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DO ACQUIRER ANNOUNCEMENT RETURNS REFLECT VALUE CREATION?

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ABSTRACT

Stock returns around acquisition announcements are widely viewed as being reflective of the net present value created by these transactions. As such, announcement returns should correlate with acquisition outcomes. Using a new measure of realized transaction-level acquisition failure, as well as acquirer firm-level performance, we show that while these outcomes can be predicted based on observable deal and firm characteristics, they are largely uncorrelated with announcement returns. Our results cast doubt on the usefulness of announcement returns as a measure of the value created in acquisitions and call for caution in other contexts.

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1 Introduction

Following the introduction of the efficient market hypothesis to financial economics in the 1970s (Fama, 1976), economists began using event studies to measure value creation in firms. Researchers have explored value creation around announcements such as corporate transactions, new corporate policies, and regulatory actions (e.g., Jarrell, Brickley, and Netter, 1988; MacKinlay, 1997; Campbell, Lo, and MacKinlay, 1997; Kaplan, 2006; Kothari and Warner, 2007). The implicit assumption in these tests is that cumulative abnormal returns (CAR) in the period surrounding the announcement of such news reflect the net present value (NPV) of expected cash flows caused by the announced event. A few decades later, CAR has become the most widely used approach by financial economists to measure value creation in mergers.[1] One would assume that a widely-used measure for value creation has been thoroughly-validated by prior literature.

In fact, the existing evidence supporting this relationship is not overwhelming, to say the least. Two early studies that use small and overlapping samples find evidence of a correlation between acquirer CAR and ex-post outcomes (Healy, Palepu, and Ruback, 1992; Kaplan and Weisbach, 1992).[2] Two later studies find that CAR is weakly correlated with some outcomes in select specifications: expected (Hoberg and Phillips, 2018) and realized (Li, 2013).[3] Other studies indicate that CAR may not be correlated with outcomes (winner underperformance in contested mergers: Malmendier, Moretti, and Peters, 2018), but rather with less value-

[1]We find that between 2007 and 2016, 6.4% of articles published in the *Journal of Finance*, *Journal of Financial Economics*, and *Review of Financial Studies* focused on mergers and acquisitions (M&As). (We consider an article to focus on M&As if its abstract contains any of the following words: merger, acquisition, M&A, deals, acquirer, target, takeover, market reaction to acquisition, goodwill, or synergy.) Of these articles, 62.4% computed measures of acquisition value creation; of this subset, 95.6% used the event study methodology.

[2]Healy et al. (1992) find that CAR is correlated with changes in industry-adjusted return on assets (ROA) in a sample of 42 acquisitions in 1979–1984. Kaplan and Weisbach (1992) study divestiture outcomes of earlier acquisitions in the 1971–1982 period and find that the 37 unsuccessful acquisitions (divested at a loss or portrayed as unsuccessful) had lower acquisition CAR than that of the 71 successful divestitures.

[3]Hoberg and Phillips (2018) find a weak correlation between CAR and only one of their expected integration measures. Importantly, however, they find the largest stock market consequences for integration difficulty in long-term returns rather than in announcement returns. Li (2013) finds a weak (and controls-dependent) correlation between CAR and realized future increases in productivity.

relevant variables: earnings-per-share (Dasgupta, Harford, and Ma, 2019) and hot markets (Rosen, 2006; Bouwman, Fuller, and Nain, 2009). Furthermore, several studies indicate that CAR is not likely to capture all available information, since characteristics known at the time of the announcement predict acquirers' future stock performance.[4] The ambiguity about CAR's information content is reflected in the conflicting inferences that researchers draw when using different measurement methods and different samples.[5] Furthermore, in contrast to the compelling idea that merger announcement CAR could flag horizontal mergers that extract value by shrinking the consumer surplus (Pittman, 2007), in practice, there is no correlation between CAR and antitrust actions over the 1964–1972 and 1980–2009 periods (Stillman, 1983; Gao, Peng, and Strong, 2017).[6] Finally, and more broadly, hundreds of studies have documented that stock prices often do not efficiently incorporate readily available information.[7]

In this study, we put merger announcement CAR through a battery of tests to assess whether it is correlated with ex-post transaction- and acquirer-level outcomes. We utilize nearly 1,900 merger announcements during the 2003–2013 period.[8] We consider both a new transaction-level measure of acquisition failure that provides a direct and quantifiable representation of acquisition performance—large goodwill write-downs or divestiture-at-a-loss—as

[4]Examples of such characteristics are engaging in stock acquisitions (Mitchell and Stafford, 2000), having abnormally high market-to-book (Rhodes-Kropf and Viswanathan, 2004; Dong, Hirshleifer, Richardson, and Teoh, 2006), and having abnormally high short interest (Ben-David, Drake, and Roulstone, 2015).

[5]For example, there is no strong consensus among economists as to whether mergers create value for the average acquirer. The sign and magnitude of acquirer CAR computed by researchers have varied depending on the time period of the study, on whether percentage or dollar returns are computed, and on the methodology used to tease out acquirer overvaluation information in stock-financed transactions. See the discussion on this issue in Andrade, Mitchell, and Stafford (2001), Moeller, Schlingemann, and Stulz (2004), Moeller, Schlingemann, and Stulz (2005), Malmendier and Tate (2008), Savor and Lu (2009), Netter, Stegemoller, and Wintoki (2011), Fich, Nguyen, and Officer (2018), and Malmendier et al. (2018).

[6]Demonstrating the deep belief in the validity of CAR, Gao et al. (2017) conclude that the lack of correlation indicates that "antitrust enforcement is not consistent with the stated aim of consumer protection."

[7]E.g., post-earnings-announcement drift (Bernard and Thomas, 1989), the accruals anomaly (Sloan, 1996), predictable events (Chang, Hartzmark, Solomon, and Soltes, 2017; Hartzmark and Solomon, 2018), linguistic information available on financial reports (Cohen, Malloy, and Nguyen, 2020), and parent-subsidiary valuation arbitrage (Lamont and Thaler, 2003).

[8]Our sample ends in 2013 rather than a more recent period because our methodology follows the acquirer for five years following the deal effective date. Our sample begins in 2003 following enhancements to goodwill disclosure rules in 2002.

well as traditional acquirer-level measures of operating and stock performance. We document that while ex-post performance outcomes can be predicted using information known at the time of the announcement (deal and acquirer characteristics), acquirer announcement returns have little relation to merger outcomes. We discuss the potential explanations for the failure of CAR to provide meaningful information. Overall, our findings cast doubt on the usefulness of CAR as a measure of acquisition value creation.

The ex-post outcome measures that we use are at the deal- and acquirer-levels. We introduce a new indicator for acquisition failure that combines large goodwill impairments and target divestiture-at-a-loss. Both components capture deals for which the realized economic value of the acquisition is less than the original purchase price, i.e., transactions that likely had a negative net present value ex-post. Prior literature has used divestiture-at-a-loss as an indicator of negative NPV;[9] however, because it is conditional on a sale, this measure likely captures only a small fraction of failed transactions. Since 2003, accounting rules have required acquirers to record goodwill at the reporting-unit level and impair it (i.e., recognize a loss) if indicated by routine tests. As such, we can identify failure at the transaction level without conditioning on a sale. We validate that large impairment serves as a robust signal of value destruction by relating our measure to several indirect symptoms of merger failure: Impaired firms are more likely to experience poor stock and operating performance, distressed delisting, and management turnover following impairment news. Our sample contains 372 transactions (or 20% of the sample) with goodwill impairment or divestiture-at-a-loss.

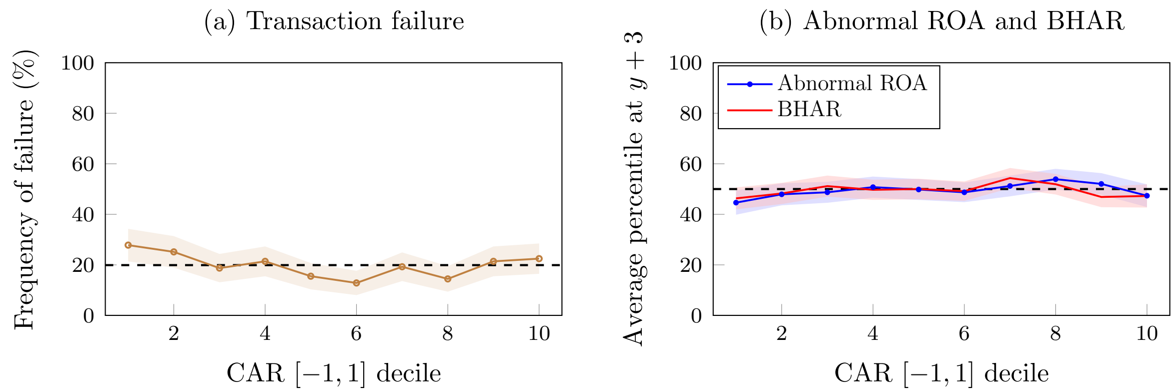
Because our failure measure only captures the left tail of outcomes, we also employ widely used acquirer-level performance measures that capture both value creation and destruction: abnormal ROA and buy-and-hold returns (BHAR) adjusted to size, market-to-book, and momentum following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW). Importantly, the three ex-post measures are positively correlated.

In our main analysis, we use three different approaches to test the validity of CAR. All

[9]Previous studies have also used target divestiture-at-a-loss as an indicator of an unsuccessful acquisition, see, e.g., Mitchell and Lehn (1990), Kaplan and Weisbach (1992), and Kaplan, Mitchell, and Wruck (2000).

Figure 1. Ex-Post Merger and Acquirer Outcomes, by CAR $[-1, 1]$ Deciles

The figure shows deal and acquirer averages by CAR decile. Panel (a) reports the fraction of failed transactions, as measured by impaired goodwill or divestiture-at-a-loss (within five years of the announcement date). Panel (b) reports the average percentile of abnormal ROA in the three years after the transaction, and the average percentile of buy-and-hold (BHAR) DGTW-adjusted three-year returns after the transaction. The shaded areas represent 95% confidence intervals. The dashed line indicates the sample average of all the variables.



three indicate that CAR has little meaningful correlation with the ex-post outcomes.

In the first approach, we conduct in-sample tests in which we measure the correlation between outcomes (deal failure, loss magnitude given failure, abnormal ROA, and DGTW-adjusted BHAR) and CAR. Figure 1 provides a simple graphical representation of the non-parametric association between CAR and ex-post outcomes. Panel (a) shows the fraction of failed transactions for each CAR decile, and Panel (b) shows the average abnormal ROA and buy-and-hold abnormal return (BHAR) percentiles for each CAR decile. The lines in both charts are flat, showing no material association.

We extend this analysis to a large set of in-sample regression analyses. We find no meaningful correlation between outcomes and CAR. In 24 regressions—including four different acquisition outcome variables, two estimation techniques, three event windows, and the inclusion of various sets of controls—CAR achieves statistical significance at the 5% level in only one and at the 10% level in only three regressions. The adjusted R^2 in these regressions is minuscule. CAR, at best, explains 0.1% of the variation in the probability of deal failure and 0.2% of the variation in abnormal ROA and DGTW-adjusted BHAR. Our results are robust to excluding acquisition failures during the financial crisis (2008) and to the inclusion of combined acquirer and target returns.

Given the weak performance of CAR, it is tempting to conclude that ex-post outcomes are simply hard to predict with the information available to investors. However, this does not seem to be the case. In fact, a standard set of acquirer and deal characteristics—known at the time of the announcement—predict ex post outcomes with adjusted R^2 ranging between 6.7% and 9.2%.

In the second approach, we conduct out-of-sample tests in which we fit regression models in the first half and predict outcomes in the second half of the sample. Again, we observe a wide disparity between the predictive ability of CAR and a characteristics model. Acquisitions in the top CAR quintile have the same realized failure rate as those in the bottom quintile: 16%. In contrast, acquisitions in the top quintile of predicted failure likelihood using characteristics have a realized failure rate of 18%, compared to 5% for those in the bottom quintile. Moreover, CAR is uncorrelated with the "predictable" component of acquisition outcomes, as predicted by characteristics known at the time of the transaction.

We corroborate our inference from the out-of-sample tests by forming portfolios of acquirers based on the predictions of CAR and characteristics. We repeat this exercise for each of the three outcome variables. The performance spread in the three-year return between the top and bottom three deciles as defined by CAR is statistically indistinguishable from zero. Conversely, the return spread between the top and bottom three deciles as determined by characteristics ranges between 7.8% and 11.5%, and is statistically significant at the 1% to 10% confidence levels.

In the third and final approach, we evaluate the reliability of economic inferences often made in academic research based on CAR. These inferences are typically based on characteristics. For example, diversifying acquisitions have negative CAR; hence, economists infer that these transactions have negative NPV, on average. To systematically perform this task, we estimate the association between CAR and each deal and acquirer characteristic. We then repeat the process for the three ex-post outcomes and each characteristic. In a final step, we compare the correlation of CAR with each characteristic to the related ex-post outcomes. Overall, we find little association between the signs and the magnitudes of the predictions by CAR and the ex-post outcomes. For example, CAR is negatively associated with acquisitions of public targets, payment with stock, acquisitions by large acquirers, large deals, and acquirers with a high Tobin's Q. The ex-post outcomes for most of these types of transactions (except stock proceeds) are positive, on average. Hence, inferences based on CAR about the value created in deals with certain characteristics do not correlate with the realized acquisition outcome measures.

In the final section, we explore potential explanations for the lack of predictability by CAR and find that the first two of the following four explanations shed some light on this issue. We caution that the economic significance of these results is minimal.

First, CAR may capture some information beyond the value created by the acquisition (e.g., information regarding acquirer standalone value). We strip the variation related to the acquirer-specific characteristics from CAR and then repeat our main analysis with the residualized CAR. We find that residualized CAR is marginally better at explaining ex-post outcomes than CAR, yet its explanatory power is minimal (maximum R^2 of 0.003). Second, uncertainty about merger outcomes could limit CAR's predictive power. Indeed, CAR has small explanatory power for the 30% of failures that take place in the first year and no explanatory power for the remaining 70%. Similarly, in the cross-section, CAR has marginally better explanatory power for acquisitions with a superior information environment. Still, even in the most favorable specification, CAR's adjusted R^2 does not exceed 0.008, whereas characteristics' explanatory power is at least quadruple that. Third, we find that variations in the size of the window used to measure CAR do not make a difference. Fourth, CAR's explanatory power might be moderated by the potential attenuation from truncation due to cancelled bids (about 7% of bids). We reweight the sample by the inverse probability weighting of completion (Wooldridge, 2007), but find no improvement in CAR's explanatory power. Moreover, there is a possibility that ex-post outcomes are endogenous in CAR (e.g., managers may "listen" to CAR). This does not seem to be an important factor since characteristics can predict outcomes (including future stock performance).

To conclude, announcement returns cannot reliably be used as a proxy for the value created in mergers. Researchers should approach inferences generated from CAR with caution. Our findings also call for caution in interpreting announcement returns in other contexts—for example, as measures of the economic value created by other types of corporate decisions or by policies announced by regulatory authorities.

2 Measuring Merger Outcomes

2.1 Transaction-Level Ex-Post Failure

Few would argue that acquisition decisions do not affect firm value. However, measuring this effect at the transaction level is challenging. Because the target is typically merged into the acquiring entity, we cannot directly observe the ex-post performance of the target or the synergies generated from the combined firms. Although prior studies have used the ex-post realized performance of acquisitions as observed in target divestiture-at-a-loss (Healy et al., 1992; Kaplan and Weisbach, 1992), this measure is conditional on the acquirer deciding to divest and on the availability of a buyer. In our sample period, divestiture-at-a-loss is rare, representing only about 1% of transactions.

We devise a new transaction-level measure of acquisition failure: goodwill impairment. While similar to the divestiture-at-a-loss measure in that it reflects a loss relative to the purchase price, goodwill impairment is not conditional on the sale of the target.

We manually construct a sample of transactions with large goodwill write-downs, which we believe yields a new and powerful setting to measure ex-post value destruction to the acquiring firm. To our knowledge, we are the first to construct a comprehensive data set that includes *transaction-specific* goodwill balances and *transaction-specific* impairment outcomes.[10] In our sample, the goodwill of about 19% of transactions was impaired within five years.

Because both measures capture deals for which the realized value is lower than the original purchase price, we combine goodwill impairment and divestiture at-a-loss into a single "failure" measure. We describe both measures below.

In some settings, our failure measure could produce misleading results. Specifically, consider the hypothetical example that all transactions have the same failure probability but different NPV conditional on success. In that case, CAR could predict the expected NPV well; however, our failure measure would show that there is no relation between CAR and the likelihood of failure (since it is constant across transactions in this example). This is, of course, a shortcoming of a binary outcome variable. An implicit assumption in using the failure binary variable is that the likelihood of failure is negatively correlated with NPV. If this assumption does not hold, then we should not expect CAR to be correlated with the failure variable.

Given this critique of the failure measure, we also construct firm-level acquisition performance measures that are not subject to this shortfall. Importantly, we find that the transaction-level failure proxy is correlated with both firm-level proxies and that inferences are largely similar across measures.

2.1.1 Goodwill Impairment

In an acquisition, the acquirer exchanges consideration (cash, stock, or both) for the target's stock or assets. In most cases, the acquirer pays more than the value of the identifiable assets of the target. As such, on the acquirer's balance sheet, the value of the target is recorded as a combination of the value of the identifiable assets and goodwill. Goodwill is the account on the acquirer's balance sheet that captures the difference between the

[10] Hayn and Hughes (2006) also trace initial goodwill balances and subsequent impairments at the transaction level, yet they exclude 55% of transactions due to insufficient information. Overall, they focus largely on the pre-2001 period, when disclosure of initial goodwill and the source of the impairment was generally less comprehensive than during our sample period.

consideration paid in the acquisition and the value of the identifiable net assets:

$$\text{Goodwill}_{\text{i}} = \text{Price}_{\text{i}} - \text{Value(Identifiable Assets)}_{\text{i}} \tag{1}$$

From an economic point of view, goodwill can include the value of (a) a standalone going-concern element, which reflects the higher value of a collection of assets over assets held independently; (b) a synergy element, which reflects the value from combining the acquirer and target businesses; and (c) any overpayment or overvaluation of the stock consideration (Johnson and Petrone, 1998; Henning, Lewis, and Shaw, 2000).

In some instances, accounting rules require occasional downward adjustments to the goodwill account (called goodwill write-downs or impairments). The impairment of goodwill can arise because of any of the following factors: overvaluation of existing target assets, overestimated synergies, or the inability to realize synergies due to firm, industry, or economy-wide shocks.[11]

The Financial Accounting Standards Board (FASB) published a new financial accounting standard, SFAS 142, effective December 2001, with the goal of increasing transparency and generating goodwill balances that better reflect the underlying economic value of the acquisition on an ongoing basis (Foster, Fletcher, and Stout, 2003). SFAS 142 introduced four significant changes to the existing rules. First, goodwill assignment and impairment tests must be conducted at the "reporting unit" level (an operating segment or one component level below a segment), making it easier to identify the goodwill recorded and the source of future impairments at the transaction level. Second, acquirers can "write up" the target's existing assets to fair value at the time of the acquisition.[12] Third, goodwill is no longer amortized but is considered an asset that can stay on the firm's balance sheet indefinitely.[13]

[11] According to Bloomberg, in August 2018, the total goodwill for all listed firms worldwide was $8 trillion relative to $14 trillion of physical assets. Examples of well-known impairments of goodwill include Microsoft's $7.6 billion 2014 write-off of Nokia goodwill, Hewlett-Packard's $8.8 billion 2012 write-off of Autonomy goodwill, and Jones Apparel Group's $810 million 2009 write-off of Nine West and Maxwell Shoe goodwill.

[12] Identifiable intangible assets, such as patents and customer lists, are no longer included in goodwill balances.

[13] Before SFAS 142, acquisition goodwill was amortized over a maximum of 40 years.

Fourth, firms must conduct annual impairment tests and tests following "material" events for reductions in the value of goodwill. If the appraised value is less than the recorded value, then a goodwill "impairment" occurs. The amount of goodwill is reduced on the balance sheet, and an impairment expense is incurred on the income statement as a component of income from continuing operations.[14]

Goodwill reflects the premium paid over the identifiable assets in nominal terms. Thus, the impairment of goodwill indicates that the remaining value of the target is lower than the nominal value paid a few years earlier at acquisition. A large goodwill impairment, therefore, likely captures value destruction. Due to the increased precision and timelines of goodwill reporting due to SFAS 142, we are able to construct goodwill balances and impairment at the transaction level, which yields a direct and quantifiable representation of acquisition failure that is transaction-specific. Appendix A.1 explains the relation between goodwill impairment and economic value destruction.

Using goodwill impairment as a measure of acquisition failure has two drawbacks. First, researchers have documented managerial discretion in the write-down decision, mainly impacting the amount and timing of the impairment.[15] In this paper, we focus on substantial impairments of goodwill, a setting in which strategic manipulation is less viable because extreme losses must be disclosed at some point. Moreover, we do not focus on the timing of write-downs. Second, goodwill cannot be increased to reflect underestimated value creation. As such, we only observe the left tail of deal outcomes.

In Appendix A, we validate goodwill impairment as a signal of value destruction. Because

[14]Prior to this rule change, SFAS 121 prescribed only nonroutine impairment tests following certain triggering events that indicated that goodwill might no longer be recoverable. Under SFAS 142, the impairment amount must be determined using a fair value approach, based on a two-step impairment test. In the first step, the fair value of the reporting unit is compared to the book value; if the fair value is less than the book value, then the second step is performed. In the second step, the fair value of the unit's (non-goodwill) net assets is determined, and the fair value of goodwill is the difference between the fair value of the unit and the fair value of the unit's identifiable net assets. The impairment amount is the excess of the book value of goodwill and the newly assessed fair-value estimate of goodwill. Firms often use a weighted combination of discounted cash flow, public comparable company multiples, and precedent merger and acquisition transaction multiples valuation techniques to determine fair value.

