# Social Media Engagement and Intangible Asset Valuation: Evidence from Mergers and Acquisitions

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**Social Media Metrics in Deal Intelligence:**
**Accounting for Intangibles**


## Abstract

Intangibles constitute a significant part of M&A deal value, but their values are often not directly incorporated in financial statements. We investigate whether user engagement metrics from social media platforms contain useful information in deal evaluation, particularly for the intangible components. We find that user engagement metrics (e.g., favorites and retweets) from targets' Twitter accounts can exhibit significant explanatory power on the value of relevant intangible assets acquired, both on a standalone basis and incremental to summary accounting numbers such as revenue. Price multiples based on retweets exhibit a significant negative association with deal announcement returns in transactions involving private targets. Further, price multiples based on retweets are also informative of acquirers' subsequent purchase price adjustments on private targets after deal announcements. Overall, our findings suggest that social media can provide useful alternative data in deal evaluation, especially when the deal involves private targets.



**Keywords**: intangible asset, M&A, social media, alternative data, deal intelligence, private firms

## 1. Introduction

While intangible assets are increasingly important to corporate value in the knowledge-based economy, not all intangible assets are reflected as assets in the financial statements. Intangibles in corporate balance sheets mainly derive from those acquired in M&A transactions. Investments related to internally generated intangible assets are typically expensed but not capitalized. Some scholars argue that the current accounting system fails to properly account for the value of intangibles (e.g., Lev 2018). Intangible assets also represent highly significant components in M&A transactions. In the study by Shalev et al. (2013), 83% of the M&A deal value is contributed by intangible assets (including goodwill), which are subsequently capitalized in the acquirers' balance sheets. However, these intangible assets are typically not reflected in the targets' balance sheets before the transaction. While M&As play an important part in the valuation of intangible assets, little is known regarding how valuation is derived, especially for outsiders who do not have access to the data room in the deal-making process.

In this study, we explore whether alternative data from social media can be useful in the measurement of the value of intangible assets. The rapid growth of alternative corporate data outside the financial accounting system has the potential to provide valuable data points in evaluating an M&A transaction. Particularly, there has been explosive growth in the use of social media over the past decade. Firms increasingly utilize social media platforms to engage with their stakeholders. Social media users also follow firms they are interested in and react to firm-initiated posts, e.g., through favorites (likes) and retweets (shares). We consider these interactions as "user engagement" on social media. Such interactions provide massive public data trails on social media users' ongoing relationships with firms. Due to the ease of access, our study focuses on these user engagement metrics from social media in M&A deal intelligence.

Since firms often use social media as a channel for marketing and customer services, social media users are often the direct customers or end-users of firms' products and services, (Gunarathne et al. 2018; Lee et al. 2018). User engagement volumes on social media are likely correlated with its scale of operations in the real economy. Investors may utilize these metrics in assessing the announced transactions when the target firm's accounting information is not fully disclosed. Additionally, user engagement volumes on social media have the potential to capture components of intangible assets typically neglected on the balance sheet, complementing accounting metrics. While outsiders often have limited access to targets' accounting numbers, we posit that they can potentially extract value-relevant metrics from social media to provide alternative measurements of the value of intangible assets acquired, particularly on components related to a firm's brand equity or customers.

We analyze the volume of user engagement on target firms' Twitter accounts for M&A transactions announced between 2010 and 2017. Twitter is chosen as the platform of interest due to its wide adoption by firms. We focus on two user engagement metrics: favorites[1] and retweets. Favorites generally represent positive sentiment toward the tweet while retweets may indicate elevated enthusiasm by users as the tweet gets further disseminated to their followers. We scrape target firms' Twitter accounts and compute both the number of favorites and retweets received by the tweets initiated by target firms in the three months before transaction announcements (*favorites* and *retweets*). Higher volumes of user engagement on the social media platform could indicate higher brand awareness and customer satisfaction (Colicev et al. 2018).

[1] In the paper, we use the term "favorites" to refer to either favorites (star button) or likes (small heart) on Twitter. On November 13, 2015, Twitter announced a change of the star icon to a heart as Twitter finds that a heart is a more universal symbol.

