The invisible burden[*]

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Abstract

We study the role of goodwill, an important form of intangible assets arising from merger and acquisitions (M&As), on asset pricing. We find that goodwill-to-sales strongly and negatively predicts the cross-section of U.S. stock returns, especially among firms with cross-industry M&As and firms with overconfident CEOs. It remains an economically and statistically significant predictor of stock returns after adjustment for common factors. Our results suggest that goodwill-to-sales subsumes information on firm value, and stock markets underreact to this information because the fair value of goodwill is unobservable and hard to evaluate.

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1. Introduction

A firm's stock price should reflect the value of both its tangible and intangible capital. While tangible capital has been widely studied, intangible capital has also received growing attention due to its increasing importance in economic values. According to a report in *Forbes*, intangibles "have grown from filling 20% of corporate balance sheets to 80%," and they have become a crucial aspect in the determination of the market value of companies.[1] The importance of taking intangible capital into account to evaluate firm value has also been emphasized (e.g., Chan et al., 2001; Eisfeldt and Papanikolaou, 2013; Belo et al., 2014; Peters and Taylor, 2017). However, little attention has been paid to goodwill, which is the largest component of intangible capital. As shown in Figure 1, the total dollar value of goodwill in the U.S. stock markets has increased from $200 billion in 1989 to nearly $5 trillion in USD, and consists of ~60% of total intangible assets.

[Figure 1 Here]

Unlike other intangibles, goodwill arises when a firm acquires another. It is measured as the difference between the acquisition cost and the fair market value of the target's identifiable tangible and intangible net assets (Kieso et al., 2013). It may represent the premium paid by the acquirer for the target's resources (e.g., reputation, customer loyalty), as well as the expected synergy generated by the firm's components.[2] Acquirers typically pay a large premium, which is

[1] "How intangible assets are affecting company value in the stock market?", *Forbes*, accessed 19 December, 2018, <https://www.forbes.com/sites/christopherskroupa/2017/11/01/how-intangible-assets-are-affecting-company-value-in-the-stock-market/#5d772ef62b8e>.

[2] For example, Hendriksen (1982, p. 407) interprets goodwill as the attitudes of employees, suppliers, and customers. Henning et al. (2000) adopt a synergistic approach to identify the components of goodwill.

typically more than 50% of the total acquisition price (KPMG, 2009). The goodwill amount in the balance sheet is a summary of all the premiums paid from historical acquisition activities, after adjustments for regular amortizations and/or impairments.

However, a high level of goodwill does not necessarily guarantee optimistic future cash flows (Malmendier and Tate, 2008). Often, an acquirer will pay a substantial premium for the target firm but it ended up underperforming initial expectations. If cash flows generated from the combined firm are lower than expected, the balance sheet may give an overly optimistic representation of a firm's financial health even when the income statement does not justify this.[3] This indicates that the fair value of goodwill may be mispriced. Therefore, a high goodwill relative to actual cash flows could contain negative information on firm value. In an efficient capital market, this negative information should be promptly incorporated into stock prices. But as stated in Kieso et al. (2013, p. 256) the "most intangible of intangible assets", the fair value of goodwill is not observable and hard to accurately evaluate even for professional accountants, let alone general investors.[4] Thus, we hypothesize that stock markets underreact to the information on firm value subsumed in goodwill to cash flows, and a high goodwill relative to a firm's cash flows can have a negative impact on future stock returns.

We find empirical evidence consistent with this hypothesis. To construct our main test variable, we use net sales as a proxy for cash flows and calculate goodwill-to-sales (GTS) for all

[3] Having a high goodwill is not a danger signal by itself. Older firms that have done many deals inevitably have lots of goodwill. In addition, firms in high-tech and pharmaceutical sectors tend to have a high goodwill because they rely less on plants and machinery to make money.

[4] We elaborate the accounting of goodwill and its challenges in detail in Subsection 2.1.

firms with a positive goodwill amount on their balance sheets. We choose net sales as the denominator following the accounting practice that goodwill should be evaluated against expected cash flows. Net sales is a direct realized measure for cash flows; therefore, it is more appropriate for our analysis compared to total assets. Moreover, net sales itself does not explain the cross-section of stock returns during our sample period. In other words, our results based on GTS are not merely driven by fluctuations in net sales. In robustness checks, we show that our results hold with other denominators, such as total assets and net income. To take into account the variations of GTS in different industries, we compute industry-adjusted GTS (*GTS_adj*) as the difference between a firm's GTS and its industry mean GTS.[5] A value-weighted long-short portfolio that buys stocks from the lowest *GTS_adj* decile and sells stocks from the highest *GTS_adj* decile earns a four-factor-adjusted monthly return of 0.58% (*t*-statistic = 3.65). Robust results are also obtained after adjustment by other common factor models, such as the Fama-French (2015) five factors, Hou-Xue-Zhang (2015) q-factors, and Stambaugh-Yuan (2016) mispricing factors.[6] Fama-MacBeth (1973) regressions also confirm our results and suggest that the predictive power of *GTS_adj* gradually disappears during the first year after portfolio formation.

We further investigate the information content in GTS to determine the channel for underreaction. First, we consider goodwill impairment and profitability. Goodwill impairment is

[5] In the main analysis, we use the Fama-French 38 industry classification to ensure that the cross-industry variations in GTS are well adjusted and there are sufficient firms in each industry category. We have tried other industry adjustments and also GTS itself as the sorting variable and find consistent results. These results are in Appendix Table A3.

[6] These results are reported in Appendix Table A2.

a reduction in goodwill recorded on the income statement when goodwill's carrying value on the balance sheet exceeds its fair value. When an impairment occurs, the excess value of goodwill has to be written off the balance sheet, and the firm value drops. We find that a high GTS ratio leads to a high goodwill impairment and a low profitability in the subsequent fiscal year. Second, we conduct analyses using quarterly earnings announcements to support our argument. Specifically, we compute earnings surprises using standardized unexpected earnings, analyst forecast errors, and the cumulative DGTW (1997)-adjusted abnormal returns around earnings announcements. We find that under all specifications, a high GTS significantly and negatively predicts future earnings surprises. These results confirm that a high GTS ratio indeed contains negative information on future firm value.

We conduct additional tests to provide evidence to support the information channel of market underreaction. The degree of market underreaction should depend on information complexity. Studies have shown that market underreaction is more severe when the nature of the information is more complex and difficult to process (e.g., You and Zhang, 2009; Cohen and Lou, 2012; Huang, 2015). Evaluating goodwill from a cross-industry merger and acquisition (M&A) deal can be substantially more complicated, because investors need to collect and analyze detailed information from two different industries, as well as to estimate synergies generated by the combination of two different business segments. Therefore, we hypothesize that our main results should be stronger within the subsample of firms with recent cross-industry M&As. Consistent with this prediction, we find that the negative relation between *GTS_adj* and subsequent stock returns exists only among firms with recent cross-industry M&As.

We next investigate how CEO overconfidence affects the negative relation between GTS and subsequent stock returns. Overconfident CEOs are more likely to make optimistic and less accurate forecasts, delay loss recognition, adopt more aggressive accounting methods, conduct earnings management, and/or engage in financial statement fraud (Hillery and Hsu, 2011; Libby and Rennekamp, 2012; Schrand and Zechman, 2012; Ahmed and Duellman, 2013; Bouwman, 2014; Hribar and Yang, 2016; Banerjee et al., 2018). Therefore, investors find it difficult to judge the fair value of goodwill based on the biased information contained in financial reports. Moreover, overconfident CEOs are likely to pay a larger amount of goodwill for their M&A deals than other CEOs, which may have a more negative impact on the firm's fundamental value and stock returns. Based on these arguments, we hypothesize that the negative relation between GTS and subsequent stock returns should be stronger among firms with overconfident CEOs. Indeed, we find that our result in firms with overconfident CEOs is nearly three times as strong as the result in firms with non-overconfident CEOs.

One potential concern is that our results might be driven by post-M&A underperformance. It has been well documented that acquiring firms experience significant negative returns in the three-to-five-year period following M&As (Jensen and Ruback, 1983; Travlos, 1987; Loughran and Vijh, 1997; Rau and Vermaelen, 1998; Mitchell and Stafford, 2000; Andrade et al., 2001; Fuller, Netter and Stegemoller, 2002; Moeller, Schlingemann, and Stulz, 2005; Savor and Lu, 2009; Fu et al., 2013). Given that goodwill arises from M&As, it is plausible that goodwill is correlated with other factors driving post-M&A underperformance. We address this concern in three ways. First, among firms in our top GTS decile, over 40% (35%) of the firms have not done any M&As in the past three (five) years. Our main results remain robust if we exclude firms with recent M&As (see Appendix Table A4). Second, we focus on firms with recent M&As and conduct multiple subsample analyses to show that our results are not affected by deal characteristics that may be related to post-M&A underperformance, such as payment methods, tender offers, hostile takeovers, and/or multiple bidders (see Appendix Table A5). Third, we control for factors driving post-M&A underperformance and examine whether our results still hold. Two such well-known factors are market timing of overvaluation (Shleifer and Vishny, 2003; Moeller et al,, 2005; Dong et al., 2006; Savor and Lu, 2009; Fu et al., 2013) and market fooling (Louis, 2004; Gong et al., 2008). The former argues that firms with high valuations tend to acquire other firms or assets using their inflated share price, while the latter argues that firms attempting to become bidders may engage in earnings management. In both cases, inferior stock price performance should be observed in the period after the deal. Following the literature, we use book-to-market ratio as a proxy for overvaluation and accruals as a proxy for earnings management. We conduct subsample analysis based on these factors. We find that the return predictability of GTS is not subsumed by these factors (see Appendix Table A6). These three sets of analyses confirm that the GTS ratio contains additional information beyond the literature on post-M&A underperformance.

Our paper has the following contributions to the literature. First, to our knowledge, we are the first to document a negative relation between goodwill and subsequent stock returns. Our long-short trading strategy produces an average monthly return that is not only statistically significant, but also economically large, especially after adjustments by the factor models proposed by Fama and French (2015), Hou et al. (2015), and Stambaugh and Yuan (2016). Our strategy based on GTS is also tradable. Unlike many other anomalies, our results are not driven by small firms. We exclude stocks priced below $5 and market capitalization below the bottom NYSE size decile. The median NYSE size percentile in our sample is about 40%. Therefore, short selling stocks in the top *GTS_adj* decile should be relatively easy.

Our paper also contributes to the literature on the relation between intangible capital and the cross-section of stock returns. This literature can be further divided into three streams. Intellectual properties are investigated in the first stream. Empirical evidence suggests that innovation intensity, efficiency, and originality positively predict the cross-section of stock returns (Chan et al., 2001; Hirshleifer et al., 2013; Gu, 2016; Hirshleifer et al., 2017). Human capital is investigated in the second stream. It has been documented that firms with high employee satisfaction and more organizational capital have higher returns (Edmans, 2011; Eisfeldt and Papanikolaou, 2013). The effect of product branding on stock returns is examined in the third stream. Firms with low brand capital investment rates, higher brand capital intensity, and more newly registered trademarks are associated with higher future stock returns (Belo et al., 2014; Lou, 2014; Hsu et al., 2018).

