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# THE (MISSING) RELATION BETWEEN ANNOUNCEMENT RETURNS AND VALUE CREATION

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**ABSTRACT**

Acquisition announcement returns are widely considered market-based assessments of value creation. Unfortunately, the data do not support this conjecture. We show that commonly used and new measures of realized acquisition outcomes are correlated among themselves, though derived from different sources. Furthermore, these outcomes are predictable using standard information known at the announcement time. In contrast, announcement returns—also measured at the announcement time—are uncorrelated with these outcomes. Importantly, announcement returns even fail to predict the predictable components of these outcomes. Overall, there is no evidence that announcement returns capture expected or realized value creation.

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# 1 Introduction

The reaction of acquirers' stock prices to acquisition announcements has become the most commonly used statistic by economists to assess the value created by acquisitions. The cumulative abnormal returns (CAR) around the announcement date are thought to be a market-based estimate of the net present value (NPV) of the expected cash flows generated by the specific transaction. Since the 1990s, hundreds of academic studies have relied on this implicit assumption to analyze systematic patterns in acquirers' CAR and determine which investment decisions boost firms' expected future cash flows and which do not.[1] CAR is also widely used outside of academic circles. For example, regulators and courts commonly utilize CAR as acceptable proof of value generation or destruction.

Given this metric's widespread use, CAR's validity as a measure of expected value creation should rest on theoretical and empirical foundations. At the theoretical level, CAR can be interpreted as the expected value created by a specific transaction *only if* a very narrow set of conditions is met. The market must be efficient such that the acquirer's stock price response to the acquisition announcement reflects all the information available to market participants. Moreover, the announced transaction itself should be unexpected and reveal (or imply) nothing beyond the information pertaining to the transaction. In other words, the information about the transaction should be orthogonal to any information about the acquirer. If these conditions are met, then CAR can serve as a proper market-based estimate of the expected value created by the acquisition (Schwert, 1981; Jarrell, Brickley, and Netter, 1988; MacKinlay, 1997). However, corporate events rarely arise in a vacuum, so the price reaction depends on the context. Consistent with this idea, scholars have argued that CAR reflects an update *relative to* an anticipated bid, which is already baked in the price.[2] Or, the

[1] We counted the usage of CAR in the *Journal of Finance*, *Journal of Financial Economics*, and *Review of Financial Studies* between 2007 and 2016. We found that 6.4% of articles focused on M&A-related topics (i.e., used the terms merger, acquisition, M&A, deals, acquirer, target, takeover, market reaction to the acquisition, goodwill, or synergy in the Abstract). Of these articles, 62.4% computed measures of acquisition value creation. Of this subset, 95.6% used the event study methodology.

[2] See, e.g., Schipper and Thompson (1983a), Song and Walkling (2000), Cai, Song, and Walkling (2011), and Wang (2018).

announcement itself reveals new information about the quality of the management team and acquirer standalone value.[3] Furthermore, CAR may be distorted by nonfundamental, and therefore uninformative, price pressures (e.g., Mitchell, Pulvino, and Stafford, 2004). Despite these limitations to how CAR should be interpreted, corporate finance studies largely rely on CAR as a measure of the value created due to the acquisition.

At the empirical level, only sparse and mixed evidence validates the core relation between CAR and acquisition outcomes. Two early studies that use small and overlapping samples document that acquirer CAR is correlated with ex-post outcomes (Kaplan and Weisbach, 1992; Healy, Palepu, and Ruback, 1992).[4] Two later studies find, in select specifications, that CAR is weakly correlated with some of the outcomes studied: expected outcomes (Hoberg and Phillips, 2018) and realized outcomes (Li, 2013).[5] Other studies indicate that CAR may not be correlated with outcomes, such as winner underperformance in contested mergers (Malmendier, Moretti, and Peters, 2018). Several studies document that acquirers' long-run performance can be predicted by characteristics known at the time of the announcement, potentially indicating that CAR does not incorporate all available information (Mitchell and Stafford, 2000; Dong, Hirshleifer, Richardson, and Teoh, 2006; Ben-David, Drake, and Roulstone, 2015). Other studies find that CAR is correlated with variables that are generally considered less informative about value creation, such as earnings-per-share accretion (Dasgupta, Harford, and Ma, 2019) and whether market sentiment is high (Rosen, 2006; Bouwman, Fuller, and Nain, 2009).

In this study, we attempt to bridge the chasm between the wide use of CAR and the lack of clarity regarding its economic content. We conduct a systematic analysis to validate

[3] See, e.g., Asquith, Bruner, and Mullins (1983), Schipper and Thompson (1983b), Malatesta and Thompson (1985), Roll (1986), Hietala, Kaplan, and Robinson (2003), Shleifer and Vishny (2003), Bhagat, Dong, Hirshleifer, and Noah (2005), Barraclough, Robinson, Smith, and Whaley (2013), Betton, Eckbo, Thompson, and Thornburn (2014), Jacobsen (2014), and Malmendier, Opp, and Saidi (2016).

[4] Healy et al. (1992) use industry-adjusted accounting performance; their sample comprises 42 completed acquisitions. Kaplan and Weisbach (1992) use loss from a future target sale as an indicator of failure. Their sample includes 108 completed acquisitions in which the acquirer later sold the target at a loss or a profit.

[5] Hoberg and Phillips (2018) find a weak correlation between CAR and only one of their expected integration measures. Li (2013) finds a weak (and controls-dependent) correlation between CAR and realized future productivity increases.

CAR as a measure of the expected value created by acquisitions. We use a large sample of acquisition announcements and devise several proxies for ex-post acquisition performance outcomes that either have been used in earlier literature or rely on elaborated disclosure in financial reporting. These performance measures are predictable using a standard list of deal and acquirer characteristics known at the time of the announcement. However, these ex-post performance measures have no material correlation with announcement returns, indicating that announcement returns may, on average, not sufficiently capture realized value creation. Most importantly, we find no material overlap (either in sign or magnitude) between the characteristics associated with announcement returns and those associated with ex-post performance measures. These findings indicate that announcement returns, on average, fail to reflect all information available at the time of the acquisition announcement. To put it more bluntly: announcement returns fail to predict even predictable acquisition outcomes.

Our sample contains nearly 1,900 acquisition announcements by U.S. public acquirers over 11 years (2003–2013). We follow the standards in the literature concerning data screens and characteristics studied.

Our main conjecture is similar to what researchers assume when using CAR to measure the quality of announced acquisitions: that CAR is equal to the discounted expected cash flows due to the acquisition. As such, it should be, on average, correlated with acquisition outcomes, or at least with deal and acquirer characteristics correlated with these outcomes.

We use several measures to quantify the ex-post performance of acquisitions. We rely on metrics used in earlier studies in the field and on recent advancements in financial disclosure that allow for the measure of deal-specific outcomes. At the transaction level, we design an indicator to measure acquisition failure. Specifically, we manually collect information on large deal-level goodwill impairments, i.e., accounting write-offs, which indicate that the target is no longer worth its original price.[6] We supplement the impairment indicator with an

[6]Unlike other commonly used measures of performance, our goodwill impairment data are linked to *specific* transactions rather than at the overall acquirer level. We validate that goodwill impairment is a robust signal of value destruction by relating it to several indirect symptoms of failure: poor stock and operating performance, distressed delisting, and management turnover. See Internet Appendix IA.B.2.

indicator for transactions for which targets are divested in later years at a loss (as in Mitchell and Lehn, 1990; Kaplan and Weisbach, 1992; Berger and Ofek, 1996). Combining these two indicators yields a direct and quantifiable representation of acquisition failure. At the acquirer level, we employ two widely used performance measures: abnormal return-on-assets (abnormal ROA, e.g., Healy et al., 1992; Harford and Li, 2007) and characteristics-adjusted buy-and-hold long-run stock returns (DGTW-adjusted BHAR, e.g., Daniel, Grinblatt, Titman, and Wermers, 1997; Mitchell and Stafford, 2000; Dong et al., 2006; Ben-David et al., 2015).[7] Importantly, despite being derived from different sources and capturing both the left-tail and the full distribution of outcomes, these ex-post measures are positively and significantly correlated.

In the first part of the study, we document that announcement returns are uncorrelated with each acquisition outcome (deal failure, abnormal ROA, and DGTW-adjusted BHAR). We find no meaningful correlation in univariate and multivariate settings, both in- and out-of-sample, across multiple announcement return windows and estimation techniques. In over 18 regressions, CAR achieves statistical significance at the 5% level in only one regression. The adjusted $R^2$s are minuscule: At best, CAR 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.

In the main part of the study, we explore the nature of the negligible correlation between announcement returns and acquisition outcomes. We first show that acquisition outcomes can be predicted reasonably well using a standard set of deal and acquirer characteristics known at the time of the announcement. These characteristics alone can explain 9.2% of the variation in acquisition failure. They explain 6.4% and 2.8% of the variation in abnormal ROA and DGTW-adjusted BHAR. These results are consistent with those of Ellahie, Hshieh, and Zhang (2022), who developed an ex-ante measure of acquisition quality constructed from accounting information, stock price, and deal-specific data and found their measure correlates with realized outcomes.

[7]Hoberg and Phillips (2018) find that long-run stock returns are strongly correlated with integration difficulty.

Next, we use an out-of-sample setting to benchmark the predictive properties of CAR to that of the characteristics known at the time of the announcement. We fit two models in the first half of the sample: a "CAR-only" model in which the explanatory variable is CAR, and a "characteristics-only" regression model in which the explanatory variables are characteristics.

We then study the ability of the fitted values to predict acquisition outcomes in the second half of the sample. Predictions made by the characteristics-based model load at least at the 5% level for all three outcome variables (deal failure, abnormal ROA, and DGTW-adjusted BHAR). In contrast, outcomes predicted by CAR do not correlate with any of the realized outcomes. These findings demonstrate the failure of CAR to predict realized acquisition outcomes.

We also assess the relation between CAR and the *predictable* component of acquisition outcomes. We find that the "CAR-only" model does not correlate with the predicted outcome of the "characteristics-only" model created from characteristics known at the time of the announcement. These results indicate that announcement returns do not reflect all relevant information at the time of the announcement.

We corroborate our inference of a wide disparity between the predictive ability of CAR and a characteristics model by forming out-of-sample three-year trading strategies. The strategies take long positions in the acquirers predicted by the characteristics (or CAR) model to perform the best and take short positions in those predicted to do the worst. We repeat this exercise for each of the three outcome variables. The performance spread in the three-year DGTW-adjusted BHAR between the top and bottom three deciles 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 final part of the paper, we consider how inferences regarding the "types" of transactions (defined by characteristics) that create or destroy value are altered due to the lack of association between announcement returns and ex-post outcomes.

We perform this analysis in both univariate and multivariate settings. We start by considering one characteristic at a time, exploring univariate associations between CAR and characteristics, and then between ex-post outcomes and characteristics. We find that the three ex-post outcomes (deal failure, abnormal ROA, and DGTW-adjusted BHAR) are associated with similar sets of deal and acquirer characteristics. Strikingly, we find no association (in terms of sign and relative importance) between the characteristics for which CAR predicts failure or success and those associated with failure or success ex-post. We then run related tests in a multivariate setting (allowing characteristics to enter the model all at once) and find similar results. Overall, our results indicate that CAR is not directly or indirectly associated with outcomes via characteristics. These results contrast the characteristics' moderate ability to predict transaction- and firm-level acquisition outcomes.

We close the empirical analysis by assessing the CAR-based inference about value creation, as often performed in the literature (and taught in business classes). The M&A literature tends to focus on the quality of acquisitions (based on CAR) in "clusters" that are defined using a combination of characteristics. We consider the four most common characteristics used in the literature (form of payment, target public status, acquirer size, and relative transaction size) to form 16 clusters and compute the average CAR and ex-post outcome for each cluster.

We find minimal overlap in the performance of clusters based on CAR and the performance based on our ex-post outcomes. For example, the cluster considered to create the most value, stock acquisitions of private targets of large relative size by small acquirers (average CAR of +3.6%), has, in fact, the poorest ex-post outcomes among the 16 clusters. Similarly, in the cluster considered to destroy the most value, large acquirers' stock acquisitions of public targets of small relative size (average CAR of −2.8%) are associated with ex-post outcomes in the top half of the quality distribution. These results, combined with previous results, indicate that inferences generated from CAR regarding the quality of types of transactions are unreliable.

