteristic. All variables are defined in Appendix 1.

Table 3

Summary statistics of the samples of asset sales (AS) and mergers and acquisitions (MA)

Variable	N	Mean	Median	Frequency	
Panel A: Asset sales (AS)					
Seller (i.e., parent) market value ($ millions)	19,321	18,587	2,596		
Deal value ($ millions)	9,115	252	61		
Deal value/Seller market value	9,115	0.128	0.033		
Acquirer is public	16,921			7,759 (46%)	
Acquirer market value if it exists ($ millions)	7,559	11,134	1,248		
Deal value/Acquirer market value	4,232	0.271	0.067		
Cash payment	4,290			4,038 (94%)	
Seller announcement CAR (%)	18,869	0.59	0.17		
Acquirer announcement CAR (%)	7,409	1.13	0.37		
Subsidiary and seller have same 2-digit SIC	18,869			8,392 (44%)	
Subsidiary and acquirer have same 2-digit SIC	7,397			3,591 (49%)	
	0	1	2-3	4-5	>5
Number of AS in one year by seller	128,783	8,533	2,873	478	235
	1	2	3	4	5
Seller (parent) ACARE rank	4,629	4,884	4,072	3,244	2,492
Panel B: Mergers and acquisitions (MA)					
Target market value ($ millions)	5,373	1,556	278		
Acquirer is public	4,863			3,522 (72%)	
Acquirer market value ($ millions)	3,474	21,400	2,703		
Target market value/Acquirer market value	3,474	0.418	0.155		
Target and acquirer have same 2-digit SIC	3,522			2,231 (63%)	
Acquisition premium (%)	5,107	36.4	30.8		
Acquirer announcement CAR (%)	3,343	-1.14	-0.81		
	1	2	3	4	5
Target ACARE rank	950	967	1,109	1,099	1,248

Panel C: Industry distribution (%)

	Asset sales			Mergers and acquisitions	
	Seller	Subsidiary	Acquirer	Target	Acquirer
Consumer nondurables	5.8	6.5	3.8	4.2	3.1
Consumer durables	3.2	2.0	2.4	2.2	1.7
Manufacturing	12.8	12.3	10.2	9.5	8.7
Energy	7.1	6.8	7.3	3.1	3.9
Chemicals	4.6	4.4	3.9	1.7	1.8
Business equipment	11.9	14.0	14.0	19.8	17.2
Telecommunications	5.2	4.3	5.1	3.2	4.3
Utilities	4.7	3.0	5.8	2.7	2.8
Shops	6.9	8.5	5.4	8.6	6.8
Healthcare	7.0	7.2	7.1	10.3	9.8
Financials	19.2	17.0	24.2	23.7	30.0
Other	11.5	14.0	10.8	11.0	9.9

Notes: This table analyzes a sample of 140,902 firm years for summary statistics on asset sales (AS) and mergers and acquisitions (MA). It starts with all observations from the CRSP and Compustat files during 1985-2022 (year *t*) for which information on asymmetric information measure ACARE is available during the lagged year from the sample of firm years during 1984-2021 (year *t*-1) described in Table 1. That implicitly constrains the sample to observations for which

stock price at the end of year *t*-1 (beginning of year *t*) is at least $5. Panel A identifies all asset sales (AS) during 1985-2022 from the SDC files using the following criteria: 1. The divestiture dummy is coded yes. 2. The target type is subsidiary. 3. The target's Cusip is not the same as the target's ultimate parent's Cusip. 4. The merger form is acquisition of certain assets or acquisition of assets. 5. The acquisition status is completed. 6. The acquirer owns greater than 99% of target after the acquisition is completed. 7. The asymmetric information measure ACARE for the target's ultimate parent is available for the previous year using the database described in Table 1 (which implicitly requires that the parent is publicly traded, available on CRSP and Compustat, and has a stock price at last year-end of at least $5). Panel B identifies all mergers and acquisitions (MA) during the same period and from the same SDC files using the following criteria: 1. The merger form is coded as merger, acquisition, acquisition of assets, or acquisition of major interest. 2. The acquisition status is completed. 3. The acquirer owns less than 50% of target shares before acquisition and greater than 99% after acquisition. 4. The asymmetric information measure ACARE for the target firm is available for the previous year using the database described in Table 1 (which implicitly requires that the target is publicly traded, available on CRSP and Compustat, and has a stock price at last year-end of at least $5). In any column, N represents the number of observations with non-missing data for the concerned item. We determine acquirer type for both asset sales and mergers and acquisitions as follows. We first exclude tiny numbers of acquisitions (around 1%) where the acquirer type is coded as govt, mutual fund, investors, or joint venture. For the remaining cases, we code acquirer type as public if the acquirer or its ultimate parent can be found on CRSP, and private otherwise. We exclude foreign acquirers from most tests of this paper. All other variables are defined in Appendix 1.