Our paper contributes to this literature as follows. First, even though intellectual property, human capital, and product branding are all important factors for business operations, goodwill is the largest component of intangible capital and has significant economic values, which is understudied in the asset pricing literature. Second, goodwill is an outcome of the premium paid for all M&As. It is fundamentally different from other types of intangible capital. Therefore, the effect of goodwill on the cross-section of stock returns is also very different compared to other intangibles. A high goodwill relative to cash flows contains negative information on firm value. Since the fair value of goodwill is hard to evaluate, a high goodwill relative to cash flows negatively predicts the cross-section of stock returns due to market underreaction.

Finally, our paper contributes to the M&A literature by showing that GTS captures additional information beyond the literature on post-M&A underperformance. Our results suggest that bad M&A deals have a long-term negative impact on acquirers, especially for firms with cross-industry M&As and overconfident CEOs.

The rest of the paper is organized as follows. In Section 2, we discuss the accounting of goodwill, and describe our data and sample selection. The main results are presented in Section 3. In Section 4, there is additional discussion. We conclude in Section 5.

2. Background and data

In this section, we first discuss the evolution on the accounting of goodwill (Section 2.1), and then describe our data and sample selection criteria to produce our empirical results (Section 2.2).

2.1 The accounting of goodwill

Goodwill is among the most difficult-to-value assets on balance sheets. The accounting method to evaluate goodwill is usually based on estimations of future cash flows. Under APB16, SFAS141, and ASC805, goodwill should be booked using the purchase price method in which it is calculated as the difference between the acquisition cost and the fair value of the target firm's net assets. This fair value is tricky to obtain and can be sensitive to estimations based on future cash flows. In order to calculate the fair value of the acquired unit, one needs to first identify its liabilities, as well as its tangible and intangible assets, which are identifiable from the business combination. This identification step by itself could be complicated. After the identification, one needs to identify the fair market value for these assets and liabilities, which is difficult because most assets do not have an active market. Therefore, one needs to make assumptions on future cash flows and use valuation models to estimate the value of these assets. These frictions make it difficult to accurately value goodwill for any business combination.

In order to improve goodwill accounting, the Financial Accounting Standards Board in the United States has changed the rules for goodwill write-off several times during the past two decades. However, goodwill accounting is still very challenging. From 1970 to 2001, APB17 required that goodwill should be amortized over a lifetime not to exceed 40 years. This requirement was controversial, because goodwill can be an asset with an indefinite life and its value might not decrease over time. Therefore, the information value of amortization is low as it is impossible to objectively determine the timeline over which amortization should occur.

Because of this issue, FASB released SFAS121 in 1995, which required that impairment should be taken when the goodwill value falls below the undiscounted future cash flow. As a result, firms were subject to both goodwill amortization and impairment until 2001. In 2001, SFAS142 superseded APB17 and SFAS121, and goodwill is no longer amortized but only subject to an annual review for impairment based on future cash flows. When testing whether a firm is eligible for goodwill impairment, one needs to compare the carrying value of goodwill to its implied fair value, which is estimated from projected future cash flows. However, this impairment-only approach is also problematic for at least four reasons: (1) the annual impairment test is both costly and subjective; (2) the projections of future cash flows from cash generating units is often overly optimistic; (3) impairment losses tend to be identified too late; and (4) when an impairment loss is booked, the resulting information provides only weak confirmatory value for investors.

In order to reduce costs and efforts, FASB simplified the goodwill impairment test in 2017. However, this simplification is also controversial. While simpler, the new procedure can be less precise. As a result, it may "give rise to a goodwill impairment that is largely driven by other assets in the reporting unit that are underwater but are not otherwise impaired under the accounting literature." (PWC, 2017).[7]

The discretion in valuing goodwill has also left managers room for exploitation. Watts (2003), Hayn and Hughes (2006), Ramanna (2008), Ramanna and Watts (2012), Li and Sloan

[7] "Simplifying goodwill impairment testing", PWC, 2017, accessed 19 December, 2018, <https://www.pwc.com/us/en/cfodirect/publications/in-the-loop/step-2-goodwill-impairment-test.html>.

(2017), and Glaum et al. (2018) investigate the timing of goodwill impairments. They document that firms with indicators of goodwill impairments tend to delay impairments by taking advantage of the discretionary use of valuation models.

All these regulatory changes and discretionary manipulations in valuing goodwill indicate that evaluating goodwill is challenging. The fair value of goodwill is unobservable, hard to identify, and may be overly optimistic based on subjective projections of future cash flows. This subjective estimation can lead to an overstatement of goodwill as a huge part of the total assets. Therefore, the balance sheet may give an overly optimistic representation of a firm's financial health even when the income statement does not justify this. Considering that projections on future cash flows are crucial for goodwill accounting, in our main analyses, we evaluate goodwill as it relates to realized cash flow. A high goodwill and a low realized cash flow may indicate that the accounting of goodwill has been overly optimistic, which may not be fully justified by realized firm performance.

2.2 Sample construction

We start with all NYSE, AMEX, and NASDAQ firms that are covered in the Center for Research in Security Prices (CRSP) and Compustat. We impose the following restrictions: 1) a positive goodwill (Compustat data item: GDWL); 2) a price-per-share larger than $5; and 3) a market capitalization higher than the bottom NYSE size decile. To mitigate backfilling biases, a firm must be listed on Compustat for two years before it is included in the dataset (Fama and

French, 1992). We match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns from July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. We start all of our portfolio tests and regression analyses at the end of June 1989 because Compustat started reporting goodwill in 1988. Our final sample covers 1989 to 2016.

Our main variable of interest, industry-adjusted goodwill-to-sales (*GTS_adj*) is constructed as follows. We first compute goodwill-to-sales (*GTS*) as goodwill (*GDWL*) scaled by total sales (*SALE*). Based on the accounting standards outlined in Subsection 2.1, we evaluate goodwill against cash flows. Therefore, we choose net sales as the denominator following the accounting practice. Net sales is a direct measure for cash flows and it does not explain the cross-section of stock returns during our sample period. In other words, our results based on GTS are not merely driven by fluctuations in net sales. In robustness checks, we show that our results are robust with other denominators, such as total assets and net income.

To take account of the variation of GTS in different industries, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the same industry.[8] We use Fama-French's 38 industry classifications to ensure that the cross-industry variations in GTS are well-adjusted and there are sufficient firms in each industry category. We require that each industry has at least three firms to make this adjustment. In robustness checks, we consider alternative industry adjustments and obtain similar results.

[8] The results are robust if we use industry median to adjust GTS.

We control the following form characteristics: (1) *Size*, the market capitalization in billions of USD; (2) *Book-to-Market Ratio*, defined as book equity divided by market equity. We use book value from the last fiscal year-end and market value from December of last year. Other control variables include: (3) *Momentum*, defined as the cumulative returns from month $t-11$ to $t-1$; (4) *Short Term Reversal*, defined as return of month t; (5) *Idiosyncratic Volatility*, defined as the monthly standard deviation of the residuals from regressing daily returns on Fama-French's (1993) three factors; (6) *Illiquidity*, constructed after Amihud (2002); (7) *Asset Growth*, defined as the annual growth rate of total assets; (8) *Gross Profit*, defined as the difference between total revenue and the costs of goods sold, scaled by total assets; (9) *Accruals*, calculated following Sloan (1996); and (10) *Net Stock Issuance*, defined as the change in the natural log of split-adjusted shares outstanding, following Pontiff and Woodgate (2008).

The first three columns in Panel A of Table 1 report the summary statistics for our sample. The mean of GTS is 0.261, while the median is 0.132.

[Table 1 Here]

Panel B of Table 1 reports the correlation coefficient matrix for our full sample. We find that GTS has no strong correlation with well-documented firm characteristics.

We divide our full sample based on M&As and CEO overconfidence. We extract the details on M&As from the Securities Data Corporation (SDC) database. We define a cross-industry M&A as a deal in which the acquirer and the target firm belong to different Fama-French 38 industry classifications. Firms that have made at least one cross-industry M&A in the past year are included in the subsample of cross-industry M&As. Firms that have made only one M&A within the same industry in the past year are included in the subsample of same-industry M&As.

To capture CEO overconfidence, we follow Schrand and Zechman (2012) and bundle four firm characteristics that are related to CEO overconfidence: (1) *Excess Investment*, defined as capital expenditure scaled by total sales; (2) *Leverage Ratio*, defined as long- and short-term debts divided by total market value; (3) whether the firm has outstanding preferred stocks or convertible debts; and (4) whether the firm paid dividends in the previous fiscal year. We rank the first two characteristics into 10 groups in ascending order. We assign rank 10 to a firm if it has outstanding preferred stocks or convertible debts, and rank 1 otherwise. Similarly, we assign rank 10 to a firm if it did not pay dividends in the previous fiscal year, and rank 1 otherwise. Then we compute the average rank from the four characteristics as a proxy for CEO overconfidence. We require a stock to have all four characteristics to compute this proxy. A firm is defined to have an overconfident CEO if this average rank is above the top quintile. The non-overconfidence subsample contains firms with an average rank below the bottom quintile.

Summary statistics of the main variables of these subsamples are reported in Panel A of Table 1. Firms with M&As in the past year (either cross-industry or same-industry) have a higher GTS compared to our full sample average. Firms with overconfident CEOs have a higher GTS on average, compared to firms with non-overconfident CEOs.

3. Results

In this section, we first discuss our main results based on industry-adjusted GTS (Section 3.1), and then explore the information content subsumed in GTS (Section 3.2).

3.1 Goodwill-to-sales and the cross-section of stock returns

To test the relation between GTS and the cross-section of stock returns, we first conduct univariate sorting based on industry-adjusted GTS. We match *GTS_adj* for all fiscal year-ends in calendar year $t-1$ with monthly returns for July of year t to June of year $t+1$. At the end of each June, stocks are sorted into decile portfolios based on *GTS_adj*. We compute value-weighted monthly excess returns for each of the decile portfolios, as well as a long-short strategy that longs stocks in the bottom goodwill decile and shorts stocks in the top goodwill decile. The average value-weighted returns, together with Fama-French (1993) three-factor alphas and Fama-French-Carhart (1997) four-factor alphas, are reported in Table 2. We report the equal-weighted results in Appendix Table A1. They are very similar to the results we present here.

[Table 2 Here]

Table 2 presents a striking pattern that GTS negatively predicts subsequent stock returns in the cross-section. For instance, the four-factor alpha for the bottom decile portfolio is 0.31% (t-statistic = 2.07) per month. Four-factor alpha drops as *GTS_adj* increases. The four-factor alpha becomes −0.27% (t-statistic = −2.55) for the top *GTS_adj* decile. A long-short strategy that longs stocks in the bottom decile portfolio and shorts stocks in the top decile portfolio earns a four-factor-adjusted return of 0.58% per month (*t*-statistic = 3.65). Similar patterns are obtained using excess returns and after adjusted by recent factor models proposed by Fama and French (2015), Hou et al. (2015), and Stambaugh and Yuan (2016). These results are reported in Appendix A2.

In Table 3, we report the factor loadings from the four-factor model for the bottom and the top decile portfolios, as well as the long-short portfolio. Returns from the bottom and the top decile portfolios are positively correlated with the market factors, but negatively correlated with the size and momentum factors. The last row of Table 3 shows the factor loadings for the long-short portfolio. The long-short portfolio return is negatively correlated with the size and value factors, but its return cannot be merely explained by the four factors.

[Table 3 Here]

We use *GTS_adj* as the main variable following the accounting practice of evaluating goodwill based on cash flows. We also examine the robustness of our results using alternative definitions of the sorting variable and using alternative industry adjustments (or using unadjusted GTS). In Subsection 4.3, we discuss these additional results. Our main results remain qualitatively unchanged.