[15]See Elliott and Shaw (1988), Francis, Hanna, and Vincent (1996), Beatty and Weber (2006), Ramanna and Watts (2012), and Li and Sloan (2017).

there are no other direct indicators of acquisition failure, we relate our impairment measure to several indirect symptoms of merger failure. We conduct four tests. First, Appendix A.2.1 shows that the market reaction to earnings announcements that contain goodwill impairment news is negative and large in magnitude, -2.6%, on average.[16] Second, Appendix A.2.2 shows that CEOs are more likely to be fired in the period surrounding goodwill impairments than they are following negative CARs surrounding the original merger announcements. This finding indicates that the labor market regards impairment as an important signal for managerial discipline. Third, Appendix A.2.3 shows that acquirers that impair goodwill are more likely to subsequently experience distressed delisting than acquirers without impairment. Fourth, Appendix A.2.4 shows that acquirers with goodwill impairment experience poor operating and stock performance in the years following the acquisition relative to acquirers without impairment. Industry-adjusted operating performance measures such as sales growth, operating costs, and cash flows, and financial performance measures such as ROE, Tobin's Q, and cumulative returns begin to materially diverge in the years following the deal announcement for the impairment sample versus the nonimpairment sample. This finding indicates that impairment firms experience significant firm-level adverse shocks in the years following the acquisition.

2.1.2 Divestitures-at-a-Loss

The second component in the measure of deal failure is divestiture-at-a-loss. Selling a target at a loss means that the proceeds are lower than what was originally paid, less depreciation. As such, divestiture-at-a-loss likely implies a negative ex-post net present value of the acquisition. This variable was used by many canonical studies as a proxy for deal failure (e.g., Mitchell and Lehn, 1990; Kaplan and Weisbach, 1992; Healy et al., 1992; Berger and Ofek, 1996).

[16] Note that impairment news is a strictly negative piece of news about an event that has already happened. The fact that the market reaction is negative given the negative news does not conflict with the main finding of the study that CAR is not associated with future changes in cash flows.

2.2 Firm-Level Operating and Stock Performance

The value created or destroyed in a merger should express itself through the operating performance of the acquirer, and to a lesser extent, through the financial performance of the acquirer's stock.

We rely on earlier literature and use two acquirer firm-level outcomes to gauge acquisition ex-post outcomes. The acquirer-level performance measures have advantages and disadvantages relative to our transaction-level failure indicator. First, the deal failure indicator is binary and captures extreme value loss. In contrast, CAR is a continuous measure that can take both positive or negative values and may potentially capture nuanced outcomes. Our firm-level measures are continuous, can take both positive or negative values, and may potentially capture nuanced outcomes. Second, unlike our goodwill impairment and divestiture-at-a-loss measures, which are measured at the transaction level, firm-level proxies may be impacted by firm, industry, or market outcomes unrelated to the transaction. As such, they may be noisy measures of acquisition performance.

2.2.1 Abnormal ROA

First, we construct a measure of abnormal ROA, which was previously used in Healy et al. (1992), Chen, Harford, and Li (2007), and Fu, Lin, and Officer (2013). The motivation is that the "value created" in a merger needs to be reflected in future cash flows. The abnormal ROA measure reflects the change in ROA in the years following the acquisition relative to the years prior. Section 3 provides further details about this measure.

Tests that use abnormal ROA as the outcome variable are also subject to critique. In particular, our tests assume that higher NPV translates to higher cash flows in the first three years. In extreme cases, however, this might not be the case. For example, when a firm acquires a competitor, the benefits of the merger could potentially only become apparent in the very long term.

This issue, however, is not likely to be critical to our inferences. Such a scenario, while definitely present in some transactions, is likely not common. Furthermore, as we saw in Section 5.3, CAR's predictive power is tiny for outcomes in the first year after completion and nonexistent for later periods. Hence, there is no support for the claim that CAR captures some long-term benefits from rare types of mergers.

2.2.2 Buy-and-Hold Abnormal Returns

Second, we construct a measure of long-term abnormal stock returns. We note that if the market is truly efficient and prices capture the relevant information at the time of the announcement, CAR should not be correlated with future stock performance. However, our choice to consider long-term abnormal stock returns is motivated by the large literature that links long-term abnormal returns with merger characteristics.[17] Building on this literature, a finding that characteristics predict future stock performance would indicate that CAR does not capture all available information at the time of the announcement.

The abnormal returns measure is subject to the critique that an observation of no correlation between CAR and BHAR does not necessarily discredit CAR. Such a finding could simply be evidence that markets are efficient. This critique would be valid if there were no other variables that could predict BHAR. As we show later (and also as found in the literature as discussed in the introduction), characteristics have some predictive power over BHAR. Hence, lack of correlation between CAR and BHAR is likely to indicate that announcement returns do not incorporate all the available information at the time of the announcement.

3 Data

The sample of mergers and acquisitions we use comes from the Thomson Reuters Securities Data Company (SDC) Domestic Merger and Acquisition database. We include transactions that satisfy the following criteria: (a) The merger or acquisition was announced

[17]For example, several studies have documented that acquirers have low stock returns following acquisitions paid for with stock, e.g., Mitchell and Stafford (2000), Rhodes-Kropf and Viswanathan (2004), Rhodes-Kropf, Robinson, and Viswanathan (2005), Dong et al. (2006), Fu et al. (2013), and Ben-David et al. (2015).

on or after January 1, 2003, and completed by December 31, 2013; (b) the transaction value exceeds \$10 million and is at least 5% of the acquirer's market capitalization at the end of the fiscal year before the deal was announced; (c) the acquirer is a U.S. company; (d) the acquirer is a publicly traded firm; (e) the status of the deal is completed; (f) the deal is not classified as a repurchase, self-tender, recapitalization, acquisition of partial or remaining interest, reverse merger, leveraged buyout, privatization, or bankruptcy acquisition; (g) the percentage sought is at least 50%; (h) both the acquirer and target are not financial firms (SIC codes 6000–6999); and (i) Compustat has accounting data on the bidder and the Center for Research in Security Prices (CRSP) database has stock data for the month of the deal announcement.[18] These requirements result in an initial sample of 2,981 deals. Next, we exclude 258 transactions of acquirers that did not report firm-level goodwill in Compustat for the full period between the year prior to the transaction and 10 years after the transaction. We eliminate 646 deals that are not structured using purchase accounting and transactions for which we are unable to identify the deal-level goodwill allocation amount, and we omit 110 transactions that lack CRSP and Compustat data to compute key variables. These filters result in 1,967 transactions.

3.1 Announcement Returns

We follow the literature in measuring announcement returns. We estimate daily abnormal returns using the market model and a value-weighted index. The market model parameters, α_i and β_i, are estimated from 361 to 61 trading days before the deal announcement day, and r_{mt} is the CRSP value-weighted index. CARs are then computed by summing the daily abnormal returns over various event horizons. We estimate CARs for the three-day period $[-1, 1]$ and the 11-day period $[-5, 5]$ surrounding the acquisition announcement, and over the entire merger process beginning two days before the announcement and ending two days

[18] Our sample begins in 2003 because SFAS 142 was not effective until 2003 (2002 was considered a transition period). Our sample ends in 2013 as we track firms' impairment and divestiture outcomes over a five-year period.

following deal completion [Announcement $-$ 2, Close + 2].

3.2 Goodwill Impairments

Linking goodwill impairment to specific transactions is not straightforward as goodwill and impairment data reported on financial statements are based on *aggregate* firm-level data. As a result, we manually collect goodwill and impairment (if any) data. Appendix B provides further details about this data collection procedure. We begin by identifying all sample firms with firm-level goodwill impairments (600 deals). For these potentially impaired transactions, we used the Notes to Consolidated Financial Statements in the impairment year and Factiva to determine whether and how much of the impairment is due to the specific transaction in our sample. We focus on impairment within five years of the deal effective date.

Appendix Table B.1 shows that we successfully linked impairment events to specific transactions. Of the 600 transactions flagged as potentially impaired, we can credibly classify 59% as large impaired, 22% as not impaired, and 3% as small impaired (and so excluded), and we are unable to classify only 16% of transactions. We exclude 18 transactions with minor impairment (less than 25% of original goodwill) as our focus is on outcomes with a strong valuation impact. Moreover, for deals classified as impaired, for 84% of transactions, we know the source and the amount of the impairment unambiguously. Our data screening yields 355 firms with goodwill impairment within the first five years following the transaction.

3.3 Divestiture-at-a-Loss

The source data for divestiture-at-a-loss is SDC. We pull all transactions classified as divestitures, equity carve-outs, spinoffs, or two-step spinoffs. We match this sample to our main sample if the SDC target name of the divested firm matches the SDC target name of the firm in the original sample, or if the target state and target SIC code (as identified by SDC) are the same for both the divested firm and the firm in the original sample. We then manually read through each match to determine whether the divestiture is related to the original transaction. Once we verify this relation, we retain targets that were divested within five years of the deal effective date, whose divestiture transaction value is reported, and whose divestiture price is less than the original transaction price (e.g., the target was divested at a loss). We further eliminate partial divestitures of the target. Appendix B.2 describes how we collect divestiture data in more detail.

These screening procedures yield 17 transactions that were divested at a loss. Guenzel (2019) finds a similar rate of divestiture activity using SDC data. For 5,893 transactions over a 36-year period, he finds that 1.8% of targets are fully divested. His divestiture rate is slightly higher as he focuses on all divestitures, whereas we focus on divestiture-at-a-loss.

3.4 Abnormal ROA

We follow Chen et al. (2007) and compute abnormal ROA over the three-year period following the acquisition. We use three years as a plausible horizon since the median acquirer impairs or divests at a loss in the third year following the acquisition. To measure abnormal ROA, we regress the post-merger industry-adjusted three-year average ROA ($t+1, t+2, t+3$) on the pre-merger corresponding measure ($t-3, t-2, t-1$) and a constant:

$$\frac{1}{3}\sum_{t=1}^{3}[\mathrm{ROA}_{i,t} - \mathrm{ROA}_{Industry,t}] = \alpha + \beta\frac{1}{3}\sum_{t=-3}^{-1}[\mathrm{ROA}_{i,t} - \mathrm{ROA}_{Industry,t}] + \varepsilon_i, \tag{2}$$

where the residual ε_i measures the abnormal change in ROA. We define the post-merger (pre-merger) period as the three years beginning the year after (before) the deal effective date. Industry definitions are based on the Fama-French 48 industries (Fama and French, 1997). As discussed in Chen et al. (2007), this model takes into account the possibility that pre-merger operating performance could predict post-merger operating performance.

3.5 DGTW-Adjusted Buy-and-Hold Return

We measure cumulative buy-and-hold returns by accumulating DGTW-adjusted monthly returns (Daniel et al., 1997). The DGTW adjustment procedure involves adjusting returns to the returns of benchmark portfolios that are based on characteristics. Each month, we form $5 \times 5 \times 5$ portfolios based on size, book-to-market, and 12-month past returns. The monthly adjusted returns are accumulated to form buy-and-hold returns over the period of interest. In most specifications, we use a three-year horizon.

Alternative ways to adjust returns would be to use a market adjustment, beta adjustment, industry adjustment, or no adjustment at all. In unreported tests, we find that our conclusions are not sensitive to the choice of return adjustment.

3.6 Descriptive Statistics

Table 1, Panel A, shows the frequency of goodwill impairment and divestitures in event time, where the event is the year of the deal effective date. Overall, 20% of deals failed within five years (372 failed deals out of 1,870 completed deals). Of the failed sample, 30% (113) occur the year of or year after the deal effective date, and the remaining 70% happen in the following four years. In our main tests, we focus on completed transactions. In Section 5.4, we find 7% of transactions are cancelled and discuss the potential effects of withdrawn deals.

Table 1, Panel B, shows statistics for the impairment and divestiture samples. The initial goodwill allocated to the total purchase consideration is economically large. The mean dollar goodwill allocated to deals that fail is $328 million. On average, transaction-level goodwill represents 53% of the purchase price and 14% of the total assets of the acquiring firm. Goodwill impairment losses are also economically large. The average transaction-level impairment loss is $253 million, representing 87% of initial goodwill and 11% of assets. Similarly, divestiture losses are large, representing 58% of the purchase price.

Table 1, Panel C, shows summary statistics for our firm-level outcomes, abnormal ROA and DGTW-adjusted buy-and-hold returns, and Panel D shows statistics for our key deal and acquirer characteristics.

Table 1. Sample Statistics

This table provides summary statistics. Panel A shows sample statistics for the percentage of transactions with goodwill impairment or divestiture within five years of the deal effective date. Panel B shows statistics for the impairment and divestiture samples. Panel C shows summary statistics for our firm-level outcomes, abnormal ROA and DGTW-adjusted buy-and-hold returns, and Panel D shows statistics for our key deal and acquirer characteristics.

Panel A: Transaction-Level Failure Sample

	%	N
Year 0–1	6.0%	113
Year 2–3	9.1%	170
Year 4–5	4.8%	89
Impaired or divested at a loss by year 5	19.9%	372
Not impaired or divested at a loss by year 5	80.1%	1,498
Total completed deals	100.0%	1,870

Panel B: Transaction-Level Failure Statistics

	Mean	Std dev
$ Goodwill ($m)	328.2	1,310.2
Goodwill/Net purchase price	53%	23%
Goodwill/Total assets	14%	12%
Impairment $ loss ($m)	−253.4	1,150.0
Impairment/Goodwill	87%	21%
Impairment/Purchase price	45%	22%
Impairment/Total assets	11%	10%
Divestiture $ loss	−67.3	89.2
Divestiture loss/Purchase price	−58%	23%

Panel C: Firm-Level Outcome Statistics

	Mean	Std dev
Abnormal ROA	−0.005%	7.784%
DGTW-adjusted buy-and-hold returns	−2.7%	51.5%

Panel D: Deal and Acquirer Statistics

	Mean	Std dev		Mean	Std dev
Acquirer market cap ($m)	3,187	10,413	Deal value ($m)	710	2,842
Debt/Assets ($y-1$)	19%	19%	Stock only dummy	4%	20%
Free cash flow/Assets ($y-1$)	5%	16%	Mixed payment dummy	44%	50%
Tobin's Q ($y-1$)	1.88	1.19	Diversifying dummy	37%	48%
Past return (mkt-adj; $q-1$)	3.5%	20.0%	Competed dummy	0.7%	8.6%
Short interest (mean-adj; $m-1$)	1.2%	4.8%	Hostile dummy	1.0%	10.0%
Relative size (deal value/market cap)	32%	44%	Public target dummy	19.2%	39.4%

We report additional descriptive statistics in the Appendix. Appendix Table C.1 presents statistics by subsamples split by failure outcomes. It shows that transactions with future deal failures have larger deal sizes scaled by acquirer size (i.e., larger relative sizes), are more likely to include only stock in the form of payment, and are associated with smaller acquirer firms. There are no statistically significant differences between the two samples in terms of industry relatedness, the number of bidders, unsolicited or hostile bids, and target public status. Appendix Table B.3 presents the timing of goodwill impairments and divestitures-at-a-loss and shows that these events cluster in the financial crisis period, with a weak upward trend in the number of deal failures in the post-crisis period relative to the pre-crisis period. Appendix Table C.2 reports the correlation between the different outcome variables and CAR measured over various event windows. The table shows that the absolute value of the correlation coefficients across the three ex-post outcome variables ranges between 0.216 and 0.310, suggesting that the transaction- and firm-level measures capture similar outcomes. In contrast, CAR stands out as having a minuscule correlation with these variables: absolute correlation coefficients in the range of 0.002 and 0.051.

Table 2 presents average CAR and the dollar value created or destroyed, as implied by CAR. Panels A to C split the sample by transaction failure, quintiles of abnormal ROA, and quintiles of DGTW-adjusted BHAR, respectively. Panel A shows that acquirer CAR is different for the failure and no failure samples for only one of the event windows and only at the 10% statistical significance level. The average acquirer CAR $[-1, 1]$ for transactions that failed is 0.5%, while it is 1.4% for deals that did not fail within five years ($p = 0.067$). Interestingly, CARs measured over longer windows ($[-5, 5]$ or $[\text{Announcement} - 2, \text{Close} + 2]$) show no correlation. There is no difference in dollar returns between the two subsamples. Panels B and C show few statistical differences in CAR across abnormal ROA and DGTW-adjusted BHAR quintiles.

To summarize, across the three ex-post measures—transaction failure, abnormal ROA, and DGTW-adjusted BHAR—we observe only very weak correlations between CAR and acquisition outcomes. Next, we turn to formal tests of this correlation.

Table 2. Univariate Tests of the Difference in CAR, by Ex-Post Outcome

This table presents univariate statistics for subsamples defined by ex-post outcomes (Panal A: transaction failure/no failure, Panel B: quintiles of abnormal ROA, Panel C: quintiles of DGTW-adjusted BHAR). We report means for each subsample and Wilcoxon p-values for tests of differences between the subsamples.

Panel A: Acquirer Announcement Return by Transaction-Level Failure

	Window	Failure	No failure	Diff p-value
Acquirer CAR	$[-1, 1]$	0.5%	1.4%	0.067
	$[-5, 5]$	1.3%	1.3%	0.954
	[Ann−2, Cls+2]	−0.4%	0.9%	0.250
Acquirer $ return at announcement ($m)	$[-1, 1]$	−38.4	−17.7	0.532
	$[-5, 5]$	−43.7	−12.9	0.347
	[Ann−2, Cls+2]	78.5	88.8	0.888

Panel B: Acquirer Announcement Return by Firm-Level Outcome: Abnormal ROA

	CAR window	Q1 (low)	Q2–Q4	Q5 (high)	Diff p-value (Q1 vs Q5)
Acquirer CAR	$[-1, 1]$	0.5%	1.3%	1.2%	0.393
	$[-5, 5]$	0.9%	1.4%	1.5%	0.554
	[Ann−2, Cls+2]	−0.6%	1.1%	0.3%	0.523
Acquirer $ return at announcement ($m)	$[-1, 1]$	49.2	27.9	−3.5	0.356
	$[-5, 5]$	35.4	19.7	22.4	0.857
	[Ann−2, Cls+2]	201.9	98.8	38.7	0.365

Panel C: Acquirer Announcement Return by Firm-Level Outcome: DGTW-Adj BHAR

	CAR window	Q1 (low)	Q2–Q4	Q5 (high)	Diff p-value (Q1 vs Q5)
Acquirer CAR	$[-1, 1]$	1.2%	1.3%	0.9%	0.695
	$[-5, 5]$	2.0%	1.3%	0.7%	0.133
	[Ann−2, Cls+2]	0.6%	0.7%	0.7%	0.899
Acquirer $ return at announcement ($m)	$[-1, 1]$	39.1	10.5	45.5	0.864
	$[-5, 5]$	19.8	7.2	57.9	0.281
	[Ann−2, Cls+2]	90.2	79.1	197.9	0.428

4 Does CAR Predict Merger Outcomes?

Our primary goal in this study is to test whether CAR predicts merger outcomes. To do so, we explore three empirical settings: in-sample tests, out-of-sample tests, and assessment by characteristic clusters.

4.1 In-Sample Tests

4.1.1 Visual Tests

We begin by examining the unconditional relation between transaction and firm outcomes and CAR in Figure 2. We split our transaction sample into 20 equally sized bins (about 90 transactions in each bin). In Panel (a), we present, for each bin, the fraction of transactions that failed (based on goodwill impairment and divestiture at-a-loss). The panel shows little correlation between the realized likelihood of deal failure and CAR $[-1, 1]$.

Panel (b) presents a scatterplot of the realized loss (either through impairment or sale at a loss) and the expected dollar loss amount implied by CAR. Both numbers are scaled by the amount of goodwill, and we constrain each scaled measure to be between zero and one. We condition the sample on deals with negative CAR $[-1, 1]$. In addition, we plot the regression line (solid red line) between the realized loss and the predicted loss by CAR. If CAR is a good predictor of the loss amount, it should align with the diagonal dashed line. The chart shows that there is no meaningful relation between the realized magnitude of the loss and the expected loss implied by CAR.

Panels (c) and (d) show firm-level outcomes. Panel (c) presents the relation between the average realized percentile of abnormal ROA and CAR. Panel (d) presents the relation between the DGTW-adjusted buy and hold returns (in percentiles) and CAR. Neither chart shows any meaningful correlation between firm-level outcomes and CAR.

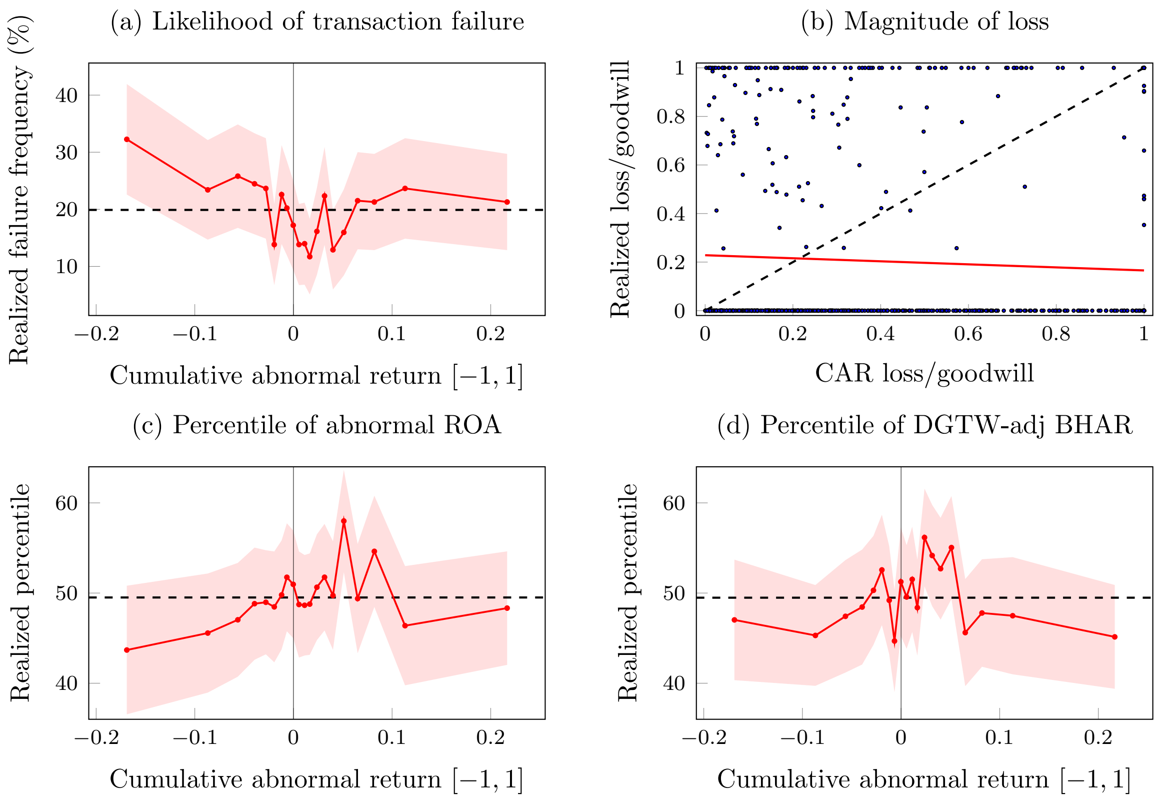
Overall, the visual tests reveal little association between transaction- and acquirer-level outcomes and CAR.