Table 4

Asymmetric information and asset sales frequency

	Dependent variable: Asset sales frequency, Poisson regressions					
Variable	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
ACARE	-0.065***		-0.013**		-0.011**	
	(-8.53)		(-2.45)		(-2.07)	
ACARE_rank		-0.154***		-0.043***		-0.037***
		(-8.77)		(-3.33)		(-2.90)
Size rank			0.365***	0.364***	0.366***	0.365***
			(39.35)	(40.24)	(39.25)	(40.12)
Book-to-market			0.468***	0.467***	0.466***	0.465***
			(9.81)	(9.75)	(9.63)	(9.56)
Return on assets			-2.369***	-2.381***	-2.440***	-2.455***
			(-5.24)	(-5.22)	(-5.42)	(-5.43)
Sales			0.117***	0.118***	0.100***	0.101***
			(5.68)	(5.69)	(4.72)	(4.74)
Cash flow			0.672*	0.682*	0.714*	0.725**
			(1.78)	(1.80)	(1.95)	(1.98)
Net leverage			1.614***	1.615***	1.646***	1.648***
			(21.38)	(21.38)	(22.31)	(22.32)
Capital expenditure			-1.253***	-1.245***	-1.521***	-1.512***
			(-3.78)	(-3.77)	(-4.10)	(-4.08)
Constant	-1.614***	-1.502***	-4.914***	-4.854***	-4.857***	-4.803***
	(-46.03)	(-31.93)	(-45.44)	(-45.18)	(-45.01)	(-44.65)
N	140,902	140,902	118,937	118,937	118,937	118,937
N with non-zero dependent variable	12,119	12,119	10,986	10,986	10,986	10,986
Pseudo R^2	0.026	0.026	0.158	0.158	0.172	0.172
Industry fixed effects	Y	Y	Y	Y		
Year fixed effects	Y	Y	Y	Y		
Industry*Year fixed effects					Y	Y
Std. errors clustered by year	Y	Y	Y	Y	Y	Y

Notes: The sample of 140,902 firm years during 1985-2022 analyzed in this table is described in Table 3. Panel A of that table also describes how the frequency of asset sales for each firm year was identified. That frequency is the dependent variable in Poisson regressions reported in this table. The focus variables are the asymmetric information measure ACARE measured during the lagged year, or its quintile rank denoted by ACARE_rank. Control variables are defined in Appendix 1 and are measured during the lagged year. Availability of control variables reduces the sample to 118,937 firm years in multivariate regressions. Fixed effects for Industry and Year, or Industry*Year, are included as shown. We use the Fama-French 12-industry classification for this purpose. Standard errors are clustered by Year. The corresponding *t*-statistics are shown in parentheses below the coefficient values. Superscripts *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels.

Table 5

Asymmetric information and targetiveness

	Dependent variable: A successful acquisition was announced (1), not announced (0), Logit regressions					
Variable	(5.1)	(5.2)	(5.3)	(5.4)	(5.5)	(5.6)
ACARE	0.025***		0.017***		0.019***	
	(6.76)		(5.03)		(5.33)	
ACARE_rank		0.073***		0.047***		0.054***
		(5.42)		(3.68)		(4.22)
Size rank			0.167***	0.164***	0.173***	0.170***
			(5.48)	(5.33)	(5.66)	(5.49)
Size rank squared			-0.020***	-0.20***	-0.020***	-0.020***
			(-7.49)	(-7.32)	(-7.67)	(-7.47)
Book-to-market			0.111*	0.110*	0.113**	0.112**
			(1.94)	(1.91)	(2.04)	(2.03)
Return on assets			-1.380***	-1.386***	-1.292***	-1.292***
			(-3.58)	(-3.60)	(-3.41)	(-3.41)
Sales			0.042*	0.043*	0.038	0.039
			(1.74)	(1.79)	(1.60)	(1.63)
Cash flow			1.186***	1.185***	1.118***	1.113***
			(2.93)	(2.93)	(2.84)	(2.82)
Net leverage			-0.188	-0.152	-0.119	-0.124
			(-0.47)	(-0.48)	(-0.40)	(-0.41)
Capital expenditure			0.143**	0.141**	0.162**	0.160**
			(2.11)	(2.07)	(2.30)	(2.27)
Constant	-3.313***	-3.394***	-3.649***	-3.689***	-3.601***	-3.653***
	(-151.50)	(-80.82)	(-33.90)	(-33.97)	(-34.03)	(-34.51)
N	140,902	140,902	118,937	118,937	117,008	117,008
N with non-zero dependent variable	5,373	5,373	4,344	4,344	4,344	4,344
Pseudo R^2	0.024	0.024	0.029	0.029	0.041	0.041
Industry fixed effects	Y	Y	Y	Y		
Year fixed effects	Y	Y	Y	Y		
Industry*Year fixed effects					Y	Y
Std. errors clustered by year	Y	Y	Y	Y	Y	Y