The primary advantage of the sorting strategy is that it offers a simple picture of how average returns vary across the spectrum of GTS without imposing a functional form on the relations. However, we cannot control for other well-documented characteristics that affect stock returns in the cross-section. Therefore, we conduct Fama and MacBeth (1973) regressions to examine whether the results from the portfolio-level analysis hold when other variables with return predictability are controlled for. Specifically, we conduct the following regressions for each month:

$$R_{i,t+1}=\alpha_t+\beta_1\times GTS\_adj_{i,t}+\beta_2\times SIZE_{i,t}+\beta_3\times BM_{i,t}+\beta_4\times MOM_{i,t}+\beta_5\times STREV_{i,t}+\beta_6\times IVOL_{i,t}$$
$$+\beta_7\times ILLIQ_{i,t}+\beta_8\times AG_{i,t}+\beta_9\times GP_{i,t}+\beta_{10}\times NS_{i,t}+\beta_{11}\times AC_{i,t}+\varepsilon_{i,t}\,, \quad (1)$$

where $R_{i,t+1}$ is the realized return on stock i in month t+1 (in percentage) and $GTS\_adj_{i,t}$ is the industry-adjusted goodwill for stock i in month t. We expect β_1 to be significantly negative. Control variables include size, book-to-market ratio, momentum, short-term reversal, idiosyncratic volatility, illiquidity, asset growth, growth profit, net stock issuance, and accruals. Detailed definitions of these control variables can be found in Subsection 2.2.

Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year t−1 with the returns from July of year t to June of year t+1 to ensure that the accounting variables are known before they are used to explain returns. All variables are winsorized at the 1% and 99% percentiles to eliminate the potential influence of outliers. We conduct the predictive regressions specified in equation (1) every month, and report the time series average of the slope coefficients for our sample over the 324 months from July 1989 to June 2016. Newey-West adjusted t-statistics are reported in parentheses.

[Table 4 Here]

Table 4 shows that our results from the Fama-MacBeth regressions are consistent with our univariate sorting results presented in Table 2. The coefficient on *GTS_adj* is significantly negative. For example, in column (2), after controlling for well-documented firm characteristics, the coefficient on *GTS_adj* is −0.173 with a Newey-West adjusted *t*-statistic of −3.28. The difference in mean *GTS_adj* between the top and bottom *GTS_adj* deciles is ~4.13. Thus, the coefficient suggests that the difference in return between the bottom and top *GTS_adj* deciles is approximately 0.71% (= 0.173×4.13) per month, which is similar in magnitude to our sorting results in Table 2. Overall, both univariate sorting and Fama-MacBeth regressions show a negative and statistically significant relation between GTS and the cross-section of stock returns.

Return predictability arising from underreaction should be short-lived. In order to show that the predictive power of *GTS_adj* is due to market underreaction, we re-run the Fama-MacBeth regression outlined in equation (1) quarter by quarter within the first year after the portfolio formation.[9] We report the time series average of the slope coefficients in each quarter in Table 5.

[Table 5 Here]

The results in Table 5 suggest that the predictive power of *GTS_adj* gradually disappears over time. The predictive power of *GTS_adj* is the strongest in Quarter 1 after the portfolio formation. The average coefficient on *GTS_adj* monotonically declines over time and becomes

[9] We appreciate the anonymous referee for this suggestion.

statistically insignificant three quarters after portfolio formation.[10] This is consistent with our conjecture that the return predictability of *GTS_adj* is due to market underreaction.

3.2 The information content in goodwill-to-sales

In the previous subsection, we document that a high GTS is negatively associated with subsequent stock returns in the cross-section. In this subsection, we present evidence suggesting that this negative return predictability is due to the fact that investors underreact to the negative information on firm value associated with a high goodwill.

We first examine whether GTS can positively predict goodwill impairment. Goodwill impairment is a reduction in goodwill recorded on the income statement. It happens when there is persuasive evidence that goodwill can no longer demonstrate financial income that is expected from it. We define goodwill-impairment-to-sales (GITS) as the ratio of goodwill impairment divided by total sales. We conduct the following fixed effects panel regression:

$$GITS_{i,t+1}=\alpha+\beta_1\times GTS_{i,t}+\beta_2\times GITS_{i,t}+\boldsymbol{\beta}_3\times \boldsymbol{Control}_{i,t}+Year\ FE+Firm\ FE+\varepsilon_{i,t}, \quad (2)$$

where $GITS_{i,t+1}$ is goodwill-impairment-to-sales for firm i in fiscal year t+1 and $GTS_{i,t}$ is GTS for firm i in fiscal year t. We expect β_1 to be significantly positive. We control for lagged GITS and other firm characteristics: size, book-to-market ratio, momentum, asset growth, net stock issuance, accruals. In addition, we include net operating assets (*NOA*), the ratio of the difference

[10] Alternatively, we can re-run the Fama-MacBeth regression in equation (1) using lagged *GTS_adj*. Similar to what is reported in Table 5, the average coefficient on *GTS_adj* is significant within the first year after portfolio formation, and becomes insignificant afterwards.

between operating assets and operating liabilities divided by total assets; and investment growth (*IG*), the annual growth rate of capital expenditure. All variables are winsorized at 1% and 99%. All independent variables are standardized to have a mean of zero and a standard deviation of one. Our analysis starts from 1996 because goodwill impairment is introduced by FASB in 1995.

[Table 6 Here]

In all specifications in Table 6, the coefficient on GTS is positive and significant, indicating that a higher GTS is associated with a higher goodwill impairment in the next fiscal year. For instance, the results in column (4) show that the coefficient on GTS is 0.005 (*t*-statistic = 3.23). This indicates that a one standard deviation increase in GTS will result in a 0.5% increase in the goodwill impairment in the next year. For reference, the mean GITS in our sample is only 0.3%. In other words, this is a 167% increase relative to the mean.

As a second test, we examine whether GTS negatively predicts profitability in the next fiscal year. We take return on assets (*ROA*), defined as net income divided by total assets, as a proxy for profitability. We regress ROA in fiscal year t+1 on GTS from fiscal year t, GITS from fiscal year t, ROA from fiscal year t, and the same set of control variables in equation (2). All variables are winsorized at 1% and 99%. All independent variables are standardized to have a mean of zero and a standard deviation of one.

$$ROA_{i,t+1}=\alpha+\beta_1\times GTS_{i,t}+\beta_2\times GITS_{i,t}+\beta_3\times ROA_{i,t}+\boldsymbol{\beta}_4\times \boldsymbol{Control}_{i,t}+Year\ FE+Firm\ FE+\varepsilon_{i,t}. \tag{3}$$

[Table 7 Here]

Table 7 shows that a higher GTS is associated with a lower ROA in the subsequent fiscal year. In all specifications, the coefficients for GTS are negative and significant. For instance, in column (4), the coefficient on GTS is −0.005 (t-statistic = −2.00). This indicates that a one standard deviation increase in GTS leads to a 0.5% decrease in ROA in the next year. For reference, the mean ROA in our sample is 3.6%. In other words, this is a 14% decrease relative to the mean.

In order to provide additional and more convincing evidence to show that a high GTS has negative value-related information on firms, we conduct further analyses using quarterly earnings announcements. We conjecture that if a high GTS indeed contains negative information on future firm value, then a high GTS before the quarterly earnings announcement should be associated with a negative earnings surprise. Following the literature (e.g., Chen et al., 2019; Cohen et al., 2019; Wang, 2019; among others), we conduct Fama-MacBeth regressions by each quarter for all firms that make earnings announcements within that quarter. Specifically,

$$
\begin{aligned}
ES_{i,t} = {} & \alpha_t + \beta_1 \times GTS\_adj_{i,-1y} + \beta_2 \times SIZE_{i,-1m} + \beta_3 \times BM_{i,-1y} + \beta_4 \times MOM_{i,-1m} + \beta_5 \times EarningsVolatility_{i,-1q} \\
& + \beta_6 \times EarningsPersistence_{i,-1q} + \beta_7 \times Log(Reporting\_Lag)_{i,t} + \beta_8 \times Log(\#ofAnlaysts)_{i,[-90,-1]} \\
& + \beta_9 \times Log(\#ofAnnouncements)_{i,t} + \beta_{10} \times AC_{i,-1y} + \beta_{11} \times ILLIQ_{i,-1m} + \beta_{12} \times Dispersion_{i,[-90,-1]} \\
& + \beta_{13} \times Revision_{i,[-90,-1]} + \varepsilon_{i,t}, \qquad (4)
\end{aligned}
$$

where $ES_{i,t}$ is earnings surprise in quarter t. The results are reported in Table 8. In the first regression (reported in column (1)), we use standardized unexpected earnings calculated from a seasonal random walk model (i.e., the difference between earnings per share before extraordinary items in quarter t and $t-4$, scaled by the price before the earnings announcement). In the second regression (reported in column (2)), we use analyst forecast error, defined as the difference between the actual earnings per share and the median of analyst forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement, scaled by the price before the earnings announcement. In regressions 3-5 (reported in columns (3)-(5)), we use the cumulative abnormal returns from [−1,+1], [−3,+3], and [−5,+5] around the earnings announcement, respectively. Our main independent variable, $GTS\_adj_{i,t}$, is industry adjusted GTS, computed in the prior fiscal year before the earnings announcement.

Control variables includes: (1) *SIZE*, the natural log of total market capitalization, computed one month before the earnings announcement; (2) *BM*, book-to-market ratio, computed in the prior fiscal year before the earnings announcement; (3) *MOM* is momentum, constructed as the cumulative return over the 11-month period ending one month before the announcement; (4) *Earnings Volatility* is measured as the standard deviation of quarterly earnings surprises from a seasonal random walk model over the preceding four years before the announcement; (5) *Earnings Persistence* is the first-order auto-regressive coefficient of quarterly earnings-per-share over the preceding four years before the announcement; (6) *Reporting Lag* is the number of days between the fiscal quarter-end date and the earnings announcement date; (7) *# of Analysts* is the number of analysts reporting earnings-per-share forecasts for the firm within 90 days before the announcement; (8) *# of Announcements* is the number of firms announcing quarterly earnings on the same earnings announcement day (or the ensuring announcement day); (9) *AC* is accruals, computed after Sloan (1996) in the prior fiscal year before the earnings announcement; (10) *ILLIQ* is illiquidity, computed after Amihud (2002) in the month before the announcement; (11) *Dispersion*, the standard deviation of analyst earnings forecast in the most recent period prior to the earnings announcement, scaled by the price before the earnings announcement; (12) *Revision* is analyst revision, the 3-month sum of scaled changes in the median analyst's earnings forecast prior to the earnings announcement, where the scaler is the stock price in the previous month.

[Table 8 Here]

Table 8 shows that, under all specifications, the coefficients on GTS are negative and significant. These results suggest that a high GTS significantly and negatively predicts future earnings surprise. For example, in column (5), after controlling for other variables that affect earnings surprise, the coefficient on *GTS_adj* is −0.484 (t-statistic = −3.26). The difference in the mean *GTS_adj* between the top and bottom GTS deciles is ~4.13. Thus, the coefficient suggests that the difference in *CAR*[−5,+5] between the bottom and top GTS deciles is 2.00% (= 0.484×4.13). Therefore, this result is not only statistically significant but also economically large.

Overall, this subsection presents strong evidence that a high GTS contains negative information on future firm value, and this information will be reflected in future goodwill impairment, profitability, and earnings announcements. Investors underreact to the information associated with GTS, and stock price slowly adjusts to reflect the true value of the firm.