In striking contrast to CAR's popularity as a measure of expected value creation, we find no evidence supporting this widely held axiom. Our analysis shows that announcement returns are not correlated with any of the realized outcome variables, nor are they correlated with the components of outcomes that can be predicted by characteristics ex-ante. These results indicate that acquirer CAR cannot reliably be used as a proxy for either expected or realized value creation in acquisitions. Furthermore, our results cast doubt on whether announcement returns incorporate all information available at the time of the announcement, as is often assumed about "market-based estimates." Researchers, therefore, should approach inferences generated using CAR with caution and should also utilize ex-post measures (or ex-ante measures that reliably correlate with ex-post measures) to assess acquisition performance.

# 2 Acquisitions Sample and Outcome Measures

In this section, we describe the construction of our acquisition sample and describe the measures we use to capture the performance of the acquisition. We employ both ex-ante and ex-post measures and metrics that capture both transaction-level and acquirer-level outcomes.

## 2.1 Acquisition Sample Construction

Our sample of mergers and acquisitions comes from the Thomson Reuters Securities Data Company (SDC) Domestic Merger and Acquisition database. Our sample starts in 2003, when we are able to begin tracking goodwill impairment at the transaction level due to the implementation of SFAS 142 in 2002. The sample ends in 2013 as we track firms' impairment and divestiture outcomes over a five-year period that ends in 2018 and tracking acquisition outcomes requires significant manual data collection.

We include transactions that satisfy the following criteria: (a) The merger or acquisition was announced 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;[8] (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 the 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. These requirements result in an initial sample of 2,981 deals.

We exclude 258 transactions by 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 either not structured using purchase accounting or for which we were unable to identify the deal-level goodwill allocation amount. We omit 110 transactions that lack the CRSP and Compustat data needed to compute key variables. These filters result in 1,967 transactions. As described below in Section 2.3.1, we collect goodwill and goodwill impairment data for each transaction. We eliminate deals for which impairment cannot be linked to a particular transaction or is of immaterial size. This further reduces our sample to 1,870 transactions.

## 2.2 Transaction-Level Ex-Ante Measure: Announcement Returns

We follow the literature in measuring announcement returns. We estimate daily abnormal returns using a market model and a value-weighted index. The market model parameters, $\alpha_i$ and $\beta_i$, are estimated from 361 to 61 trading days before the deal announcement day,

[8] We relax this filter for the analysis in Section 5.2.1, in which we explore the possibility that 7% of the withdrawn deals could explain the main results.

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 over a three-day period $[-1, 1]$ and an 11-day period $[-5, 5]$ surrounding each acquisition announcement, and over the entire acquisition process beginning two days before the announcement and ending two days following the deal completion $[\text{Announcement} - 2, \text{Close} + 2]$. 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.

## 2.3 Transaction-Level Ex-Post Measure: Transaction Failure

In general, it is challenging to measure the extent to which specific acquisitions create value for the acquirer in actuality. 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. To overcome this issue, we rely on increased transparency in accounting rules for goodwill impairment and targets that are eventually sold to construct a new transaction-level measure of acquisition failure.

We construct an indicator of whether acquisitions failed within five years of completion. In general, an acquisition is considered to have failed if it is worth less than its acquisition price. (similar definition in Kaplan and Weisbach, 1992). We detect failed transactions in the data based on either of the following events: (a) the goodwill associated with the transaction has been materially impaired, or (b) the target was sold at a loss. Hence, acquisition failure indicates whether either event took place.

In our sample, 20% of deals failed within five years. Of the subset of failed acquisitions, 30% occurred the year of or the year after the deal's effective date, and the remaining 70% of failures happened in the following four years. Further statistics about the distribution of failure events are provided in Appendix Table B.1, Panel A.

In the following subsections, we explain why goodwill impairment and divestiture-at-a-loss are reasonably good indicators of acquisition failure, and we describe how they are measured in the data.

### 2.3.1 Transaction Failure: Goodwill Impairment

To detect goodwill impairments, we manually construct a sample of transactions with large goodwill write-downs identified at the transaction level. These data offer a direct and quantifiable representation of acquisition failure.

Large goodwill write-down or "impairment" events, for three reasons, yield a powerful setting to measure ex-post value destruction in the acquiring firm. First, goodwill, which is defined as the portion of the purchase price in excess of the fair value of the targets identifiable net assets, reflects the going concern value of the target, the value of expected synergies, and overpayment. Therefore, the write-down of goodwill reflects value destruction caused by any of the following factors: overvaluation of existing assets, overestimated synergies, or the inability to realize synergies due to firm, industry, or economy-wide shocks. Second, the quality of goodwill impairment data has improved in recent years. The Statement of Financial Accounting Standards 142, passed in 2001, was implemented with the intent that unsuccessful acquisitions would be reflected more precisely and in a more timely manner in firms' financial statements. After the completion of an acquisition, firms must conduct routine annual impairment tests and nonroutine tests following "material" events to check for reductions in the value of goodwill.[9] The new standard also requires increased transparency for goodwill and impairment reporting at the reporting unit rather than at the firm level, making it easier to link impairment to a specific triggering transaction. Third, prior research has documented that goodwill impairment events are value relevant.[10]

We provide evidence that goodwill impairment is a signal of value destruction by re-

[9] In September 2011, FASB modified SFAS 142, so that formal valuations to produce comparisons of fair value and carrying value of a reporting unit are only required when certain qualitative indicators of impairment exist.

[10] See 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).

lating our impairment measure to several indirect symptoms of acquisition failure. First, the market reaction to earnings announcements that contain goodwill impairment news is negative and large in magnitude, $-2.6\%$ on average (Internet Appendix IA.B.2.1).[11] Second, CEOs are more likely to be fired in the period surrounding goodwill impairments than following negative CARs surrounding the original acquisition announcements (Internet Appendix IA.B.2.2). This finding indicates that the labor market regards impairment as an important signal for managerial discipline. Third, acquirers that impair goodwill are more likely to experience distressed delisting than acquirers without impairment subsequently (Internet Appendix IA.B.2.3). Fourth, acquirers with goodwill impairment experience poor operating and stock performance in the years following the acquisition relative to acquirers without impairment (Internet Appendix IA.B.2.4).

One drawback of goodwill impairment as a measure of acquisition failure is the potential for subjectivity. Researchers have documented managerial discretion in the write-down decision, mainly about the amount and timing of the impairment.[12] In this paper, we focus on substantial goodwill impairments, a setting in which strategic manipulation is less viable because extreme losses must be revealed at some point.[13] As we classify goodwill impairments as an ex-post measure of acquisition failure, the timing of write-downs does not matter as long as there is a write-down.

Linking goodwill impairment to specific transactions is not straightforward because 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. We begin by identifying all sample firms with firm-level goodwill impairments. For these potentially impaired transactions, we use 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

[11] 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 this stale negative news does not conflict with the main finding of the study that CAR is not associated with future changes in cash flows.

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

[13] Our sample includes impairment that is at least 5% of acquirers' assets and 25% of initial goodwill.

specific transaction in our sample. We focus on impairment within five years of the deal's effective date.[14]

Appendix A.1 provides further details about this data collection procedure and shows that we successfully linked impairment events to specific transactions. As reported in Appendix Table B.1, we find that goodwill impairments are common: 19% of transactions in our sample experience an impairment event. These events are substantial: the average impairment constitutes 87% of total transaction-level goodwill, 45% of the total purchase price, and 11% of acquirer assets. Overall, the aggregate impairment loss in our sample is $102 billion.

### 2.3.2 Transaction Failure: Divestiture-at-a-Loss

Early studies of value creation by M&As looked at whether a transaction was sold at a later date at a loss. Despite the selection concern (which targets are divested at a later date), divestitures allow introspection into firms' original acquisition decisions (Mitchell and Lehn, 1990; Kaplan and Weisbach, 1992; Berger and Ofek, 1996). Divestiture-at-a-loss, therefore, is considered another proxy for ex-post acquisition failure.

To identify divestitures, we collect from SDC 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 (i.e., the target was divested at a

[14] To our knowledge, we are the first to construct a comprehensive dataset 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 was generally less comprehensive.

loss). We further eliminate partial divestitures of the target. Appendix A.2 describes how we collect divestiture data in greater detail.

Our procedure yields 17 transactions that were divested at a loss and whose goodwill was not impaired in earlier years.[15] On average, the losses recorded in divestitures-at-a-loss are large, representing 58% of the original purchase price (see Appendix Table B.1, Panel B).

## 2.4 Firm-Level Ex-Post Measure: Abnormal Return-on-Assets

Some studies approximate the contribution of acquisitions to the acquirers' cash flows by calculating their abnormal ROA (e.g., Healy et al., 1992; Chen, Harford, and Li, 2007; Fu, Lin, and Officer, 2013). The motivation is that the change in the acquirer's cash flows can be detected relative to an industry counterfactual.

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

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

where the residual $\varepsilon_i$ measures the abnormal change in ROA. We define the post-acquisition (pre-acquisition) period as the three years beginning the year after (before) the deal's 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-acquisition operating performance could predict post-acquisition operating performance.

[15] For comparison, Guenzel (2019) finds a similar rate of divestiture activity using SDC data. For 5,893 transactions over 36 years, 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 divestitures recorded at a loss.

## 2.5 Firm-Level Ex-Post Measure: Long-Term Abnormal Returns

Another measure widely used in the literature for value creation is long-term buy-and-hold abnormal stock returns (BHAR). In theory, if CAR captures all the information about the value created, then abnormal long-run returns should not be predictable based on information known at the time of the announcement. However, a large literature has documented that deal- and acquirer-level characteristics explain long-term abnormal returns (Mitchell and Stafford, 2000; Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf, Robinson, and Viswanathan, 2005; Dong et al., 2006; Fu et al., 2013; Ben-David et al., 2015). At face value, this literature may imply that CAR may not capture all the information available at the time of the announcement. However, CAR may still be a useful indicator for value creation, for example, if it is correlated with future returns but systematically over- or under-reacted.

We measure cumulative buy-and-hold returns by accumulating DGTW-adjusted monthly returns (Daniel et al., 1997) since the deal's completion. The DGTW adjustment procedure involves adjusting returns by the returns of benchmark portfolios based on characteristics. Each month, we form $5 \times 5 \times 5$ portfolios based on size, the book-to-market ratio, and 12-month past returns. The monthly adjusted returns are accumulated to form buy-and-hold returns over the three years beginning the month following the deal's effective date.[16]

## 2.6 Descriptive Statistics of Outcome Measures

Table 1 Panel A shows summary statistics for our measures. On average, 19.5% of transactions experience impairment or divestiture-at-loss events. The average acquirer has a small positive abnormal ROA of 0.12% and DGTW-adjusted buy-and-hold returns of −2.4% in the three years following the acquisition. On average, announcement returns are positive: the three-day and 11-day CARs and the CAR over the announcement to deal-closing period range from 0.42% to 1.19%.

[16] Alternative ways to adjust returns would be to use a market adjustment, beta adjustment, industry adjustment, or no adjustment. In unreported tests, our conclusions are not sensitive to the choice of return adjustment.

**Table 1. Descriptive Statistics of the Measures**

This table reports descriptive statistics of the ex-ante and ex-post measures of acquisition quality. Panel A presents summary statistics, and Panel B shows correlations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Panel A: Summary Statistics**

| | Mean | Median | Std Dev | P10 | P90 |
|---|---|---|---|---|---|
| Failure Dummy | 19.50% | 0.00% | 39.63% | 0.00% | 100.00% |
| Abnormal ROA | 0.12% | 0.21% | 7.67% | −6.04% | 7.00% |
| DGTW-adjusted BHAR | −2.40% | −5.07% | 51.60% | −62.78% | 61.52% |
| $\mathrm{CAR}[-1, 1]$ | 1.14% | 0.86% | 7.66% | −6.57% | 9.36% |
| $\mathrm{CAR}[-5, 5]$ | 1.19% | 1.01% | 10.45% | −10.20% | 13.08% |
| $\mathrm{CAR}[\mathrm{Ann}-2, \mathrm{Cls}+2]$ | 0.42% | 0.55% | 17.24% | −18.95% | 19.67% |

**Panel B: Correlations**

| | | | | CAR | | |
|---|---|---|---|---|---|---|
| | Failure | Ab ROA | Adj-BHAR | $[-1, 1]$ | $[-5, 5]$ | $[\mathrm{Ann}-2, \mathrm{Cls}+2]$ |
| Failure Dummy | 1.000 | | | | | |
| Abnormal ROA | −0.216*** | 1.000 | | | | |
| DGTW-adjusted BHAR | −0.309*** | 0.310*** | 1.000 | | | |
| $\mathrm{CAR}[-1, 1]$ | −0.035 | 0.051** | −0.031 | 1.000 | | |
| $\mathrm{CAR}[-5, 5]$ | −0.002 | 0.011 | −0.041* | 0.735*** | 1.000 | |
| $\mathrm{CAR}[\mathrm{Ann}-2, \mathrm{Cls}+2]$ | −0.033 | 0.030 | 0.002 | 0.490*** | 0.539*** | 1.000 |

Of particular interest are the correlations between our three ex-post outcome variables, as well as the correlations between the ex-post outcomes variables and CAR. Table 1 Panel B 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 these measures capture similar outcomes. In contrast, CAR has little correlation with these ex-post acquisition outcome measures, with absolute correlation coefficients ranging from 0.002 to 0.051.