Notes: The sample of 140,902 firm years during 1985-2022 analyzed in this table is described in Table 3. Panel B of that table also describes the subset of firm years during which an ultimately successful acquisition was announced. The dependent variable in the logit regressions of this table is a targetiveness dummy that equals one when a successful acquisition is announced during a firm year, and zero otherwise. The focus variables are the asymmetric information measure ACARE measured during the lagged year, or its quintile rank denoted by ACARE_rank. Control variables are defined in Appendix 1 and are measured during the lagged year. Availability of control variables reduces the sample to 118,937 firm years in multivariate regressions (5.3) and (5.4). Fixed effects for Industry and Year, or Industry*Year, are included as shown. We use the Fama-French 12-industry classification for this purpose. The sample is reduced a little more in Regressions (5.5) and (5.6) because the more stringent fixed effects cannot be calculated in some cases. Standard errors are clustered by Year. The corresponding *t*-statistics are shown in parentheses below the coefficient values. Superscripts *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels.

Table 6

Asymmetric information changes around natural disasters

	Treatment firms				**Control firms**			
	Unadjusted values		**Adjusted** values		**Unadjusted** values		**Adjusted** values	
Measure →	N	ACARE	N	ACARE	N	ACARE	N	ACARE
Quarter t ↓		Mean		Mean		Mean		Mean
-8	1,017	6.75	1,017	6.75	5,029	6.50	5,029	6.50
-7	1,025	6.48	1,025	6.48	5,112	5.90	5,112	5.90
-6	1,040	6.41	1,040	6.41	5,153	5.97	5,153	5.97
-5	1,044	6.44	1,044	6.44	5,237	5.96	5,237	5.96
-4	1,063	6.28	1,063	6.28	5,293	6.34	5,293	6.34
-3	1,081	6.25	1,081	6.25	5,387	6.13	5,387	6.13
-2	1,090	6.05	1,090	6.05	5,432	6.04	5,432	6.04
-1	1,102	5.99	1,102	5.99	5,504	6.27	5,504	6.27
0	1,104	6.28	1,104	6.29	5,505	6.28	5,505	6.28
1	1,099	6.78	1,104	6.78	5,482	6.53	5,505	6.54
2	1,089	7.01	1,104	6.93	5,423	6.37	5,505	6.40
3	1,083	6.75	1,104	6.78	5,376	6.22	5,505	6.20
4	1,067	6.48	1,104	6.47	5,301	6.01	5,505	6.00
5	1,050	6.69	1,104	6.72	5,224	6.44	5,505	6.43
6	1,029	6.44	1,104	6.64	5,161	6.21	5,505	6.25
7	1,007	6.10	1,104	6.26	5,085	5.98	5,505	6.01
8	989	6.22	1,104	6.43	5,029	5.83	5,505	5.94
Cumulative evidence over longer windows from before to after natural disasters								
-4 to -1	4,336	6.14	4,336	6.14	21,616	6.20	21,616	6.20
1 to 4	4,338	6.76	4,416	6.74	21,582	6.29	22,020	6.29
Difference		0.62***		0.60***		0.09		0.09
(t-statistic)		(4.03)		(3.94)		(1.36)		(1.31)
-8 to -1	8,462	6.32	8,462	6.32	42,147	6.14	42,147	6.14
1 to 8	8,413	6.57	8,832	6.63	42,081	6.20	44,040	6.22
Difference		0.25**		0.31***		0.06		0.08*
(t-statistic)		(2.12)		(2.61)		(1.33)		(1.65)

Notes: We collect the treatment sample of firms affected by natural disasters (ND) from the Sheldus™ database, which is a county-level database that covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods and heavy rainfall. We include all publicly-listed firms that were headquartered in counties that incurred a damage of at least $1 billion in 2021 dollars and which had a stock price of at least $5 as of the month before the natural disaster. Control firms are chosen from a sample of never hit by a billion-dollar natural disaster firms. For each treatment firm, we choose, with replacement, five control firms with the same Fama-French 12 industry classification that are the closest in market value as of month -1 and had a stock price of at least $5. However, we use quarterly time scale in this table. Thus, the asymmetric information measure ACARE is based on only the current quarter's data. Unadjusted value refer to mean values of ACARE calculated using the sample of surviving firms in an event quarter after ND. Those unadjusted values suffer from a survivorship bias because firms most impacted by the natural disaster are likely to have higher asymmetric information and more likely to disappear from the sample. To correct for this survivorship bias during quarters 1 to 8, we forward-fill the ACARE values for disappearing firms using the last available values before they disappear. This gives the adjusted values. In the lower panel, the statistical significance of differences in values of asymmetric information measures from before to after natural disaster are calculated using a t-test for means. Superscripts *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels.