4. Further Discussion

The results documented thus far suggest that stock markets underreact to the information on firm value subsumed in GTS. In this section, we conduct additional subsample analyses to support this channel and examine the robustness of our results.

4.1 M&As: cross-industry vs. same-industry

Studies have shown that market underreaction is more severe when the nature of the information is more complex and more difficult to process (e.g., You and Zhang, 2009; Cohen and Lou, 2012; Huang, 2015). Evaluating goodwill from a cross-industry M&A can be substantially more complicated than evaluating goodwill from a same-industry M&A, because investors need to collect and analyze detailed information from two industries, as well as to estimate synergies generated by the combination of two different business segments. Therefore, we expect a stronger negative relation between goodwill and subsequent stock returns for firms with cross-industry M&As.

To examine this prediction, we conduct independent double sorting based on M&As and industry-adjusted GTS. We define a cross-industry M&A as a deal in which the acquirer and the target firm belong to different Fama-French 38 industry classifications.[11] Firms that have made any cross-industry M&A deals in the past year are included in the subsample of cross-industry M&As. Firms that have only made M&As within the same industry in the past year are included

[11] We consider other industry classifications to define cross-industry M&As and find similar results. These results are reported in Appendix Table A8.

in the subsample of same-industry M&As. Due to reduced sample size, we sort industry-adjusted GTS by terciles independently.

[Table 9 Here]

We report the value-weighted average monthly excess returns and alphas for the double sort in Table 9. The results 9 show that the negative relation between GTS and subsequent stock returns only exist in the subsample with cross-industry M&As. For firms with cross-industry M&As, a trading strategy that longs stocks in the bottom industry-adjusted GTS tercile and shorts stocks in the top industry-adjusted GTS tercile yields a four-factor alpha of 0.77% per month (t-statistic = 2.37). In contrast, for firms that only conduct same-industry M&A deals, this trading strategy has a four-factor alpha of 0.27% (t-statistic = 0.90). Similar patterns are obtained using excess returns and three-factor alphas.

These results further support our main finding that stock markets underreact to the information subsumed in GTS. Because evaluating the information in GTS from past cross-industry M&As is a more complex and difficult job, the underreaction effect is stronger for firms with cross-industry M&As.

4.2 CEO overconfidence

We next investigate how CEO overconfidence affects the negative relation between GTS and subsequent stock returns. Overconfident CEOs are more likely to make optimistic and less accurate forecasts, delay loss recognition, adopt more aggressive accounting methods, conduct earnings management, and engage in financial statement fraud (Hillery and Hsu, 2011; Ahmed and Duellman, 2013; Libby and Rennekamp, 2012; Schrand and Zechman, 2012; Bouwman, 2014; Hribar and Yang, 2016; Banerjee et al., 2018). Therefore, investors may find it difficult to judge the fair value of goodwill based on the biased information released from financial reports. Moreover, overconfident CEOs are likely to pay a larger amount of goodwill for their M&As than other CEOs, leading to a more negative impact on the firm's fundamental value and stock returns.[12] Based on these arguments, we hypothesize that the negative relation between *GTS_adj* and subsequent stock returns should be stronger among firms with overconfident CEOs.

We conduct an independent double sort based on CEO overconfidence and *GTS_adj*. The definition for overconfident CEOs is described in Subsection 2.2.

[Table 10 Here]

We report the value-weighted average monthly excess returns and alphas for the double sorting in Table 10. The results show that the negative relation between industry-adjusted GTS and subsequent stock returns is stronger in the subsample of overconfident CEOs. For firms with overconfident CEOs, a trading strategy that longs stocks in the bottom GTS quintile and shorts stocks in the top GTS quintile yields a four-factor alpha of 0.69% per month (*t*-statistic = 3.17). However, for firms with non-overconfident CEOs, this trading strategy only yields a four-factor alpha of 0.26% (*t*-statistic = 1.86). Similar patterns are obtained using excess returns and three-factor alphas. These results further support our main finding that stock markets underreact

[12] We thank the anonymous referee for this valuable suggestion.

to the information subsumed in GTS.

4.3. Robustness

4.3.1 Alternative specifications

We report equal-weighted portfolio returns in Appendix Table A1. The return patterns are similar to the value-weighted results reported in Table 2. The long-short portfolio earns a four-factor adjusted return of 0.75% per month (*t*-statistic = 4.26).

Our main results in Table 2 are also robust after controlling for other factors. In Appendix Table A2, we report adjusted returns based on the following: (1) Fama-French (2015) five factors; (2) Fama-French-Carhart six factors; (3) Hou-Xue-Zhang (2015) q-factors; (4) Stambaugh-Yuan (2016) mispricing factors; and (5) DGTW benchmark portfolio returns. Our long-short strategy is robust across all these alternative return adjustments.

We next examine whether our main results are sensitive to different industry adjustments in Appendix Table A3. For our main analysis (also reported in column (1) of Appendix Table A3), we use industry-adjusted GTS based on the Fama-French 38 industries. In order to show that our results are not driven by industry adjustments, in column (2), we report sorting results by using GTS without industry adjustments. We still find a significantly negative relation between GTS and subsequent stock returns in the cross-section.

We consider other industry adjustments in Appendix Table A3, such as Fama-French

5/17/30/48 industries, and 1-/2-digit SIC codes. All these alternative industry adjustments produce consistent results that GTS is negatively associated with subsequent stock returns in the cross-section.

Our results are robust across alternative definitions of the sorting variable. After controlling for the Fama-French-Carhart six factors, the same long-short strategy earns 0.54% per month (t-statistic = 2.77) based on goodwill-to-assets, and earns 0.41% per month (t-statistic = 2.34) based on goodwill-to-net-income.

4.3.2 Alternative explanation

A potential alternative explanation for our results is that the negative relation between GTS and future stock returns might be driven by post-M&A underperformance. It has been well documented that acquiring firms experience significant negative stock returns in the 3-5 years subsequent to acquisitions (Jensen and Ruback, 1983; Travlos, 1987; Loughran and Vijh, 1997; Rau and Vermaelen, 1998; Mitchell and Stafford, 2000; Andrade et al., 2001; Fuller et al., 2002; Moeller et al., 2005; Savor and Liu, 2009; Fu et al., 2013). Given that goodwill arises from acquisitions, it is plausible that goodwill is correlated with other factors driving post-M&A underperformance.

We address this concern in three ways. First, among firms in our top GTS decile, over 40% (35%) of the firms have not done any M&As in the past three (five) years. To further confirm that our results are not merely driven by recent M&A events, we reconduct our portfolio sorting as for Table 2 using only firms without any M&As in the past three (five) years (see Appendix Table A4). We find similar results. For example, among firms without M&As in the past three years, a trading strategy that longs stocks in the bottom GTS decile and shorts stocks in the top GTS decile yields a value-weighted four-factor-adjusted return of 0.62% per month (t-statistic = 3.01).

Second, we focus on firms with recent M&As and conduct multiple subsample analyses to show that our results are not affected by deal characteristics that may be related to post-M&A underperformance. We repeat our main analysis for Table 2 and present the results in Appendix Table A5 for firms with cash-only deals (Panel A), stock deals (Panel B), non-tender offer deals (Panel C), non-hostile takeovers (Panel D), and single bidder deals (Panel E). Due to reduced sample size, we sort our sample into tercile portfolios. We find consistent results in all these panels. All results in Appendix Table A5 confirm that GTS captures a new aspect beyond the literature on the relation between deal characteristics and post-M&A underperformance.

Finally, we control for factors driving post-M&A underperformance in our full sample and examine whether our results still hold. Two such factors are the market timing of overvaluation (Shleifer and Vishny, 2003; Moeller et al., 2005; Dong et al., 2006; Savor and Lu, 2009; Fu et al., 2013) and market fooling (Louis, 2004; Gong et al., 2008). The former suggests that firms with high valuations tend to acquire other firms or assets using their inflated share price, while the latter suggests that firms attempting to become bidders may engage in earnings management. In both cases, inferior stock price performance should be observed in the period subsequent to the deal. Following the literature, we use book-to-market ratio as a proxy for overvaluation and accruals as a proxy for earnings management. We conduct subsample analysis based on these factors and report double sorting results in Appendix Table A6. The return predictability of GTS is not subsumed by these factors.

These three sets of analyses show that GTS captures a new aspect beyond the literature on post-M&A underperformance, and the negative relation between GTS and future stock returns cannot be merely explained by these stylized facts.

4.3.3 Additional evidence on underreaction

To further confirm that market underreaction is the true driving force of our findings, we examine whether the negative return predictability by GTS becomes stronger for firms that attract less investor attention and incur high market frictions.[13] Results are provided in Appendix Table A7. In Panels A-C, we use market capitalization, analyst coverage, and institutional ownership to proxy for the level of investors' attention, respectively. The results suggest that our main results are stronger for firms with a low level of investor attention (i.e., for small firms, and for firms with low analyst coverage and low institutional ownership). For example, among small firms, a trading strategy that longs stocks in the bottom GTS quintile and shorts stocks in the top GTS quintile yields a four-factor adjusted monthly return of 0.83% (t-statistic = 4.89). On the other hand, among big firms, the same trading strategy only earns a four-factor adjusted return of about 0.46% per month (t-statistic = 3.66). Similar results are obtained using analyst coverage

[13] We thank the anonymous referee for this valuable suggestion.

and institutional ownership as well.

We use idiosyncratic volatility and illiquidity to proxy for market frictions, respectively, and report the results in Panels D and E in Appendix Table A7. These results suggest that our main results are stronger for firms with a high market friction (i.e., for firms with high idiosyncratic volatility and high illiquidity). For example, among high idiosyncratic volatility firms, the long-short strategy yields a four-factor adjusted monthly return of 0.80% (*t*-statistic = 3.24). On the other hand, among low idiosyncratic volatility firms, the same trading strategy only earns a four-factor adjusted return of 0.35% per month (*t*-statistic = 3.19). Similar results are obtained using illiquidity as well.

Overall, these double sort results provide further support that our main finding is indeed driven by the underreaction to the information contained in GTS.

5. Conclusion

In this paper, we study the asset pricing implications for the largest intangible asset, goodwill. We argue that goodwill-to-sales (GTS) contains information on firm value, and investors underreact to this information because the fair value of goodwill is hard to evaluate. We conjecture that stocks with a high GTS should experience lower subsequent returns.

Consistent with our hypothesis, we show that stocks with a high GTS underperform stocks with a low GTS, especially among firms with more complex M&As and firms with overconfident CEOs. This negative relation is robust across different empirical specifications, and captures a new aspect beyond the stylized facts documented in the literature on post-M&A underperformance. The predictive power decays over time and disappears within three years of portfolio formation. Moreover, a high GTS positively predicts future goodwill impairment, and negatively predicts future profitability and earnings surprises. Overall, our results suggest that GTS contains information on firm value, and stock markets underreact to this information because its fair value is unobservable and hard to evaluate.

Our research has the following implications. First, investors should take GTS into consideration when evaluating stocks. They should avoid stocks with a high GTS because this high level of goodwill may not be well justified by realized cash flows, and these stocks tend to experience lower returns. Second, when making acquisition decisions, managers from acquirers should evaluate business combinations more rationally and accurately to avoid a huge invisible burden (i.e., goodwill) on the balance sheet of the combined firm. Last, regulators should also pay close attention to the GTS ratio, especially during M&A booms. Stock markets with a huge aggregate goodwill could spell trouble for corporate earnings and lead to painful write-offs.