4.1.2 Univariate and Multivariate Tests

We next consider simple in-sample tests in which we explore whether CAR has explanatory power in regressions of future deal failure on announcement returns. The results are shown in Table 3. This table reports regressions with goodwill impairment and divestiture-

Figure 2. Ex-Post Outcomes and CAR $[-1, 1]$

Panel (a) plots the propensity of impairment or divestiture (the percentage of transactions with realized failure) for each acquirer CAR $[-1, 1]$ quantile (the solid red line). Observations are sorted into 20 equally sized bins based on their CAR $[-1, 1]$. The light red shading indicates 95% confidence intervals. The horizontal black dashed line represents the unconditional likelihood of impairment/divestiture in our sample (19.9%). Panel (b) presents a scatterplot of realized versus expected value loss implied by CAR. Both realized and expected loss are scaled by initial goodwill. This panel is constructed using only firms with a negative market response to the acquisition announcement, and measures are bounded between zero and the value of goodwill. We compute the acquirer dollar loss at announcement by multiplying CAR $[-1, 1]$ by the acquirer market capitalization 50 days prior to the announcement. The dashed line shows a diagonal line (representing perfect alignment). The solid red line is the regression line between the realized loss and the predicted loss by CAR. Panels (c) and (d) present the average realized percentile of abnormal ROA and DGTW-adjusted buy and hold returns, respectively, for each quantile of CAR. The light red shading represents 95% confidence intervals.



at-a-loss outcomes as the dependent variable and acquirer CARs over various windows surrounding the deal announcement as the key independent variable of interest. The regressions use various estimation windows commonly used in the literature: three-day (±1 trading days) around the announcement, ten-day (±5 trading days) around the announcement, and two days before the announcement to two days after the completion date. CAR may understate absolute value expectations if the probability of deal completion is uncertain; the use of the long window that includes the deal completion date overcomes this issue as the probability of completion has moved toward one. Panel A reports the results of ordinary least squares (OLS) and logit regressions that model the probability of goodwill impairment or divestiture within five years of the deal effective date. Panel B reports the results of OLS and tobit regressions that focus on the magnitude of the impairment or divestiture loss.

The results in Table 3, Panel A, show that CAR, at best, explains 0.1% of the variation in the probability of goodwill impairment or divestiture-at-a-loss (Columns (2)–(4)).[19] The coefficient on CAR is not statistically significant in any of the six models. CAR remains insignificant when year (Column (5)); year and industry (Column (6)); and year, industry, firm, and deal characteristics (Column (7)) are included as controls. The characteristics are log market capitalization, leverage, and free cash flow scaled by previous-year assets, Tobin's Q, previous-quarter market-adjusted stock returns, previous-month short interest, relative deal size, and indicators for stock-only consideration, mixed payment, diversifying acquisition, hostile deal, competed bidding, and public targets. In terms of economic significance, for the logit regression in Column (4) of Table 3, Panel A, a dramatic move from the highest quartile of announcement returns (+4.5% CAR) to the lowest quartile of announcement returns (−2.3% CAR) only increases the probability of impairment from 20.2% to 21.2%.

We next examine the ability of CAR to predict the magnitude of future impairment or divestiture losses. After all, CAR is often interpreted to reflect the dollar value lost or gained by the acquirer stemming from the transaction (Agrawal, Jaffe, and Mandelker, 1992; Smith and Kim, 1994, among others). However, observed goodwill impairment cannot be larger than the goodwill allocated at the time of the transaction. Hence, we scale both the dependent variable (dollar impairment or divestiture loss) and the independent variable (acquirer dollar CAR $[-1, 1]$) by the transaction's initial goodwill. Therefore, scaled-dollar failure is set to zero for transactions without impairment or divestiture loss, and scaled-dollar CAR is set to zero if CAR is positive. Table 3, Panel B, shows that the coefficient

[19]Note that our sample drops from 1,870 to 1,805 due to missing data for specific controls.

Table 3. Acquirer CAR and the Probability and Magnitude of Deal Failure

This table reports results from regressions of transaction failure measures on acquirer cumulative abnormal returns (CAR). In Panel A, the dependent variable is a dummy for impairment or divestiture loss. In Panel B, we scale both the dependent variable (dollar impairment or divestiture loss) and the independent variable (acquirer dollar CAR $[-1, 1]$) by initial goodwill. Scaled dollar failure is set to zero for transactions without impairment or divestiture loss, and scaled dollar CAR is set to zero for transactions with positive CAR. Column (1) includes only year, industry, and the following characteristics as independent variables: the log of market capitalization, leverage and cash flows scaled by previous-year assets, Tobin's Q, previous-quarter market-adjusted stock returns, previous-month short interest, relative size, and a dummy variable for stock-only, mixed-payment, diversifying, hostile deals and deals with competition and public targets. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants (coefficients not reported).

Panel A: Probability of Failure

Dependent variable:	Failure Dummy						
CAR window:	n.a.	$[-1, 1]$	$[-5, 5]$	[Ann−2, Cls+2]	$[-1, 1]$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Regression:	OLS						
Acquirer CAR	Controls only	-0.194 (0.132)	-0.012 (0.099)	-0.087 (0.059)	-0.133 (0.131)	-0.140 (0.132)	-0.214 (0.132)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,805	1,805	1,805	1,804	1,805	1,805	1,805
Adjusted R^2	0.092	0.001	-0.001	0.001	0.040	0.043	0.093
Regression:	Logit						
Acquirer CAR	Controls only	-1.248 (0.861)	-0.075 (0.634)	-0.552 (0.376)	-0.891 (0.881)	-0.974 (0.889)	-1.500* (0.852)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,805	1,805	1,805	1,804	1,805	1,805	1,805
Pseudo R^2	0.117	0.001	0.000	0.001	0.049	0.057	0.119

Panel B: Magnitude of Failure

Dependent variable:	Scaled $ Failure						
Regression:	OLS				Tobit		
CAR window:	n.a.	$[-1, 1]$	$[-5, 5]$	[Ann−2, Cls+2]	$[-1, 1]$	$[-5, 5]$	[Ann−2, Cls+2]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scaled $ CAR (imputed from CAR)	Controls only	0.023 (0.025)	−0.020 (0.021)	−0.012 (0.020)	0.282 (0.308)	−0.263 (0.272)	−0.127 (0.246)
Controls	Year, Ind Char	–	–	–	–	–	–
Observations	1,805	1,805	1,804	1,803	1,805	1,804	1,803
Adjusted R^2	0.087	0.000	0.000	0.000			
LR chi-squared					0.830	0.940	0.270
Prob > chi-squared					0.361	0.331	0.605

on scaled-dollar CAR is not statistically significant at the 10% level in any of the OLS (Columns (2)–(4)) or tobit regressions (Columns (5)–(7)).

To provide a relative benchmark, we now test whether the deal and acquiring firm characteristics that were known at the time of the acquisition announcement are correlated with future deal failure. To do so, we include the log of market capitalization, debt scaled by previous-year assets, free cash flow scaled by previous-year assets, Tobin's Q, market-adjusted stock returns in the previous quarter, short interest in the previous month, relative size (deal value relative to acquirer market capitalization), and a dummy variable for stock-only, mixed-payment, diversifying, and hostile deals and deals with competition and with public targets. The full results are reported in Appendix Table D.1.

The results in Table 3, Panel A, Column (1) show that year and industry controls and deal and firm characteristics alone can explain 9.2% of the variation in merger failure, measured as goodwill impairment or divestiture. In contrast, CAR, at best, explains 0.1% of the variation (Column (2)–(4)). Column (7) shows that adding CAR to the model with industry controls and deal and firm characteristics provides little benefit: Adjusted R^2 increases from 9.2% to 9.3%. The results in Table 3, Panel B, which focuses on the magnitude of losses, yield similar inferences.

If the market reaction to the announcement provides additional information related to deal value creation over and above the information contained in deal and firm characteristics, then the CAR-alone model (Table 3, Panels A and B, Columns (2)–(4)) should perform well—however, it does not. And the CAR and characteristics model (Column (7)) should outperform the characteristics-only model (Column (1))—it does not either. Deal and firm characteristics, also known ex-ante at the deal announcement date, dominate acquirer CAR as predictors.

In Table 4, we conduct in-sample tests for our firm-level ex-post acquisition outcome measures: abnormal ROA (Panel A) and DGTW-adjusted BHAR (Panel B). The results are reported in a similar manner to Table 3. In Panel A (where abnormal ROA is the de-

Table 4. Acquirer CAR and Acquirer Operating and Financial Performance

This table reports OLS regressions of acquirer outcome measures on acquirer cumulative abnormal returns (CAR) measured over various windows. In Panel A, the dependent variable is abnormal ROA. In Panel B, the dependent variable is DGTW-adjusted buy-and-hold returns. In both panels, Column (1) includes only year, industry, and characteristics as independent variables. In Columns (2)–(4) CAR is the only independent variable, and Column (5)–(7) include both CAR and controls as independent variables. The characteristics we include as controls are log market capitalization, leverage and free cash flow scaled by previous-year assets, Tobin's Q, previous-quarter market-adjusted stock returns, previous-month short interest, relative deal size, and a dummy variable for stock-only, mixed-payment, diversifying, competed, hostile, and public target deals. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Panel A: Abnormal ROA

Dependent variable:	Abnormal ROA						
CAR window:	n.a.	[−1, 1]	[−5, 5]	[Ann−2, Cls+2]	[−1, 1]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer CAR	Controls only	0.051*	0.008	0.013	0.049	0.047	0.064**
		(0.031)	(0.021)	(0.013)	(0.030)	(0.030)	(0.030)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,707	1,707	1,707	1,707	1,707	1,707	1,707
Adjusted R^2	0.064	0.002	0.000	0.000	0.008	0.034	0.067

Panel B: DGTW-Adjusted Buy-and-Hold Return

Dependent variable:	DGTW-adj BHAR						
CAR window:	n.a.	[−1, 1]	[−5, 5]	[Ann−2, Cls+2]	[−1, 1]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer CAR	Controls only	−0.193	−0.219*	0.001	−0.203	−0.152	−0.091
		(0.178)	(0.123)	(0.076)	(0.178)	(0.180)	(0.182)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,805	1,805	1,805	1,804	1,805	1,805	1,805
Adjusted R^2	0.029	0.000	0.001	0.000	0.000	0.006	0.028

pendent variable) and Panel B (where DGTW-adjusted BHAR is the dependent variable), Columns (2)–(4), the coefficient on acquirer CAR has the correct sign and is statistically significant at the 10% level for only one of the six regressions. In Table 4, Panel A, Column (2), CAR explains 0.2% of the variation in abnormal ROA. Similarly, in Columns (5)–(7), which include year and industry controls and firm and deal characteristics, the coefficient on acquirer CAR is the correct sign and statistically significant at the 5% level for one of six regressions. Similar to the results in Table 3, the results in Table 4, Panels A and B, Column (1), show that year and industry controls and deal and firm characteristics alone can explain 6.4% and 2.9% of the variation in abnormal ROA and buy-and-hold returns, respectively, relative to the CAR-only models in Columns (2)–(4) that never exceed 0.2%.

We conduct several robustness tests of our in-sample results. First, in Appendix Table G.1, Columns (1) and (2), we show that our results are robust to including transactions that were announced both before (2003–2007) and after (2010–2013) the financial crisis. As in the results reported in Table 3, the coefficient on acquirer CAR is not statistically significant in either period. Overall, we find little evidence that the lack of predictive power of announcement returns is driven by the massive, and arguably unanticipated, financial crisis.

Second, we examine the combined returns of the target and the acquirer. Our main tests explore whether *acquirer* announcement returns can detect ex-post acquisition outcomes. Here, we instead look at whether the combined returns of the target and acquirer, which reflect total expected synergy gains (as opposed to the division of synergy gains), can predict acquisition outcomes. We focus on the subsample of transactions with public targets (only 19% of the sample) and compute combined dollar gains by summing the product of acquirer CAR and acquirer market capitalization 50 days prior to the deal announcement date and the product of target CAR and target market capitalization 50 days prior to the deal announcement date. We compute combined percentage returns by dividing combined dollar gains by the sum of acquirer and target market capitalization. The results are reported in Appendix Table G.1, Column (3). As with the results reported in Table 3, the coefficient on combined CAR is not statistically significant.

Third, indicators of transaction-level failure may not be apparent for well-performing firms. Recall that goodwill impairment tests are performed at the reporting-unit level. When several targets operate under a single reporting unit, operating performance improvements by one target may obscure poor operating performance of the failed acquisition, thereby stalling goodwill impairment. We address this issue in Appendix Table E.1. Our results are similar when we consider relatively large transactions. For acquisitions that are large relative to the size of the acquirer, it is less likely that other businesses can hide value reductions in the target. Although the coefficient on CAR is statistically significant at the 10% level for failure and abnormal ROA outcomes, the R^2 indicates that CAR explains only 0.3% and 0.4% of the variation in merger failure and ROA, respectively. Further, for our transaction-level failure measure, we focus on extreme impairments and do not consider the timing of the impairment—such value destruction is difficult to mask over time.

To summarize, our in-sample tests indicate that CAR is unable to detect merger outcomes. In most specifications, the relation between CAR and the merger outcome is not statistically different from zero. When CAR is statistically significant, the economic magnitude of the relation is small. Our in-sample tests also show that, in fact, characteristics known at the time of the announcement perform materially better than CAR in predicting merger outcomes.

4.2 Out-of-Sample Tests

In this section, we delve deeper into the predictive properties of CAR and characteristics. Thus far, we have used only in-sample tests. In this section we compare the ability of CAR versus characteristics-based model to predict deal and acquirer outcomes out-of-sample.

4.2.1 Out-of-Sample Predictions Versus Realized Outcomes

To conduct our out-of-sample tests, we use the following approach. We estimate a CAR-only OLS regression model that uses our transaction- and firm-level ex-post outcome measures as the dependent variable and CAR as the independent variable. We also estimate a characteristics-only OLS regression model that uses our transaction- and firm-level ex-post outcome measures as the dependent variable and the characteristics used in Table 3 as the independent variables. (Note that we do not include industry and year controls.) For both regressions, we use the first half of the sample, 2003–2007, as a fit period to estimate coefficients. Then, we use the parameter estimates from this first period to predict outcomes in the second half of the sample, 2008–2013 (i.e., the imputed probability of transaction failure within five years of the deal effective date). Our analysis examines the ability of characteristics and CAR to predict failure in the second period, which is out-of-sample, i.e., was not used to estimate the model's parameters.[20]

Table 5. Out-of-Sample: Predicted Versus Realized Outcomes

We first estimate OLS regressions of deal outcome measures on CAR $[-1, 1]$ only and characteristics only using only the first half of transactions (2003–2007) as a fit period to estimate coefficients. We then use the parameter estimates from this first half to predict outcomes in the second half of the sample. In Panel A, we assess the correlation between realized outcomes and predicted outcomes by the CAR-only model (Columns (1), (3), (5)) and the characteristics-only model (Columns (2), (4), (6)). In Panel B, we assess the correlation between the predicted outcome by the characteristics-only model and acquirer CAR. Standard errors are reported in parentheses below coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Predicted Versus Realized Outcomes

Dependent variable:	Realized Outcome					
	Failure dummy		Abnormal ROA		DGTW-adj BHAR	
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted based on CAR	1.093		0.572		−0.228	
	(1.235)		(0.674)		(0.446)	
Predicted based on characteristics		0.421***		0.516***		0.340**
		(0.094)		(0.127)		(0.136)
Observations	882	882	841	841	882	882
Adjusted R^2	0.000	0.021	0.000	0.024	0.000	0.006

Panel B: Is CAR Correlated with the "Predictable" Component of Outcomes?

Dependent variable:	Predicted Outcome by a Characteristics Model					
	Failure dummy		Abnormal ROA		DGTW-adj BHAR	
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer CAR $[-1, 1]$	0.062		−0.015		−0.106	
	(0.069)		(0.009)		(0.065)	
Acquirer CAR $[-5, 5]$		0.066		−0.017**		−0.073
		(0.047)		(0.007)		(0.049)
Observations	882	882	841	841	882	882
Adjusted R^2	0.000	0.002	0.002	0.005	0.004	0.003

We next assess the quality of the predictions made by CAR and the characteristics-

[20] One drawback of this methodology is that market participants could not have implemented it. Specifically, the window of observing some of the outcomes of transactions that took place during the first period overlaps with the second period.

based model out-of-sample. We present the results in Table 5, Panel A, which shows that the predicted outcome by CAR is not correlated with the realizations of any of the three outcomes. In contrast, the predicted outcome by the characteristics-based model is positive (correct direction) and significant at the 1% and 5% confidence levels.

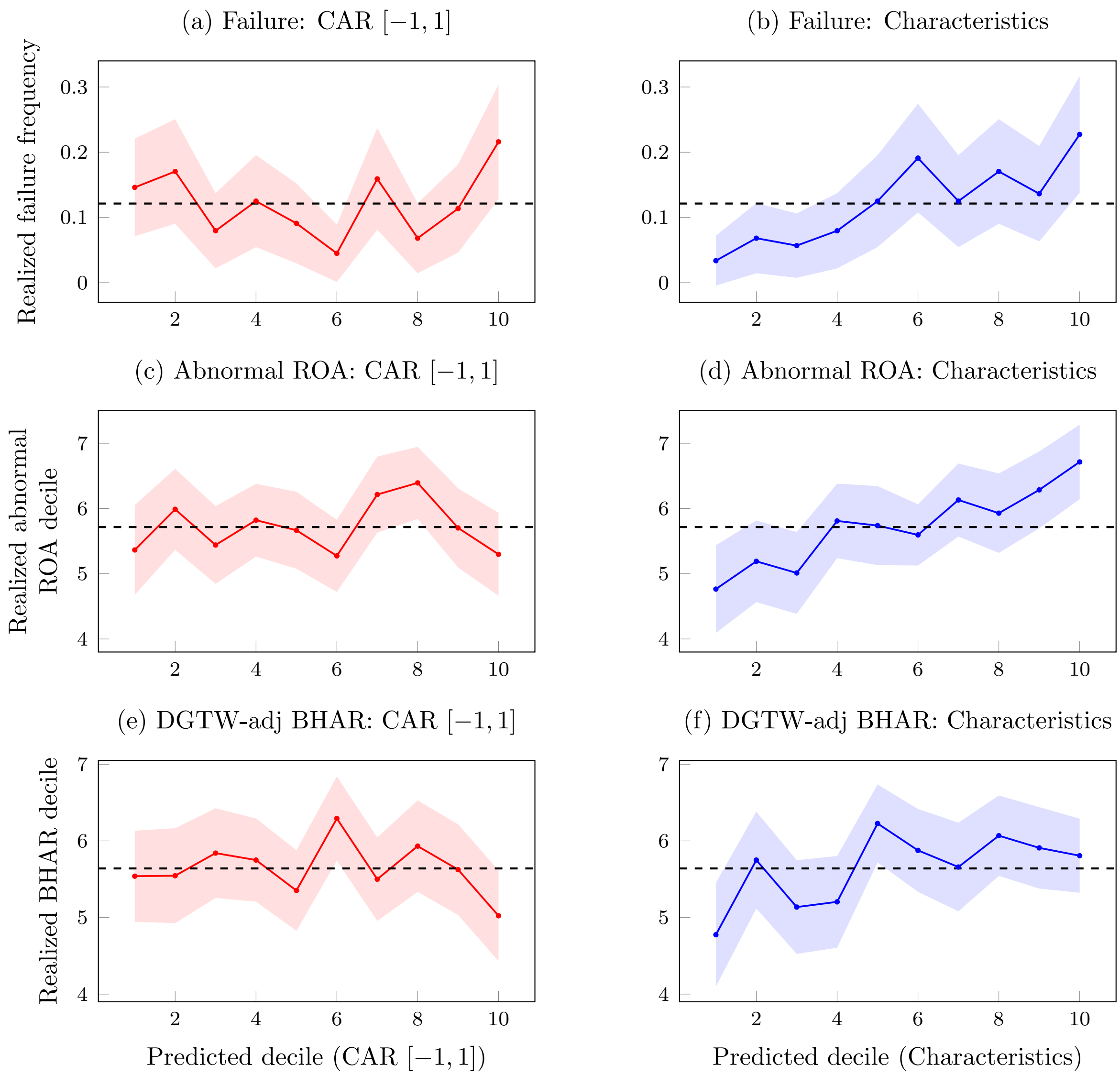
Our analysis so far has identified a set of characteristics that are useful in predicting acquisition outcomes out-of-sample. When acquisitions are announced, is the announcement CAR correlated with the out-of-sample characteristics-based prediction (which we already know is a good one)? We investigate this issue in Panel B of Table 5. Results show that acquirer CAR in the later sample is not even correlated with the *predictable* part of merger outcomes.

In Figure 3, we present out-of-sample tests graphically that are similar in spirit to the tests reported in Table 5. For the transaction-level failure measure (impairment or divestiture-at-a-loss), we estimate logit models of failure on CAR or characteristics. We then use the coefficients estimated in the first half of the sample to estimate the predicted probability of failure *decile* in the second half of the sample. Then, for each predicted probability decile, we report the fraction of transactions with realized failure. Similarly, for the abnormal ROA and DGTW-adjusted buy-and-hold outcome variables, we estimate OLS models of outcomes on CAR or characteristics. We again use the coefficients estimated in the first half of the sample to estimate the predicted outcome *decile* in the second half of the sample. Then, for each predicted outcome decile, we report the realized outcome decile.