Table 7

Matched pairs tests of changes in asset sales frequency and targetiveness after natural disasters: Controlling for industry and size effects

Panel A: ***Asset sales*** *frequency*

	Treatment firms			Control firms			Difference in asset sales per 100 firm quarters
Quarter *t*	N	Total asset sales	Asset sales per 100 firm quarters	N	Total asset sales	Asset sales per 100 firm-quarters	
-8	1,017	31	3.05	5,029	166	3.30	-0.25
-7	1,025	42	4.10	5,112	166	3.25	0.85
-6	1,040	41	3.94	5,153	189	3.67	0.27
-5	1,044	51	4.89	5,237	204	3.90	0.99
-4	1,063	41	3.86	5,293	188	3.55	0.31
-3	1,081	47	4.35	5,387	231	4.29	0.06
-2	1,090	34	3.12	5,432	229	4.22	-1.10
-1	1,102	35	3.18	5,504	194	3.52	-0.35
0	1,104	38	3.44	5,505	198	3.60	-0.15
1	1,099	33	3.00	5,482	192	3.50	-0.50
2	1,089	40	3.67	5,423	198	3.65	0.02
3	1,083	31	2.86	5,376	244	4.54	-1.68
4	1,067	35	3.28	5,301	240	4.53	-1.25
5	1,050	40	3.81	5,224	238	4.56	-0.75
6	1,029	35	3.40	5,161	222	4.30	-0.90
7	1,007	35	3.48	5,085	243	4.78	-1.30
8	989	49	4.95	5,029	222	4.41	0.54
Cumulative evidence over longer windows							
-4 to -1	4,336	157	**3.62**	21,616	842	**3.90**	**-0.27**
1 to 4	4,338	139	**3.20**	21,582	874	**4.05**	**-0.85*****
-8 to -1	8,462	322	**3.81**	42,147	1,567	**3.72**	**0.09**
1 to 8	8,413	298	**3.54**	42,081	1,799	**4.28**	**-0.73*****

Panel B: ***Acquisition announcements***

	Treatment firms			Control firms			Difference in acquisitions per 100 firm quarters
Quarter *t*	N	Total acquisitions	Acquisitions per 100 firm quarters	N	Total acquisitions	Acquisitions per 100 firm-quarters	
0	1,104	2	0.18	5,505	24	0.44	-0.25
1	1,099	6	0.55	5,482	36	0.66	-0.11
2	1,089	6	0.55	5,423	34	0.63	-0.08
3	1,083	10	0.92	5,376	34	0.63	0.29
4	1,067	11	1.03	5,301	31	0.58	0.45
5	1,050	6	0.57	5,224	25	0.48	0.09
6	1,029	7	0.68	5,161	28	0.54	0.14
7	1,007	17	1.69	5,085	28	0.55	1.14
8	989	7	0.71	5,029	42	0.84	-0.13
Cumulated over longer windows							
1 to 4	4,338	33	0.76	21,582	135	0.63	**0.13**
1 to 8	8,413	70	0.83	42,081	258	0.61	**0.22****

Table 7 continued…

Notes: The treatment sample of firms affected by natural disasters is described in Table 6. We match each treatment firm with five control firms with the same two-digit SIC code that are the closest in market value of equity at the end of quarter -1 and are not affected by a natural disaster during the event period analyzed in this table. Panel A reports the frequencies of firms and asset sales (AS) during each event quarter for both treatment and control firms, and Panel B does the same for mergers and acquisitions (MA). The event window spans -8 to +8 quarters around the quarter of natural disaster for AS, but only 0 to +8 quarter for MA. The reason is that a firm continues to exist after an AS but dies after an MA. Thus, firms that exist in quarter 0 could not have had a successful MA event in the before window. The lower parts of each panel show cumulative numbers of N, total asset sales, and asset sales per 100 firm-quarters aggregated over longer windows of four or eight quarters. The last column in every row shows the difference in asset sales per 100 firm quarters for treatment firms and control firms during the period covered by that row. The statistical significance of this last number is calculated using a χ^2test. Superscripts *, **, and *** denote statistical significance of differences in asset sales frequency at the 10, 5, and 1 percent levels.

Table 8

Multivariate tests of changes in asset sales frequency after natural disasters

	Dependent variable: Asset sales frequency				
Variable	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
Post ND * Treatment	-0.202**	-0.186*	-0.152	-0.186*	-0.153
	(-2.17)	(-1.95)	(-1.44)	(-1.94)	(-1.45)
Post ND	0.199***	0.149**	0.087	0.149**	0.088
	(3.10)	(2.28)	(1.47)	(2.27)	(1.49)
Treatment	0.037	0.039	-0.010	0.038	-0.011
	(0.53)	(0.54)	(-0.13)	(0.53)	(-0.14)
ACARE		-0.022***	-0.024***		
		(-4.51)	(-4.74)		
ACARE_rank				-0.075***	-0.076***
				(-3.88)	(-3.57)
Book-to-market			-0.130***		-0.134***
			(-2.58)		(-2.69)
Return on assets			-8.853***		-8.586***
			(-5.71)		(-5.62)
Sales			-0.925***		-0.948***
			(-6.50)		(-6.59)
Cash flow			8.180***		8.097***
			(4.70)		(4.70)
Net leverage			1.728***		1.712***
			(21.68)		(21.65)
Capital expenditure			-0.391		-0.372***
			(-0.29)		(-0.27)
Constant	-3.447***	-3.262***	-3.342***	-3.170***	-3.247***
	(-103.57)	(-72.38)	(-56.88)	(-47.22)	(-42.20)
N	107,629	100,767	84,460	100,767	84,460
N with non-zero dependent variable	3,545	3,545	2,965	2,965	2,965
Pseudo R^2	0.012	0.014	0.050	0.013	0.049
Quarter fixed effects	Y	Y	Y	Y	Y
Std. errors clustered by quarter	Y	Y	Y	Y	Y