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Table 1: Summary statistics

This table reports the descriptive statistics of firm characteristics. In Panel A, we report the summaries for different samples. Columns (1)-(3), we report the summary statistics for our main sample. This sample contains all common shares traded in NYSE, AMEX, and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than \$5, and a market capitalization higher than the bottom NYSE size decile. In Column 4-9, we report descriptive statistics for subsamples based on past M&As. Firms that have only made M&As within the same industry in the past year are included in the subsample of same-industry M&A. In columns (10)-(15), we report descriptive statistics for subsamples based on CEO overconfidence. In Panel B, we report the correlation matrix for our full sample. Goodwill-to-sales (*GTS*) is defined as goodwill divided by total sales. *SIZE* is the market capitalization in billions of US dollars. *BM* is book-to-market ratio, defined as book equity over market equity. *MOM* is momentum, defined as the cumulative returns from month $t-11$ to $t-1$. *STREV* is short-term reversal, defined as return of month t. *IVOL* is idiosyncratic volatility, defined as the monthly standard deviation of the residuals from regressing daily returns on Fama-French (1993) three factors. *ILLIQ* is illiquidity constructed following Amihud (2002). *AG* is asset growth, defined as the annual growth rate of total assets. *GP* is gross profit, defined as the difference between total revenue and costs of goods sold, scaled by total assets. *AC* is accruals calculated following Sloan (1996). *NS* is net stock issuance, defined as the change in the natural log of split-adjusted shares outstanding, following Pontiff and Woodgate (2008). Our sample period is 1989 to 2016.

Panel A: Firm Characteristics

	Full Sample			Cross-Industry M&A			Same-Industry M&A			Overconfidence			Non-overconfidence		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
GTS	0.261	0.132	0.348	0.358	0.236	0.383	0.402	0.250	0.442	0.335	0.175	0.420	0.205	0.106	0.281
SIZE	4.758	0.861	13.10	10.50	1.581	22.30	7.358	1.573	16.90	3.707	0.845	10.30	5.825	1.137	14.40
BM	0.575	0.489	0.385	0.492	0.418	0.334	0.485	0.408	0.342	0.652	0.551	0.442	0.533	0.461	0.339
MOM	0.138	0.091	0.438	0.092	0.061	0.434	0.110	0.068	0.447	0.139	0.077	0.494	0.134	0.106	0.344
STREV	0.009	0.008	0.115	0.006	0.007	0.121	0.008	0.006	0.123	0.008	0.007	0.127	0.010	0.009	0.095
IVOL	0.019	0.016	0.012	0.020	0.017	0.013	0.021	0.017	0.013	0.021	0.018	0.013	0.016	0.013	0.010
ILLIQ	0.081	0.003	0.713	0.070	0.003	0.514	0.104	0.003	1.050	0.083	0.004	0.726	0.040	0.002	0.349
AG	0.174	0.082	0.357	0.327	0.155	0.509	0.372	0.187	0.532	0.241	0.095	0.456	0.106	0.064	0.235
GP	0.328	0.301	0.225	0.349	0.322	0.178	0.363	0.332	0.198	0.267	0.24	0.175	0.345	0.331	0.248
AC	0.012	0.011	0.151	0.031	0.023	0.159	0.022	0.016	0.141	0.013	0.011	0.176	0.010	0.012	0.128
NS	0.040	0.006	0.141	0.082	0.011	0.195	0.097	0.017	0.203	0.067	0.012	0.173	0.016	0.001	0.111

Panel B: Correlation Matrix											
	GTS	*SIZE*	*BM*	*MOM*	*STREV*	*IVOL*	*ILLIQ*	*AG*	*GP*	*AC*	*NS*
GTS	1.000										
SIZE	0.144	1.000									
BM	-0.021	-0.254	1.000								
MOM	-0.026	0.128	0.126	1.000							
STREV	-0.006	-0.020	-0.027	-0.141	1.000						
IVOL	-0.022	-0.399	0.029	-0.117	0.130	1.000					
ILLIQ	0.001	-0.097	0.026	-0.038	-0.022	0.091	1.000				
AG	0.223	-0.054	-0.152	-0.085	0.033	0.176	0.003	1.000			
GP	-0.278	-0.072	-0.291	0.006	0.011	0.046	0.008	-0.098	1.000		
AC	-0.021	-0.048	-0.024	-0.029	0.012	0.023	-0.008	0.164	0.027	1.000	
NS	0.190	-0.096	-0.038	-0.024	0.023	0.149	0.005	0.559	-0.135	-0.038	1.000

Table 2: Decile portfolio value-weighted returns: 1989-2016

This table reports the value-weighted average monthly excess returns and alphas to portfolios sorted on industry-adjusted goodwill-to-sales. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX, and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into decile portfolios based on *GTS_adj*. Portfolios are rebalanced at the end of each June. The average difference in return between the bottom and the top decile portfolios are reported in the last column. We report excess returns, Fama-French three-factor alphas, and Fama-French-Carhart four-factor alphas respectively. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All returns and alphas are in percentage.

	Goodwill-to-Sales Deciles										
	Low	2	3	4	5	6	7	8	9	High	Low − High
Excess returns	1.06***	0.95***	0.87***	1.15***	0.95***	0.85***	0.85***	0.97***	0.60**	0.59**	0.47***
	(3.70)	(3.76)	(2.72)	(3.59)	(3.36)	(3.07)	(3.38)	(3.60)	(2.05)	(2.06)	(2.67)
Three-factor alpha	0.27*	0.16	-0.07	0.25	0.00	-0.07	0.01	0.03	-0.37***	-0.33***	0.60***
	(1.69)	(1.08)	(-0.53)	(1.59)	(0.03)	(-0.60)	(0.11)	(0.28)	(-3.12)	(-2.78)	(3.57)
Four-factor alpha	0.31**	0.10	0.02	0.26*	0.10	0.02	0.04	0.10	-0.32***	-0.27**	0.58***
	(2.07)	(0.69)	(0.18)	(1.72)	(0.86)	(0.28)	(0.34)	(0.92)	(-2.80)	(-2.55)	(3.65)

Table 3: Factor loading

This table presents the results of time series regressions of the bottom and the top decile portfolio returns sorted by industry-adjusted goodwill-to-sales, as well as the long-short portfolio returns on Fama-French (1993) three factors and Carhart (1997)'s momentum factor. All portfolio returns are value-weighted. The sample contains all common shares traded in NYSE, AMEX, and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than \$5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX, and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry-adjustment, we exclude stocks with a share price less than \$5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into decile portfolios based on *GTS_adj*. Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively

	Alpha	MKTRF	SMB	HML	UMD
Low	0.31**	0.94***	-0.18**	-0.14*	-0.05
	(2.07)	(17.31)	(-2.43)	(-1.74)	(-0.77)
High	-0.27**	1.02***	-0.02	0.20**	-0.08
	(-2.55)	(25.35)	(-0.29)	(2.28)	(-1.61)
Low − High	0.58***	-0.08	-0.15**	-0.34***	0.03
	(3.65)	(-1.11)	(-2.26)	(-2.63)	(0.39)

Table 4: Fama-MacBeth regression: 1989-2016

This table reports the average coefficients and their respective Newey-West adjusted t-statistics from monthly firm-level cross-sectional regressions. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. We first compute goodwill-to-sales (*GTS*) as goodwill divided by total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	(1)	(2)
GTS_adj	-0.270***	-0.173***
	(-3.81)	(-3.28)
SIZE		-0.067*
		(-1.80)
BM		0.073
		(0.42)
MOM		0.334
		(0.98)
STREV		-2.888***
		(-5.15)
IVOL		-17.474***
		(-2.65)
ILLIQ		-0.011
		(-0.25)
AG		-0.188*
		(-1.68)
GP		0.447**
		(2.18)
NS		-0.883***
		(-3.24)
AC		-0.126
		(-0.60)
Number of months	324	324
Avg. number of firms per month	1,351	1,099
R-squared	0.003	0.064

Table 5 Fama-MacBeth regressions within Year 1

This table reports the average coefficients for each quarter in the first year after portfolio formation, and their respective Newey-West adjusted *t*-statistics from monthly firm-level cross-sectional regressions. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than \$5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. We first compute goodwill-to-sales (*GTS*) as goodwill divided by total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. We compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	(1)	(2)	(3)	(4)
	Qtr 1	Qtr 2	Qtr 3	Qtr 4
GTS_adj	-0.219**	-0.190*	-0.154*	-0.131
	(-2.35)	(-1.95)	(-1.80)	(-1.61)
SIZE	-0.052	-0.064	-0.178**	0.026
	(-0.76)	(-0.65)	(-2.36)	(0.35)
BM	-0.001	-0.693***	0.350	0.638**
	(-0.00)	(-2.88)	(1.18)	(2.21)
MOM	1.061**	0.786***	0.284	-0.794
	(2.53)	(2.93)	(0.66)	(-1.07)
STREV	-2.161***	-1.380	-5.403***	-2.611***
	(-3.34)	(-1.11)	(-5.45)	(-2.72)
IVOL	-21.073**	-22.426**	-21.517	-5.029
	(-2.50)	(-2.45)	(-1.60)	(-0.40)
ILLIQ	0.208**	0.115	-0.249*	-0.119
	(2.35)	(1.45)	(-1.72)	(-1.07)
AG	-0.237*	-0.113	-0.373*	-0.027
	(-1.74)	(-0.60)	(-1.73)	(-0.11)
GP	0.434	1.121***	-0.223	0.457
	(1.14)	(3.27)	(-0.74)	(1.28)
NS	-1.082***	-1.037**	-0.055	-1.379***
	(-3.17)	(-2.34)	(-0.10)	(-3.75)
AC	-0.221	-0.556	-0.074	0.349
	(-0.60)	(-1.49)	(-0.26)	(0.85)
Number of months	81	81	81	81
Avg. number of firms per month	1,099	1,099	1,099	1,099
R-squared	0.059	0.064	0.070	0.064

Table 6: Regression of goodwill impairment on goodwill-to-sales

This table reports the results of panel regressions of goodwill impairment on lagged variables including goodwill-to-sales and other control variables. The dependent variable, goodwill-impairment-to-sales (*GITS*), is the ratio of goodwill impairment in fiscal year *t*+1 over total sales. Independent variables include: goodwill-to-sales (*GTS*), the ratio of goodwill over total sales; lagged goodwill-impairment-to-sales from fiscal year *t*; size (*SIZE)*, book-to-market ratio (*BM*), momentum (*MOM*), asset growth (*AG*), net stock issuance (*NS*), accruals (*AC*), net operating assets (*NOA*), and investment growth (*IG*). All independent variables are winsorized at 1% and 99% and standardized to have a mean of zero and a standard deviation of one. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile, a positive goodwill impairment, as well as sufficient data to compute control variables. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	(1)	(2)	(3)	(4)
GTS	0.003***	0.004***	0.005***	0.005***
	(5.08)	(5.40)	(4.35)	(3.23)
GITS(t)	0.001***	0.001***	-0.001**	-0.001*
	(3.31)	(2.89)	(-2.12)	(-1.68)
SIZE		-0.001***	0.005***	0.005***
		(-3.58)	(2.83)	(2.87)
BM		0.002***	0.003***	0.003***
		(7.17)	(6.88)	(4.34)
MOM		-0.001*	-0.000	-0.000
		(-1.91)	(-0.07)	(-0.07)
AG		0.001**	0.000	0.000
		(2.30)	(0.76)	(0.85)
NS		0.001*	0.001	0.001
		(1.67)	(1.32)	(1.46)
AC		-0.000	-0.000	-0.000
		(-0.45)	(-0.17)	(-0.20)
NOA		-0.001	0.000	0.000
		(-1.14)	(0.17)	(0.23)
IG		-0.000	0.000	0.000
		(-0.05)	(0.75)	(0.70)
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Cluster	Firm	Firm	Firm	Firm, Year
N	37,528	28,716	28,716	28,716
R-squared	0.018	0.026	0.114	0.114