If the model has predictive power, then the realized impairment/divestiture rate should increase monotonically as we move from decile 1 (low predicted probability) to decile 10 (high predicted probability). Alternatively, if the model lacks predictive power, the realized failure rate should be close to 12% (the unconditional failure rate in the second half of the sample) for all deciles. Focusing first on Panel (a), we see little evidence of significant predictive power for the CAR-only model. The realized failure rate is nonmonotonic as we move from decile 1 to 10. Moreover, realized failure rates are close to 12% for many deciles, although there is

Figure 3. Out-of-Sample: Predicted Versus Realized Outcomes

These figures report out-of-sample results. We use the first half of the sample, 2003–2007, to fit logit models of deal failure and OLS regressions of abnormal ROA and DGTW-BHAR deciles. Using the estimates, we obtain predicted outcome deciles in the second half of the sample, 2008–2013. For our transaction-level measure, for each predicted probability decile, we report the fraction of transactions with realized failure. For our firm-level measures, for each predicted decile, we report the realized outcome decile. Panels (a), (c), and (e) include only acquirer CAR $[-1, 1]$ as an independent variable. Panels (b), (d), and (f) include only deal and firm characteristics as the independent variables. The dashed line indicates the unconditional realized failure rate and the unconditional realized outcome decile (for ROA and BHAR) for the second half of the sample. The shaded portion represents the 95% confidence interval.



an elevated fraction of failures in the highest predicted probability decile (i.e., transactions with the most negative CARs). In contrast, Panel (b), the characteristics-only model, shows a stable positive upward trend, indicating that deciles with higher predicted failure are associated with a higher fraction of realized failure rates. In Panel (a), the CAR-only model, the realized failure rate average is 16% for the two highest predicted probability deciles and 16% for the two lowest predicted probability deciles. In Panel (b), the characteristics-only model, the realized failure rate average is 18% for the two highest predicted probability deciles and only 5% for the two lowest predicted probability deciles.

The results for the firm-level outcome variables are generally similar. In Panels (c) and (e)—the CAR only model—realized outcome deciles vary little from the unconditional average decile in the second half of the sample (as indicated by the dashed line) across predicted outcome deciles, whereas Panels (d) and (f)—the characteristics-only model—show an upward trend in realized outcome deciles as we move from low predicted to high predicted deciles.

In sum, the out-of-sample tests reiterate the conclusion from the earlier in-sample tests: CAR has only very weak predictive power in regard to predicting merger outcomes.

4.2.2 Trading on CAR Versus Characteristics

We further substantiate our conclusion about CAR's lack of predictability by devising a trading strategy. In Table 6, similar to our out-of-sample tests in Table 5, we use the first half of the sample of completed acquisitions to estimate models of ex-post performance measures (deal failure, abnormal ROA, and DGTW-adjusted BHAR) as a function of either CAR or deal and acquirer characteristics. We use these estimates to predict outcomes in the second half of the sample. We then formulate a trading strategy in which we buy the top 30% of acquirers based on the predicted outcome and sell the bottom 30% of acquirers. The positions are held for three years starting 10 days from the deal effective date.

We summarize the trading results (using DGTW-adjusted BHAR to compute returns) in Table 6. Column (1), for example, shows that buying a portfolio that contains acquirers with the highest CARs (top three deciles) yields abnormal returns of −2.2% over three years. The portfolio that contains acquirers with the worst CARs (bottom three deciles) yields similar

Table 6. Trading Strategy Based on CAR and Characteristics

This table reports three-year equal-weighted DGTW portfolio returns computed beginning 10 days following the deal effective date. In Column (1), we estimate a logit regression of deal failure, and in Columns (3) and (5) we estimate OLS regressions of abnormal ROA and DGTW-adjusted BHAR, respectively, on CAR $[-1, 1]$ using the early 50% of the sample (sorted by deal effective date). We then compute the imputed outcome for the late 50% of the sample and sort predicted values into 10 outcome deciles. We report the equal-weighted three-year DGTW buy-and-hold returns for acquirers in the bottom three and top three deciles and the p-value for the difference test between the two portfolios. Columns (2), (4), and (6) are computed analogously except we use the characteristics model to predict outcomes.

Predicted variable:	Failure dummy		Abnormal ROA		DGTW-adj BHAR	
Prediction model:	CAR	Characteristics	CAR	Characteristics	CAR	Characteristics
	(1)	(2)	(3)	(4)	(5)	(6)
	3-Year DGTW-Adjusted BHAR					
Buy top 3 deciles	−2.2%	4.7%	−2.4%	2.9%	−2.6%	2.4%
Sell bottom 3 deciles	−2.6%	−6.8%	−3.0%	−4.9%	−2.2%	−6.8%
Difference	0.4%	11.5%	0.6%	7.8%	−0.4%	9.2%
p-value	0.926	0.004	0.882	0.058	0.926	0.022

abnormal returns of −2.6%. These two abnormal returns are not statistically different. In contrast, in the characteristics model, the portfolio with the lowest predicted failure likelihood yields 4.7% after three years, and the portfolio based on the highest predicted failure likelihood yields −6.8%. The performance difference between these portfolios is +11.5% and is statistically different at the 1% significance level. We find similar, albeit slightly weaker, results for the other ex-post measures.

4.3 Performance by Category: Which Deals Create Value?

Another way to investigate the validity of CAR is to cluster transactions by characteristics and examine ex-post outcomes per cluster. The M&A literature often groups transactions by deal or acquirer characteristics and makes inferences about the value created for specific types of transactions. For example, if CAR for the average public target is negative, one might infer that acquiring a typical public target destroys value. How reliable are these inferences? We address this question in multiple ways.

4.3.1 Univariate Tests: One Characteristic at a Time

First, we explore univariate associations of CAR and characteristics. Specifically, we run 14 regressions of CAR on observed characteristics (one characteristic per regression). After recording the coefficients, we replace CAR with the three ex-post outcomes and repeat the exercise. Overall, we have 56 coefficients (14×4). All acquirer characteristics are computed prior to the announcement. Leverage, free cash flows, assets, and Tobin's Q are computed in the year prior to the announcement, and past returns and short interest are computed in the quarter and month prior to the announcement, respectively.[21]

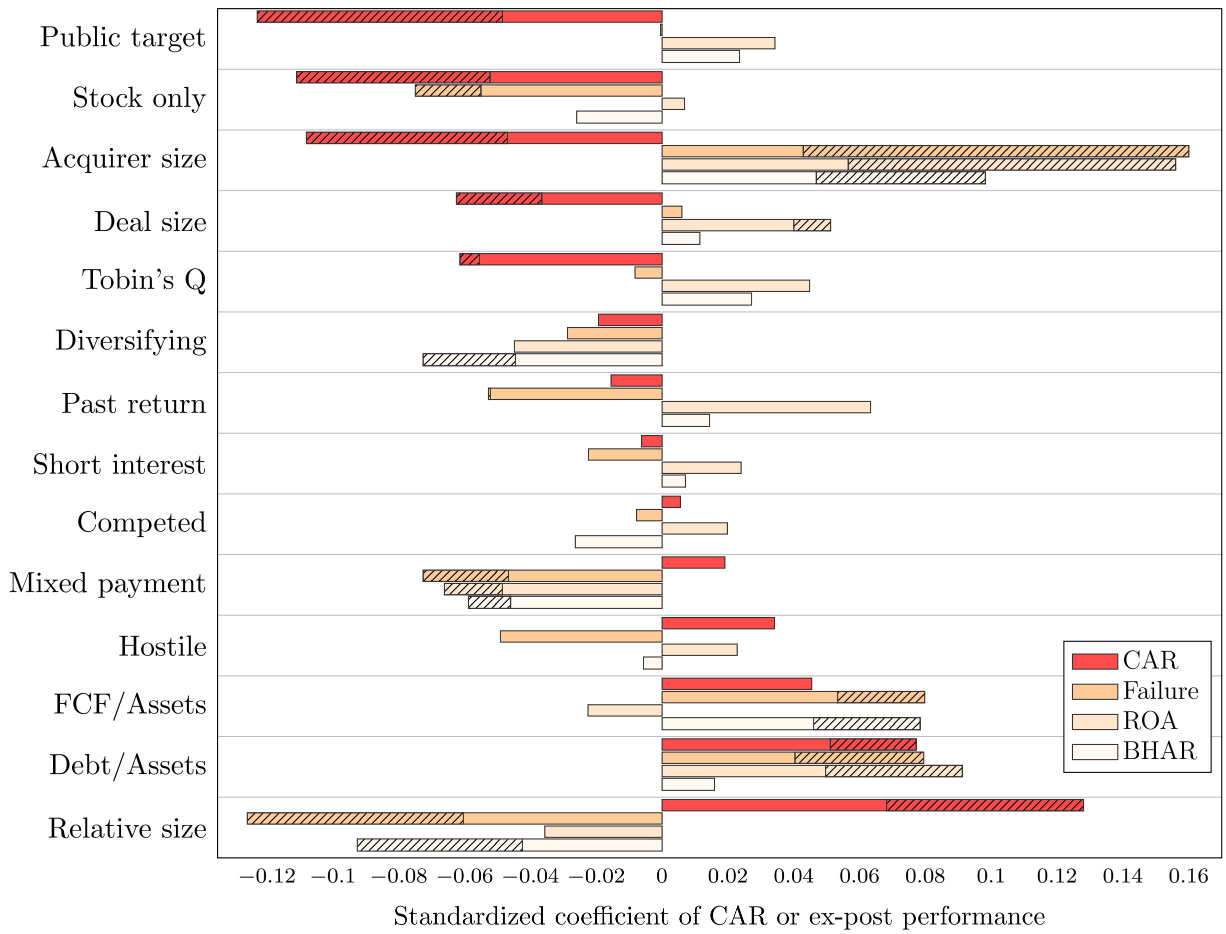
To compare predictions of CAR across characteristics and to the realized outcomes, we standardize the coefficients and present them in Figure 4. The coefficients are sorted by characteristics that predict the lowest CAR (public target and stock-only transactions and large acquirers) to those that predict the highest CAR (large relative size transactions and acquirers with high leverage and free cash flow). In general, the relations between CAR and characteristics that we document in our sample match those found in earlier studies that explored the relationship between CAR and characteristics, although often in different time periods and samples. We also add to the figure the standardized coefficients from the remaining regressions, i.e., the coefficients of ex-post outcomes on characteristics. To ease interpretation, we switch the sign on the failure regressions so that they are comparable to the other measures of performance and to CAR.

The results in Figure 4 show that the three ex-post outcomes are correlated among themselves. In other words, characteristics that are associated with a high likelihood of failure (e.g,. high relative size) are also associated with poor ex-post performance, as indicated by low abnormal ROA and low BHAR. This fact provides further validation that our newly introduced measure of deal failure indeed captures acquisition failure.

[21] This test also helps address an errors-in-variables critique. Specifically, our main tests regress ex-post outcomes on announcement returns. Standard regression analysis assumes that regressors are observed without noise. CAR, however, could be noisy, and hence may lead to coefficients that are attenuated—an econometric issue often referred to as errors-in-variables in the literature. However, in this section, CAR is the dependent variable rather than the independent variable.

Figure 4. CAR and Ex-Post Performance, by Characteristic

The bar chart shows the standardized coefficient for regressions for which the dependent variable is CAR, failure, abnormal ROA, or DGTW-adjusted buy-and-hold returns (BHAR) on various deal and firm characteristics. Each characteristic enters each regression individually (univariate regressions). We switch the sign on the failure regressions so that they are comparable to the other measures of performance and to CAR. The red bar indicates the standardized coefficient from regressions in which CAR is the dependent variable, and the three lighter bars indicate regressions for which failure, abnormal ROA, and DGTW-adjusted BHAR are the dependent variables. The patterned portion of the bars indicate a coefficient that is larger than 1.96 standard errors of the standardized coefficient, i.e., statistically significant at least at 5% level. All acquirer characteristics are computed prior to the announcement: Leverage, free cash flows, assets, and Tobin's Q are computed in the year prior to the announcement and past returns and short interest are computed in the quarter and month prior to the announcement, respectively.



Strikingly, Figure 4 shows no association (in terms of sign and relative importance) between the characteristics for which CAR predicts failure or success and the characteristics that are associated with failure or success ex-post. For example, transactions with public targets or large acquirer size are associated with lower CARs but are not associated with an increased rate of failure, low abnormal ROA, or low BHAR.

One might wonder whether the mismatch between the characteristics-based predictions of CAR is an artifact of our specific sample period. To check whether our results can be generalized, we split the sample (transactions completed in 2003–2007 and 2008–2013) and reproduce the chart for the two time periods. The results are in Appendix E (Figure E.1). The charts show that the patterns are similar for the two periods and the full sample in Figure 4. For both time periods, there is often a mismatch between the characteristics that CAR links to acquisition success or failure and the characteristics that are associated with ex-post outcomes.

Overall, the results in this section show that the inferences about the quality of merger decisions by deal and acquirer characteristics are inconsistent with the outcomes ex post. This does not appear to be a fluke, but rather a robust result over time.

4.3.2 Multivariate Tests

Next, we generalize these tests. Instead of conducting 14 regressions of CAR on characteristics, we run a single regression of CAR on all characteristics. And instead of comparing the outcomes characteristic-by-characteristic, we compare them all at once.

In Table 7, we regress CAR (calculated using different windows) on deal and acquirer characteristics. In the right columns, we report the sign that we would expect CAR to have, based on similar specifications in which ex-post outcomes are regressed on deal and acquirer characteristics. For example, CAR loads negatively on acquirer size, which could be interpreted as transactions with negative NPV. In contrast, ex-post outcomes reflect greater success for transactions associated with larger acquirers.

Overall, the results in Table 7 show that when deal and firm characteristics predict successful (unsuccessful) realized merger outcomes, these same characteristics often predict unsuccessful (successful) outcomes if we regard the sign of CAR as a proxy for the success of the outcome.

Table 7. Acquirer Announcement Returns and Characteristics

This table reports the results of the regression of announcement returns over three return windows ($[-1, 1]$, $[-5, 5]$, $[\text{Announcement} - 2, \text{Close} + 2]$) on deal and firm characteristics using OLS. The results are based on the full sample of both completed and withdrawn deals in Columns (1) and (2) and completed deals in (3). Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Dependent variable:	Acquirer CAR					
CAR window:	$[-1, 1]$	$[-5, 5]$	[Ann−2, Cls+2]	Predicted Sign Implied by...		
	(1)	(2)	(3)	Failure	ROA	BHAR
Log acquirer market cap ($b)	−0.003**	−0.008***	−0.011***	(+)	(+)	(+)
	(0.001)	(0.002)	(0.003)			
Debt/Assets ($y-1$)	2.554**	3.941**	4.645*	(+)	(+)	(+)
	(1.117)	(1.610)	(2.657)			
FCF/Assets ($y-1$)	0.025**	0.067***	0.063**			(+)
	(0.012)	(0.017)	(0.029)			
Tobin's Q ($y-1$)	−0.001	−0.001	−0.005			
	(0.002)	(0.002)	(0.004)			
Past return (adj; $q-1$)	−0.002	−0.008	−0.029		(+)	
	(0.011)	(0.017)	(0.025)			
Short interest (adj; $m-1$)	0.014	−0.003	−0.058	(−)		
	(0.041)	(0.054)	(0.084)			
Relative size	0.025***	0.020**	0.019	(−)		(−)
	(0.006)	(0.008)	(0.017)			
Stock-only dummy	−0.040***	−0.037**	−0.113***	(−)		
	(0.011)	(0.015)	(0.032)			
Mixed-payment dummy	−0.005	0.001	−0.006	(−)	(−)	(−)
	(0.004)	(0.005)	(0.008)			
Diversifying dummy	−0.004	0.002	−0.008	(−)	(−)	(−)
	(0.004)	(0.005)	(0.008)			
Competed dummy	0.015	0.004	0.035			(−)
	(0.013)	(0.035)	(0.075)			
Hostile	0.021	0.035	0.043			
	(0.023)	(0.027)	(0.053)			
Public target	−0.022***	−0.012*	−0.019			
	(0.005)	(0.007)	(0.015)			
Industry controls	No	No	No			
Observations	1,934	1,934	1,804			
Adjusted R^2	0.052	0.039	0.039			

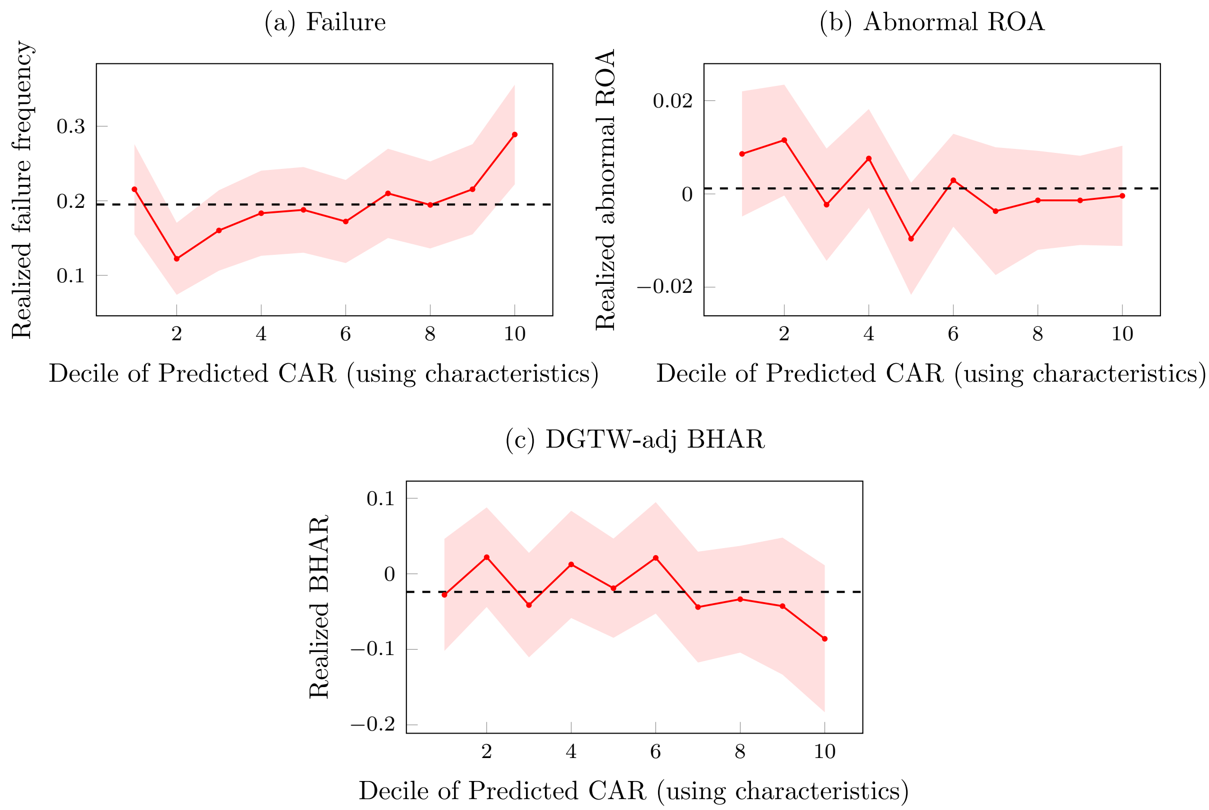
4.3.3 Combining CAR-Based Inferences into a Single Predictor

We can also construct a single measure of predicted deal success based on characteristics. For example, a stock transaction of a public target by a large acquirer would be considered to be a value-destroying transaction as all of these characteristics are associated with negative

CAR. Using the sample of completed transactions, we compile the individual coefficients by predicting CAR from Table 7, Column (1). The in-sample predicted CAR summarizes the associations of CAR with all of the regressors. We then sort the predicted CAR into deciles such that the top (bottom) deciles contain transactions that have characteristics associated with high (low) CAR, implying that, on average, they should predict high (low) NPV transactions.

Figure 5. A Single CAR-Based Predictor and Realized Outcomes

We utilize the coefficients in Table 7 Column (1) (the regression of CAR on characteristics) to obtain an in-sample predicted CAR for the sample of completed transactions, i.e., a summary of what CAR would be given the set of deal and acquirer characteristics. We then sort the predicted CAR into deciles. For each predicted CAR decile, we report (solid red line) realized failure frequency (Panel (a)), average realized abnormal ROA (Panel (b)), and average realized DGTW-adjusted BHAR (Panel (c)). The red shading indicates the 95% confidence intervals.



Our analysis uses these predictive regressions to explore whether high-NPV transactions according to CAR are indeed associated with better ex-post outcomes. In Figure 5, Panels (a), (b), and (c), we present the ex-post occurrence of failure and outcomes with respect to predicted CAR deciles. Panel (a) shows that the likelihood of failure is higher for transactions with characteristics for which CAR is higher, on average—the sign is clearly wrong. Panels (b) and (c) show no relation between ex-post performance, as measured by abnormal ROA and BHAR, and the combined CAR predictor.

Overall, our results indicate that CAR is not associated with outcomes either directly or indirectly via characteristics. These results are in contrast to the moderate ability of characteristics to predict transaction- and firm-level acquisition outcomes.

5 The Information Contained in CAR

So far, we have seen that CAR has little predictive power over merger outcomes. However, as described earlier, CAR is widely viewed as informative of the value created or destroyed by the transaction.

We consider four potential explanations for the lack of predictability by CAR: *i*) CAR is an aggregated signal that includes both deal and non-deal related information, *ii*) CAR is noisy due to uncertainty about acquisition outcomes at the time of the announcement, *iii*) CAR is mismeasured (i.e., window size around announcement), *iv*) CAR has an attenuation due to truncation from cancelled bids or endogeneity due to feedback effects.