Notes: This table presents multivariate difference-in-difference tests of asset sales frequency over an event window of -8 to +8 quarters surrounding natural disasters. The sample includes 107,629 firm quarters that are the sum of all firm quarters for treatment and control firms during this window as shown in Table 7. But it excludes 83 firm quarters that are dropped by the SAS program because there are not enough data to calculate the quarterly fixed effects. Because our control firms are chosen to match on industry and size, we do not include size rank as another control variable or industry fixed effects. All control variables are defined in Appendix 1 and calculated for the previous quarter. Among difference-in-difference variables, Post ND is a dummy variable that equals one for quarters 1 to 8, zero otherwise, and Treatment is a dummy variable that equals one for treatment firms, zero otherwise. The dependent variable in all regressions is the frequency of asset sales during a firm quarter, which may be greater than 1, so we estimate coefficients using the Poisson model. Standard errors are clustered by quarter. The corresponding *t*-statistics are shown in parentheses below the coefficient values. Superscripts *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels.

Table 9

Asymmetric information and acquirer type in asset sales or mergers and acquisitions: Univariate tests

ACARE rank →	1	2	3	4	5	All
Number of firm years →	28,122	28,343	28,257	28,199	27,981	140,902
Panel A: Asset sales						
To public acquirers	2,033	1,992	1,582	1,268	884	7,759
To private acquirers	2,111	2,272	1,967	1,569	1,243	7,575
Both public and private	4,144	4,264	3,549	2,837	2,127	16,921
Proportion private (%)	50.9	53.3	55.4	55.3	58.4	54.1
Chi-square (4) statistic to test the equality of proportions	38.08***					
Panel B: Mergers and acquisitions						
By public acquirers	677	669	717	701	758	3,522
By private acquirers	186	231	281	287	356	1,341
Both public and private	863	900	998	988	1,114	4,863
Proportion private (%)	21.6	25.7	28.2	29.0	32.0	27.6
Chi-square (4) statistic to test the equality of proportions	29.27***					

Notes: The samples of 16,921 asset sales and 4,863 mergers and acquisitions are described in Table 3. The identification procedure for public vs. private acquirers is described in Table 3. This table shows the frequency of public and private acquirers for asset sales and mergers and acquisitions arranged by quintile rank of the asymmetric information measure ACARE. Superscripts *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels.

Table 10

Asymmetric information and acquirer type in asset sales or mergers and acquisitions: Multivariate tests

*Panel A: Acquirer type in **asset sales***

	Dependent variable: Acquirer is public (1), private (0)			
Variable	(10.1)	(10.2)	(10.3)	(10.4)
ACARE	-0.014***		-0.019***	
	(-4.02)		(-4.75)	
ACARE_rank		-0.029***		-0.038***
		(-4.09)		(-4.53)
Deal value rank			0.031***	0.032***
			(7.75)	(7.71)
Constant	-0.697***	-0.682***	-0.661***	-0.648***
	(-45.36)	(-36.21)	(-22.09)	(-17.82)
N	16,921	16,921	7,842	7,842
Pseudo R^2	0.012	0.012	0.013	0.012
Year fixed effects	Y	Y	Y	Y
Clustered by year	Y	Y	Y	Y

*Panel B: Acquirer type in **mergers and acquisitions***

	Dependent variable: Acquirer is public (1), private (0)			
Variable	(10.5)	(10.6)	(10.7)	(10.8)
ACARE	-0.008***		-0.009***	
	(-2.61)		(-3.01)	
ACARE_rank		-0.029***		-0.035***
		(-4.02)		(-4.25)
Size rank			0.027***	0.027***
			(6.39)	(6.35)
Book-to-market			-0.128***	-0.132***
			(-3.93)	(-4.05)
Net leverage			-0.082***	-0.087***
			(-3.03)	(-3.28)
Constant	-0.269***	-0.223***	-0.311***	-0.251***
	(-16.09)	(-10.05)	(-7.50)	(-5.47)
N	4,863	4,863	4,826	4,826
Pseudo R^2	0.008	0.008	0.012	0.012
Year fixed effects	Y	Y	Y	Y
Clustered by year	Y	Y	Y	Y