Our M&A sample requires targets to have operated Twitter accounts before transaction announcements and acquirers to be U.S.-listed. We hand-collect the information on purchase price allocation from acquirers' 10-K filings after the transaction is consummated. Due to the discretion in purchase price allocation documented in the prior literature (e.g., Shalev et al. 2013), we consider the total value of brand-related intangibles, customer-related intangibles, and goodwill as the relevant intangibles (*intangibles*) that social media metrics may have value relevance with. In our sample, *intangibles* constitute over 75% of the deal value. To facilitate the interpretation of the magnitude of explanatory powers, we compare social media metrics vis-à-vis revenue, which is the most widely disclosed accounting metric in M&A transactions. Our main sample thus also requires data availability on the target's revenue.

To explore the value relevance of social media metrics, we assess whether the volume of user engagements in targets' Twitter accounts exhibits significant explanatory powers on the value of relevant intangibles recognized by acquirers. We first examine the explanatory power of each metric (*favorites*, *retweets*, and *revenue*) on *intangibles* on a standalone basis. Similar to *revenue*, both Twitter metrics (*favorites*, *retweets*) exhibit a significant positive association with the value of *intangibles*. Between *favorites* and *retweets*, the model that uses *retweets* exhibits the closest $R^2$ compared to the model that uses *revenue*. These findings suggest that social media metrics can be useful for intangible valuation when used on a standalone basis.

We further explore whether these social media metrics can complement accounting numbers in intangible valuation. Specifically, we examine whether *favorites* and *retweets* exhibit explanatory powers on the value of *intangibles* incremental to that of *revenue*. In models that utilize both revenue and social media metrics as the independent variables, both *favorites* and *retweets* remain statistically significant in explaining the value of *intangibles*. The inclusion of *revenue* in the model only modestly decreases the coefficient estimates on *favorites* or *retweets*, suggesting that a significant part of the signals contained in these social media metrics are not subsumed by revenue. Using both *retweets* and *revenue* increases the model $R^2$ by 0.05 (~16%) relative to the model that uses *revenue* only. Thus, jointly considering both social media metrics and accounting numbers can improve the model's explanatory power on the value of intangibles.

As intangibles comprise a significant component of deal values, we next evaluate the usefulness of these social media metrics to investors in deal evaluation. While acquirers and deal advisories can access a myriad of proprietary financial and operating information from targets through extensive due diligence, outside investors only have access to public information that varies by the disclosure choice of transacting parties. If the target is private, investors potentially have much higher valuation uncertainty with a more limited information set and a lack of publicly traded prices. Outside scrutiny is likely more difficult if acquirers disclose little target financial information in deal announcements. Thus, investors may have to resort to using third-party data in deal evaluation. If social media metrics are indeed value relevant, we posit that investors should find social media metrics useful in their initial deal evaluation involving private targets during transaction announcements.

We construct transaction price multiples based on Twitter user engagement metrics, similar in spirit to price multiples typically used in transaction comparable analyses. Specifically, we create *price/favorites* and *price/retweets* respectively as the ratio of the total purchase price to the volume of favorites and retweets received by the target's Twitter accounts in the three months before transaction announcements. For comparison, we also create *price/revenue* by dividing the total purchase price by the target's revenue before transaction announcements. Higher multiples likely represent an overvaluation of the target firm's intangible assets with reference to the metrics. We then examine whether the market reactions to deal announcements reflect the information contained in these transaction price multiples. If investors are using information that is consistent with the price multiples in deal evaluation, transaction announcement returns should be negatively associated with these multiples. We find that the *price/retweets* multiple exhibits a significant negative association with transaction announcement returns in transactions with private targets. The evidence is consistent with some investors incorporating the signals contained in *retweets* in their evaluation of private targets in deal announcements.

Next, we investigate whether investors' reactions to deal announcements involving private targets are well-informed using the signals from *retweets*. Specifically, we examine the informativeness of the *price/retweets* multiple on acquirers' subsequent purchase price adjustments on the target. The extensive post-announcement due diligence process should have the potential to uncover some of the signals contained in social media metrics. Consistent with investors' reactions during deal announcements, we find that the *price/retweets* multiple exhibits a significant negative association with the percentage change in the implied enterprise value of the target from initial deal announcements to deal closings in transactions involving private targets. This finding is consistent with the usefulness of *retweets* in deal evaluation but acquirers do not fully incorporate its signals in the initial valuation of private targets before deal announcements.