5.1 Separating NPV from Standalone Information

We begin this analysis by decomposing CAR into four components:

$$\text{CAR}_{i,j} = p \cdot \text{Deal NPV}_{i,j} + \text{Acquirer Info}_{i,j} + \text{Noise}_{i,j} + \varepsilon_{i,j}. \tag{3}$$

where $\text{CAR}_{i,j}$ is the CAR associated with the announcement of i by acquirer j. $p{\cdot}\text{Deal NPV}_{i,j}$ is CAR's approximation of the NPV of transaction i, which could potentially depend on the characteristics of firm j and has probability of completion p. $\text{Acquirer Info}_{i,j}$ is the information in CAR that is revealed through the transaction about standalone value of the acquirer j, which could in principle be related to the characteristics of i.[22] Noise$_{i,j}$ is a systematic noise component. Since it is systematic, this component is correlated with the characteristics of the transaction i or the acquirer j. It reflects information that investors believe is related to value creation, but, in reality, is not.[23] ε_i is a noise component that is uncorrelated with characteristics, perhaps due to market frictions and limits to arbitrage.[24]

Our objective is to isolate the NPV component. To do so, we first strip variations in announcement returns that are related to the acquirer j. Ideally, we would decompose the components of CAR, isolate the component related to expected value creation, and explore whether this component of CAR contains information that is correlated with the ex-post outcomes. While we are not able to seamlessly achieve this goal, we conduct two tests to ascertain the role that information unrelated to value creation plays in the ability to detect ex-post outcomes.

Table 8. Ex-post Outcomes and Residualized Acquirer CAR

This table reports regressions of ex-post outcomes on residualized CAR $[-1,1]$. The residual is computed from the regression in Table 7, Column (1). Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Dependent variable:	Failure dummy	Abnormal ROA	DGTW-adj BHAR
	(1)	(2)	(3)
Residual of acquirer CAR $[-1,1]$	−0.214*	0.065***	−0.091
	(0.127)	(0.025)	(0.165)
Observations	1,805	1,707	1,805
Adjusted R^2	0.001	0.003	0.000

In the first test, we regress CAR on the deal and firm characteristics presented in Ta-

[22]For example, CAR may include information related to acquirer overvaluation (Shleifer and Vishny, 2003). CAR may also reflect an update about the skill of the management, its acquisition policy, or the growth potential of the acquirer (e.g., Schipper and Thompson, 1983; Asquith, Bruner, and Mullins, 1983; Roll, 1986; Hietala, Kaplan, and Robinson, 2003; Barraclough, Robinson, Smith, and Whaley, 2013; Malmendier, Opp, and Saidi, 2016; Wang, 2018; Bennett and Dam, 2019; Irani, 2020).

[23]One example is the fixation of investors on earnings-per-share (EPS) dilution or accretion (Dasgupta et al., 2019). Another example is wishful thinking of investors, e.g., driven by sentiment. This component could be correlated with the characteristics of the transaction i or the acquirer j.

[24]For example, announcement returns may also reflect price pressure from arbitrageurs (e.g., Mitchell, Pulvino, and Stafford, 2004).

ble 7 and obtain the residual—the element of CAR that is orthogonal to characteristics (i.e., information related to characteristics of firm j and to acquisition i). We then regress our transaction-level and firm-level acquisition outcomes on this residual. The results are reported in Table 8. In Column (1), failure is explained by the residualized CAR with a 10% statistical significance level, and in Column (2), abnormal ROA is explained by the residualized CAR with a 1% statistical significance level; both coefficients' signs are correct. Column (3) shows that residualized CAR is not correlated with BHAR. Although these results might seem to signal that CAR contains some information relevant to value creation, we note that the R^2 is virtually zero: it ranges from 0.000 to 0.003.

Overall, the results in this section indicate that while CAR contains some information relevant to value creation—information that is not captured by characteristics—this is not likely to be a full explanation for the inability of CAR to capture ex-post outcomes.

5.2 Outcome Uncertainty and Information Environment

M&A transactions are inherently complex and involve a high degree of uncertainty. It is possible that due to this uncertainty, outcomes are difficult to predict. Our results in Section 4.1.2 show that this explanation cannot be complete, as outcomes are sufficiently predictable by characteristics known at the time of the transaction, both in-sample and out-of-sample.

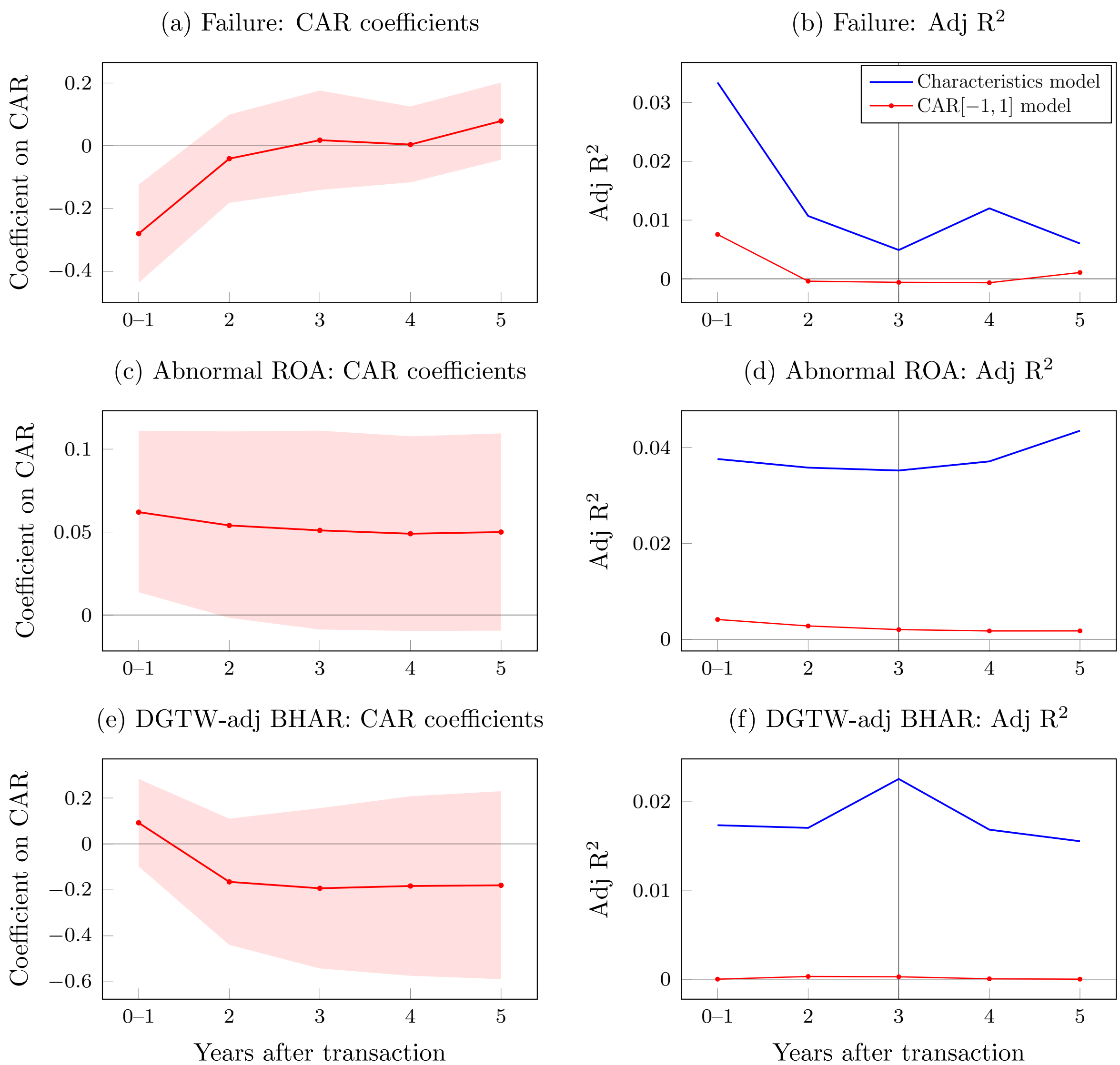
Nevertheless, we conduct two additional tests that consider the information environment at the time of the acquisition announcement.

First, we test whether CAR is better at predicting short-term outcomes than long-run ones, e.g., failure within the first year as opposed to within five years.

We rerun the earlier regressions (as in Tables 3 and 4), where the dependent variable is the outcome within a particular time period relative to the deal effective date (up to five years). In Figure 6, we plot the coefficient on CAR (Panels (a), (c), and (e)) and the adjusted R^2 (Panels (b), (d), and (f)). In addition, to provide a benchmark, we add to the latter set

Figure 6. Performance of CAR Versus the Characteristics-Based Model

Panel (a) reports the coefficients of OLS regressions of failure on CAR $[-1, 1]$. Panels(c) and (e) are similar, except the dependent variable is abnormal ROA and DGTW-adjusted BHAR, respectively. Panel (b), (d), and (f) report the adjusted R^2 from these regressions of acquisition outcomes on CAR and also the adjusted R^2 for similar regressions of acquisition outcomes on the deal and firm characteristics reported in Table 3. In Panels (a) and (b), in the Year 1 regression, a goodwill impairment or divestiture within one year dummy is the dependent variable. In the Year 2 regression, firms with impairment or divestiture within one year are excluded, and the dependent variable is a dummy for impairment or divestiture in Year 2. In the Year 3 regression, firms with impairment or divestiture in Years 1 or 2 are excluded, and the dependent variable is a dummy for impairment or divestiture in Year 3. Year 4 and Year 5 regressions are computed in a similar fashion. In Panels (c)–(f) we measure abnormal ROA and BHAR at the end of Years 1, 2, 3, 4, and 5. In Panels (a), (c), and (e) the light shaded region indicates the 95% confidence interval.



of panels the R^2 from the standard regression of deal and acquirer characteristics (without industry or year fixed effects).

The figure shows that CAR is statistically significant only for failure and abnormal ROA outcomes that take place in the first year. The R^2 for first-year predictions is 0.008 for failure. Later outcomes are unrelated to CAR, despite the fact that they can be predicted using deal and acquirer characteristics with R^2 of 1% (failure dummy) to 4% (abnormal ROA).

Overall, these results provide evidence that CAR performs better for outcomes that occur in a short period relative to the deal completion date. However, the weak explanatory power, as well as the superior performance of characteristics, makes CAR a somewhat ineffective predictor of value creation even in the short term.

We next consider the information environment at the time of the announcement. Does the market have enough information to accurately measure value creation? Appendix E shows that, on the margin, CAR's ability to detect value destruction is better in certain subsamples that likely have superior information environments. For example, when transaction-level failure is the dependent variable, the coefficient on CAR is statistically significant for stock deals (which often result in a shareholder vote), for public targets, and for large acquirers and large deals. (More information is likely to be generated by analysts and other news sources.) We note that although the coefficient on CAR is statistically significant in certain subsamples, the R^2 remains very low in all subsamples.

5.3 Timing of Information Incorporation

Another possibility we consider is that the window around the event is not defined properly. So far, our results in Section 4.1.2 show that the lack of predictability exists for both short windows (three or 10 trading days) around the announcement and a longer window between the announcement and deal completion date. These windows are typically used in the M&A literature.

The information included in CAR may be an update of an earlier information or prior that investors had. In other words, part of the information about the expected value created by the merger may already be impounded in the price before the announcement due to leakage or anticipation of the acquisition.[25] To address this concern, we follow Schipper and Thompson (1983) and extend the measurement period of CAR to begin 41 days prior to the announcement and end one day following the announcement. The results, reported in Table G.1, Column (4), show that extending the window does not change our inference about CAR's lack of predictability. Although we are unable to identify the exact timing of the acquisition-related information incorporation, the consistency of our results across event windows indicates this is unlikely the primary driver of the inability of CAR to capture outcomes.

5.4 Truncation Due to Withdrawals or Feedback Endogeneity

So far, our analysis implicitly assumes that the deals that are completed are a random sample of those that were announced, and that ex-post outcomes are not affected by management who heed announcement returns. These assumptions may not hold. This empirical issue plagues the few papers that provide some support for CAR (e.g., Healy et al., 1992; Kaplan and Weisbach, 1992) and most studies that use CAR to make inferences about value creation.

5.4.1 Truncation Effect: Withdrawn Deals

To put things in perspective, 129 transactions were cancelled in our sample (6.7% of all announcements). Despite the low occurrence, withdrawn deals may result in a truncation bias (due to the elimination of 6.7% of transactions) if the truncation is not random. For example, if CAR is very negative—implying that the merger destroys value—managers may be more likely to withdraw the bid before the merger is completed.

Our sample allows us to draw limited conclusions about the existence of truncation effects.

[25] See the following studies that raise this possibility: Schipper and Thompson (1983), Schwert (1996), Bhattacharya, Daouk, Jorgenson, and Kehr (2000), Mitchell et al. (2004), Edmans, Goldstein, and Jiang (2012), Offenberg and Officer (2012), Wang (2018), Bennett and Dam (2019), and Irani (2020).

It is reasonable to assume that withdrawing a transaction in response to negative CAR serves as an upper bound for the feedback effects, i.e., the extent to which management listens to CAR conditional on deal completion.

We first consider the distribution of acquirer announcement returns. Of the completed deals in our sample, 20% are associated with a large and negative market reaction (i.e., CAR of less than −4%), indicating that many transactions are completed despite a negative CAR. Moreover, of our impaired or divested-at-a-loss transactions, 27% are associated with large positive CARs (i.e., CAR greater than 4%), indicating that the market often gets the sign of the outcome incorrect.

Table 9. Probability of Withdrawal and Acquirer CAR

This table reports regressions of deal withdrawal on acquirer cumulative abnormal returns (CAR) measured over various windows. The top panel uses OLS regressions and the bottom panel uses logit regressions. Column (1) reports an OLS model using only deal and firm characteristics. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Dependent variable:	Withdrawn Dummy					
CAR window:	n.a.	[−1, 1]	[−5, 5]	[−1, 1]		
	(1)	(2)	(3)	(4)	(5)	(6)
Regression:	OLS					
Acquirer CAR	Controls only	−0.147* (0.084)	−0.116** (0.059)	−0.131 (0.083)	−0.137 (0.084)	−0.094 (0.073)
Controls	Year, Ind, Char	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,934	1,934	1,934	1,934	1,934	1,934
Adjusted R^2	0.404	0.002	0.002	0.024	0.036	0.394
Regression:	Logit					
Acquirer CAR	Controls only	−2.407* (1.362)	−1.890** (0.939)	−2.223 (1.399)	−2.305 (1.460)	−2.087 (1.610)
Controls	Year, Ind, Char	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,805	1,934	1,934	1,934	1,934	1,934
Pseudo R^2	0.447	0.004	0.005	0.051	0.082	0.449

We explore this issue further in Table 9. We focus on the full sample of withdrawn and completed deals, and in Columns (2) and (3) we regress a withdrawn dummy on acquirer CAR in both an OLS and logit model. In Column (1), we include only the characteristics used in Table 4, and in Columns (4), (5), and (6) we include CAR and year; year and industry; and year, industry, and characteristics controls, respectively. In Columns (2) and (3), the correlation between withdrawal and CAR is statistically significant at least at the 5% level. When controls are included in Columns (4)–(6), the coefficient on CAR is no longer significant. CAR has little economic significance: In Column (2), the marginal effect indicates that for every one percentage point reduction in CAR, the probability of withdrawal increases by 0.12%, or increases from the unconditional probability of 6.67% to 6.79%. This weakness can also be observed in the small R^2, which ranges from 0.002 to 0.005. In contrast, in Column (1), the R^2 in the characteristics model ranges from 0.404 to 0.447.

To further assess whether CAR's lack of predictive power is driven by selection through withdrawals, we implement a correction by using inverse probability weighting (Wooldridge, 2007).[26] This method has two stages. In the first stage, the likelihood of completion (= 1 − Withdrawal) is estimated as in Table 9 using the full sample. Specifically, we estimate a logit regression of the probability of completion on acquirer CAR and deal and firm characteristics. In the second stage, we rerun the main analysis (as in Tables 3 and 4), this time weighting observations with the inverse probability of completion. This method provides greater weight to observations that are more likely to have been withdrawn. The results of the analysis are presented in Appendix F. Overall, the results are similar to those in Tables 3 and 4.

5.4.2 Feedback Effects

In addition to truncation effects that happen because of withdrawals, there could be feedback effects, meaning that managers adjust their actions in response to CAR. For instance, given a negative CAR, managers may allocate more resources to ensure that the combined entity is well-integrated. Such feedback would mute the result between CAR and outcomes.

The empirical evidence on whether management indeed listens to the market and changes

[26] A similar method was implemented in Bhagat, Dong, Hirshleifer, and Noah (2005).

its course of action is mixed. Several studies test whether mergers are likely to be withdrawn following negative announcement returns. Jennings and Mazzeo (1991) find no evidence of such a relationship. Conversely, Luo (2005) and Kau, Linck, and Rubin (2008) present findings that are consistent with this idea.

Our dataset does not allow us to test the distortion that feedback effects create. However, we note that feedback effects will also be incorporated into the hundreds of M&A studies that use CAR to draw conclusions about value creation. If management listened to the market and modified its resource allocation in response to CAR, CAR would not capture much about value creation after this adjustment has been made. Furthermore, the fact that characteristics can predict outcomes in-sample and out-of-sample suggests that the feedback effect may not be very substantial.

6 Conclusion

We investigate whether CAR measured around merger announcements can be interpreted as a viable metric of value creation, as widely used in the M&A literature. We propose a new transaction-level measure of realized deal failure, which combines impairment of acquisition goodwill and divestiture-at-a-loss. In addition, we use acquirer-level measures of ex-post performance: abnormal ROA and characteristics-adjusted stock performance.

We document that CAR has no meaningful correlation with the deal outcomes or acquirer future performance. CAR fails to predict both the occurrence and magnitude of transaction failure. Our tests produce non-results across different specifications, in-sample and out-of-sample, for CAR measured over different event windows, and with the inclusion of year or industry controls, or deal and firm characteristics. We find that a simple prediction model that uses standard deal and firm characteristics, all known ex-ante at the deal announcement date, dominates announcement returns in predicting future acquisition outcomes in all horizons and specifications.

One might wonder why CAR fails to predict value creation in the context of mergers but succeeds in other contexts. We argue that while CAR in other contexts may get the direction of the news right, it is not clear that it can assess the likelihood and impact of future events. It is not a surprise that positive earning surprise news are followed by positive CAR, and that news about lawsuits result in negative CAR. However, once there is uncertainty about future outcomes (e.g., lawsuit outcome), there is no evidence, to our best knowledge, that the CAR truly reflects the expected impact of the news. In other words, there is no evidence that within a population of news, e.g., lawsuits, CAR correlates with the expected outcome: probability of success and magnitude conditional on success. Such tasks are extremely difficult, especially for relatively rare events, like mergers, lawsuits, and new governance policies. In fact, even in the most frequent and standardized events—earnings announcements—investors appear to process information inefficiently. Investors understand that beating a forecast is good news, and therefore stock prices react positively to earnings surprises. Yet, despite thousands of earnings announcements events *every quarter*, investors systematically underreact to earnings surprises (Bernard and Thomas, 1989) and do not fully account for seasonal patterns (Hartzmark and Solomon, 2018) and accruals reversals (Sloan, 1996).

Unlike earnings announcements, acquisitions are rare and are not tainted *a priori* as good or bad news. Acquirers typically engage in arm's length transactions in which they exchange cash (or stock) for physical and intangible assets. Therefore, a reasonable assumption would be that acquisitions have zero NPV. Investors typically have little knowledge about the critical factors for successful integration such as the nature of synergies, the talent of the mid-level management team, and the compatibility of merged information systems. Hence, it makes sense that CAR does not convey much information. In addition, in light of the research showing inefficiencies in the reaction to earnings announcements, it may not be surprising that characteristics have some predictive power that has gone unnoticed by investors. What is surprising, however, is the importance that economists give to CAR.

Our paper makes two main contributions to the literature. First, our results indicate that the CAR, computed at the announcement date, is not a reliable predictor of ex-post value creation or destruction. Second, for ex-ante evaluations of deal quality, some other forecasting variables (deal characteristics) dominate CAR. For ex-post evaluations of deal quality, goodwill impairment and divestiture-at-a-loss are sound measures for deal failure.

The main takeaway from our analysis is that CAR should not be trusted as a valid forward-looking measure of the value created in mergers and potentially in other corporate events and policies.

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Appendix A The Economics and Validation of the Goodwill Impairment Measure

Our main measure of transaction-level deal failure is goodwill impairment. We first explain how the accounting for goodwill and its impairment can help detect value destruction in mergers.

We then provide tests that validate goodwill impairment events as a signal of value destruction. We first conduct an event study surrounding earnings announcement dates for which goodwill impairment news is released. To further validate impairment as a robust measure of deal failure, we conduct three additional tests that focus on ex-post firm-level indirect symptoms of deal failure around goodwill impairments: CEO turnover, distressed delisting, and poor stock and operating performance.