Notes: The samples of 16,921 asset sales and 4,863 mergers and acquisitions are described in Table 9. In each case, we determine the acquirer type from SDC files as described in Table 3. The dependent variable in Logit regressions of this table is an Apublic dummy that equals one if the acquirer type is public, and zero if the acquirer type is private. The independent variables are inspired by Bargeron et al. (2008), who find that targets of private acquirers are characterized by smaller size, lower growth, and higher debt relative to targets of public acquirers. We proxy target firm size by deal value rank for asset sales and size rank for mergers and acquisitions. We measure firm growth by book-to-market and debt by net leverage. Appendix 1 describes the calculation of these variables. Deal size is available in less than half of asset sales while book-to-market and net leverage are not available. Standard errors are clustered by year. The corresponding *t*-statistics are shown in parentheses below the coefficient values. Superscripts *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels.

Internet Appendix

to "Asymmetric Information and Asset Sales versus Mergers and Acquisitions"

Robustness Tests

Table 4 – VOLATILITY

Asymmetric information and asset sales frequency

Robustness test using stock return volatility as an alternative measure of asymmetric information

	Dependent variable: Asset sales frequency, Poisson regressions					
Variable	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
VOLATILITY	-2.270***		-0.363***		-0.390**	
	(-7.95)		(-2.59)		(-2.57)	
VOLATILITY_rank		-0.329***		-0.054***		-0.054**
		(-10.85)		(-2.70)		(-2.52)
Size rank			0.361***	0.360***	0.361***	0.360***
			(35.79)	(35.23)	(35.28)	(34.85)
Book-to-market			0.469***	0.469***	0.465***	0.465***
			(9.70)	(9.63)	(9.41)	(9.56)
Return on assets			-2.470***	-2.409***	-2.545***	-2.495***
			(-5.51)	(-5.23)	(-5.75)	(-5.49)
Sales			0.117***	0.118***	0.100***	0.100***
			(5.70)	(5.67)	(4.71)	(4.70)
Cash flow			0.663*	0.647*	0.702*	0.700*
			(1.79)	(1.80)	(1.96)	(1.91)
Net leverage			1.605***	1.613***	1.639***	1.645***
			(21.09)	(21.11)	(21.97)	(22.02)
Capital expenditure			-1.195***	-1.191***	-1.464***	-1.463***
			(-3.54)	(-3.51)	(-3.86)	(-3.83)
Constant	-1.024***	-1.041***	-4.804***	-4.798***	-4.715***	-4.723***
	(-9.64)	(-13.75)	(-35.54)	(-36.60)	(-34.22)	(-35.67)
N	140,902	140,902	118,937	118,937	118,937	118,937
N with non-zero dependent variable	12,119	12,119	10,986	10,986	10,986	10,986
Pseudo R^2	0.040	0.042	0.158	0.158	0.172	0.172
Industry fixed effects	Y	Y	Y	Y		
Year fixed effects	Y	Y	Y	Y		
Industry*Year fixed effects					Y	Y
Std. errors clustered by year	Y	Y	Y	Y	Y	Y

Notes: This table is identical to Table 4 in the main text in all respects, except that it uses total stock return volatility calculated over the year as a measure of asymmetric information in place of ACARE. Please see that table for all details.

Table 5 – VOLATILITY

Asymmetric information and targetiveness

Robustness test using stock return volatility as an alternative measure of asymmetric information

	Dependent variable: A successful acquisition was announced (1), not announced (0), Logit regressions					
Variable	(5.1)	(5.2)	(5.3)	(5.4)	(5.5)	(5.6)
VOLATILITY	0.409***		0.133		0.259**	
	(4.84)		(1.08)		(2.37)	
VOLATILITY_rank		0.096***		0.045**		0.069***
		(5.96)		(2.22)		(3.67)
Size rank			0.172***	0.171***	0.181***	0.178***
			(5.65)	(5.65)	(5.92)	(5.87)
Size rank squared			-0.020***	-0.20***	-0.021***	-0.020***
			(-7.82)	(-7.65)	(-8.00)	(-7.77)
Book-to-market			0.110*	0.114*	0.119**	0.123**
			(1.88)	(1.94)	(2.09)	(2.16)
Return on assets			-1.402***	-1.373***	-1.265***	-1.241***
			(-3.70)	(-3.53)	(-3.43)	(-3.25)
Sales			0.050**	0.047**	0.044*	0.041*
			(2.12)	(1.97)	(1.93)	(1.78)
Cash flow			1.215***	1.204***	1.136***	1.120***
			(3.01)	(2.94)	(2.91)	(2.80)
Net leverage			0.141**	0.145**	0.165**	0.168**
			(2.12)	(2.12)	(2.39)	(2.42)
Capital expenditure			-0.152	-0.172	-0.133	-0.155
			(-0.49)	(-0.53)	(-0.44)	(-0.49)
Constant	-3.358***	-3.469***	-3.625***	-3.715***	-3.642***	-3.747***
	(-84.85)	(-67.74)	(-25.39)	(-25.71)	(-26.47)	(-26.81)
N	140,902	140,902	118,937	118,937	117,008	117,008
N with non-zero dependent variable	5,373	5,373	4,344	4,344	4,344	4,344
Pseudo R^2	0.023	0.024	0.029	0.029	0.041	0.041
Industry fixed effects	Y	Y	Y	Y		
Year fixed effects	Y	Y	Y	Y		
Industry*Year fixed effects					Y	Y
Std. errors clustered by year	Y	Y	Y	Y	Y	Y