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

# 3 Predicting Acquisition Outcomes Using CAR

## 3.1 In-Sample Tests: Visual Examination

We begin by examining the unconditional relation between transaction- and acquirer-level outcomes and CAR. The implicit assumption behind the use of CAR as an estimate of value creation is that CAR is positively correlated with ex-post outcomes.

The results of the visual examination are presented in Figure 1. We sort CAR$[-1, 1]$ into 20 equally-sized bins (about 90 transactions in each bin) and present the related outcome statistics.

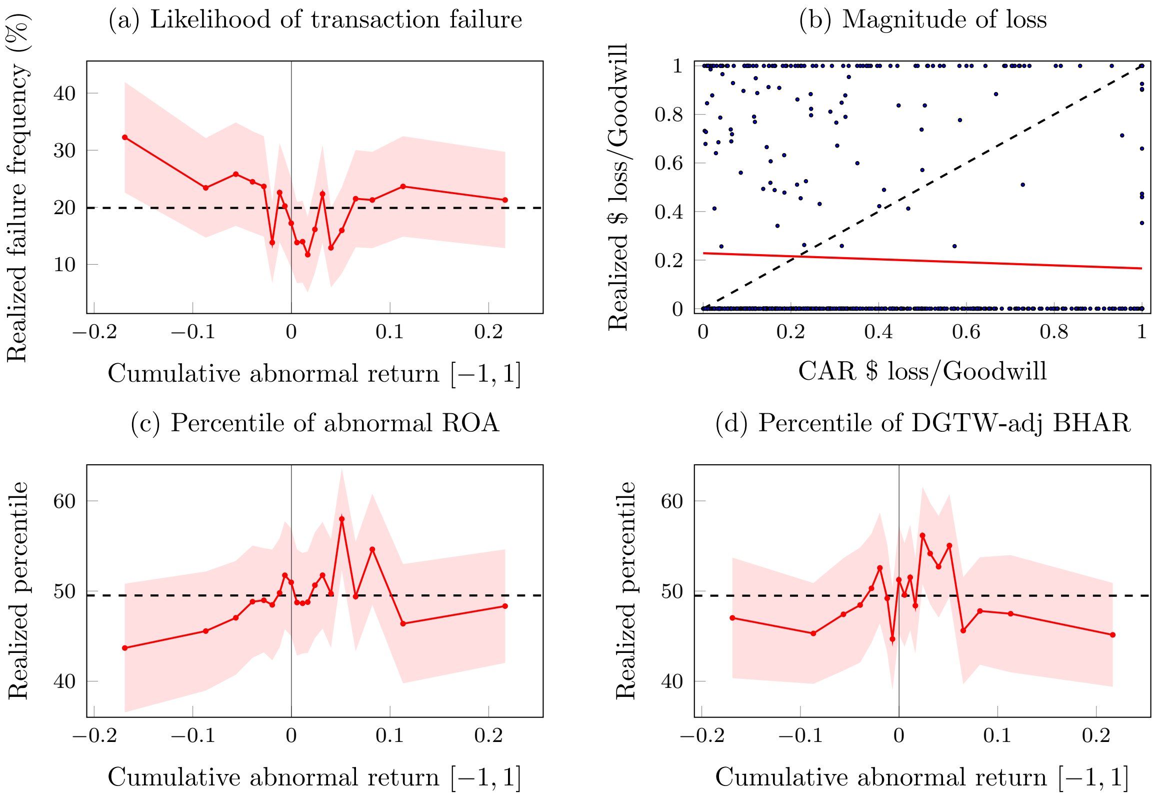
In Panel (a), we present the fraction of transactions that failed (based on goodwill impairment and divestiture at-a-loss). The panel shows little correlation between the realized likelihood of deal failure and CAR vigintiles. Panel (b) presents a scatter plot of the realized dollar loss (either through impairment or divestiture-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 relationship 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 (percentiles within the sample) and CAR vigintiles. Panel (d) presents the relation between the DGTW-adjusted BHAR (percentiles within the sample) and CAR vigintiles. Neither chart shows any meaningful correlation between firm-level outcomes and CAR.

Overall, a first visual pass reveals no meaningful association between transaction- and acquirer-level outcomes and CAR.

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

Panel (a) plots the propensity of impairment or divestiture (the percentage of transactions with realized failure) for each acquirer's CAR$[-1, 1]$ vigintile (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-at-a-loss in our sample. Panel (b) presents a scatter plot of dollar realized versus expected value loss implied by CAR. Both realized and expected losses 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 the 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 vigintile of CAR. The light red shading represents 95% confidence intervals.




## 3.2 In-Sample Tests: Univariate and Multivariate Analyses

Next, we explore the correlation between the various outcome variables and CAR in a regression framework. Table 2 reports regressions with acquisition outcome measures as the dependent variables and acquirer CARs over various windows surrounding the deal announcement as the key independent variables of interest. Panel A reports the results of logit regressions that model the probability of failure within five years of the deal's effective date. Panel B reports the results of ordinary least squares (OLS) regressions with abnormal ROA as the dependent variable, and Panel C reports the results of OLS regressions with DGTW-adjusted buy-and-hold returns as the dependent variable. Some regressions include the following acquirer and deal characteristics as controls: 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.

The results in Table 2, Panel A, show that CAR explains 0.1% of the variation in the probability of failure (Columns (1)–(3)).[17] The coefficient on CAR is not statistically significant in any of the three models. In Panel A, CAR remains insignificant when year (Column (4)); year and industry (Column (5)); and year, industry, and characteristics (Column (6)) are included as controls. Column (7) includes year and industry fixed effects and characteristics only, as a benchmark for their explanatory power.[18]

The results are qualitatively similar when considering firm-level outcome measures. In Panels B and C of Table 2, we conduct in-sample tests for our firm-level ex-post acquisition outcome measures. In Panel B, which uses abnormal ROA as the dependent variable, the coefficient on acquirer CAR has the correct sign but is statistically significant at the 10% level for only two of the six regressions. In Panel C, where DGTW-adjusted BHAR is the dependent variable, the coefficient on acquirer CAR does not have the correct sign or is statistically insignificant in all six regressions. In Panels B and C of Table 2, in Column (1), CAR explains 0.2% (at most) of the variation in abnormal ROA and DGTW-adjusted BHAR.

We conduct several robustness tests of our in-sample results. First, in Appendix Table C.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.

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

[18]We also find that CAR also cannot predict magnitudes or scaled-dollar losses associated with impairment or divestiture (Internet Appendix Table IA.C.1, Panel B). As in Table 2, Panel A, the coefficient on scaled-dollar CAR is not statistically significant at the 10% level in any of the six regressions.

## Table 2. Acquirer CAR and Acquisition Outcomes

This table reports results from regressions of acquisition outcome measures on acquirer cumulative abnormal returns (CAR). The dependent variable is a failure dummy (logit; Panel A), abnormal ROA (Panel B), and DGTW-adjusted buy-and-hold returns (Panel C). In Columns (1)–(3), CAR is the only independent variable, and in addition to CAR, Column (4) includes year fixed effects, Column (5) includes year and industry fixed effects, and Column (6) includes year and industry fixed effects, as well as characteristics as independent variables. Column (7) includes only year and industry fixed effects, and characteristics as independent variables. Controls include log market capitalization, leverage, and free cash flow scaled by lagged 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. ***, **, 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: | [−1, 1] | [−5, 5] | [Ann − 2, Cls + 2] | [−1, 1] | | | n.a. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CAR | −1.248 | −0.075 | −0.552 | −0.891 | −0.974 | −0.214 | Controls |
| | (0.861) | (0.634) | (0.376) | (0.881) | (0.889) | (0.132) | only |
| Controls | – | – | – | Year | Year, Ind | Year, Ind, Char | Year, Ind, Char |
| Observations | 1,805 | 1,805 | 1,804 | 1,805 | 1,805 | 1,805 | 1,805 |
| Pseudo $R^2$ | 0.001 | 0.000 | 0.001 | 0.049 | 0.057 | 0.093 | 0.092 |

**Panel B: Abnormal ROA**

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

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

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

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, for the subsample of acquisitions in which the target is public (19% of acquisitions), we explore whether the combined CAR of acquirers and targets is informative about the acquisition outcomes. Additionally, in this set of regressions, CAR does not appear to have any meaningful predictive power (Appendix Table C.1, Column (3)).

To summarize, our in-sample tests show that CAR is uninformative about acquisition outcomes. In most specifications, the relation between CAR and the acquisition outcome is not statistically different from zero. When CAR is statistically significant, the magnitude of the variation explained is minute.

# 4 Predicting Outcomes: CAR Versus Characteristics

In this section, in addition to announcement returns, we also consider the predictive properties of other ex-ante measures, specifically, deal and firm characteristics that are also known at the time of the transaction announcement. These ex-ante characteristics serve as a relative benchmark that allows us to better gauge the performance of CAR in predicting acquisition performance realizations.

We consider the standard characteristics utilized in the M&A literature: the logarithm of market capitalization, leverage, 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, competing bidders, and public targets.

## 4.1 In-Sample Tests

We demonstrate the in-sample predictive power of deal and acquirer characteristics in Table 2, presented in the previous section. Column (7) of Panels A–C shows that year and industry controls and deal and firm characteristics alone can explain 9.2% of the variation in acquisition failure (Panel A), 6.4% of the variation in abnormal ROA (Panel B), and 2.8% of the variation in DGTW-adjusted BHAR (Panel C). In contrast, CAR, at best, explains 0.2% of the variation (Columns (2)–(4)) across all three panels.[19] Notice also that in Column (6) of all three panels, CAR increases the explanatory power of outcomes in a model with industry controls and deal and firm characteristics by a meager 0.1%.

To summarize, if the market reaction to the announcement provides additional information related to deal value creation over and above the information contained in the deal and firm characteristics, then the CAR-alone model should perform well (Columns (1)–(3) in all panels in Table 2). It does not. In addition, a model that combines CAR and the characteristics model (Column (6)) should significantly outperform the characteristics-only model (Column (7)). It does not. Deal and firm characteristics, also known at the deal announcement date, dominate acquirer CAR as predictors.

## 4.2 Out-of-Sample Tests

Next, we compare the ability of CAR versus characteristics-based models to predict deal and acquirer outcomes in out-of-sample settings.

### 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 Column (7) of Table 2 as the independent variable. (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

[19] The full results are reported in Appendix Tables D.1 and D.2.

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's effective date). Our analysis examines the ability of characteristics and CAR to predict outcomes in the second period, which is an out-of-sample because this later period was not used to estimate the model's parameters.[20]

### Table 3. 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 (2008–2013). In Panel A, we assess the correlation between realized outcomes and predicted outcomes produced 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) |
| CAR$[-1, 1]$ | 0.062 | | −0.015 | | −0.106 | |
| | (0.069) | | (0.009) | | (0.065) | |
| 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 |

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

We then compare the quality of the predictions made by CAR and the characteristics-based model out-of-sample. We present the results in Table 3. Panel A 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 for all three outcomes.

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 3, which reports results for regressions of the predicted outcome by the characteristics-only model on acquirer CAR. Results show that acquirer CAR in the later sample is either not correlated with the *predictable* part of acquisition outcomes or has the wrong sign.