A.1 The Relation Between NPV and Goodwill Impairment

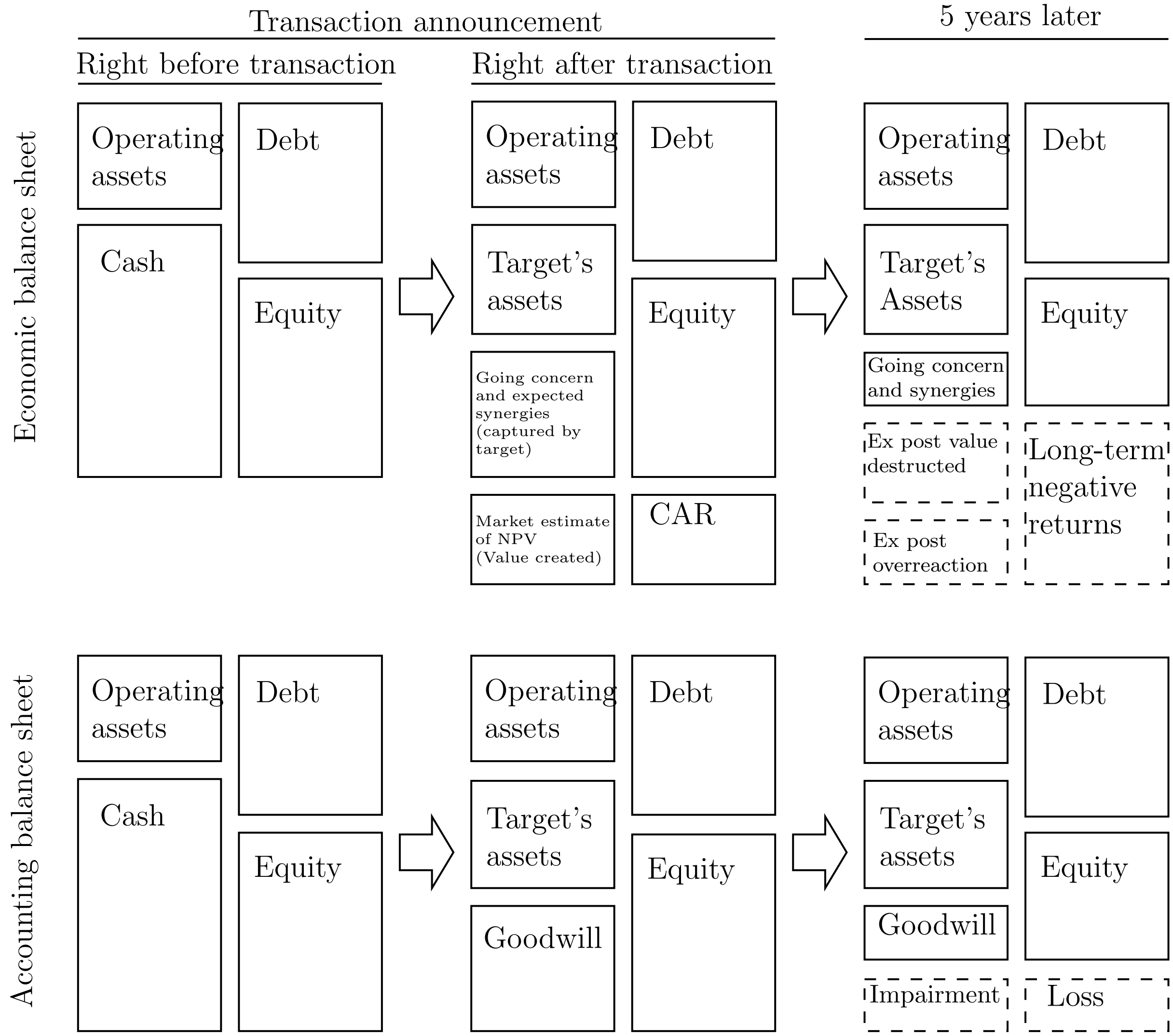
Financial reports, guided by accounting principles, are designed to mirror the economic activity of firms subject to some principles, e.g., conservativeness. Merger accounting, especially since the introduction of SFAS 142 as discussed below, reports declines (but not appreciation) in the value of acquired targets below the nominal acquisition price through goodwill impairment. To a great extent, the interpretation of goodwill impairment is similar to that of a divestiture-at-a-loss—the value of the target is lower than what was paid. The difference is that the valuation is made by the firm's auditors rather than by a transaction price in an arm's length transaction.

Figure A.1 illustrates the evolution of the acquirer's balance sheet around the transaction and in the long run. Once the transaction is completed, the value of the acquirer's net assets does not change: Cash (or own-issued stock) is replaced by the assets of the target.

There is one caveat though. Often, the acquirer pays above the market value of the identifiable assets. SFAS 142 dictates that identifiable assets (e.g., buildings, intellectual

Figure A.1. Illustration of Acquirer's Economic and Accounting Balance Sheets

The figure presents the evolution over time of an acquirer's economic balance sheet (top three panels) and accounting balance sheet (bottom three panels) around the acquisition.



property that was purchased by the target) are registered on the acquirer's balance sheet at market value. The remaining gap in value between the acquisition price and the value of the identifiable assets is registered as goodwill on the acquirer's balance sheet. This process is shown in the bottom-left panels of Figure A.1.

Notice that the accounting balance sheet and the economic balance sheet divert once the acquisition takes place. The financial statements always record a new acquisition as a zero-NPV transaction, i.e., the value of the acquirer's net assets does not change. However, when the acquirer is a public firm, the market value of the equity often adjusts once an announcement is made. Economists often believe that the adjustment reflects the NPV due to the acquisition. Hence, the market value of the acquirer is believed to already incorporate the present value of the market's expectation of the cash flows associated with the transaction.

In the years following the transaction, the value of the assets registered on the financial statements may change in various ways. In particular, SFAS 142 requires the firm to conduct periodic reviews of the value of the goodwill and adjust it downward (called impairment), if needed. Except perhaps for extreme cases, the impairment of the goodwill means that the value of the acquired assets is lower than the nominal proceeds originally paid for the acquisition, implying that the ex-post NPV of the transaction is negative.

For example, consider a transaction which was impaired in year 3. Let the value of the target in year 3 be expressed as a fraction of what was paid for in year 0, $PV_3 = \lambda C_0$. Hence, the NPV of this transaction, would be

$$\begin{aligned} \text{NPV} &= -C_0 + \frac{C_1}{1+r} + \frac{C_2}{(1+r)^2} + \frac{C_3}{(1+r)^3} + \frac{PV_3}{(1+r)^3} \\ &= \frac{C_1}{1+r} + \frac{C_2}{(1+r)^2} + \frac{C_3}{(1+r)^3} - \left(1 - \frac{\lambda}{(1+r)^3}\right) C_0. \end{aligned} \tag{4}$$

If 50% of the purchase price were recorded as goodwill (similar to the average transaction in our sample; see Table 1) and half of this goodwill were impaired in year 3, then $\lambda = 0.75$. Let us further assume that the discount rate r is 10%. With the reasonable assumption that the intermediate cash flows were not unusually large, this transaction has a negative NPV.[27]

Divesting a subsidiary at a loss works in a similar manner. Selling at a loss means that the proceeds from the sale are lower than what was paid, implying that the transaction was a negative NPV transaction. This was the motivation in Kaplan and Weisbach (1992), who

[27] In this case, in order for the transaction to have a positive NPV, the present value of the cash flows in the first three years should be at least $\left(1 - \frac{0.75}{(1+r)^3}\right) C_0 = 0.44 C_0$. In other words, the present value of the cash flows in the first three years should be greater than 44% of the amount that was originally paid. This is highly unlikely.

classify unsuccessful acquisitions primarily as divestitures-at-a-loss.

The right panels of Figure A.1 presents the hypothetical economic value decline and the impairment of goodwill. The firm is required by SFAS 142 to conduct annual reviews of the value of the goodwill. The firm's auditors may realize sometime in the future that the value ascribed to the transaction in the past can no longer be justified, and therefore, the goodwill will be impaired. Hence, the accounting system mirrors value declines through the impairment of goodwill.

A.2 Validating Goodwill Impairment as a Measure of Value Destruction

In this section, we provide evidence that the impairment of goodwill is indeed likely to reflect an unsuccessful transaction. To do so, we examine (a) the market's reaction to the news that goodwill of a past transaction has been impaired, (b) management turnover around the announcement about the impairment, (c) distressed delistings following the impairment announcement, and (d) the operating and financial performance of the acquirer after the deal announcement.

A.2.1 Market Response to Impairment News

We test whether goodwill impairment is perceived by investors as conveying negative news, i.e., a recognition that value has been lost. Our test replicates prior research in the accounting literature that has documented that goodwill impairment events are value relevant.[28]

We use Compustat quarterly data to identify the first quarter in which each transaction in our impairment sample experienced a goodwill write-down as well as the earnings announcement date for that quarter. Unique earnings announcement dates for an acquirer

[28] In tune with this literature, we interpret this result as a response to a revelation of *past* value destruction. See, e.g., Henning and Stock (1997), Chen, Kohlbeck, and Warfield (2004), Bens, Heltzer, and Segal (2011), Gu and Lev (2011), and Li, Shroff, Venkataraman, and Zhang (2011).

are included in the sample only once if multiple transactions experience a goodwill impairment announcement for a particular acquirer on the same earnings announcement date. We create three control samples. First, for the nonimpairment sample, we generate pseudo impairment dates on earnings announcements three years following the deal effective date (the mean time to impairment is 2.8 years from Table 1). Our second control sample, "Matched Control Sample 1" includes firms that announce earnings in the same quarter and have the same fiscal year-end and two-digit SIC code as the impaired firm. Our third control sample, "Matched Control Sample 2" includes firms that announce earnings in the same quarter and have the same fiscal year-end and two-digit SIC code as the impaired firm, and are in the same market capitalization tercile as the impaired firm. To avoid the estimation of market model parameters in both the pre- and post-acquisition periods, we compute market-adjusted returns using the Center for Research in Security Prices (CRSP) value-weighted index.

Table A.1 shows the results over four event windows. For the impairment sample, cumulative abnormal returns are negative and statistically different from zero for all four event windows (mean CARs range from -2.3% to -3.0%). For the three control samples, the market response to earnings announcements is not statistically different from zero for most event windows and is significantly positive in some windows. Importantly, the market response to earnings announcements containing goodwill impairment is statistically lower than the three control samples for all event windows. Although earnings announcements contain other information in addition to goodwill impairment news, the results are suggestive that the market considers goodwill impairment events to be bad news.

A.2.2 CEO Turnover Around Goodwill Impairment

We consider both the likelihood of CEO turnover following the deal and the timing of turnover for the impairment sample. We track turnover events between deal announcement and four years subsequent to the first impairment event. This analysis is conducted at the CEO-impairment level. If a CEO is associated with multiple impairment events, we retain

Table A.1. Market Reaction to Goodwill Impairment News

This table reports the mean cumulatative abnormal returns (CAR) surrounding quarterly earnings announcement dates. For the Impairment sample, we focus on the first earnings announcement for which a goodwill impairment is announced for a particular transaction. Unique earnings announcement dates for an acquirer are included in the sample only once if multiple transactions experience a goodwill impairment announcement for a specific acquirer on the same earnings announcement date. For the Nonimpairment sample, we generate "pseudo" impairment dates three years (the mean time to impair) following the deal close date. We also create two matched samples of control firms that did not announce impairment news. "Control1" is a matched sample that includes firms that announce earnings in the same quarter and have the same fiscal year-end and two-digit SIC code as the impaired firm. "Control2" is a matched sample that includes firms that announce earnings in the same quarter and have the same fiscal year-end and two-digit SIC code and are in the same market capitalization tercile as the impaired firm. CARs are based on market-adjusted returns using the Center for Research in Security Prices (CRSP) value-weighted index. The event period is listed in brackets. Difference refers to the differences between the Impairment and Control samples. Tests for differences are based on the t-test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. "ns" denotes mean CARs or differences that are not statistically different from zero.

Sample:	Impairment	Nonimpair	Control1	Control2	Difference (t-test)		
Window	(1)	(2)	(3)	(4)	(1)−(2)	(1)−(3)	(1)−(4)
CAR $[-1, 1]$	−2.6% ***	0.3% ns	0.3% ns	0.0% ns	−2.9% ***	−2.9% ***	−2.6% ***
CAR $[0, 1]$	−2.7% ***	0.2% ns	0.1% ns	−0.3% ns	−2.9% ***	−2.8% ***	−2.4% ***
CAR $[-5, 5]$	−2.3% *	0.3% ns	0.5% **	0.7% **	−2.6% **	−2.9% ***	−3.0% **
CAR $[-10, 10]$	−3.0% **	0.5% ns	1.2% ***	1.8% ***	−3.5% **	−4.1% ***	−4.7% ***

only the transaction with the largest impairment amount. We identify three types of forced CEO turnover: (1) internal turnover (fired by the board), (2) takeover turnover, and (3) bankruptcy turnover. Turnover events are identified using proxy statements, press releases, and news articles in Factiva. We follow Weisbach (1995), Parrino (1997), and Lehn and Zhao (2006) in identifying turnover events. If the CEO is reported as fired, forced from his or her position, or departed due to unspecified policy differences, then the CEO is classified as experiencing an internal turnover event. If the CEO is under the age of 65 and the reason for departure is unrelated to death, poor health, or the acceptance of another position, or if it is announced that the CEO is retiring and yet the announcement is not at least six months before succession, then the CEO is classified as experiencing an internal turnover event. For firms that are acquired, if we are unable to find evidence that the CEO retained a role in the acquiring entity, then the CEO is classified as experiencing a takeover turnover event. For firms that enter bankruptcy, if we are unable to find evidence that the CEO retained his or her job during the bankruptcy process, then the CEO is classified as experiencing a bankruptcy turnover event.

Table A.2, Panel A, presents results for the full sample of transactions in the impairment sample. We find that 45% of CEOs experience a turnover event between deal announcement and four years following the impairment, indicating that close to half of the impairment sample CEOs are disciplined by the labor market. To provide a relative comparison, Jenter and Lewellen (2020) show that, unconditional on acquisition activity, on average, 12% of CEOs experience turnover in a given year. For acquiring firms (that may or may not experience impairment), Lehn and Zhao (2006) find a 47% CEO turnover propensity within five years of the deal announcement date.

However, our main interest is the timing of the turnover, to assess whether the CEO departure results from the market's assessment of value destruction at deal announcement or results from the subsequent impairment event itself. If value destruction is anticipated, CEOs should be more likely to be fired immediately following the acquisition announcement rather than the impairment. We find that 13% of impaired firm CEOs are terminated in the year of or year following the deal effective year, whereas 41% are fired in the year of or year following the impairment year.

To summarize, the results in Table A.2, Panel A, indicate that the majority of turnover events in the impairment sample do not result from anticipated value destruction at the deal announcement, but rather because of deal failure as intimated by goodwill impairment. To be specific, CEO turnover events are three times more likely to occur immediately following the impairment as opposed to the deal announcement. This implies that the labor market considers impairment to be a proxy for deal failure.

A.2.3 Acquirers Distressed Delisting

Table A.2, Panel B shows univariate statistics on the number of acquirer firms that exit the public markets within 10 years of the deal effective date. Public market exit data are obtained using the CRSP delisting code. Acquirers are categorized as "Merged/Went

Table A.2. Post-Deal Performance for Firms with Goodwill Impairment

Panel A reports univariate statistics for CEO turnover for the sample of firms experiencing a goodwill impairment. We track CEO turnover events between deal announcement and four years subsequent to the first impairment event. Panel B shows univariate statistics on the number of acquirer firms that exit the public markets within 10 years of the deal effective date. Panel C reports median industry-adjusted accounting performance in the third year subsequent to deal announcement. Tests for differences between samples are based on the t-test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Post-Deal CEO Turnover for the Goodwill Impairment Sample

Impairment sample	#	%
% Turnover between deal announcement year and impairment year + 4	142	45%
Firms subject to internal turnover	118	38%
Firms subject to takeovers	19	6%
Firms subject to bankruptcy	5	2%
% Turnover year of or year after deal effective year (% of total sample)	19	13%
% Turnover year of or year after impairment year (% of total sample)	58	41%

Panel B: Post-Deal Public Market Exits

Sample:	Impairment		Nonimpairment			
	#	%	#	%	Difference	
Merged/went private	95	29%	533	37%	−8.6%	***
Delisted	31	9%	42	3%	6.5%	***
Bankrupt/liquidated	10	3%	5	0%	2.7%	***

Panel C: Industry-Adjusted Accounting Performance During 3 Years After Deal

	Impairment sample	Nonimpairment sample	Difference	
Sales growth	−4.4%	1.0%	−5.4%	***
COGS/Sales	1.8%	−2.1%	3.9%	***
SGA/Assets	0.0%	−2.9%	2.9%	***
PPE Growth	−4.5%	0.9%	−5.4%	***
FCF/Assets	−2.1%	1.4%	−3.6%	***
ROA	−0.9%	1.8%	−2.7%	***
ROE	−6.3%	1.9%	−8.1%	***
Tobin's Q	−22.0%	1.0%	−23.0%	***
Earnings/Price	−2.6%	0.6%	−3.2%	***

Private" for delisting codes 200–390 and code 573. Acquirers are classified as "Delisted" for delisting codes between 500 and 600 (excluding 573 and 574) and as "Bankrupt/Liquidated" for delisting codes 400–490 and code 574. We retain only one observation when an acquirer in the impairment or nonimpairment sample announces multiple transactions in the same year.

We notice from Table A.2, Panel B, that firms in the impairment sample are significantly more likely to be delisted and to go through a bankruptcy or liquidation process than firms in the nonimpairment sample. In contrast, firms in the nonimpairment sample are substantially more likely to merge or go private. These findings imply that impairment is a good proxy for deal failure.

A.2.4 Acquirers' Long-Term Performance

We examine industry-adjusted accounting and stock performance for the three years after the deal announcement. We retain only one observation when an acquirer in the impairment or nonimpairment sample announces multiple transactions in the same year. We report the following median performance measures, adjusted by the median Fama-French 48 industry value: sales growth; cost of goods sold (COGS) scaled by sales; selling, general, and administrative expenses (SG&A) scaled by sales; property, plant, and equipment (PPE) growth; free cash flow (FCF) scaled by assets; return on assets (ROA); return on equity (ROE); Tobin's Q, and the earnings-to-price ratio.

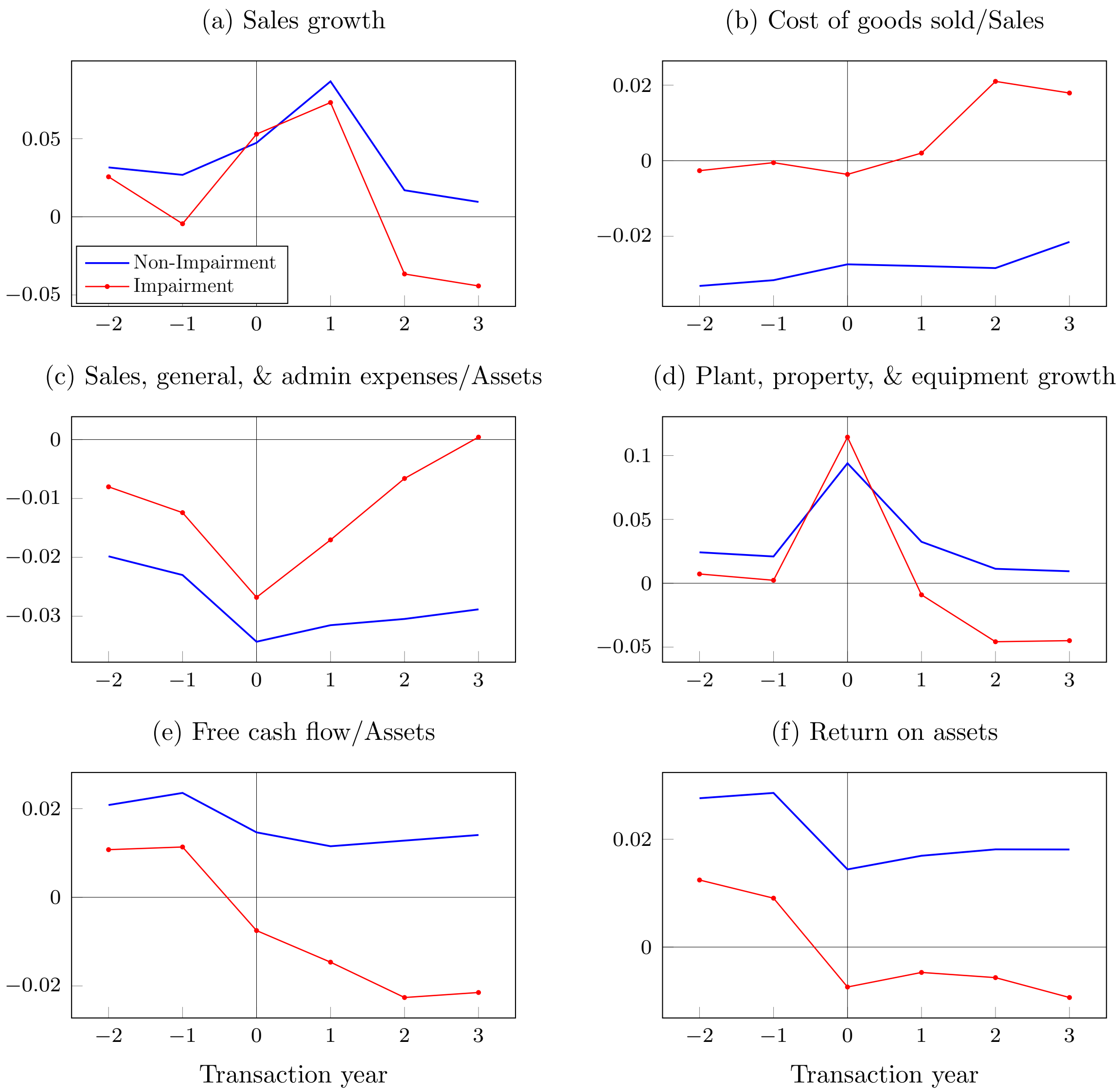
Table A.2, Panel C, reports median industry-adjusted statistics and tests of statistical differences between the nonimpairment and impairment samples. We observe statistically superior performance for the nonimpairment sample relative to the impairment sample for the three years following the acquisition announcement for all nine performance measures.

Figure A.2, Panels (a)–(f), show the operating performance from one year before to three years following the acquisition. Across panels, we generally observe that industry-adjusted performance measures begin to materially diverge in the years following the deal announcement for the impairment sample (shown in red line) and the nonimpairment sample (shown in blue lines), indicating that impairment firms encounter significant firm-level adverse shocks in the years following the acquisition. For many of the measures, the divergence begins in the year following the acquisition but widens further two years following the acquisition.