Notes: This table is identical to Table 5 in the main text in all respects, except that it uses total stock return volatility calculated over the year as a measure of asymmetric information in place of ACARE. Please see that table for all details.

Table 8 –VOLATILITY

Multivariate tests of changes in asset sales frequency after natural disasters

Robustness test using stock return volatility as an alternative measure of asymmetric information

	Dependent variable: Asset sales frequency				
Variable	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
Post ND * Treatment	-0.202**	-0.185*	-0.151	-0.190**	-0.157
	(-2.17)	(-1.94)	(-1.44)	(-2.00)	(-1.49)
Post ND	0.199***	0.157**	0.096	0.156**	0.094
	(3.10)	(2.39)	(1.64)	(2.37)	(1.59)
Treatment	0.037	0.049	0.003	0.056	0.007
	(0.53)	(0.67)	(0.04)	(0.78)	(0.09)
VOLATILITY		-1.212***	-1.802***		
		(-3.70)	(-5.82)		
VOLATILITY_rank				-0.172***	-0.203***
				(-5.93)	(-7.51)
Book-to-market			-0.095*		-0.091*
			(-1.76)		(-1.74)
Return on assets			-10.520***		-10.535**
			(-7.03)		(-7.13)
Sales			-0.904***		-0.861***
			(-6.21)		(-5.92)
Cash flow			8.461***		8.816***
			(4.99)		(5.22)
Net leverage			1.761***		1.726***
			(21.90)		(21.29)
Capital expenditure			0.319		0.543
			(0.23)		(0.40)
Constant	-3.447***	-3.118***	-3.125***	-2.878***	-2.938***
	(-103.57)	(-37.66)	(-36.55)	(-30.63)	(-31.92)
N	107,629	100,767	84,460	100,767	84,460
N with non-zero dependent variable	3,545	3,545	2,965	2,965	2,965
Pseudo R^2	0.012	0.014	0.052	0.016	0.052
Quarter fixed effects	Y	Y	Y	Y	Y
Std. errors clustered by quarter	Y	Y	Y	Y	Y

Notes: This table is identical to Table 8 in the main text in all respects, except that it uses total stock return volatility calculated over the year as a measure of asymmetric information in place of ACARE. Please see that table for all details.

Table 4 – IDIOSYNCRATIC VOLATILITY

Asymmetric information and asset sales frequency

Robustness test using idiosyncratic stock return volatility as an alternative measure of asymmetric information

	Dependent variable: Asset sales frequency, Poisson regressions					
Variable	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
IDIO-VOLATILITY	-3.186***		-0.642***		-0.665***	
	(-11.01)		(-3.91)		(-3.89)	
IDIO-VOLATILITY_rank		-0.411***		-0.091***		-0.092***
		(-16.63)		(-4.59)		(-4.33)
Size rank			0.352***	0.349***	0.352***	0.350***
			(33.66)	(33.99)	(33.07)	(33.45)
Book-to-market			0.464***	0.468***	0.459***	0.463***
			(9.43)	(9.42)	(9.12)	(9.10)
Return on assets			-2.544***	-2.494***	-2.610***	-2.577***
			(-5.71)	(-5.40)	(-5.90)	(-5.65)
Sales			0.121***	0.122***	0.103***	0.104***
			(5.92)	(5.92)	(4.89)	(4.90)
Cash flow			0.649*	0.660*	0.687*	0.714*
			(1.76)	(1.74)	(1.92)	(1.95)
Net leverage			1.602***	1.614***	1.637***	1.647***
			(20.93)	(21.02)	(21.80)	(21.87)
Capital expenditure			-1.148***	-1.130***	-1.419***	-1.402***
			(-3.39)	(-3.33)	(-3.73)	(-3.67)
Constant	-0.814***	-0.834***	-4.663***	-4.637***	-4.575***	-4.559***
	(-8.86)	(-14.07)	(-33.34)	(-34.92)	(-32.32)	(-34.03)
N	140,902	140,902	118,937	118,937	118,937	118,937
N with non-zero dependent variable	12,119	12,119	10,986	10,986	10,986	10,986
Pseudo R^2	0.052	0.054	0.158	0.158	0.173	0.173
Industry fixed effects	Y	Y	Y	Y		
Year fixed effects	Y	Y	Y	Y		
Industry*Year fixed effects					Y	Y
Std. errors clustered by year	Y	Y	Y	Y	Y	Y

Notes: This table is identical to Table 4 in the main text in all respects, except that it uses idiosyncratic stock return volatility calculated over the year as a measure of asymmetric information in place of ACARE. Please see that table for all details.