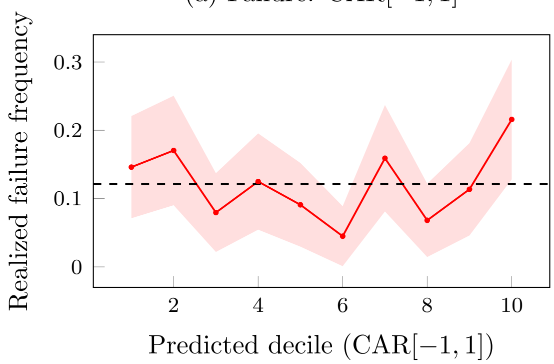
In Figure 2, we present out-of-sample tests graphically that are similar in spirit to the tests reported in Table 3. For the transaction-level failure measure (impairment or divestiture-at-a-loss), we estimate logit models of failure on CAR or characteristics. We then use the coefficients estimated in 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 failure 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

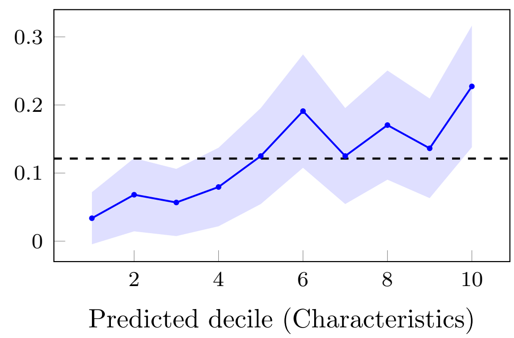
## Figure 2. Out-of-Sample: Predicted Versus Realized Outcomes

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-adjusted BHAR deciles. Using the estimates, we obtain predicted outcome deciles for 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 abnormal ROA and DGTW-adjusted BHAR) for the second half of the sample. The shaded portion represents the 95% confidence interval.

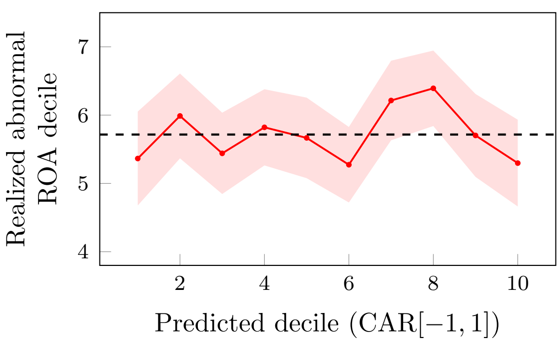
(a) Failure: CAR$[-1, 1]$



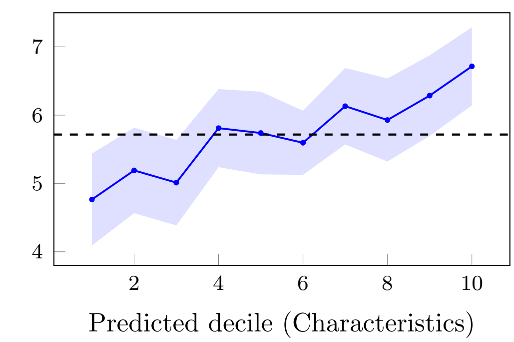

(b) Failure: Characteristics



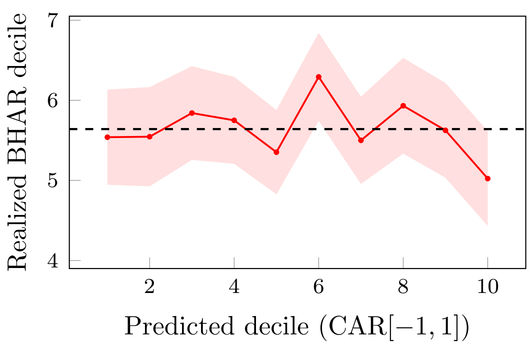

(c) Abnormal ROA: CAR$[-1, 1]$



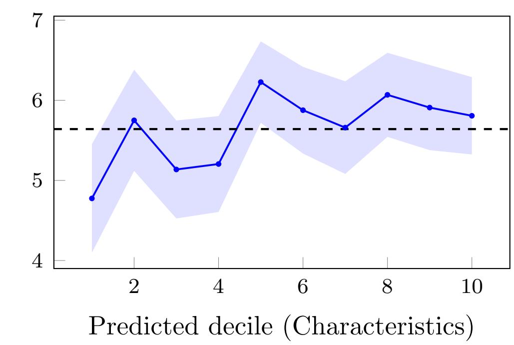

(d) Abnormal ROA: Characteristics




(e) DGTW-adj BHAR: CAR$[-1, 1]$




(f) DGTW-adj BHAR: Characteristics



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 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.

Another way to make this point is to notice that 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 acquisition outcomes, whereas acquisition outcomes can be predicted relatively well by characteristics known at the time of the announcement. These results relate to Ellahie et al. (2022), who developed an implied return-on-equity improvement measure (IRI) that quantifies the minimum post-acquisition ROE in the target firm that the acquirer must generate to justify the price paid for the target. The measure, which serves as an ex-ante index of acquisition quality, is constructed using multiple aspects of the transaction that include deal, target, and acquirer information, and it requires inputs generated from stock, accounting, and transaction-related data. The authors find that acquirers with high IRI are associated with lower stock returns, worse accounting performance, and higher firm-level goodwill write-downs in the years following the acquisition.

### 4.2.2 Trading on CAR Versus Characteristics

We further substantiate our conclusion about CAR's lack of predictive ability by devising a trading strategy. In Table 4, similar to our out-of-sample tests in Table 3, we use the first half of the sample (2003–2007) 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 (2008–2013). 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 after the deal's effective date.

**Table 4. Trading Strategy Based on CAR and Characteristics**

This table reports three-year equal-weighted DGTW-adjusted 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 years of the sample (2003–2007). We then compute the imputed outcome for the later years of the sample (2008–2013) and sort predicted values into 10 outcome deciles. We report the equal-weighted three-year DGTW-adjusted BHAR 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 | | 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 |

We summarize the trading results (using DGTW-adjusted BHAR to compute returns) in Table 4. 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 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 Which Deals Create Value?

Another way to investigate the performance of CAR is to consider the quality of inferences regarding deal quality generated from announcement returns relative to ex-post measures. To do so, we consider "types" of transactions (defined by deal, target, or acquirer characteristics) that CAR predicts will create or destroy the most value, and then relate these deal types to realized outcomes. 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

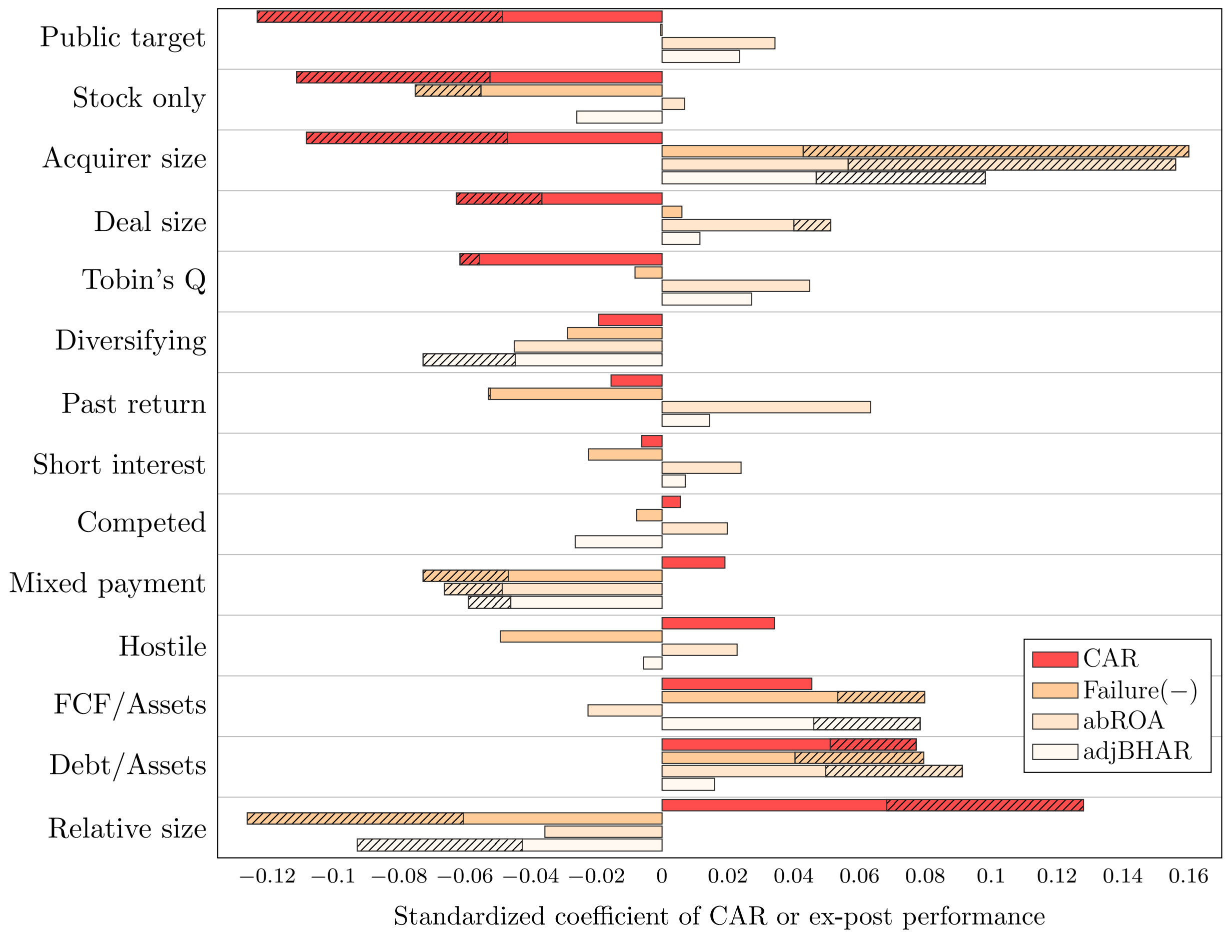
First, we explore univariate associations of CAR and characteristics. Specifically, we run 14 regressions of CAR on observed characteristics (one characteristic per regression). After recording the coefficients, we replace CAR with the three ex-post outcomes and repeat the exercise. Overall, we have 56 coefficients ($14 \times 4$). 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. Past returns and short interest are computed in the quarter and month prior to the announcement, respectively.[21]

To compare how characteristics predict CAR and how characteristics predict realized outcomes, we standardize the coefficients and present them in Figure 3. The coefficients are sorted by characteristics that predict the lowest CAR (public target, stock-only transactions, large acquirers) to those that predict the highest CAR (large relative size transactions, acquirers with high leverage, free cash flow). In general, the relations between CAR and characteristics that we document match those found in earlier studies that explore the relation between CAR and characteristics, although often in different periods and samples. We also add 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.

[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 3. Correlation of CAR and Outcomes with Characteristics**

The bar chart shows the standardized coefficients for regressions in which the dependent variable is CAR, failure, abnormal ROA, or DGTW-adjusted buy-and-hold returns (BHAR) on the 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 bars indicate the standardized coefficients 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. Past returns and short interest are computed in the quarter and month prior to the announcement, respectively.




Two important inferences can be drawn from Figure 3.

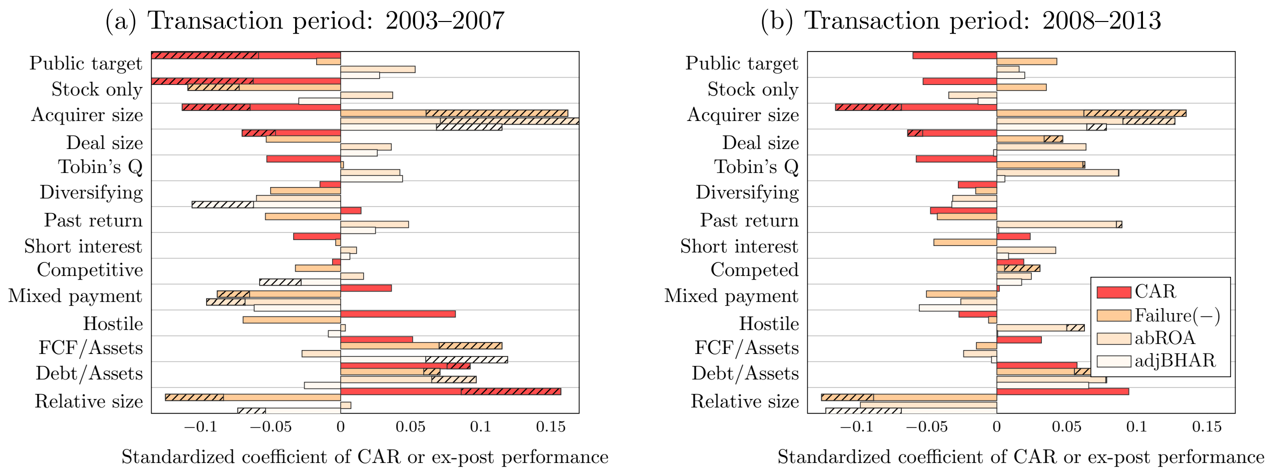
First, the three ex-post outcomes are all correlated. This finding implies that characteristics associated with a high likelihood of failure (e.g., high relative size) are also associated with poor ex-post performance, as indicated by low abnormal ROA and low DGTW-adjusted BHAR. This fact provides further validation of our three proxies for acquisition quality.