On top of the uncertainty in valuation, agency problems in M&A transactions (e.g., managerial hubris) may result in overpriced deals, with implications for future goodwill impairments. We further examine the informativeness of the *price/retweets* multiple on subsequent goodwill impairments by acquirers. If acquirers do not fully incorporate the useful signals from social media metrics even with post-announcement due diligence, the *price/retweets* multiple could exhibit a positive association with subsequent goodwill impairments. Consistent with this, the results show that the *price/retweets* multiple exhibits a marginally significant positive association with the amount of subsequent goodwill impairment by acquirers.

In additional analyses, we explore whether targets' business models moderate the explanatory powers of Twitter metrics on the value of *intangibles*. We find that the superiority of revenue's explanatory power vs. Twitter metrics mainly derives from targets with a business-to-business (B2B) model. Among deals involving targets with a business-to-consumer (B2C) model, *revenue* no longer exhibits a significant association with the value of *intangibles.* However, both *favorites* and *retweets* remain statistically significant in explaining the value of *intangibles*. In the subsample with B2C targets, *retweets* also generate higher model $R^2$ than revenue. These results indicate that user engagement metrics on Twitter, especially *retweets,* are particularly useful in assessing the value of *intangibles* for B2C firms.

We also separately examine the explanatory power of various components of the total purchase price. We find that social media metrics exhibit significant explanatory powers for each component of related intangibles, including marketing-related intangibles, customer-related intangibles, and accounting goodwill, but not tangible assets. Revenue exhibits significant explanatory power on the tangibles, customer-related intangibles, and accounting goodwill, but not marketing-related intangibles. This suggests that social media metrics are primarily useful for intangible valuation in deal intelligence and can complement accounting numbers which work better with tangibles.

To supplement our main analyses which consider only *flow* metrics *favorites, retweets,* and *revenue,* we examine several alternative metrics from social media and financial statements. We find that *retweets* can also provide explanatory power incremental to earnings. We also consider two *stock* metrics: the number of Twitter account followers and total assets. We find that the number of followers also exhibits a significant positive association with the value of *intangibles* but total asset only displays a marginally insignificant association. Further, both *favorites* and *retweets* provide explanatory powers incremental to the number of followers.

Our study contributes to the M&A literature. Probably limited by data availability, prior studies largely focus on public targets in assessing the role of information in M&A transactions (e.g., Raman, Shivakumar, and Tamayo 2013; Skaife and Wangerin 2013; McNichols and Stubben 2015; Martin and Shalev 2017). A sizable proportion of transactions involve private targets with little disclosed accounting information. Our finding suggests that targets' social media metrics can be useful information in deal intelligence, especially for investors in their evaluation of an announced or rumored deal involving private targets. This study sheds light on social media as a potential channel through which the market acquires and impounds information related to private targets in deal announcements. Transaction pricing multiples based on *retweets* appear to be informative of subsequent purchase price adjustments for private targets. Despite the generally documented positive market reactions to private target M&A announcements (e.g., Chang 1998; Moeller, Schlingemann, and Stulz 2004; Officer, Poulsen, and Stegemoller 2008), our findings shed light on potential issues with the valuation of certain private targets at initial deal announcements.

The study also contributes to the literature on the accounting for intangibles. Some scholars argue that the current financial accounting system does not perform well in accounting for intangible assets (e.g., Lev and Zarowin 1999; Srivastava 2014). In the M&A setting, prior studies also reveal issues with managerial discretion over purchase price allocation (e.g., Shalev et al. 2013). Other studies find that the recognized fair value of intangibles can be predictive of future payoffs (e.g., Blann et al. 2020; McInnis and Monsen, 2021). Recently, standard setters have put goodwill accounting as one of the top items on their current agenda. We find that transaction pricing multiples based on retweets appear to be informative of acquirers' future goodwill impairments. Overall, our study sheds light on the potential in using social media metrics to complement the valuation of intangible assets or to strengthen the reporting of their fair values, especially for deals involving private targets.