Figure A.3, Panels (a)–(d), show the financial performance from two years before to three

Figure A.2. Operating Performance and Goodwill Impairment

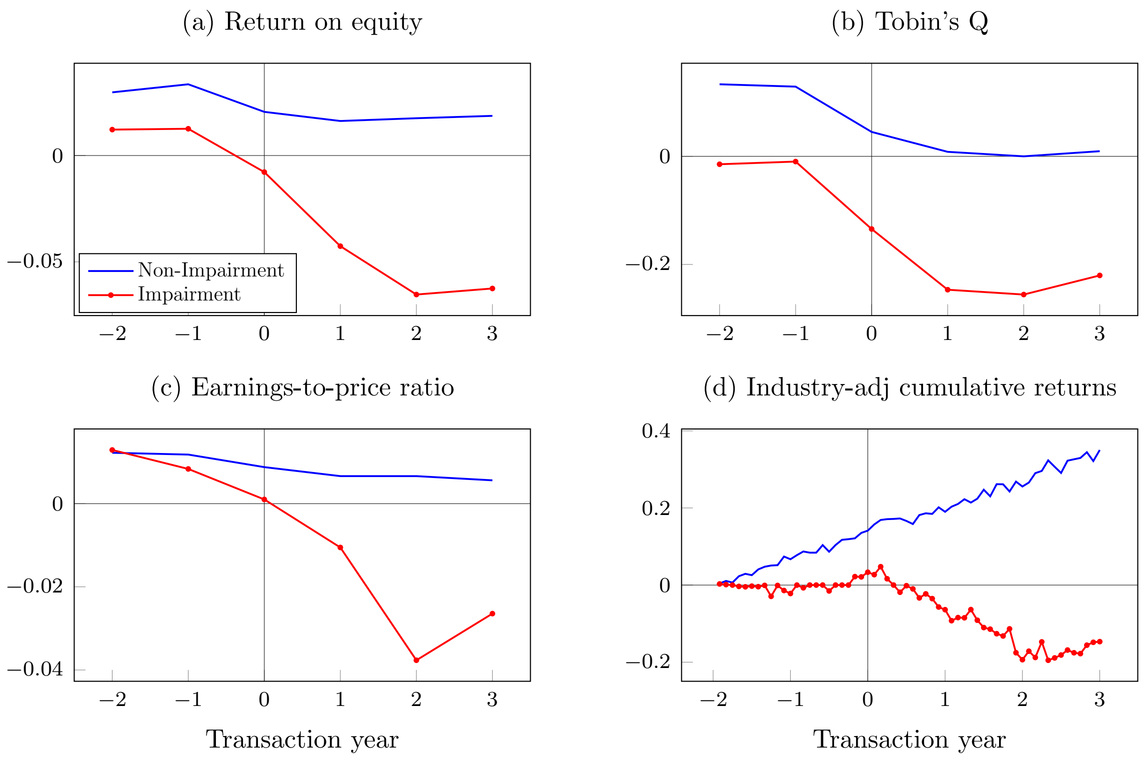
The figure shows the industry-adjusted operating performance of acquirers that impaired goodwill relative to acquirers that did not impair goodwill. The period begins two years before the merger and ends three years after the merger. Panel (a) shows sales growth. Panel (b) shows the cost of goods sold /sales. Panel (c) shows sales, general, & administrative expenses /assets. Panel (d) shows plant, property, & equipment growth. Panel (e) shows free cash flow/assets. Panel (f) shows the return of assets.



years subsequent to the acquisition. Note here that the gap between the blue and red lines increases not so much at but after the deal announcement. Figure A.3, Panel (d), shows that the returns to the realized impairment sample remain relatively flat at the announcement but begin to decline dramatically thereafter. Returns to the realized nonimpairment sample continue their steady growth, and so the gap between the two subsamples widens.

Figure A.3. Financial Performance and Goodwill Impairment

The figure shows the industry-adjusted financial performance of acquirers that impaired goodwill relative to acquirers that did not impair goodwill. The period begins two years before the merger and ends three years after the merger. Panel (a) shows the return on equity. Panel (b) shows Tobin's Q. Panel (c) shows the earnings-to-price ratio. Panel (d) shows industry-adjusted buy-and-hold cumulative returns.



To conclude, all three panels of Table A.2, as well as Figures A.2 and A.3, provide strong evidence that firms in the impairment sample experience all symptoms of deal failure—forced CEO turnover, delistings, bankruptcies, poor accounting, and stock performances—supporting our conclusion that goodwill impairment is a good proxy for deal failure.

Appendix B Sample Construction and Key Variables

B.1 Goodwill Impairments

We start with 2,981 deals. Appendix Table B.1, Panel A, describes the next set of screens. We exclude 258 transactions associated with acquirers that do not report target-level goodwill in Compustat for the full period between the year prior to and 10 years subsequent to the transaction. This requirement reduces the sample to 2,723. The Compustat goodwill and impairment data are based on aggregate firm-level data, and so it is not directly possible to identify transaction-specific measures. To identify the amount of goodwill recorded for each transaction in our sample, we read through the Notes to Consolidated Financial Statements in the first 10-K filing following the deal effective date. Following an acquisition, the notes include an "Acquisitions" section, which presents the preliminary allocations of the aggregate purchase price based on the assets and liabilities estimated at fair values to line items such as net tangible assets, identifiable intangible assets, and goodwill. We eliminate 646 transactions that are not structured using purchase accounting and transactions for which we are unable to identify the deal-level goodwill allocation amount, resulting in a sample of 2,077 transactions with initial goodwill data. Of these, 110 lack the CRSP or Compustat data required to compute key variables. That brings the sample size down to 1,967.

To identify goodwill impairments in the data, we follow Bens et al. (2011). We initially screen for potential goodwill impairments by flagging instances in which the Compustat variable "Impairments of Goodwill Pretax" (item 368) is at least 5% of previous-year total acquirer assets in any year between the year of the acquisition and 10 years following the acquisition. This requirement ensures that the impairment event has detectable valuation effects. Of the 1,967 transactions in the sample, 600 deals are associated with a firm-level impairment within 10 years of the deal effective date. Because Compustat item 368 is aggregate firm-level impairment, we use the Notes to Consolidated Financial Statements in the impairment year to determine whether and how much of the impairment is due to the

Table B.1. Sample Construction for Goodwill Impairments

The table shows the sample construction. Panel A includes transactions from SDC that were announced from January 2003 and completed by December 2013. Sample screens are described in the main text. Panel B describes the classification of the "potentially impaired" transactions. For this sample, we read through the 10-K Notes and Factiva to identify the target(s) that triggered the impairment. * indicates that the exact impairment amount is unknown; the total amount allocated to the deal is based on target goodwill relative to total segment goodwill. ** indicates that the exact impairment amount is unknown; the total amount allocated to the deal is based on target goodwill relative to total firm goodwill. Panel C shows the final sample composition.

Panel A: Sample Construction

# Deals	2,981
Less: Transactions without firm-level goodwill in Compustat	258
Less: Transactions by firms that do not report deal-level goodwill data in the 10-K or not structured under Purchase Accounting	646
Less: Transactions lacking CRSP and Compustat data to compute key variables	110
Total	1,967
# Transactions without acquiring firm-level impairment within 5 years of deal effective date	1,367
# Transactions "potentially impaired" with acquiring firm-level impairment within 5 years	600

Panel B: Classification of "Potentially Impaired" Transactions

Deals classified in goodwill impairment sample	
Impairment linked directly to target and exact impairment amount can be identified	297
Impairment linked directly to target, other targets in segment also linked*	11
Impairment linked directly to target, other targets in firm also linked**	34
Target is in impaired segment, target goodwill < 20% of segment goodwill*	13
Total (% of deals potentially impaired)	355 (59%)
Deals classified in no goodwill impairment sample	
Impairment is not in target's segment or 10-K specifies other target as source of impairment	131
Total (% of deals potentially impaired)	131 (22%)
Deals excluded from sample: cannot classify as impaired or not impaired	
Target is in impaired segment, but target goodwill is < 20% of segment goodwill	39
Impairment cannot be directly linked to a target(s) or segment	57
Total (% of deals potentially impaired)	96 (16%)
Deals excluded from sample: immaterial impairments	
Impairment linked to target, but impairment < 25% of original goodwill	18
Total (% of deals potentially impaired)	18 (3%)

Panel C: Final Goodwill Impairment Sample Summary

Impairment sample	355
Nonimpairment sample	1,498

specific transaction in our sample. We also read through news articles and press releases in Factiva if more information is required.

In many instances, the source and the amount of the impairment assigned to each target is straightforward. In the most uncomplicated scenarios, the targets with goodwill impairment and the amount of target-level impairment are directly listed in the Notes section of the 10-K, or the firm writes off the entirety of its goodwill balance. In other scenarios, the Notes lists the reporting unit(s) that suffered the loss. We search the 10-K, the Notes, and Factiva in the year of the goodwill allocation to determine the reporting unit(s) to which the target's goodwill is allocated. If target goodwill is 100% of the impaired reporting unit goodwill, the amount of impairment attributable to the target is straightforward. For 297 transactions in the potentially impaired sample of 600, we are able to link the impairment directly to the target and can determine the exact impairment amount.

In 45 other instances, the target is listed as impaired in the Notes, but the impairment amount is unknown due to other targets also triggering the impairment. If the impairment is at the reporting-unit level, we set target impairment equal to unit impairment $\times$ (target goodwill / unit goodwill). If the impairment is reported at the consolidated firm level, we set target impairment equal to total impairment $\times$ (target goodwill / total goodwill). Note that we are interested in not only the magnitude but also the probability of impairment events, and the latter will be unaffected by errors in the estimated size of the impairment.

For some transactions, we are uncertain as to the source and amount of the impairment. If the target is in the impaired segment and target goodwill is at least 20% of segment goodwill, we conclude that it is reasonably likely that the target has been impaired and include these 13 transactions in the impairment sample. We estimate the size of the impairment using the relative size of target goodwill as described above. Therefore, of the 600 "potentially impaired" deals, we can classify $297 + 45 + 13 = 355$ as "impaired deals."

For 131 transactions flagged as potentially impaired, we determine that the impairment is not in the target's segment or that other targets have been listed as the source of the impairment. These transactions are included in the nonimpairment sample. For 96 transactions, we cannot link the impairment to a specific reporting unit or target goodwill is less than 20% of segment goodwill, and as such, we cannot reasonably classify the transactions as impaired or not impaired. We exclude these transactions from the sample. Finally, because we are interested in extreme value destruction, we focus only on material goodwill impairment events and exclude 18 transactions with identified goodwill impairments that are less than 25% of the original goodwill.

Appendix Table B.1, Panel B, shows that we have were able to successfully link impairment events to specific transactions: Of 600 transactions flagged as potentially impaired, we can credibly classify 59% as large-impaired, 22% as not impaired, and 3% as small-impaired (and so are excluded), and we are unable to classify only 16% of transactions. Moreover, for 84% (297/355) transactions classified as impaired, we know unambiguously the source and the amount of the impairment. To our knowledge, we are the first to construct a comprehensive data set that includes transaction-specific goodwill balances and transaction-specific impairment outcomes in the post-SFAS 142 period. Hayn and Hughes (2006) also trace initial goodwill balances and subsequent impairments at the transaction level, but they exclude 55% of transactions due to insufficient information. Overall, they focus largely on the pre-SFAS 142 period, a time when the disclosure of initial goodwill and the source of the impairment were generally less comprehensive. Appendix Table B.1, Panel C, summarizes the final sample of 355 transactions in the impairment sample and 1,498 transactions in the nonimpairment sample.

B.2 Divestitures

To construct the divestiture sample, we begin by pulling all transactions in SDC between January 2003 and August 2019 that were completed and were classified as divestitures, equity carve-outs, one- or two-step spinoffs. We then match our sample of 1,870 completed transactions (described in Table 1) to the divestiture sample if (1) the SDC target name of the divested firm matches the SDC target name of the firm in the original sample, or (2) the target state and target SIC code (as identied by SDC) are the same for both the divested firm and the firm in the original sample. These two matching requirements yield 305 "potential" matches. We then manually check each transaction to ensure that the divestiture is related to the original transaction and manually collect the divestiture amount if it is not reported in SDC. This step yields 116 verified matches. Of the 116 verified matches, we then retain transactions that were divested within five years of the deal effective date (58) and that are not already flagged with goodwill impairment (43). Finally, we require that the divestiture transaction value be reported and that the divestiture price be less than the original transaction price (implying that the target was divested at a loss). This yields 17 divested transactions. Appendix Table B.2 shows the details.

Table B.2. Sample Construction for Divestitures-at-a-Loss

To construct the divestiture sample, we begin by pulling all transactions in SDC between 2003 and August 2019 that were completed and had acquisition techniques of divestiture, equity carve-out, spinoff, or two-step spinoff. We then match our sample of 1,870 completed transactions (described in Table 1) to the divestiture sample if (a) the SDC target name of the divested firm matches the SDC target name of the firm in the original sample, or (b) the target state and target SIC code (as identified by SDC) are the same for both the divested firm and the firm in the original sample. These two matching requirements yield 305 "potential" matches. We then manually check each transaction to ensure that the divestiture is related to the original transaction and manually collect the divestiture amount if it is not reported in SDC. This step yields 116 verified matches. Of these matches, we then retain transactions that were divested within five years of the deal effective date (58) and that are not already flagged with goodwill impairment (43). Finally, we require that the divestiture transaction value be reported and that the divestiture price be less than the original transaction price (implying that the target was divested at a loss). This yields 17 divested transactions that occurred at a loss.

All deals in SDC between 2003 and August 2019 that were completed and had acquisition techniques of "divestiture, equity carve-out, spinoff, two-step spinoff"	43,355
Match 1: Retain if SDC target name in original sample matches SDC target name in divestiture sample	305
Match 2: Retain if target state and target primary SIC code in original sample matches SDC target state and target primary SIC code in divestiture sample	381
Total "potential" matches	686
Verified matches after manual data check	116
Retain if divestiture occurred within 5 years of deal effective date	58
Retain if transaction was not already impaired	43
Retain if divestiture price is reported	17
Retain if divestiture price is less than the original transaction price (i.e., a loss)	17

B.3 Time Trend of Acquisition Failures

Appendix Table B.3 shows the frequency of goodwill impairments and divestitures-at-a-loss by deal effective year cohort. The sample is based on goodwill impairment or divestiture between the deal effective year and five years subsequent to the deal effective year. The sample includes 372 unique acquisitions that experience impairment or divestiture events and 1,498 acquisitions that do not experience a goodwill impairment or divestiture event. Deal failures are more common for deals completed in the early sample period, between 2003 and 2008. Looking at the frequency of deal failures by announcement year (columns), not surprisingly, these events cluster in the financial crisis period, with the most occurring in 2008. We see a weak upward trend in the number of deal failures through time, with an average of 16 each year between 2003 and 2007 and 27 each year between 2009 and 2017. Transactions may have multiple goodwill write-downs. There are 456 impairments or divestitures associated with the 372 unique transactions with goodwill write-downs or divestiture loss.

Table B.3. Goodwill Impairment/divestiture-at-a-loss, By Year

This table shows the number of goodwill impairments and divestitures-at-a-loss by year for each deal effective year cohort. This table includes only completed transactions. The sample is based on goodwill impairment or divestiture between the deal effective year and five years subsequent to the deal effective year. The sample includes 372 unique acquisitions that experience impairment or divestiture-at-a-loss events. There are 1,498 acquisitions that are completed that do not experience a goodwill impairment or divestiture event.

	# of Goodwill Impairments/Divestitures															Impair/Divest		Unique deals	
Year	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14	‘15	‘16	‘17	#	%	#	%Year’s deals
2003	1	3	5	7	3	14	0	0	0	0	0	0	0	0	0	33	7%	31	22%
2004	0	4	10	9	10	30	11	0	0	0	0	0	0	0	0	74	16%	57	30%
2005	0	0	2	6	9	28	10	3	0	0	0	0	0	0	0	58	13%	50	29%
2006	0	0	0	1	8	37	16	4	7	0	0	0	0	0	0	73	16%	60	26%
2007	0	0	0	0	3	34	24	10	5	5	0	0	0	0	0	81	18%	63	28%
2008	0	0	0	0	0	14	6	3	4	6	3	0	0	0	0	36	8%	31	22%
2009	0	0	0	0	0	0	2	3	5	2	1	0	0	0	0	13	3%	9	10%
2010	0	0	0	0	0	0	0	1	4	4	3	2	4	0	0	18	4%	16	10%
2011	0	0	0	0	0	0	0	0	1	8	8	6	5	4	0	32	6%	24	16%
2012	0	0	0	0	0	0	0	0	0	0	2	2	8	2	3	17	3%	13	7%
2013	0	0	0	0	0	0	0	0	0	0	1	7	7	3	3	21	3%	18	10%
Total	1	7	17	23	33	157	69	24	26	25	18	17	24	9	6	456		372	

Appendix C Additional Summary Statistics

Appendix C provides additional summary statistics. Appendix Table C.1 reports deal and acquiring firm characteristics for firms with and without transaction-level failure (Panel A), for firms in various quantiles of abnormal ROA (Panel B) and DGTW-adjusted BHAR (Panel C). Appendix Table C.2 reports correlations between our key measures of ex-ante performance (CAR) and realized ex-post performance (failure, abnormal ROA, and BHAR).

Table C.1. Summary Statistics by Sample Splits

Panel A: Transaction-Level Failure Statistics

	Full sample	Failure	No failure	p-value (Fail vs no fail)
\$ Goodwill (\$m)	336.5	315.4	341.7	0.722
Goodwill/net purchase price	51.3%	53.0%	50.9%	0.131
Goodwill/total assets	10.4%	13.7%	9.6%	< 0.001
Acquirer market cap (\$m)	3,187	1,457	3,617	< 0.001
Debt/Assets ($y-1$)	18.9%	16.1%	19.6%	0.000
Free cash flow/Assets ($y-1$)	5.0%	2.7%	5.6%	0.010
Tobin's Q ($y-1$)	1.88	1.89	1.88	0.936
Past return (mkt-adj; $q-1$)	3.5%	5.4%	3.0%	0.063
Short interest (mean-adj; $m-1$)	1.2%	1.4%	1.1%	0.385
Deal value (\$m)	710	645	726	0.629
Relative size (deal value/market cap)	32.2%	43.6%	29.4%	< 0.001
Stock-only dummy	4.1%	6.5%	3.5%	0.033
Mixed-payment dummy	44.4%	52.4%	42.5%	0.001
Diversifying dummy	36.7%	40.1%	35.9%	0.144
Competed dummy	0.7%	0.8%	0.7%	0.889
Hostile dummy	1.0%	1.9%	0.8%	0.146
Public target dummy	19.2%	18.8%	19.3%	0.834

Panel B: Firm-Level Outcome ROA Statistics

	Q1 (low)	Q2–Q4	Q5 (high)	p-value (Q1 vs Q5)
Acquirer market cap (\$m)	1,777	3,359	4,550	0.003
Debt/Assets ($y-1$)	14.8%	20.1%	18.6%	0.007
Free cash flow/Assets ($y-1$)	0.7%	6.9%	3.7%	0.059
Tobin's Q ($y-1$)	1.86	1.78	2.22	0.000
Past return (mkt-adj; $q-1$)	1.8%	3.2%	6.7%	0.005
Short interest (mean-adj; $m-1$)	1.2%	0.9%	1.6%	0.310
Deal value (\$m)	499	752	808	0.209
Relative size (deal value/market cap)	33.8%	33.1%	26.1%	0.007
Stock-only dummy	6.5%	2.8%	5.6%	0.638
Mixed-payment dummy	48.6%	44.0%	41.5%	0.059
Diversifying dummy	39.8%	37.7%	33.6%	0.087
Competed dummy	0.8%	0.5%	1.4%	0.478
Hostile dummy	0.8%	0.8%	1.7%	0.315
Public target dummy	18.4%	20.2%	18.1%	0.923

Table C.1. Summary Statistics by Sample Splits (Cont.)

Panel C: Firm-Level Outcome BHAR Statistics

	Q1 (low)	Q2–Q4	Q5 (high)	p-value (Q1 vs Q5)
Acquirer market cap ($m)	1,629	3,651	3,353	0.013
Debt/Assets ($y-1$)	18.6%	18.9%	19.3%	0.605
Free cash flow/Assets ($y-1$)	1.3%	6.0%	5.9%	0.001
Tobin's Q ($y-1$)	1.85	1.87	1.96	0.230
Past return (mkt-adj; $q-1$)	2.7%	3.8%	3.1%	0.792
Short interest (mean-adj; $m-1$)	1.3%	1.1%	1.3%	0.980
Deal value ($m)	407	849	597	0.189
Relative size (deal value/market cap)	43.5%	29.4%	29.4%	0.000
Stock-only dummy	6.7%	3.2%	4.3%	0.149
Mixed-payment dummy	50.3%	43.9%	40.4%	0.007
Diversifying dummy	44.4%	36.5%	29.9%	< 0.001
Competed dummy	1.1%	0.8%	0.3%	0.179
Hostile dummy	1.1%	0.8%	1.6%	0.525
Public target dummy	15.8%	20.0%	20.3%	0.106

Table C.2. Correlation Table

This table reports the correlation of CAR, measured across three windows around the transaction announcement date, and the three performance measures: a transaction failure dummy, abnormal ROA, and 3-year DGTW-adjusted BHAR. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	CAR					
	$[-1,1]$	$[-5,5]$	$[\text{Ann}-2,\text{Cls}+2]$	Failure	ROA	BHAR
CAR $[-1,1]$	1.000					
CAR $[-5,5]$	0.735***	1.000				
CAR $[\text{Ann}-2,\text{Cls}+2]$	0.490***	0.539***	1.000			
Failure dummy	−0.035	−0.002	−0.033	1.000		
Abnormal ROA	0.051**	0.011	0.030	−0.216***	1.000	
3-year DGTW-adj BHAR	−0.031	−0.041*	0.002	−0.309***	0.310	1.000

Appendix D Characteristics-Based Model

Appendix Table D.1 presents a characteristics-based model for predicting transaction-level failure, measured by whether the acquisition's goodwill was impaired within five years of the transaction or whether the target was sold at a loss within that time frame. This table reports OLS regressions with goodwill impairment or divestiture outcomes as the dependent variable and deal and acquirer characteristics as the key independent variables of interest. In Columns (1)–(4), the dependent variable is a dummy for impairment or divestiture. In Columns (5) and (6), the dependent variable is scaled-dollar impairment/divestiture loss. This variable is scaled by initial goodwill. In Column (4), we include CAR, and in Column (8) we include scaled acquirer dollar loss imputed from CAR. Appendix Table D.2 is similar except the dependent variables are abnormal ROA (Columns (1)–(4)) and DGTW-adjusted BHAR (Columns (5)–(8)).