Table 5 – IDIOSYNCRATIC VOLATILITY

Asymmetric information and targetiveness

Robustness test using idiosyncratic stock return volatility as an alternative measure of asymmetric information

	Dependent variable: A successful acquisition was announced (1), not announced (0), Logit regressions					
Variable	(5.1)	(5.2)	(5.3)	(5.4)	(5.5)	(5.6)
IDIO-VOLATILITY	0.493***		0.181		0.297***	
	(5.90)		(1.50)		(2.67)	
IDIO-VOLATILITY_rank		0.109***		0.054***		0.074***
		(7.53)		(3.07)		(4.43)
Size rank			0.175***	0.174***	0.185***	0.182***
			(5.75)	(5.79)	(6.07)	(6.08)
Size rank squared			-0.021***	-0.20***	-0.021***	-0.020***
			(-7.86)	(-7.68)	(-8.08)	(-7.83)
Book-to-market			0.113*	0.115**	0.121**	0.123**
			(1.92)	(1.98)	(2.12)	(2.18)
Return on assets			-1.387***	-1.356***	-1.257***	-1.230***
			(-3.66)	(-3.48)	(-3.40)	(-3.20)
Sales			0.049**	0.046*	0.044*	0.040*
			(2.08)	(1.93)	(1.91)	(1.76)
Cash flow			1.212***	1.195***	1.133***	1.110***
			(3.00)	(2.91)	(2.91)	(2.77)
Net leverage			0.142**	0.146**	0.165**	0.169**
			(2.14)	(2.16)	(2.40)	(2.42)
Capital expenditure			-0.156	-0.179	-0.135	-0.160
			(-0.50)	(-0.55)	(-0.45)	(-0.50)
Constant	-3.377***	-3.515***	-3.653***	-3.760***	-3.663***	-3.784***
	(-94.19)	(-74.89)	(-26.16)	(-27.29)	(-27.03)	(-28.08)
N	140,902	140,902	118,937	118,937	117,008	117,008
N with non-zero dependent variable	5,373	5,373	4,344	4,344	4,344	4,344
Pseudo R^2	0.024	0.025	0.029	0.029	0.041	0.041
Industry fixed effects	Y	Y	Y	Y		
Year fixed effects	Y	Y	Y	Y		
Industry*Year fixed effects					Y	Y
Std. errors clustered by year	Y	Y	Y	Y	Y	Y

Notes: This table is identical to Table 5 in the main text in all respects, except that it uses idiosyncratic stock return volatility calculated over the year as a measure of asymmetric information in place of ACARE. Please see that table for all details.

Table 8 – IDIOSYNCRATIC VOLATILITY

Multivariate tests of changes in asset sales frequency after natural disasters

Robustness test using idiosyncratic stock return volatility as an alternative measure of asymmetric information

	Dependent variable: Asset sales frequency				
Variable	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
Post ND * Treatment	-0.202**	-0.185*	-0.152	-0.192**	-0.160
	(-2.17)	(-1.94)	(-1.45)	(-2.03)	(-1.52)
Post ND	0.199***	0.157**	0.097*	0.158**	0.097
	(3.10)	(2.41)	(1.65)	(2.41)	(1.64)
Treatment	0.037	0.054	0.009	0.063	0.015
	(0.53)	(0.74)	(0.11)	(0.88)	(0.19)
IDIO-VOLATILITY		-1.747***	-2.445***		
		(-4.88)	(-7.10)		
IDIO-VOLATILITY_rank				-0.223***	-0.271***
				(-7.65)	(-9.36)
Book-to-market			-0.083		-0.071
			(-1.48)		(-1.29)
Return on assets			-11.128***		-11.332**
			(-7.37)		(-7.60)
Sales			-0.848***		-0.779***
			(-5.85)		(-5.37)
Cash flow			8.554***		9.026***
			(4.99)		(5.27)
Net leverage			1.781***		1.752***
			(21.67)		(21.17)
Capital expenditure			0.535		1.068
			(0.39)		(0.78)
Constant	-3.447***	-3.051***	-3.086***	-2.747***	-2.816***
	(-103.57)	(-39.04)	(-37.68)	(-29.91)	(-29.84)
N	107,629	100,767	84,460	100,767	84,460
N with non-zero dependent variable	3,545	3,545	2,965	2,965	2,965
Pseudo R^2	0.012	0.016	0.054	0.018	0.056
Quarter fixed effects	Y	Y	Y	Y	Y
Std. errors clustered by quarter	Y	Y	Y	Y	Y

Notes: This table is identical to Table 8 in the main text in all respects, except that it uses idiosyncratic stock return volatility calculated over the year as a measure of asymmetric information in place of ACARE. Please see that table for all details.