Second, and strikingly, Figure 3 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 low CARs but are not associated with an increased rate of failure, low abnormal ROA, or low DGTW-adjusted BHAR.

One might wonder whether this mismatch is an artifact of our specific sample period. To check this, we split the sample into two periods—transactions completed in 2003–2007 and transactions completed in 2008–2013—and reproduce the chart for the two time periods. The results are presented in Figure 4. The charts show that the patterns are similar for the two halves of the sample. For both time periods, there is often a mismatch between the types of deals predicted to do well or to destroy value by CAR and the ex-post realizations of these deal types. Also important, the ex-post outcomes associated with the different acquisition characteristics are consistent across the two halves of the sample; hence, they are not likely to be driven by noise.

**Figure 4. Correlation of CAR and Outcomes with Characteristics, by Period**

The bar charts show the standardized coefficient for regressions in which the dependent variable is CAR, failure, abnormal ROA, or DGTW-adjusted BHAR on the various deal and firm characteristics. Panel (a) comprises transactions completed in 2003–2007, Panel (b) comprises transactions completed in 2008–2013. 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 bars indicate the standardized coefficients 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. 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.




Overall, the results in this section show that the inferences about the quality of acquisition decisions generated by CAR are inconsistent with the inferences generated from ex-post measures. This finding does not appear to be a fluke, but rather a robust result over time.

### 4.3.2 Multivariate Tests

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

In Table 5, 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

**Table 5. Characteristics Associated with CAR and with Ex-Post Outcomes**

The left-hand side of this table reports results from the OLS regression of announcement returns over three return windows ($[-1,1]$, $[-5,5]$, [Announcement$-2$, andClose$+2$]) on deal and firm characteristics. Standard errors are reported in parentheses under the coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All regressions include constants, the coefficients of which are not reported. On the right-hand side of this table, 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. We only report signs that are statistically significant at the 10% level or higher. See Appendix Table D.1 and Appendix Table D.2 for these specifications.

| Dependent variable: | Acquirer CAR | | | | | |
|---|---|---|---|---|---|---|
| CAR window: | $[-1,1]$ | $[-5,5]$ | [Ann$-2$, Cls$+2$] | Predicted Sign Implied by... | | |
| | (1) | (2) | (3) | Failure | Ab ROA | Adj-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 | 1,805 | 1,805 | 1,804 | | | |
| Adjusted $R^2$ | 0.052 | 0.039 | 0.039 | | | |

based on similar specifications in which ex-post outcomes are regressed on deal and acquirer characteristics. We only report signs that are statistically significant at the 10% level or higher. 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 5 show that when deal and firm characteristics predict successful (unsuccessful) realized acquisition 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. For example, for the 10 characteristics that are statistically significant in the three right columns when outcomes are the dependent variables, the coefficient on the characteristic in the three left columns when CAR is the dependent variable is either the wrong sign or not statistically significant for seven of the characteristics.

#### 4.3.3 Combining CAR-Based Inferences into a Single Predictor

We further consider the combination of characteristics, as is often used in the M&A literature. Earlier studies have found that announcement returns are persistently associated with particular characteristics. Hence, based on the belief that announcement returns measure value creation, researchers have concluded that deals with certain characteristics create value for acquirers, on average, while others destroy value.

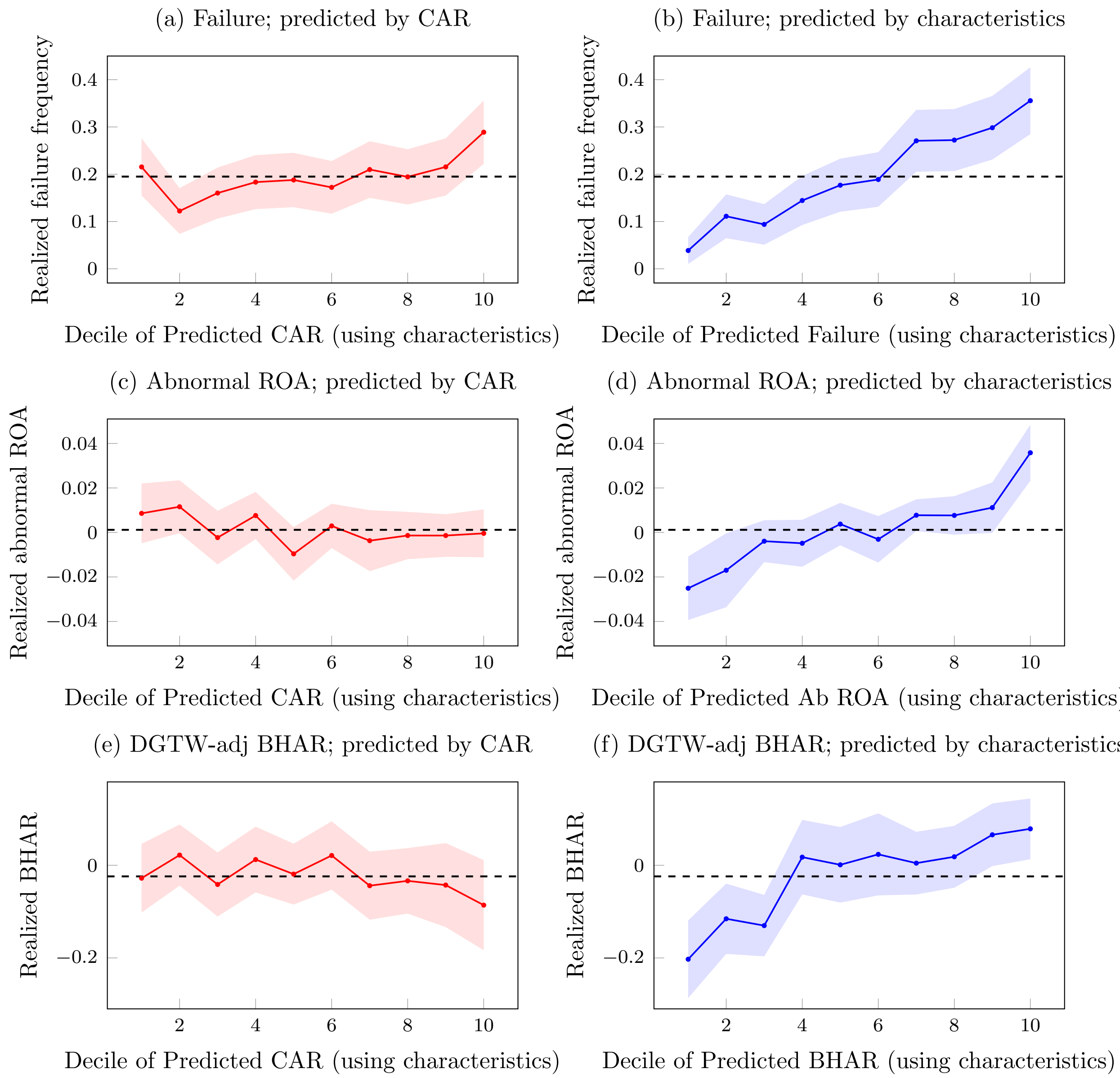
We construct a single measure of CAR-predicted deal success based on characteristics. For example, a stock transaction of a public target by a large acquirer would be considered to be a value-destroying transaction as all of these characteristics are associated with negative CAR. We first compile the individual coefficients by predicting CAR from Table 5, 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.

Our analysis uses these predictive regressions to explore whether high-NPV transactions according to CAR are indeed associated with better ex-post outcomes. In the three panels on the left-hand side of Figure 5, Panels (a), (c), and (e), 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 (c) and (e) show no relation between ex-post performance, as measured by abnormal ROA and DGTW-adjusted BHAR, and the combined CAR predictor.

We next test whether characteristics do a better job of predicting ex-post outcomes. We utilize the coefficients in Column (1) of Appendix Table D.1 to obtain an in-sample failure predicted by characteristics, and then sort these predicted failures into deciles. We use the coefficients in Columns (1) and (5) of Appendix Table D.2 to obtain in-sample abnormal ROA predicted by characteristics and in-sample predicted DGTW-adjusted BHAR predicted by characteristics, respectively. We then sort these two predicted variables into deciles. On the right-hand side of Figure 5, for each predicted decile, we report realized failure frequency (Panel (b)), average realized abnormal ROA (Panel (d)), and average realized DGTW-adjusted BHAR (Panel (f)). All three panels show a positive slope, suggesting that characteristics are good predictors of ex-post outcomes.

## Figure 5. CAR-Based Predictors versus Characteristics-Based Predictors

We utilize the coefficients in Table 5, Column (1) (a 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. On the left-hand side of the figure, for each predicted CAR decile, we report (solid red line) realized failure frequency (Panel (a)), average realized abnormal ROA (Panel (c)), and average realized DGTW-adjusted BHAR (Panel (e)). The red shading indicates the 95% confidence intervals. We utilize the coefficients in Column (1) of Appendix Table D.1 to obtain in-sample predicted failure, and then sort predicted failures into deciles. We use the coefficients in Columns (1) and (5) of Appendix Table D.2 to obtain in-sample predicted abnormal ROA and in-sample predicted DGTW-adjusted BHAR, respectively, and sort the predicted variables into deciles. On the right-hand side of the figure, for each predicted decile, we report (solid blue line) realized failure frequency (Panel (b)), average realized abnormal ROA (Panel (d)), and average realized DGTW-adjusted BHAR (Panel (f)). The blue shading indicates the 95% confidence intervals.



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.

## 4.4 Following the Literature's Advice

We zoom in on determinants of acquisition quality that have been discussed in the literature (and taught in the classroom) most commonly: form of payment, target status as public or private, acquirer size, and relative transaction size.[22] In total, we form 16 combinations of these characteristics (in their binary forms).

We classify acquisitions into the relevant characteristic combinations and calculate both their average CAR and their average ex-post outcomes. Table 6 presents the results for the 16 characteristic combinations. The combinations are sorted by their average CARs. To facilitate interpretation, statistics within each column are color-coded from red (signifying the worst performance) to green (signifying the best performance) for each measure.

The table shows no positive association between announcement returns and ex-post outcomes. If anything, the association is negative. The transactions ranked as having the best performance according to CAR (+3.6%) have the following acquisition characteristics: not limited to cash, private target, small acquirer, and large relative size. However, their ex-post outcomes are the worst: 32% of them fail; their average abnormal ROA is −0.8%; and their average DGTW-adjusted BHAR is −10%. In contrast, the bottom half of the characteristic combinations according to CAR are almost all ranked in the top half of outcomes.

Overall, these results reiterate our earlier findings demonstrating that CAR is not a reliable indicator of acquisition quality.

[22] For research that links announcement returns to these four characteristics see, e.g., Travlos (1987), Morck, Shleifer, and Vishny (1990), Chang (1998), Andrade, Mitchell, and Stafford (2001), Fuller, Netter, and Stegemoller (2002), Moeller, Schlingemann, and Stulz (2004), Moeller, Schlingemann, and Stulz (2005), Faccio, McConnell, and Stolin (2006), Officer (2007), Bayazitova, Kahl, and Valkanov (2012), Harford, Humphry-Jenner, and Powell (2012), and Schneider and Spalt (2022).