Table D.1. Characteristics-Based Model: Transaction Failure

This table reports OLS regressions with goodwill impairment or divestiture outcomes as the dependent variable and deal and acquirer characteristics as the key independent variables of interest. In Columns (1)–(4), the dependent variable is a dummy for impairment or divestiture. In Columns (5) and (6), the dependent variable is scaled-dollar impairment/divestiture loss. This variable is scaled by initial goodwill. In Column (4), we include CAR, and in Column (8) we include scaled acquirer dollar loss imputed from CAR. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Dependent variable:	Failure				Scaled $ Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
Log acquirer market cap ($b)	−0.034***	−0.027***	−0.030***	−0.031***	−0.029***	−0.029***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Debt/Assets ($y-1$)	−16.070***	−17.916***	−21.271***	−20.862***	−17.671***	−17.673***
	(4.705)	(4.654)	(4.771)	(4.781)	(4.300)	(4.298)
FCF/Assets ($y-1$)	−0.112	−0.139**	−0.161**	−0.157**	−0.126**	−0.122**
	(0.073)	(0.068)	(0.068)	(0.068)	(0.060)	(0.060)
Tobin's Q ($y-1$)	0.001	−0.012	−0.008	−0.008	−0.010	−0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Past return (adj; $q-1$)	0.080	0.095*	0.093*	0.093*	0.079	0.077
	(0.054)	(0.053)	(0.053)	(0.053)	(0.049)	(0.049)
Short interest (adj; $m-1$)	0.328*	0.342*	0.399**	0.401**	0.332*	0.325*
	(0.197)	(0.193)	(0.192)	(0.192)	(0.174)	(0.175)
Relative size	0.090***	0.093***	0.088***	0.093***	0.044*	0.046**
	(0.029)	(0.030)	(0.029)	(0.029)	(0.022)	(0.023)
Stock-only dummy	0.123**	0.117**	0.119**	0.110*	0.086*	0.084*
	(0.061)	(0.057)	(0.058)	(0.058)	(0.050)	(0.050)
Mixed-payment dummy	0.039**	0.039**	0.031*	0.030	0.034**	0.034**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.017)	(0.017)
Diversifying dummy	0.035*	0.039**	0.034*	0.033*	0.020	0.020
	(0.019)	(0.019)	(0.019)	(0.019)	(0.017)	(0.017)
Competed dummy	0.038	0.031	0.039	0.042	0.067	0.069
	(0.111)	(0.103)	(0.107)	(0.106)	(0.103)	(0.103)
Hostile	0.154	0.135	0.135	0.139	0.135	0.137
	(0.113)	(0.109)	(0.108)	(0.107)	(0.099)	(0.099)
Public target	0.018	0.009	0.014	0.009	0.005	0.005
	(0.025)	(0.025)	(0.025)	(0.025)	(0.021)	(0.022)
CAR / Scaled $ loss				−0.214		0.024
(imputed from CAR)				(0.132)		(0.025)
Year controls	No	Yes	Yes	Yes	Yes	Yes
Industry controls	No	No	Yes	Yes	Yes	Yes
Observations	1,805	1,805	1,805	1,805	1,805	1,805
Adjusted R^2	0.050	0.086	0.092	0.093	0.087	0.087

Table D.2. Characteristics-Based Model: Firm-Level Outcomes

This table reports OLS regressions with abnormal ROA and DGTW-adjusted buy-and-hold returns (BHAR) as the dependent variables and deal and acquirer characteristics as the key independent variables of interest. In Columns (1)–(4), the dependent variable is abnormal ROA. In Columns (5)–(8), the dependent variable is DGTW-adjusted BHAR. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Dependent variable:	Abnormal ROA				DGTW-adjusted BHAR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log acquirer market cap ($b)	0.007***	0.006***	0.007***	0.007***	0.020**	0.019**	0.024***	0.023**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)	(0.009)	(0.009)	(0.009)
Debt/Assets ($y-1$)	3.466***	3.511***	3.390***	3.300***	7.165	7.585	15.005**	15.177**
	(1.036)	(1.028)	(1.099)	(1.094)	(7.019)	(7.057)	(7.526)	(7.549)
FCF/Assets ($y-1$)	−0.021	−0.022	−0.018	−0.020	0.213***	0.195**	0.240***	0.242***
	(0.018)	(0.018)	(0.018)	(0.019)	(0.077)	(0.078)	(0.078)	(0.079)
Tobin's Q ($y-1$)	0.003	0.004	0.003	0.002	0.008	0.008	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)	(0.012)	(0.012)	(0.012)
Past return (adj; $q-1$)	0.024*	0.026**	0.027**	0.027**	0.062	0.066	0.066	0.066
	(0.013)	(0.012)	(0.012)	(0.012)	(0.067)	(0.068)	(0.068)	(0.068)
Short interest (adj; $m-1$)	0.008	0.013	0.006	0.006	−0.141	−0.149	−0.249	−0.248
	(0.047)	(0.047)	(0.046)	(0.047)	(0.279)	(0.277)	(0.276)	(0.276)
Relative size	−0.003	−0.003	−0.003	−0.005	−0.095***	−0.097***	−0.085***	−0.083***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.029)	(0.029)	(0.029)	(0.030)
Stock-only dummy	−0.005	−0.004	−0.005	−0.002	−0.068	−0.063	−0.061	−0.065
	(0.013)	(0.013)	(0.013)	(0.013)	(0.079)	(0.079)	(0.080)	(0.081)
Mixed-payment dummy	−0.009**	−0.009**	−0.007*	−0.006*	−0.043*	−0.043*	−0.030	−0.030
	(0.004)	(0.004)	(0.004)	(0.004)	(0.025)	(0.025)	(0.025)	(0.025)
Diversifying dummy	−0.007*	−0.007*	−0.005	−0.005	−0.084***	−0.087***	−0.080***	−0.080***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.025)	(0.025)	(0.025)	(0.025)
Competed dummy	0.012	0.014	0.014	0.012	−0.187*	−0.187*	−0.199*	−0.198*
	(0.018)	(0.018)	(0.019)	(0.020)	(0.107)	(0.106)	(0.105)	(0.105)
Hostile	0.016	0.018	0.017	0.016	0.009	0.007	0.027	0.028
	(0.019)	(0.019)	(0.020)	(0.020)	(0.119)	(0.122)	(0.116)	(0.117)
Public target	−0.004	−0.003	−0.003	−0.002	0.024	0.029	0.015	0.013
	(0.005)	(0.005)	(0.004)	(0.004)	(0.032)	(0.032)	(0.032)	(0.032)
CAR $[-1,1]$				0.064**				−0.091
				(0.030)				(0.182)
Year controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry controls	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1,707	1,707	1,707	1,707	1,805	1,805	1,805	1,805
Adjusted R^2	0.035	0.040	0.064	0.067	0.023	0.021	0.029	0.028

Appendix E Subsamples by Characteristic

Table E.1 presents regressions of outcome variables on CAR $[-1,1]$. The samples are split by deal (Panel A) and acquirer (Panel B) characteristics. For example, the first regression in Panel A reports results for regressions of failure, abnormal ROA, and BHAR on CAR $[-1,1]$ for the sample of stock-only and the sample of cash-only deals. In the remainder of Panel A, we repeat these regressions for the public and private target, diversifying and nondiversifying, below- and above-median relative size (transaction size relative to acquirer size), and below- and above-median deal size subsamples. In Panel B, we consider sample splits based on acquirer size, leverage, free cash flows, Tobin's Q, and pre-deal stock returns. The anticipated coefficient is negative for the regressions of the failure dummy and positive for the regressions with ROA and DGTW-adjusted BHAR.

Figure E.1 reproduces Figure 4 for two subperiods, by completion date: 2003–2007 (Panel (a)) and 2008–2013 (Panel (b)).

Table E.1. CAR Performance by Subsamples Based on Characteristics

This table reports results for OLS regressions of outcome variables on CAR $[-1, 1]$. Panels A and B present results of regressions using subsamples split by deal and acquirer characteristics, respectively. Standard errors are reported in parentheses under coefficients. The outcome variables are failure dummy (goodwill impairment or divestiture-at-a-loss within five years), abnormal return on assets (ROA), and DGTW-adjusted buy-and-hold returns (BHAR). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Panel A: Sample Splits by Deal Characteristics

Dependent variable:	Failure	ROA	BHAR	Failure	ROA	BHAR
Sample:	Stock only			Cash only		
Acquirer CAR $[-1, 1]$	−1.079*	−0.044	1.576*	−0.248	0.039	−0.485
	(0.582)	(0.136)	(0.857)	(0.179)	(0.044)	(0.324)
Observations	70	66	70	934	883	934
Adjusted R^2	0.025	0.000	0.031	0.001	0.000	0.003
Sample:	Public target			Private target		
Acquirer CAR $[-1, 1]$	−0.859***	−0.011	0.127	−0.008	0.077**	−0.262
	(0.285)	(0.054)	(0.322)	(0.147)	(0.037)	(0.210)
Observations	343	330	343	1,462	1,377	1,462
Adjusted R^2	0.029	0.000	0.000	0.000	0.004	0.001
Sample:	Diversifying deal			Nondiversifying deal		
Acquirer CAR $[-1, 1]$	−0.070	0.126**	0.326	−0.258	0.006	−0.493**
	(0.215)	(0.053)	(0.283)	(0.168)	(0.036)	(0.222)
Obs	662	635	662	1,143	1,072	1,143
Adjusted R^2	0.000	0.015	0.001	0.002	0.000	0.004
Sample:	Below-median relative size			Above-median relative size		
Acquirer CAR $[-1, 1]$	−0.104	0.041	−0.366	−0.294*	0.057*	−0.062
	(0.206)	(0.076)	(0.392)	(0.166)	(0.030)	(0.193)
Observations	902	855	902	903	852	903
Adjusted R^2	0.000	0.000	0.001	0.003	0.004	0.000
Sample:	Below-median deal size			Above-median deal size		
Acquirer CAR $[-1, 1]$	0.017	0.057	−0.087	−0.386**	0.053	−0.264
	(0.194)	(0.053)	(0.284)	(0.185)	(0.034)	(0.225)
Observations	902	845	902	903	862	903
Adjusted R^2	0.000	0.001	0.000	0.006	0.004	0.001

Table E.1. CAR Performance by Subsamples Based on Characteristics (Cont.)

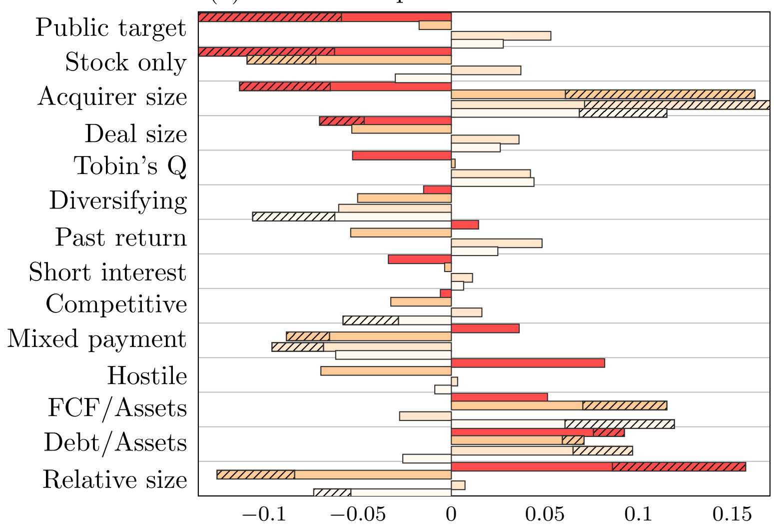
Panel B: Sample Splits by Acquirer Characteristics

Dependent variable:	Failure	ROA	BHAR	Failure	ROA	BHAR
Sample:	Below-median acquirer size			Above-median acquirer size		
Acquirer CAR $[-1, 1]$	−0.003	0.060	−0.008	−0.627***	0.064	−0.409
	(0.180)	(0.041)	(0.239)	(0.175)	(0.044)	(0.257)
Observations	903	839	903	902	868	902
Adjusted R^2	0.000	0.002	0.000	0.014	0.004	0.003
Sample:	Below-median leverage			Above-median leverage		
Acquirer CAR $[-1, 1]$	0.141	0.066	−0.218	−0.552***	0.026	−0.160
	(0.176)	(0.044)	(0.268)	(0.191)	(0.041)	(0.227)
Observations	903	855	903	902	852	902
Adjusted R^2	0.000	0.003	0.000	0.010	0.000	0.000
Sample:	Below-median FCF			Above-median FCF		
Acquirer CAR $[-1, 1]$	−0.303*	0.021	−0.051	−0.060	0.086*	−0.363
	(0.181)	(0.041)	(0.232)	(0.191)	(0.047)	(0.270)
Observations	902	859	902	903	848	903
Adjusted R^2	0.002	0.000	0.000	0.000	0.007	0.002
Sample:	Below-median Tobin Q			Above-median Tobin Q		
Acquirer CAR $[-1, 1]$	−0.561***	0.074**	0.345	0.079	0.041	−0.605**
	(0.205)	(0.029)	(0.237)	(0.169)	(0.050)	(0.253)
Observations	903	859	903	902	848	902
Adjusted R^2	0.009	0.006	0.001	0.000	0.000	0.007
Sample:	Below-median previous return			Above-median previous return		
Acquirer CAR $[-1, 1]$	−0.157	0.028	−0.335	−0.232	0.074**	−0.039
	(0.195)	(0.049)	(0.241)	(0.178)	(0.037)	(0.261)
Observations	903	847	903	902	860	902
Adjusted R^2	0.000	0.000	0.001	0.001	0.005	0.000

Figure E.1. CAR and Ex-Post Performance, by Characteristic, by Period

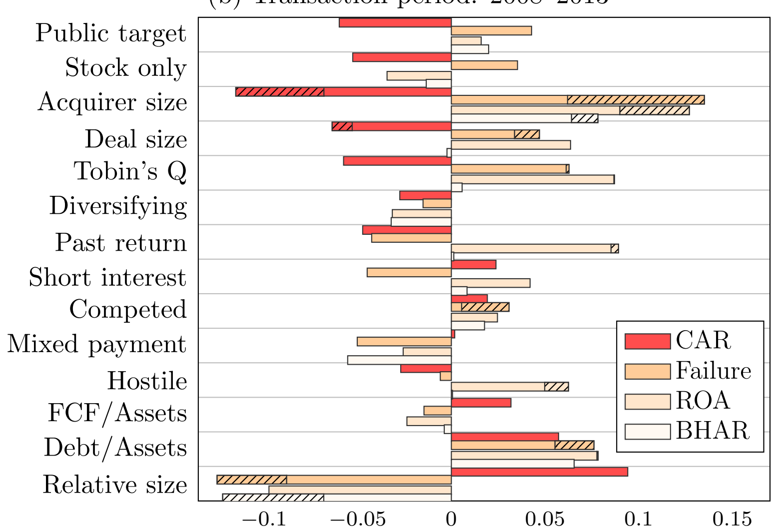
The bar chart shows the standardized coefficient for regressions for which the dependent variable is CAR, failure, abnormal ROA, or DGTW-adjusted buy-and-hold returns (BHAR) on various deal and firm characteristics. Each characteristic enters each regression individually (univariate regressions). We switch the sign on the failure regressions so that they are comparable to the other measures of performance and to CAR. The red bar indicates the standardized coefficient from regressions in which CAR is the dependent variable, and the three lighter bars indicate regressions for which failure, abnormal ROA, and DGTW-adjusted BHAR are the dependent variables. The patterned portion of the bars indicates a coefficient that is larger than 1.96 standard errors of the standardized coefficient, i.e., statistically significant at least at the 5% level. All acquirer characteristics are computed prior to the announcement; leverage, free cash flows, assets, and Tobin's Q are computed in the year prior to the announcement, and past returns and short interest are computed in the quarter and month prior to the announcement, respectively.

(a) Transaction period: 2003–2007



Standardized coefficient of CAR or ex-post performance

(b) Transaction period: 2008–2013



Standardized coefficient of CAR or ex-post performance

Appendix F Withdrawn Deals

In this section, we consider the importance of selection due to withdrawn deals. We implement a correction through inverse probability weighting (Wooldridge, 2007). This method has two stages. In the first stage, the likelihood of completion ($= 1 -$ Withdrawal) is estimated as in Table 9 using the full sample. Specifically, we estimate a logit regression of the probability of completion on acquirer CAR and deal and firm characteristics. In the second stage, we rerun the main analysis (as in Table 3 and Table 4) but here the observations are weighted with the inverse probability of completion. This method provides greater weight to observations that are more likely to have been withdrawn. In Panel A, the dependent variable is a dummy for impairment or divestiture-at-a-loss. In Panel B, the dependent variable is abnormal ROA. In Panel C, the dependent variable is DGTW-adjusted buy-and-hold returns.

Table F.1. Accounting for Withdrawn Deals: Inverse Probability Weighting

This table reports regressions of transaction failure measures and acquirer performance on acquirer cumulative abnormal returns (CAR). In Panel A, the dependent variable is a dummy for impairment or divestiture-at-a-loss. In Panel B, the dependent variable is abnormal ROA. In Panel C, the dependent variable is DGTW-adjusted buy-and-hold returns. In all panels, Column (1) includes only year, industry, and characteristics as independent variables. Columns (2)–(4) include only CAR as the independent variable, and Columns (5)–(7) include both CAR and controls as independent variables. The characteristics are the log of market capitalization, leverage and cash flows scaled by previous-year assets, Tobin's Q, previous-quarter market-adjusted stock returns, previous-month short interest, relative size, and indicators for stock-only, mixed-payment, diversifying, competed, hostile, and public target deals. Observations are inversely weighted by the probability of the completion of the deal, which is estimated in a logit regression of deal completion on the characteristics described above. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Panel A: Probability of Failure

Dependent variable:	Failure Dummy						
CAR window:	n.a.	$[-1,1]$	$[-5,5]$	$[\text{Ann}-2, \text{Cls}+2]$	$[-1,1]$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer CAR	Controls	−0.311*	−0.077	−0.100	−0.259*	−0.226	−0.291**
	only	(0.159)	(0.120)	(0.080)	(0.157)	(0.147)	(0.142)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,805	1,805	1,805	1,804	1,805	1,805	1,805
Adjusted R^2	0.107	0.003	0.000	0.002	0.042	0.052	0.109

Panel B: Abnormal ROA

Dependent variable:	ROA						
CAR window:	n.a.	$[-1,1]$	$[-5,5]$	[Ann-2, Cls+2]	$[-1,1]$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer CAR	Controls	0.035	−0.007	0.002	0.037	0.037	0.052
	only	(0.033)	(0.024)	(0.015)	(0.032)	(0.033)	(0.032)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,707	1,707	1,707	1,707	1,707	1,707	1,707
Adjusted R^2	0.060	0.001	0.000	0.000	0.010	0.033	0.062

Panel C: DGTW-Adjusted Buy-and-Hold Return

Dependent variable:	DGTW-adj BHAR						
CAR window:	n.a.	$[-1,1]$	$[-5,5]$	$[\text{Ann}-2, \text{Cls}+2]$	$[-1,1]$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer CAR	Controls	−0.113	−0.245**	−0.046	−0.120	−0.066	0.019
	only	(0.189)	(0.122)	(0.092)	(0.186)	(0.184)	(0.187)
Controls	Year, Ind, Char	–	–	–	Year	Year, Ind	Year, Ind, Char
Observations	1,805	1,805	1,805	1,804	1,805	1,805	1,805
Adjusted R^2	0.037	0.000	0.002	0.000	0.000	0.011	0.036

Appendix G Robustness Tests

We next consider whether our main results reported in Table 3 are robust to samples that exclude impairments or divestiture losses during the financial crisis, to replacing acquirer CAR with combined target and acquirer CAR, and to using longer event windows to reflect anticipation or leakage.

In Table G.1, we report OLS regressions with goodwill impairment or divestiture outcomes as the dependent variable. Column (2) restricts the sample to transactions announced in the post-crisis period between 2010 and 2013, and Column (1) restricts the sample to transactions announced in the pre-crisis period between 2003 and 2007. The independent variable for Columns (1) and (2) is CAR $[-1, 1]$. We next focus on the sample of transactions with public targets. In Column (3), the independent variable is combined CAR, which is the sum of acquirer dollar return and target dollar return scaled by the sum of acquirer and target market capitalization 50 days prior to announcement. Dollar return is computed by multiplying CAR $[-1, 1]$ by the market capitalization 50 days prior to the announcement. To account for the possibility of anticipation, in Column (4), the independent variable is acquirer CAR, computed over a long $[-41, 1]$ event window.

Table G.1. Robustness Tests

This table reports the results of OLS regressions with goodwill impairment or divestiture outcomes as the dependent variable. Column (2) restricts the sample to transactions announced in the post-crisis period between 2010 and 2013, and Column (1) restricts the sample to transactions announced in the pre-crisis period between 2003 and 2007. The independent variable for Columns (1) and (2) is CAR $[-1, 1]$. In Column (3), the independent variable is combined CAR, which is the sum of acquirer dollar return and target dollar return scaled by the sum of acquirer and target market capitalization 50 days prior to the announcement. Dollar return is computed by multiplying CAR $[-1, 1]$ by the market capitalization 50 days prior to the announcement. To account for the possibility of anticipation, in Column (4), the independent variable is acquirer CAR, computed over a long $[-41, 1]$ event window. Standard errors are reported in parentheses under coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported.

Panel A: Transaction-Level Failure

Dependent variable:	Failure Dummy			
CAR window:	$[-1, 1]$		Acq + Tgt $[-1, 1]$	$[-41, 1]$
Sample:	2003–2007	2010–2013	Public targets	All
	(1)	(2)	(3)	(4)
Acquirer CAR	−0.138	−0.044	−0.466	−0.088
	(0.194)	(0.199)	(0.283)	(0.063)
Observations	923	647	325	1,805
Adjusted R^2/Pseudo R^2	0.000	0.000	0.006	0.001

Panel B: Abnormal ROA

Dependent variable:	Abnormal ROA			
CAR window:	$[-1, 1]$		Acq + Tgt $[-1, 1]$	$[-41, 1]$
Sample:	2003–2007	2010–2013	Public targets	All
	(1)	(2)	(3)	(4)
Acquirer CAR	0.059	0.043	−0.063	0.019
	(0.045)	(0.046)	(0.057)	(0.015)
Observations	866	616	314	1,707
Adjusted R^2	0.002	0.001	0.002	0.001

Panel C: DGTW-Adjusted Buy-and-Hold Return

Dependent variable:	DGTW-Adjusted Buy-and-Hold Return			
CAR window:	$[-1, 1]$		Acq + Tgt $[-1, 1]$	$[-41, 1]$
Sample:	2003–2007	2010–2013	Public targets	All
	(1)	(2)	(3)	(4)
Acquirer CAR	−0.470*	0.110	0.214	0.076
	(0.272)	(0.244)	(0.309)	(0.082)
Observations	923	647	325	1,805
Adjusted R^2	0.003	0.000	0.000	0.000