Table 7: Regression of ROA on goodwill-to-sales

This table reports the results of panel regressions of return-on-assets on lagged variables including goodwill-to-sales and other control variables. The dependent variable, return-on-assets (*ROA*), is net income over total assets from fiscal year *t*+1. Independent variables include: goodwill-to-sales (*GTS*), the ratio of goodwill over total sales from fiscal-year *t*; goodwill-impairment-to-sales (*GITS*) from fiscal year *t*; lagged return-on-assets from fiscal year *t*; size (*SIZE)*, book-to-market ratio (*BM*), momentum (*MOM*), asset growth (*AG*), net stock issuance (*NS*), accruals (*AC*), net operating assets (*NOA*), and investment growth (*IG*). All independent variables are winsorized at 1% and 99% and standardized to have a mean of zero and a standard deviation of one. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile, a positive goodwill impairment. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	(1)	(2)	(3)	(4)
GTS	-0.015***	-0.007***	-0.005**	-0.005**
	(-14.75)	(-8.18)	(-2.38)	(-2.00)
GITS		0.004***	0.000	0.000
		(6.29)	(0.79)	(0.50)
ROA(t)		0.487***	0.100***	0.100***
		(35.85)	(7.71)	(5.23)
SIZE		0.006***	-0.004	-0.004
		(9.15)	(-1.19)	(-1.00)
BM		-0.016***	-0.026***	-0.026***
		(-19.43)	(-22.37)	(-9.19)
MOM		0.010***	0.005***	0.005***
		(14.32)	(7.42)	(6.47)
AG		-0.007***	0.005***	0.005***
		(-6.42)	(3.73)	(3.69)
NS		-0.003***	0.001	0.001
		(-3.01)	(0.84)	(1.09)
AC		-0.001**	0.001	0.001
		(-2.08)	(1.64)	(1.52)
NOA		0.008***	-0.008***	-0.008***
		(7.05)	(-3.71)	(-3.74)
IG		-0.002**	0.001	0.001
		(-2.29)	(1.06)	(1.07)
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Cluster	Firm	Firm	Firm	Firm, Year
N	35,481	28,720	28,720	28,720
R-squared	0.043	0.386	0.525	0.525

Table 8: Fama-MacBeth regressions on earnings surprises

This table reports the average coefficients and their respective Newey-West adjusted *t*-statistics from firm-level quarterly cross-sectional regressions of proxies for earnings surprise on lagged variables including industry-adjusted goodwill-to-sales and other control variables. In Column 1, standardized unexpected earnings is calculated from a seasonal random walk model, i.e., the difference between earnings per share before extraordinary items in quarter *t* and *t*−4, scaled by the price before the announcement. In Column 2, analyst forecast error is defined as the difference between the actual earnings per share and the median of analyst forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement, scaled by the price before the announcement. Columns 3-5 reports the regression results using the cumulative abnormal returns from [−1,+1], [−3,+3], and [−5,+5] around the earnings announcement, respectively. Our main independent variable, *GTS_adj* is industry adjusted goodwill-to-sales, computed in the prior fiscal year before the earnings announcement. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
Variable	*SUE*	*Forecast Error*	*CAR[-1,+1]*	*CAR[-3,+3]*	*CAR[-5,+5]*
GTS_adj	-0.148***	-0.023**	-0.223***	-0.360***	-0.484***
	(-3.20)	(-2.27)	(-3.05)	(-3.18)	(-3.26)
SIZE	0.034**	0.006	-0.060**	-0.089**	-0.144***
	(2.30)	(1.27)	(-2.21)	(-2.55)	(-4.38)
BM	-0.096	0.017**	0.098**	0.040	0.045
	(-1.31)	(2.34)	(2.03)	(0.54)	(0.52)
MOM	1.963***	0.216***	0.148	-0.213	-0.363
	(11.93)	(7.59)	(1.01)	(-1.08)	(-1.48)
Earnings Volatility	-1.052	-0.392***	-0.936***	-1.858***	-1.771***
	(-1.03)	(-2.68)	(-3.00)	(-2.83)	(-2.92)
Earnings Persistence	-0.237***	0.006	-0.194***	-0.163**	-0.067
	(-4.18)	(0.50)	(-2.68)	(-2.20)	(-0.86)
Log(Reporting Lag)	-0.000	-0.001***	-0.008***	-0.011***	-0.011***
	(-0.04)	(-3.43)	(-2.77)	(-3.21)	(-2.86)
Log(# of Analysts)	-0.041	0.015*	0.130**	0.194***	0.322***
	(-1.24)	(1.80)	(2.44)	(2.74)	(3.72)
Log(# of Announcements)	0.054**	0.015***	-0.037	-0.088*	-0.088
	(2.46)	(3.47)	(-1.10)	(-1.90)	(-1.38)
AC	-0.161	0.010	-0.947***	-1.195***	-1.389***
	(-0.94)	(0.52)	(-4.11)	(-3.75)	(-3.80)
ILLIQ	-0.648	-0.390**	-0.243	-0.435	-0.899
	(-1.08)	(-2.01)	(-0.18)	(-0.25)	(-0.42)

Dispersion	-1.049***	-0.188***	-0.340***	-0.417***	-0.476***
	(-8.64)	(-6.83)	(-3.13)	(-2.80)	(-2.97)
Revision	1.836***	0.223***	0.532***	0.625***	0.618***
	(10.65)	(8.32)	(4.26)	(4.44)	(3.50)
N	108	108	108	108	108
Avg. num. of firms/qtr	966	966	964	964	964
R-squared	0.125	0.089	0.029	0.033	0.038

Table 9: Independent double sorting based on cross-industry M&A: 1989-2016

This table reports the value-weighted average monthly excess returns and alphas to portfolios double sorted on industry-adjusted goodwill-to-sales and mergers and acquisitions (M&As). We define a cross-industry M&A as a deal in which the acquirer and the target belong to different Fama-French 38 industry classifications. Firms that have made any cross-industry M&A deals in the past year are included in the subsample of cross-industry M&A. Firms that have only made M&A deals within the same industry in the past year are included in the subsample of same-industry M&A. We sort industry-adjusted goodwill independently based on whole sample terciles. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile, and at least one M&A deal from the last year. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry-adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks with at least one acquisition in the previous year are double sorted into terciles portfolios based on *GTS_adj* and the M&As independently. Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

	Cross-industry M&A				**Same-industry M&A**			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.23***	1.08***	0.57*	0.66**	1.12***	1.15***	0.98***	0.14
	(3.54)	(2.71)	(1.91)	(2.20)	(4.53)	(4.15)	(2.97)	(0.55)
Three-factor alpha	0.37	0.15	-0.40**	0.77**	0.31	0.19	0.09	0.22
	(1.35)	(0.62)	(-2.34)	(2.47)	(1.59)	(1.08)	(0.42)	(0.83)
Four-factor alpha	0.51*	0.27	-0.26*	0.77**	0.38*	0.27	0.11	0.27
	(1.72)	(1.12)	(-1.68)	(2.37)	(1.72)	(1.54)	(0.55)	(0.90)
Avg. # of firms	23	27	48		45	39	54	

Table 10: Independent double sorting based on CEO overconfidence: 1989-2016

This table reports the value-weighted average monthly excess returns and alphas to portfolios double sorted on industry-adjusted goodwill-to-sales and CEO overconfidence. As suggested by Schrand and Zechman (2012), we bundle up 4 firm characteristics that are related to CEO overconfidence: (1) excess investment; (2) leverage ratio; (3) whether the firm has outstanding preferred stocks or convertible debts; (4) whether the firm paid dividends in the previous fiscal year. We rank the first two characteristics into 10 groups in the ascending order separately. We assign rank 10 to a firm if it has outstanding preferred stocks or convertible debts and 1 otherwise. Similarly, we assign rank 10 to a firm if it did not pay dividends in the previous year and 1 otherwise. Then we compute the average rank from the four characteristics as a proxy for CEO overconfidence. A firm is defined to have an overconfident CEO if this average rank is above the top quintile. Non-overconfidence subsample contains firms with an average rank below the bottom quintile. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile, and a non-missing proxy for CEO overconfidence. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks with non-missing proxy for CEO overconfidence are double sorted into quintile portfolios based on *GTS_adj* and the average rank of CEO overconfidence independently. Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

	Overconfidence Sample						**Non-overconfidence Sample**					
	Low	2	3	4	High	Low-High	Low	2	3	4	High	Low-High
Excess return	1.20***	1.04***	0.63	0.91**	0.40	0.80***	1.04***	0.99***	0.96***	0.99***	0.88***	0.16
	(3.47)	(3.05)	(1.60)	(2.54)	(1.17)	(3.32)	(4.88)	(3.57)	(3.71)	(3.70)	(3.40)	(1.23)
Three-factor alpha	0.23	0.01	-0.53**	-0.18	-0.62***	0.85***	0.27*	0.07	0.06	0.07	-0.04	0.31**
	(1.34)	(0.07)	(-2.33)	(-1.02)	(-4.10)	(3.66)	(1.88)	(0.67)	(0.60)	(0.43)	(-0.32)	(2.48)
Four-factor alpha	0.24	0.10	-0.37**	-0.10	-0.45***	0.69***	0.27*	0.12	0.17*	0.15	0.01	0.26*
	(1.38)	(0.75)	(-2.01)	(-0.55)	(-3.50)	(3.17)	(1.75)	(1.08)	(1.67)	(1.13)	(0.05)	(1.86)
Avg. # of firms	65	56	55	60	90		68	87	93	85	58	