**Table 6. Acquisition Outcomes and CAR Grouped by Characteristics**

This table reports the average of the acquisition outcome variables and CAR for acquisitions grouped by the characteristics identified by the extant literature as being correlated with CAR. *Rank* is the average rank of the three outcome variables. To facilitate interpretation, statistics within each column are color-coded from red (signifying the worst performance) to green (signifying the best performance) for each measure.

| Acquisition characteristics | | | | | | Ex-post outcomes | | | |
|---|---|---|---|---|---|---|---|---|---|
| Cash Only | Public Target | Large Acquirer | Large Relative Size | N | Avg CAR[−1, 1] | Failure | Ab ROA | Adj-BHAR | Avg Rank |
| | | | Y | 281 | 0.036 | 0.317 | −0.008 | −0.102 | 1 |
| Y | | Y | Y | 117 | 0.035 | 0.145 | 0.015 | −0.013 | 12 |
| Y | | | Y | 200 | 0.026 | 0.225 | −0.003 | −0.050 | 6 |
| Y | Y | | Y | 27 | 0.024 | 0.259 | 0.006 | −0.088 | 5 |
| | | Y | Y | 96 | 0.020 | 0.177 | −0.002 | −0.136 | 4 |
| Y | Y | Y | Y | 65 | 0.014 | 0.169 | 0.008 | −0.048 | 9 |
| | | | | 176 | 0.012 | 0.261 | −0.018 | −0.038 | 2 |
| Y | | | | 193 | 0.005 | 0.161 | −0.017 | 0.007 | 7 |
| | | Y | | 174 | 0.004 | 0.138 | 0.007 | −0.053 | 10 |
| | Y | | | 12 | 0.002 | 0.167 | 0.023 | 0.015 | 12 |
| Y | | Y | | 274 | 0.002 | 0.120 | 0.015 | 0.063 | 15 |
| Y | Y | Y | | 77 | −0.001 | 0.104 | 0.016 | 0.031 | 16 |
| Y | Y | | | 6 | −0.019 | 0.167 | 0.008 | 0.043 | 11 |
| | Y | Y | Y | 100 | −0.027 | 0.240 | 0.001 | 0.024 | 8 |
| | Y | | Y | 45 | −0.028 | 0.289 | −0.016 | −0.030 | 3 |
| | Y | Y | | 27 | −0.028 | 0.148 | 0.011 | 0.088 | 14 |

# 5 The Information Contained in CAR

Our tests thus far indicate that announcement returns may fail to capture both expected and realized value creation in acquisitions. In the final section of our analysis, we consider three potential explanations for CAR's lack of predictive ability: (a) CAR is noisy due to uncertainty about acquisition outcomes at the time of the announcement; (b) CAR has an attenuation due to truncation from cancelled bids or endogeneity due to feedback effects; and (c) CAR is mismeasured (i.e., window size around announcement).[23]

[23]There are other explanations for the failure of CAR, most notably (as described in the Introduction) related to the fact that CAR is an aggregate signal that captures both transaction and acquirer standalone related information. We acknowledge that this issue likely materially contributes to the problem, but it is difficult to address. 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 outcomes. Of course, all studies that utilize CAR to assess value creation will suffer from this issue.

## 5.1 Outcome Uncertainty and the Information Environment

M&A transactions are inherently complex and involve a high degree of uncertainty. This uncertainty could make outcomes difficult to predict. Our results in Section 4 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 Table 2), where the dependent variable is the outcome within a particular time period relative to the deal's effective date (up to five years). In Figure 6, we plot the coefficients 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 of panels the $R^2$ from the standard regression of deal and acquirer characteristics (without industry or year fixed effects).

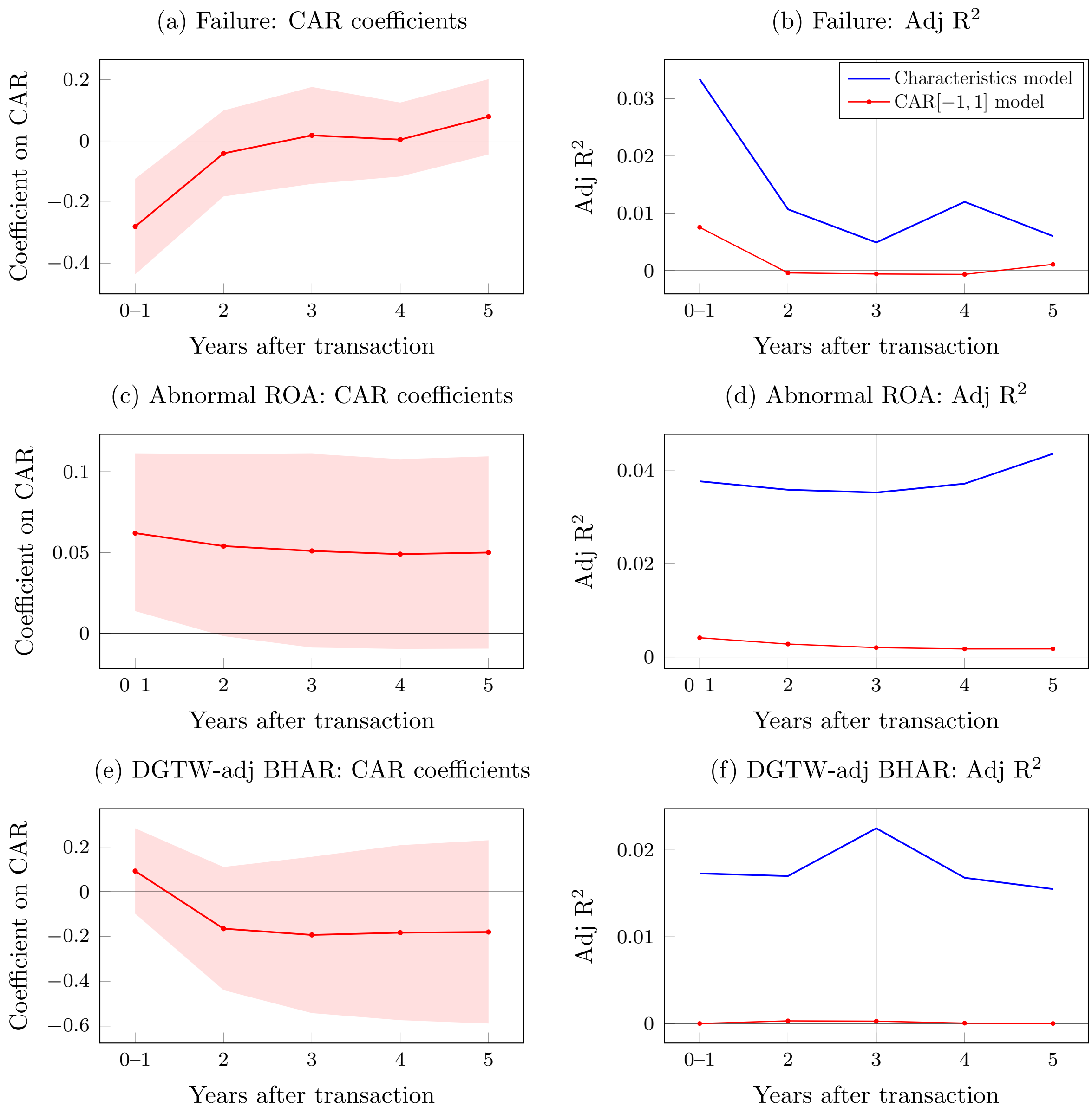
The figure shows that CAR is statistically significant only for failure and abnormal ROA outcomes that take place in the first year. The $R^2$ for first-year predictions is 0.8% for failure. Later outcomes are unrelated to CAR, even though they can be predicted reasonably well using deal and acquirer characteristics with an $R^2$ of 2% (DGTW-Adjusted BHAR) to 4% (abnormal ROA).

These results provide some evidence that CAR performs better for outcomes that occur relatively soon after the deal completion date. However, the weak explanatory power as well as the superior performance of characteristics known at the time of the announcement makes CAR a somewhat ineffective predictor of value creation even in the short term.

Second, we consider the information environment at the time of the announcement. Does the market have enough information to accurately measure value creation? Appendix IA.D shows that, on the margin, CAR's ability to detect value destruction is better in certain sub-samples that likely have superior information environments. For example, when transaction-

## Figure 6. Predictive Performance of CAR vs 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. Panels (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 deal and firm characteristics. In Panels (a) and (b), in the Year 1 regression, the dependent variable is the failure dummy. In the Year 2 regression, we exclude firms with failed transactions within one year, and the dependent variable is the failure dummy in Year 2. The Year 3 regression excludes firms with failed transactions in Years 1 or 2, and the dependent variable is the failure dummy in Year 3. Year 4 and Year 5 regressions are computed in a similar fashion. In Panels (c)–(f), we measure abnormal ROA and DGTW-adjusted 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.



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.

## 5.2 Truncation Due to Withdrawals or Feedback Endogeneity

So far, our analysis implicitly assumes that completed deals are a random sample of those that were announced, and that ex-post outcomes are not affected by management who heeds 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.

### 5.2.1 Truncation Effect: Withdrawn Deals

In our sample, 129 transactions were canceled (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 acquisition destroys value—managers may be more likely to withdraw the bid before the acquisition is completed.

Our sample allows us to draw limited conclusions about the existence of truncation effects. 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, 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 7. Probability of Withdrawal and Acquirer CAR**

This table reports regressions of deal withdrawal on acquirer cumulative abnormal returns (CAR) measured over various windows. The sample includes the 1,805 transactions that were completed and 129 transactions that were withdrawn. The top panel uses OLS regressions, and the bottom panel uses logit regressions. Column (1) reports the results of 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 | | | | | |
| 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 | | | | | |
| 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 | 1,934 | 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 formally explore this issue further in Table 7. This table reports the results of regressions of deal withdrawal on acquirer CAR measured over various windows. The top panel uses OLS regressions and the bottom panel uses logit regressions. In Column (1), we include only characteristics. In Columns (2) and (3), we include only the acquirer CAR. 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 10% 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).[24] This method has two stages. In the first stage, the likelihood of completion (= 1 − Withdrawal) is estimated as in Table 7 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 2), weighting observations with the inverse probability of completion. This method puts greater weight on observations that are more likely to have been withdrawn. The results of the analysis are presented in Appendix E. Overall, the results are similar to those in Table 2. The coefficient on CAR achieves statistical significance in 4 of the 18 regressions, but the $R^2$ remains small.

### 5.2.2 Feedback Effects

In addition to truncation effects that happen because of withdrawals, our main analysis could suffer from 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 relation between CAR and outcomes.

The empirical evidence on whether management indeed listens to the market and changes its course of action is mixed. Several studies test whether acquisitions 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 data set does not allow us to test the distortion that feedback effects create. However,

[24] A similar method was implemented in Bhagat et al. (2005).

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. Furthermore, the fact that characteristics can predict outcomes in-sample and out-of-sample suggests that the feedback effect may not be substantial.

## 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 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 dates. These windows are typically used in the M&A literature.

The information included in CAR may be an update to earlier information or investor beliefs. In other words, part of the information about the expected value created by the acquisition 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 (1983b) 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 C.1, Column (4), show that extending the window does not change our inference about CAR's lack of predictive ability. 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 to be the primary driver of the inability of CAR to capture outcomes.

[25] See the following studies that raise this possibility: Betton et al. (2014), 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).

# 6 Conclusion

We re-evaluate and challenge a widely-used metric in the financial literature, namely, that abnormal returns surrounding acquisition announcements can be interpreted as a viable measure of expected and realized value creation. We use three measures of ex-post acquisition outcomes: one transaction-level measure of realized deal failure— goodwill impairment and divestiture-at-a-loss—and two acquirer-level measures of ex-post performance, abnormal ROA, and characteristics-adjusted long-run stock performance. We find that these measures, despite capturing different aspects of acquisition performance, are correlated.

We first document that CAR has no meaningful correlation with either transaction-specific outcomes or measures of the acquirer's future performance. Thus, acquisition announcement returns seem to not sufficiently capture realized acquisition outcomes.

In the main part of the study, we show that a standard list of deal and acquirer characteristics known at the time of the announcement can, unlike CARs, predict acquisition outcomes reasonably well. We use this superior predictability to assess the relation between CAR and the predictable component (using these characteristics) of acquisition outcomes and find no relation. Thus, announcement returns appear to fail to reflect all information available at the time of the acquisition announcement and are likely unable to sufficiently capture expected acquisition outcomes.

We show that the poor performance of CAR results in unreliable inferences regarding the types of transactions (i.e., stock vs. cash deals, public vs. private targets, or large vs. small acquirers) that create or destroy value. Overall, our results indicate that researchers should approach inferences generated from CAR with caution and should also utilize ex-post measures (or ex-ante measures that reliably correlate with ex-post measures) to assess acquisition performance.

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# Appendix A Sample Construction of Acquisition Failures and Sample Statistics

## A.1 Goodwill Impairments

We start with 2,981 deals. Appendix Table A.1, Panel A, describes the next set of filters. 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 that 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 either not structured using purchase accounting or 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's effective date. Because Compustat item 368 is the aggregate firm-level impairment, we use the Notes to Consolidated Financial Statements in

## Table A.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 filters 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 the 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 |

the impairment year to determine whether and how much of the impairment is due to the 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 are 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 list 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; 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 A.1, Panel B, shows that we 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) of the 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 was generally less comprehensive. Appendix Table A.1, Panel C, summarizes the final sample of 355 transactions in the impairment sample and 1,498 transactions in the nonimpairment sample.

## A.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, and one- or two-step spinoffs. We then match our sample of 1,870 completed transactions (described in Table B.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 these 116 verified matches, we 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 A.2 shows the details.

**Table A.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 B.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 the transaction was not already impaired | 43 |
| Retain if divestiture price is reported | 17 |
| Retain if the divestiture price is less than the original transaction price (i.e., a loss) | 17 |

## A.3 Time Trend of Acquisition Failures

Appendix Table A.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 (355) or divestiture (17) 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. A total of 456 impairments or divestitures are associated with the 372 unique transactions with goodwill write-downs or divestiture loss.

**Table A.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 B Additional Summary Statistics

Appendix Table B.1 reports deal and acquiring firm characteristics for the sample. 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.

Appendix Table B.2 reports deal and acquiring-firm characteristics for firms with and without transaction-level failure (Panel A), for acquirers, split by quintiles of abnormal ROA (Panel B) and DGTW-adjusted BHAR (Panel C).

## Table B.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 Percentages**

| | % | 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 BHAR | −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% |

## Table B.2. 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 Abnormal 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 B.2. 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 |

Appendix Table B.3 presents the 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.

## Table B.3. Univariate Tests of the Difference in CAR, by Ex-Post Outcome

This table presents univariate statistics for subsamples defined by ex-post outcomes (Panel 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 |
|---|---|---|---|---|
| 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) |
|---|---|---|---|---|---|
| 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) |
|---|---|---|---|---|---|
| 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 |
| $ CAR 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 |

# Appendix C Robustness Tests

We next consider whether our main results 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 Panel A of Table C.1, we report the results of OLS regressions in which the dependent variable is goodwill impairment or divestiture outcomes. The dependent variable is abnormal ROA in Panel B, and is DGTW-adjusted buy-and-hold returns in Panel C. Column (1) restricts the sample to transactions announced in the pre-crisis period between 2003 and 2007, and Column (2) restricts the sample to transactions announced in the post-crisis period between 2010 and 2013. The independent variable in 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 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.

## Table C.1. Robustness Tests

Panel A reports the results of OLS regressions with goodwill impairment or divestiture outcomes as the dependent variable. The dependent variable is abnormal ROA in Panel B, and is DGTW-adjusted buy-and-hold returns in Panel C. Column (1) restricts the sample to transactions announced in the pre-crisis period between 2003 and 2007, and Column (2) restricts the sample to transactions announced in the post-crisis period between 2010 and 2013. The independent variable in 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) |
| 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) |
| 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 BHAR | | | |
|---|---|---|---|---|
| CAR window: | $[-1, 1]$ | | Acq + Tgt $[-1, 1]$ | $[-41, 1]$ |
| Sample: | 2003–2007 | 2010–2013 | Public targets | All |
| | (1) | (2) | (3) | (4) |
| 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 |

# 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 (6) 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 for Predicting 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 (6) 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 Dummy | | | | 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 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 ($= 1 - \text{Withdrawal}$) is estimated as in Table 7 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 2), 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 E.1. Accounting for Withdrawn Deals: Inverse Probability Weighting

This table reports the results from 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) |
| CAR | Controls only | −0.311* (0.159) | −0.077 (0.120) | −0.100 (0.080) | −0.259* (0.157) | −0.226 (0.147) | −0.291** (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: | Abnormal ROA | | | | | | |
|---|---|---|---|---|---|---|---|
| CAR window: | n.a. | $[-1,1]$ | $[-5,5]$ | [Ann-2, Cls+2] | $[-1,1]$ | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CAR | Controls only | 0.035 (0.033) | −0.007 (0.024) | 0.002 (0.015) | 0.037 (0.032) | 0.037 (0.033) | 0.052 (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-Adjusted BHAR | | | | | | |
|---|---|---|---|---|---|---|---|
| CAR window: | n.a. | $[-1,1]$ | $[-5,5]$ | $[\text{Ann}-2, \text{Cls}+2]$ | $[-1,1]$ | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CAR | Controls only | −0.113 (0.189) | −0.245** (0.122) | −0.046 (0.092) | −0.120 (0.186) | −0.066 (0.184) | 0.019 (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 |

# Internet Appendix

# Appendix IA.A CAR's Validity: Existing Evidence

Two early studies that use small and overlapping samples find evidence of a correlation between acquirer CAR and ex-post outcomes such as divestitures-at-a-loss (Kaplan and Weisbach, 1992) and accounting performance (Healy et al., 1992).[26] Two later studies find that CAR is weakly correlated with some outcomes in select specifications: expected (Hoberg and Phillips, 2018) and realized (Li, 2013).[27]

Other studies indicate that CAR may not be correlated with outcomes, such as winner underperformance in contested acquisitions (Malmendier et al., 2018), leveraged acquirers (Krishnan and Yakimenko, 2021), acquirers' short interest (which predicted underperformance) (Ben-David et al., 2015), and implied return-on-equity improvement (Ellahie et al., 2022). Instead, CAR appears to be correlated with less value-relevant variables: earnings-per-share (Dasgupta et al., 2019) and hot markets (Rosen, 2006; Bouwman et al., 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.[28]

The ambiguity about CAR's information content is reflected in the conflicting inferences that researchers draw when using different measurement methods and different samples. For example, there is no strong consensus among economists as to whether acquisitions 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

[26]Healy et al. (1992) find that CAR is correlated with changes in industry-adjusted return-on-assets (ROA) in a sample of 42 acquisitions between 1979 and 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.

[27]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.

[28]Examples of such characteristics are engaging in stock acquisitions (Mitchell and Stafford, 2000), having an abnormally high market-to-book ratio (Rhodes-Kropf and Viswanathan, 2004; Dong et al., 2006), and having abnormally high short interest (Ben-David et al., 2015).

dollar returns are computed, and on the methodology used to tease out acquirer overvaluation information in stock-financed transactions. See the discussion of this issue in Andrade et al. (2001), Moeller et al. (2004), Moeller et al. (2005), Malmendier and Tate (2008), Savor and Lu (2009), Netter, Stegemoller, and Wintoki (2011), Fu et al. (2013), Fich, Nguyen, and Officer (2018), and Malmendier et al. (2018).

As an example of the poor relationship between announcement returns and acquisition outcomes, consider the case of horizontal acquisitions. One might hope that announcement CAR could flag horizontal acquisitions that extract value by shrinking the consumer surplus (Pittman, 2007). In practice, however, there is no correlation between CAR and antitrust actions over 1964–1972 and 1980–2009 periods (Stillman, 1983; Gao, Peng, and Strong, 2017).[29]

[29]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."

# Appendix IA.B Economics and Validation of the Goodwill Impairment Measure

Our main measure of transaction-level deal failure is goodwill impairment. We first explain how accounting for goodwill and its impairment can help detect value destruction in acquisitions. We then provide tests that validate goodwill impairment events as a signal of value destruction.

## IA.B.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. Business combinations 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.

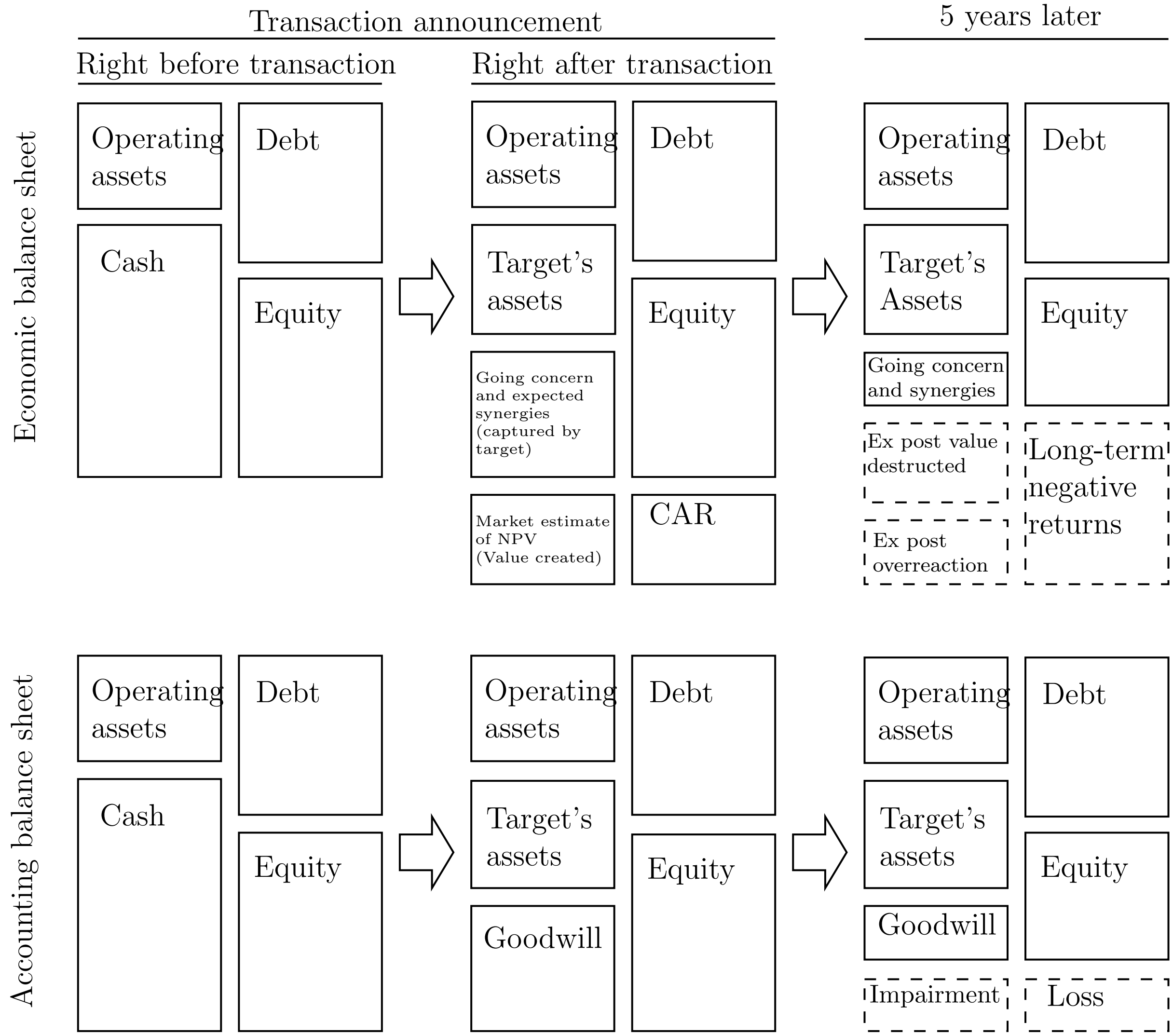
Figure IA.B.1 illustrates the evolution of the acquirer's balance sheet around the transaction and in the long run. Once the transaction is completed, the value of the acquirer's net assets does not change: Cash (or own-issued stock) is replaced by the assets of the target.

We note 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 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 IA.B.1.

Notice that the accounting balance sheet and the economic balance sheet divert once the

**Figure IA.B.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.




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 that 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

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

If 50% of the purchase price were recorded as goodwill (similar to the average transaction in our sample; see Table B.1) and half of this goodwill was 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.[30]

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

The right panels of Figure IA.B.1 present 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

[30] 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.

goodwill will be impaired. Hence, the accounting system mirrors value declines through the impairment of goodwill.

#### IA.B.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 consideration paid in the acquisition and the value of the identifiable net assets:

$$\text{Goodwill}_{\text{i}} = \text{Price}_{\text{i}} - \text{Value(Identifiable Assets)}_{\text{i}} \tag{3}$$

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.[31]

The Financial Accounting Standards Board (FASB) published a new financial accounting standard, SFAS 142, effective December 2001, with the goal of increasing transparency and

[31] 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.

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.[32] Third, goodwill is no longer amortized but is considered an asset that can stay on the firm's balance sheet indefinitely.[33] 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.[34]

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 IA.B.1 explains the relation between goodwill

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

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

[34]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 acquisition transaction multiples valuation techniques to determine fair value.

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.[35] 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, our measure of failure depends on the existence of an impairment, not on its timing.

Second, goodwill cannot be increased to reflect underestimated value creation. As such, we only observe the left tail of deal outcomes. 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.

### IA.B.2 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.

[35] See Elliott and Shaw (1988), Francis et al. (1996), Beatty and Weber (2006), Ramanna and Watts (2012), and Li and Sloan (2017).

#### IA.B.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 documenting that goodwill impairment events are value relevant.[36]

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 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; see Table B.1.) Our second control sample, "Matched Control Sample 1," comprises 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," is made up of 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 IA.B.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

[36] 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 et al. (2004), Bens et al. (2011), Gu and Lev (2011), and Li et al. (2011).

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.