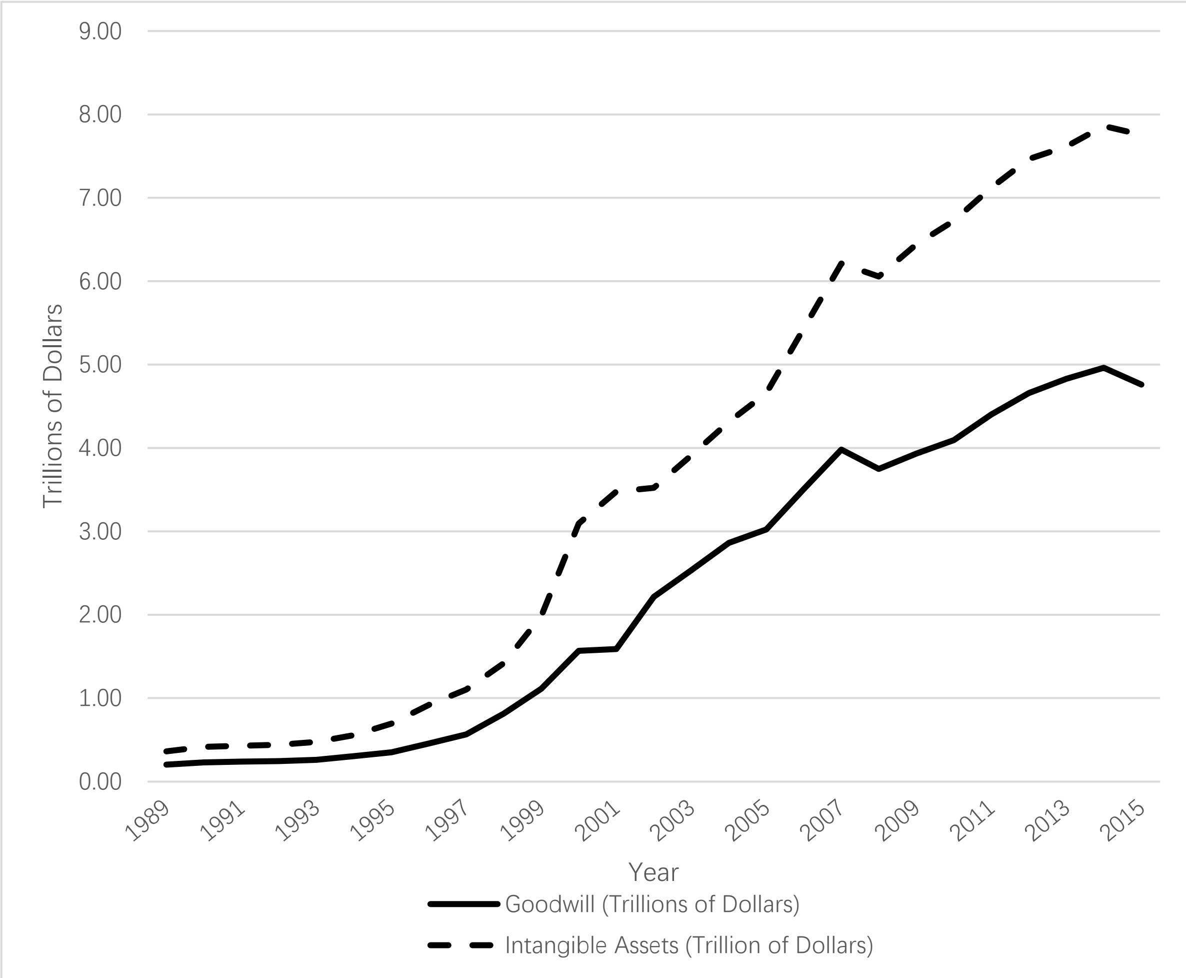

Figure 1. Time series of aggregate goodwill and aggregate intangible assets

This figure shows the time series of the aggregate goodwill and aggregate intangible assets value across all U.S. listed firms on Compustat. The sample period is from 1989 to 2016. The unit of measure is trillion dollars.

Table A1: Decile portfolio equal-weighted returns: 1989-2016

This table reports the equal-weighted average monthly excess returns and alphas to portfolios sorted on industry-adjusted goodwill-to-sales. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than \$5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry-adjustment, we exclude stocks with a share price less than \$5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into decile portfolios based on *GTS_adj*. Portfolios are rebalanced at the end of each June. The average difference in return between the bottom and the top decile portfolios are reported in the last column. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

	Goodwill-to-Sales Deciles										
	Low	2	3	4	5	6	7	8	9	High	Low − High
Excess returns	1.29***	1.14***	1.10***	1.17***	1.02***	0.95***	0.98***	0.92***	0.86***	0.48	0.81***
	(4.37)	(4.39)	(3.94)	(4.19)	(3.43)	(3.18)	(3.28)	(3.26)	(3.03)	(1.52)	(4.43)
Three-factor alpha	0.30*	0.15	0.07	0.16	-0.04	-0.11	-0.09	-0.12	-0.20*	-0.56***	0.86***
	(1.92)	(1.27)	(0.47)	(1.47)	(-0.38)	(-0.93)	(-0.73)	(-0.85)	(-1.80)	(-3.34)	(4.33)
Four-factor alpha	0.42***	0.24**	0.22	0.27***	0.10	0.07	0.10	0.04	-0.06	-0.33**	0.75***
	(2.86)	(2.28)	(1.50)	(2.70)	(0.99)	(0.77)	(0.94)	(0.31)	(-0.61)	(-2.41)	(4.26)

Table A2: Alternative factor models and DGTW adjusted returns

This table presents value-weighted portfolio alphas on Fama-French (2015) five factors, Fama-French-Carhart six factors, Hou-Xue-Zhang (2015) q-factors, Stambaugh-Yuan (2016)'s mispricing factors, and DGTW adjusted portfolio returns. We report alphas and adjusted returns for the bottom and the top goodwill-to-sales decile, as well as a trading strategy that longs stocks from the bottom decile and shorts stocks from the top decile. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into decile portfolios based on *GTS_adj*. Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

	Low	High	Low − High
Five-factor alpha	0.16	-0.36***	0.52***
	(1.25)	(-2.76)	(2.96)
Six-factor alpha	0.18	-0.28***	0.46***
	(1.44)	(-2.64)	(2.88)
q-factor alpha	0.25**	-0.33**	0.58***
	(2.07)	(-2.24)	(3.05)
m-factor alpha	0.30**	-0.23**	0.53***
	(2.50)	(-2.05)	(2.92)
DGTW Adjusted Returns	0.17*	-0.32***	0.49***
	(1.74)	(-3.56)	(3.78)

Table A3: Alternative industry adjustments to goodwill-to-sales

This table reports the value-weighted average monthly excess returns and alphas to portfolios sorted on goodwill-to-sales with different industry adjustments. In column (1), we use Fama-French 38 industries, which is our main result in Table 2. In column (2), we do not adjust goodwill-to-sales by industry. In column (3), we use Fama-French 48 industries. In column (4), we use Fama-French 30 industries. In column (5), we use Fama-French 17 industries. In column (6), we use Fama-French 5 industries. In column (7), we use 1-digit SIC codes. In column (8), we use 2-digit SIC codes. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as goodwill divided by total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into decile portfolios based on industry-adjusted goodwill-to-sales. Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low	1.06***	1.07***	1.10***	1.15***	1.16***	0.96***	0.97***	0.99***
	(3.70)	(3.94)	(4.30)	(3.87)	(4.72)	(2.75)	(3.30)	(3.57)
High	0.59**	0.69**	0.69**	0.69**	0.57*	0.59**	0.64**	0.66**
	(2.06)	(2.39)	(2.54)	(2.48)	(1.92)	(2.00)	(2.33)	(2.41)
Low − High	0.47***	0.38**	0.41**	0.46***	0.59***	0.37*	0.33**	0.33**
	(2.67)	(2.19)	(2.51)	(2.74)	(3.05)	(1.72)	(2.36)	(2.10)
Three-factor alpha	0.60***	0.37**	0.56***	0.57***	0.76***	0.50***	0.35**	0.39**
	(3.57)	(2.25)	(3.66)	(3.33)	(4.15)	(2.61)	(2.40)	(2.35)
Four-factor alpha	0.58***	0.33**	0.49***	0.50***	0.63***	0.52**	0.29**	0.38**
	(3.65)	(2.05)	(3.35)	(2.92)	(3.75)	(2.46)	(2.07)	(2.29)

Table A4. Subsample analysis: without recent M&As

This table reports the value-weighted average monthly excess returns and alphas to portfolios sorted on industry-adjusted goodwill-to-sales. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have no M&As in the past three years (column (1)) or past five years (column (2)), have a positive goodwill at fiscal year-end, a price-per-share larger than $5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into decile portfolios based on *GTS_adj*. Portfolios are rebalanced at the end of each June. Newey-West adjusted t-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

GTS Deciles	Without M&A from Past 3 Years	Without M&A from Past 5 Years
Low	1.02	1.06
2	1.12	1.13
3	0.90	0.89
4	0.98	1.12
5	1.15	0.94
6	0.75	0.78
7	0.83	0.83
8	1.00	1.05
9	0.79	0.83
High	0.56	0.58
Low − High	0.46**	0.48**
	(2.18)	(2.05)
Three-factor alpha	0.60***	0.59**
	(2.78)	(2.47)
Four-factor alpha	0.62***	0.59***
	(3.01)	(2.70)

Table A5. Subsample analyses based on deal characteristics

This table reports the value-weighted average monthly excess returns and alphas to portfolios sorted on industry-adjusted goodwill-to-sales for subsamples based on the characteristics of the most recent M&A deal in the past three years. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have made cash-only deals (Panel A), stock deals (Panel B), single bidder deals (Panel C), non-tender offer deals (Panel D), non-hostile takeover deals (Panel E), have a positive goodwill at fiscal year-end, a price-per-share larger than $5, and a market capitalization higher than the bottom NYSE size decile. Following Fama and French (1992), we match accounting data for all fiscal year-ends in calendar year $t-1$ with the returns for July of year t to June of year $t+1$ to ensure that the accounting variables are known before the returns they are used to explain. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted into tercile portfolios based on *GTS_adj*. Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

Panel A: Cash-only Deals					
Low	Medium	High	Low-High	3F alpha	4F alpha
1.29***	1.46***	0.94***	0.35*	0.47**	0.45**
(4.83)	(4.15)	(3.56)	(1.73)	(2.30)	(2.18)
Panel B: Stock Deals					
Low	Medium	High	Low-High	3F alpha	4F alpha
1.08***	0.82***	0.48	0.60***	0.71***	0.63***
(3.91)	(2.67)	(1.47)	(2.60)	(3.17)	(2.70)
Panel C: Single Bidder					
Low	Medium	High	Low-High	3F alpha	4F alpha
1.14***	1.03***	0.74***	0.40***	0.50***	0.46***
(4.61)	(3.51)	(2.69)	(3.06)	(3.73)	(3.08)
Panel D: Non-Tender Offer					
Low	Medium	High	Low-High	3F alpha	4F alpha
1.15***	0.97***	0.73***	0.42***	0.50***	0.46***
(4.30)	(3.27)	(2.70)	(3.31)	(3.92)	(3.32)
Panel E: Non-Hostile Takeover					
Low	Medium	High	Low-High	3F alpha	4F alpha
1.11***	1.06***	0.72***	0.39***	0.48***	0.45***
(4.25)	(3.68)	(2.66)	(2.75)	(3.68)	(3.00)

Table A6: Independent double sorting based on book-to-market ratio and accruals: 1989-2016

This table reports the value-weighted average monthly excess returns and alphas to two sets of independently double sorted portfolios. Panel A reports the value-weighted average monthly excess returns and alphas to portfolios double sorted on industry-adjusted goodwill-to-sales and book-to-market ratio. Panel B reports similar results for portfolios double sorted on industry-adjusted goodwill-to-sales and accruals. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile, and a non-missing measure of book-to-market ratio or accruals. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are double sorted independently based on *GTS_adj* and book-to-market ratio (Panel A) or accruals (Panel B). Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

Panel A: Book-to-Market Ratio

	Low BEME			High BEME		
	Low	High	Low-High	Low	High	Low-High
Excess return	1.12***	0.70***	0.42***	1.10***	0.82***	0.28**
	(4.78)	(2.61)	(3.04)	(3.78)	(2.93)	(2.46)
Three-factor alpha	0.30***	-0.23**	0.53***	0.10	-0.22*	0.32**
	(3.15)	(-2.24)	(4.17)	(0.82)	(-1.86)	(2.43)
Four-factor alpha	0.30***	-0.17*	0.47***	0.15	-0.12	0.27**
	(3.19)	(-1.90)	(3.66)	(1.30)	(-1.20)	(2.09)

Panel B: Accruals

	Low Accruals			High Accruals		
	Low	High	Low-High	Low	High	Low-High
Excess return	1.18***	0.85***	0.33**	1.17***	0.73***	0.44***
	(4.77)	(3.44)	(1.97)	(4.83)	(2.75)	(3.33)
Three-factor alpha	0.36***	-0.06	0.42**	0.28*	-0.26*	0.54***
	(2.87)	(-0.50)	(2.51)	(1.92)	(-1.89)	(3.91)
Four-factor alpha	0.33***	0.00	0.33**	0.28**	-0.19	0.47***
	(2.71)	(0.02)	(2.13)	(2.18)	(-1.52)	(3.41)

Table A7: Independent double sorting based on investors' attention and market friction

This table reports the value-weighted average monthly excess returns and alphas to five sets of independently double sorted portfolios. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. We use Fama-French 38 industry classifications, and require that each industry should have at least 3 firms to make this adjustment. After the industry adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks are sorted independently based on *GTS_adj* and market capitalization (Panel A), analyst coverage (Panel B), institutional ownership (Panel C), idiosyncratic volatility (Panel D), illiquidity (Panel E). Portfolios are rebalanced at the end of each June. Newey-West adjusted *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

Panel A: Market Capitalization

	Small Firm			Big Firm		
	Low	High	Low − High	Low	High	Low − High
Excess return	1.43***	0.60*	0.83***	1.07***	0.75***	0.32**
	(4.75)	(1.88)	(4.97)	(4.51)	(2.82)	(2.05)
Three-factor alpha	0.39***	-0.48***	0.87***	0.29***	-0.20**	0.49***
	(3.09)	(-3.48)	(5.11)	(2.86)	(-2.26)	(3.83)
Four-factor alpha	0.39***	-0.44***	0.83***	0.30***	-0.16**	0.46***
	(3.32)	(-3.04)	(4.89)	(3.24)	(-1.96)	(3.66)

Panel B: Analyst Coverage

	Low ACOV			High ACOV		
	Low	High	Low − High	Low	High	Low − High
Excess return	0.95***	0.34	0.61**	1.12***	0.75***	0.37***
	(2.97)	(1.00)	(2.19)	(4.81)	(2.83)	(3.29)
Three-factor alpha	0.02	-0.59***	0.61**	0.26***	-0.22**	0.48***
	(0.09)	(-2.64)	(2.42)	(2.76)	(-2.34)	(4.44)
Four-factor alpha	0.11	-0.57**	0.68**	0.26***	-0.15*	0.41***
	(0.55)	(-2.57)	(2.49)	(2.85)	(-1.89)	(3.99)

(Continued)

(Continued)

Panel C: Institutional Ownership						
	Low IO			High IO		
	Low	High	Low − High	Low	High	Low − High
Excess return	1.05***	0.66**	0.39**	1.14***	0.87***	0.27**
	(4.21)	(2.38)	(2.36)	(4.13)	(3.33)	(2.21)
Three-factor alpha	0.25***	-0.28***	0.53***	0.15	-0.16	0.31**
	(2.71)	(-3.79)	(4.17)	(1.13)	(-0.96)	(2.14)
Four-factor alpha	0.27***	-0.23***	0.50***	0.16	-0.06	0.22
	(3.22)	(-3.40)	(4.25)	(1.29)	(-0.40)	(1.61)
Panel D: Idiosyncratic Volatility						
	Low IV			High IV		
	Low	High	Low − High	Low	High	Low − High
Excess return	1.00***	0.79***	0.21	1.36***	0.56	0.80***
	(4.81)	(2.83)	(1.26)	(3.65)	(1.50)	(3.28)
Three-factor alpha	0.27***	-0.14	0.41***	0.32*	-0.59***	0.91***
	(2.95)	(-1.10)	(3.46)	(1.67)	(-3.35)	(3.48)
Four-factor alpha	0.27***	-0.08	0.35***	0.34*	-0.46***	0.80***
	(2.94)	(-0.77)	(3.19)	(1.83)	(-2.86)	(3.24)
Panel E: Illiquidity						
	Low Illiquidity			High Illiquidity		
	Low	High	Low − High	Low	High	Low − High
Excess return	1.07***	0.72***	0.35***	1.22***	0.53*	0.69***
	(4.59)	(2.68)	(2.66)	(4.34)	(1.80)	(4.57)
Three-factor alpha	0.24***	-0.23***	0.47***	0.20	-0.54***	0.74***
	(2.75)	(-2.73)	(4.32)	(1.64)	(-3.99)	(4.49)
Four-factor alpha	0.23***	-0.18**	0.41***	0.31***	-0.37***	0.68***
	(2.86)	(-2.36)	(3.93)	(2.74)	(-3.14)	(4.29)

Table A8: Independent double sorting based on cross-industry M&A: 1989-2016

This table reports the value-weighted results to portfolios double sorted on industry-adjusted goodwill-to-sales and M&As. We define a cross-industry M&A as a deal in which the acquirer and the target belong to different industry classifications. In Panels A and B, we use four-digit and three-digit SIC codes for industry classifications, respectively. In Panels C, D, E, and F, we use Fama-French 17, 30, 48, and 49 industry classifications, respectively. Firms that have made any cross-industry M&A deals in the past year are included in the subsample of cross-industry M&A. Firms that have only made M&A deals within the same industry in the past year are included in the subsample of same-industry M&A. We sort industry-adjusted goodwill independently based on whole sample terciles. The sample contains all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end, a price-per-share larger than $5, a market capitalization higher than the bottom NYSE size decile, and at least one M&A deal from the last year. At the end of each June, we first compute goodwill-to-sales (*GTS*) as the ratio of goodwill to total sales for all common shares traded in NYSE, AMEX and NASDAQ that have a positive goodwill at fiscal year-end. Then, we compute industry-adjusted GTS (*GTS_adj*) as the difference between GTS and the mean GTS from the industry. After the industry-adjustment, we exclude stocks with a share price less than $5 or with a market capitalization below the bottom NYSE size decile. The rest of the stocks with at least one acquisition in the previous year are double sorted into terciles portfolios based on *GTS_adj* and the M&As independently. Portfolios are rebalanced at the end of each June. Newey-West *t*-statistics are reported in parentheses. Our sample period is 1989 to 2016. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All returns and alphas are in percentage.

Panel A: Four-Digit SIC

	Cross-industry M&A				Same-industry M&A			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.27***	1.17***	0.78***	0.49***	0.70**	0.97***	0.59**	0.11
	(4.91)	(3.71)	(2.79)	(3.08)	(2.50)	(2.95)	(1.99)	(0.48)
Three-factor alpha	0.45***	0.20	-0.17*	0.62***	-0.15	-0.01	-0.28	0.13
	(3.79)	(1.52)	(-1.74)	(4.36)	(-0.85)	(-0.02)	(-1.26)	(0.53)
Four-factor alpha	0.50***	0.31**	-0.11	0.61***	-0.20	0.12	-0.19	-0.01
	(3.69)	(2.43)	(-1.20)	(3.89)	(-1.16)	(0.64)	(-0.96)	(-0.04)
Number of firms	44	44	72		24	23	29	

Panel B: Three-Digit SIC

	Cross-industry M&A				Same-industry M&A			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.23***	1.22***	0.77***	0.46***	1.10***	0.91***	0.72**	0.38*
	(4.76)	(3.83)	(2.84)	(2.63)	(4.12)	(2.98)	(2.40)	(1.84)
Three-factor alpha	0.40***	0.25*	-0.18	0.58***	0.27*	-0.05	-0.17	0.44**
	(3.34)	(1.66)	(-1.61)	(3.69)	(1.74)	(-0.29)	(-0.94)	(2.06)
Four-factor alpha	0.46***	0.36**	-0.13	0.59***	0.26	0.08	-0.07	0.33
	(3.43)	(2.56)	(-1.20)	(3.43)	(1.59)	(0.53)	(-0.44)	(1.47)
Number of firms	34	37	62		35	29	40	

Panel C: Fama-French 17 Industries								
	Cross-industry M&A				Same-industry M&A			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.37***	1.12***	0.78***	0.59**	1.03***	1.07***	0.73***	0.30**
	(4.58)	(3.13)	(2.69)	(2.40)	(3.94)	(3.74)	(2.78)	(2.00)
Three-factor alpha	0.59***	0.17	-0.16	0.75***	0.15	0.11	-0.18	0.33**
	(3.10)	(0.75)	(-1.40)	(3.31)	(1.13)	(0.81)	(-1.38)	(2.08)
Four-factor alpha	0.68***	0.25	-0.08	0.76***	0.15	0.25**	-0.12	0.27
	(3.33)	(1.19)	(-0.74)	(3.22)	(1.10)	(2.30)	(-1.00)	(1.60)
Number of firms	19	22	39		49	45	63	

Panel D: Fama-French 30 Industries								
	Cross-industry M&A				Same-industry M&A			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.38***	1.04***	0.75***	0.63***	0.92***	1.13***	0.71***	0.21
	(4.91)	(3.28)	(2.64)	(3.25)	(3.80)	(3.98)	(2.63)	(1.30)
Three-factor alpha	0.52***	0.07	-0.20*	0.72***	0.10	0.19	-0.19	0.29*
	(3.09)	(0.43)	(-1.85)	(4.02)	(0.77)	(1.45)	(-1.30)	(1.67)
Four-factor alpha	0.61***	0.21	-0.13	0.74***	0.10	0.29**	-0.12	0.22
	(3.37)	(1.28)	(-1.21)	(3.68)	(0.77)	(2.48)	(-0.96)	(1.20)
Number of firms	25	27	47		43	40	54	

Panel E: Fama-French 48 Industries								
	Cross-industry M&A				Same-industry M&A			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.38***	1.23***	0.80***	0.58***	0.83***	1.05***	0.67**	0.16
	(5.04)	(3.56)	(2.87)	(2.91)	(3.44)	(3.86)	(2.40)	(1.04)
Three-factor alpha	0.56***	0.27	-0.15	0.71***	-0.01	0.11	-0.24	0.23
	(3.93)	(1.57)	(-1.33)	(3.91)	(-0.09)	(0.76)	(-1.51)	(1.35)
Four-factor alpha	0.62***	0.40**	-0.09	0.71***	0.01	0.17	-0.15	0.16
	(3.70)	(2.45)	(-0.87)	(3.58)	(0.06)	(1.46)	(-1.09)	(0.87)
Number of firms	29	31	52		39	36	50	

Panel F: Fama-French 49 Industries								
	Cross-industry M&A				Same-industry M&A			
	Low	Medium	High	Low − High	Low	Medium	High	Low − High
Excess return	1.34***	1.24***	0.82***	0.52***	0.91***	1.07***	0.64**	0.27
	(4.97)	(3.62)	(2.98)	(2.61)	(3.60)	(3.83)	(2.25)	(1.47)
Three-factor alpha	0.52***	0.27	-0.12	0.64***	0.07	0.12	-0.26*	0.33*
	(3.83)	(1.64)	(-1.06)	(3.59)	(0.46)	(0.82)	(-1.66)	(1.70)
Four-factor alpha	0.57***	0.41**	-0.07	0.64***	0.10	0.20	-0.16	0.26
	(3.64)	(2.51)	(-0.68)	(3.35)	(0.68)	(1.63)	(-1.18)	(1.25)
Number of firms	29	31	53		39	35	48	