**Table IA.B.1. Market Reaction to Goodwill Impairment News**

This table reports the mean cumulative abnormal returns (CAR) surrounding quarterly earnings announcement dates. For the Impairment sample, we focus on the first earnings announcement when 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 average 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% *** |

### IA.B.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. In independent work, Cowan, Jeffrey, and Wang (2019) perform a similar analysis and reach the conclusion that goodwill impairment is a good indicator of CEO underperformance.

We track turnover events between the 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 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 IA.B.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 the 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 (2021) 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, which allows us 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

**Table IA.B.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 the 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 market within 10 years of the deal effective date. Panel C reports median industry-adjusted accounting performance in the third year subsequent to the 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% | *** |

the year of or year following the impairment year.

To summarize, the results in Table IA.B.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 that is signaled 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 finding implies that the labor market considers impairment to be a proxy for deal failure.

#### IA.B.2.3 Acquirers Distressed Delisting

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

#### IA.B.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 IA.B.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 IA.B.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 acquisition and ends three years after the acquisition. 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.

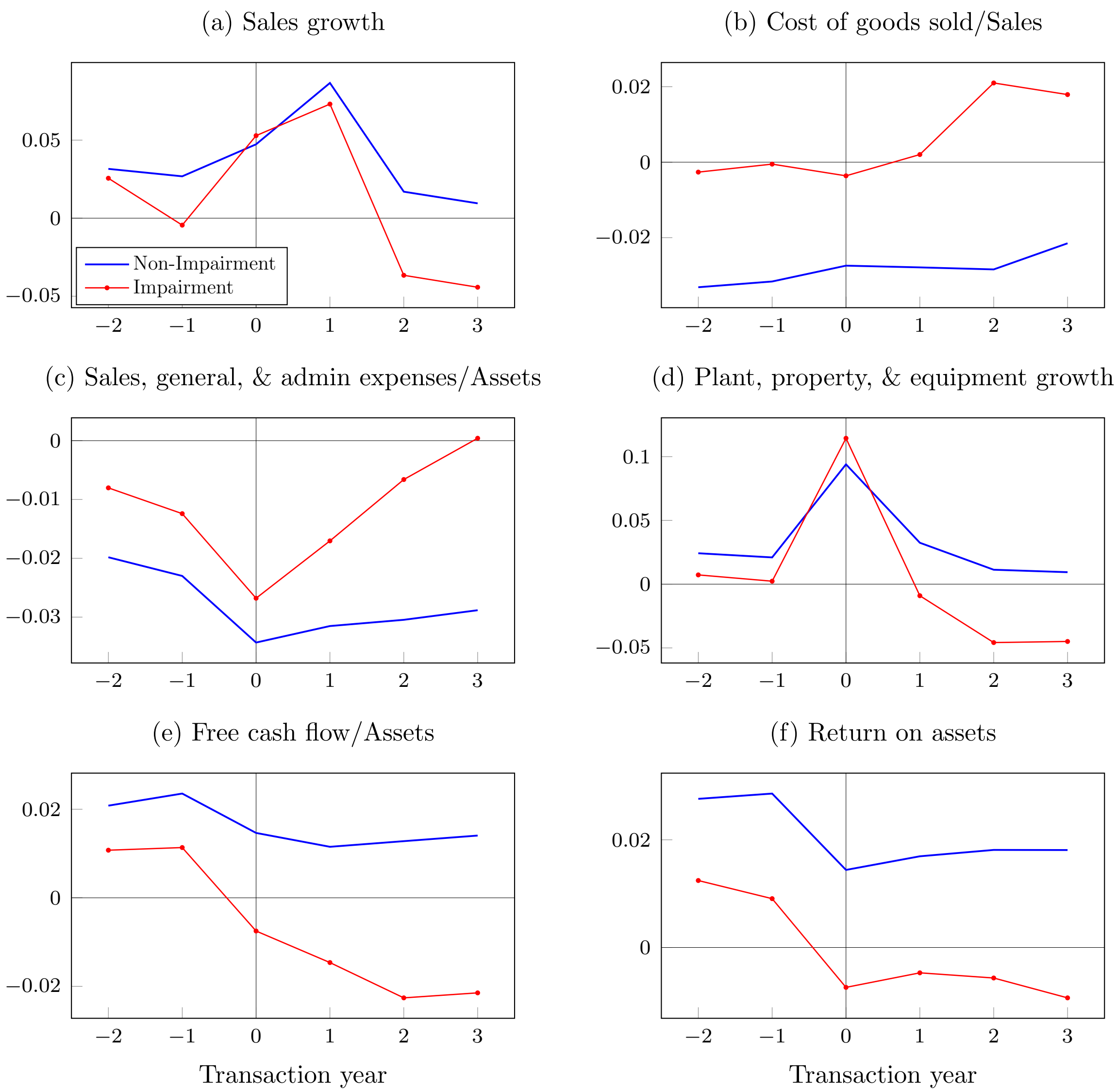



Figure IA.B.2, Panels (a)–(f), show the operating performance from one year before to three years following the acquisition. Across panels, we generally observe that industry-adjusted performance measures begin to materially diverge in the years following the deal announcement for the impairment sample (red lines) and the nonimpairment sample (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 IA.B.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 acquisition and ends three years after the acquisition. 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.

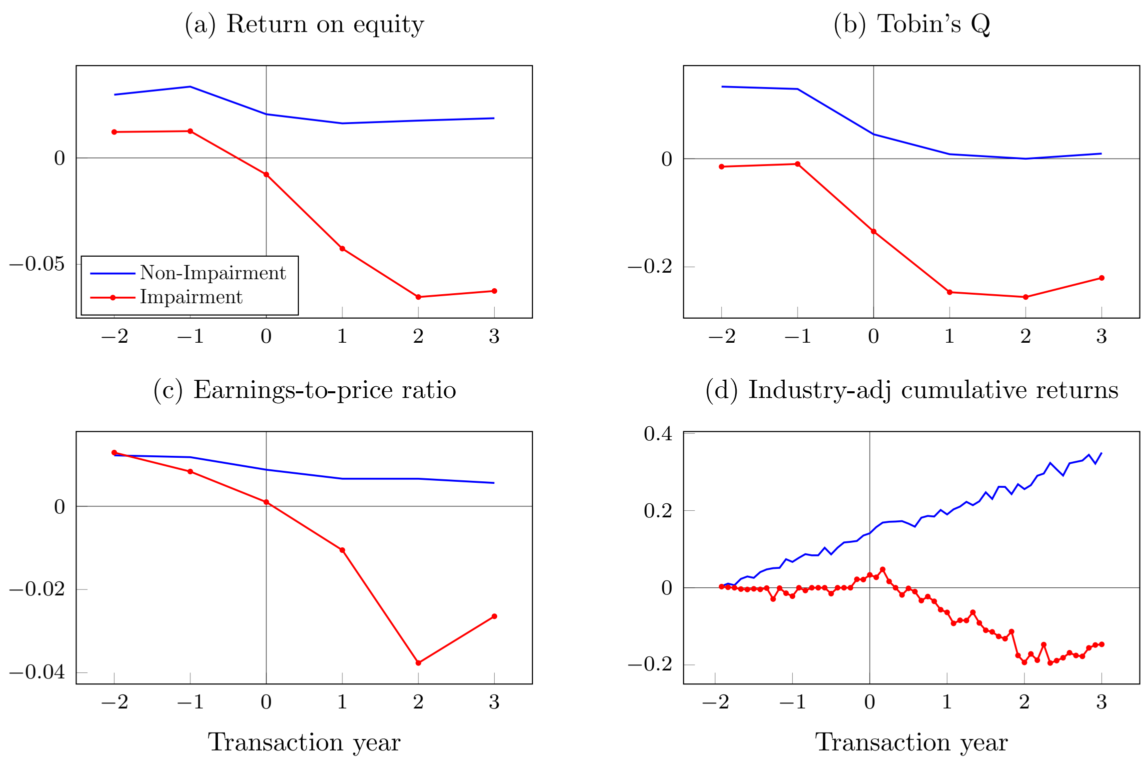



Figure IA.B.3, Panels (a)–(d), show the financial performance from two years before to three years after the acquisition. Note here that the gap between the blue and red lines increases not so much at but after the deal announcement. Figure IA.B.3, Panel (d), shows that the returns to the realized impairment sample remain relatively flat at the announcement but begin to decline dramatically after that. Returns to the realized nonimpairment sample continue their steady growth; consequently, the gap between the two subsamples widens.

To conclude, all three panels of Table IA.B.2, as well as Figures IA.B.2 and IA.B.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 IA.C CAR and the Probability and Magnitude of Failure

Appendix Table IA.C.1 reports the results of regressions that use goodwill impairment and divestiture-at-a-loss outcomes as the dependent variable and acquirer CARs over various windows surrounding the deal announcement as key independent variables. Panel A reports the results regressions (OLS) that model the probability of goodwill impairment or divestiture within five years of the deal effective date, and Panel B reports the results of OLS and tobit regressions that focus on the magnitude of the impairment or divestiture loss.

The results in Appendix Table IA.C.1, Panel A, show that CAR explains 0.1% of the variation in the probability of goodwill impairment or divestiture-at-a-loss (Columns (1)–(3)).[37] The coefficient on CAR is not statistically significant in any of the three models (Columns (1)–(3)) in Panel A. CAR remains statistically insignificant when year (Column (4)) and when year and industry (Column (5)) are included as controls. Column (7) shows that these controls alone, without CAR, explain 9.2% of the variation.

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 created or destroyed as a result of 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. Appendix Table IA.C.1, Panel B, shows that the coefficient on scaled-dollar CAR is not statistically significant at the 10% level in any of the OLS (Columns (1)–(3)) or tobit regressions (Columns (4)–(6)).

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

## Table IA.C.1. Acquirer CAR and 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, and the regression is an OLS regression. 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 (7) 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, 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 (OLS) | | | | | | |
|---|---|---|---|---|---|---|---|
| CAR window: | $[-1,1]$ | $[-5,5]$ | $[\text{Ann}-2,\text{Cls}+2]$ | $[-1,1]$ | | | n.a. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CAR | −0.194 | −0.012 | −0.087 | −0.133 | −0.140 | −0.214 | Controls |
| | (0.132) | (0.099) | (0.059) | (0.131) | (0.132) | (0.132) | only |
| Controls | – | – | – | Year | Year, Ind | Year, Ind, Char | Year, Ind, Char |
| Observations | 1,805 | 1,805 | 1,804 | 1,805 | 1,805 | 1,805 | 1,805 |
| Adjusted $R^2$ | 0.001 | −0.001 | 0.001 | 0.040 | 0.043 | 0.093 | 0.092 |

**Panel B: Magnitude of Impairment/Divestiture at Loss**

| Dependent variable: | Scaled $ Failure | | | | | | |
|---|---|---|---|---|---|---|---|
| | OLS | | | Tobit | | | OLS |
| CAR window: | $[-1,1]$ | $[-5,5]$ | $[\text{Ann}-2,\text{Cls}+2]$ | $[-1,1]$ | | | n.a. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CAR-implied scaled $ loss | 0.023 | −0.020 | −0.012 | 0.282 | −0.263 | −0.127 | Controls |
| | (0.025) | (0.021) | (0.020) | (0.308) | (0.272) | (0.246) | only |
| Controls | – | – | – | – | – | – | Year, Ind Char |
| Observations | 1,805 | 1,804 | 1,803 | 1,805 | 1,804 | 1,803 | 1,805 |
| Adjusted $R^2$ | 0.000 | 0.000 | 0.000 | | | | 0.087 |
| LR chi-squared | | | | 0.83 | 0.94 | 0.27 | |
| Prob > chi-squared | | | | 0.36 | 0.33 | 0.60 | |

# Appendix IA.D Subsamples by Characteristic

Appendix Table IA.D.1 presents the results from regressions of outcome variables on CAR$[-1, 1]$. The samples are split by deal (Panel A) and acquirer characteristics (Panel B). 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 deals 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. If CAR had the correct sign for the prediction, its coefficient should be negative and significant for all the regressions in which the dependent variable is failure, and its coefficient should be positive and significant for all the regressions in which the dependent variable is abnormal ROA or DGTW-adjusted BHAR. We rarely see this result in Table IA.D.1

## Table IA.D.1. CAR Performance by Characteristics-Based Subsamples

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 a 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 | Ab ROA | Adj-BHAR | Failure | Ab ROA | Adj-BHAR |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 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 IA.D.1. CAR Performance by Characteristics-Based Subsamples (Cont.)

**Panel B: Sample Splits by Acquirer Characteristics**

| Dependent variable: | Failure | Ab ROA | Adj-BHAR | Failure | Ab ROA | Adj-BHAR |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 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's Q | | | Above-median Tobin's 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 |