Finally, our study contributes to the burgeoning literature on alternative data. Prior literature has examined the usefulness of alternative data in primarily predicting stock returns in the secondary market, such as investor opinions on social media (e.g., Chen et al., 2014), consumer opinion (e.g., Huang 2018), employer reviews (e.g., Green et al. 2019), etc. Our study sheds light on another potential application of alternative data in finance by demonstrating the usefulness of social media metrics in deal intelligence, particularly concerning the valuation of intangible assets, an area with deficiencies with traditional data. In particular, we find that *retweets* can perform better than *revenue* in explaining the value of marketing-related intangibles recognized by acquirers. *Retweets* also perform better than *revenue* in explaining the value of *intangibles* of B2C firms recognized by acquirers.

## 2. Background and Hypotheses

### 2.1. Intangible Assets

Intangible assets are assets (not including financial assets) that lack physical substance. Brand recognition and intellectual property, such as patents, trademarks, and copyrights, are some examples of intangible assets. Lev (2018) estimates that the US private sector's investment rate in intangibles almost doubled between 1977 and 2016.

While intangible assets are increasingly critical to corporate value in the digital economy, not all of these intangible assets are reflected as assets in the financial statements. Investments related to internally generated intangible assets are typically expensed but not capitalized. Lev and Zarowin (1999) argue that "it is in the accounting for intangibles that the present system fails most seriously", mainly due to the mismatch of costs with revenues. Srivastava (2014) finds that a major cause for a decline in earnings quality is the increasing intangible intensity among listed firms in the US. Gu and Lev (2017) further argue that conventional GAAP earnings-based security analysis has lost much of its usefulness for investors and investors should switch to using a broader long-term competitive analysis using non-GAAP data.

Mergers and acquisitions provide a unique occasion in which the intangible assets of the target firm are recognized as individually identifiable intangible assets and part of goodwill by the acquirer. Acquired intangibles are generally recognized using a fair value basis at the time of the transaction. However, practitioners often find it challenging to conduct valuations on intangible assets. Intangible assets are typically highly illiquid, and it is often difficult to observe the market prices of comparable assets due to their complexity. Thus, their measurements can be relatively unreliable. Practitioners utilize a mix of market, income, and cost approaches to conduct valuations on intangible assets (CGMA 2012). Due to the lack of detailed disclosure, outsiders may also find it difficult to verify the value measurement of intangible assets.

### 2.2. User Engagement on Social Media

There has been explosive growth in the use of social media since the late 2000s. Active social media users surpassed 3.8 billion people in January 2020 (DataReportal 2020), generating a massive amount of data trails on social media platforms. Data from social media has become a popular source of alternative data in the financial services industry (e.g., Kolanovic and Smith 2019; Grennan and Michaely 2020). Many firms set up social media accounts to engage with their customers and investors. Twitter is one of the popular social media platforms that have emerged over the past decade. Jung et al. (2017) find that close to 50% of S&P 500 firms utilize Twitter to disseminate information to external stakeholders in early 2013. Social media users can follow firms of interest and react to firm-initiated posts on social media. As social media may garner the wisdom of crowds, some firms also actively monitor social media to gauge customer feedback and brand buzz.

Prior literature has examined how firms utilize the Twitter platform to disseminate information (e.g., Blankespoor et al. 2014; Jung et al. 2017). Based on the “wisdom of the crowd” conjecture, another stream of accounting literature examines the individual or aggregate information content of third-party tweets about public firms, e.g., their association with product demand (e.g., Gong et al. 2017; Rui et al. 2013) and stock returns (e.g., Bollen et al. 2011; Deng et al. 2018; Bartov et al. 2018). These studies generally focus on tweets generated by social media users, who tweet about things that they are interested in or concerned about, sometimes tagging public firms. Our study focuses on social media users’ reactions to tweets initiated by firms.

Twitter users often follow companies from which they are interested in getting the latest updates, whether as customers, investors, employees, or other stakeholders. When a firm initiates a tweet, it draws varying levels of reactions from its followers and other Twitter users through hashtags (or cashtags) following or algorithmic recommendations. Twitter users may ignore the tweet, or react by clicking the favorites button, replying to the tweet, or even retweeting it to their followers. Users’ actions on the social media posts of firms, such as favorites, retweets, and replies, reflect the level of user engagement on social media by the firm (Lee et al. 2018; Hughes et al. 2019). Achieving engagement is a key objective for firms to use social media (Lee et al. 2018).

### 2.3. Accounting for M&As

In M&A, accounting goodwill arises as the excess of the total purchase price over the net amounts assigned to the identifiable tangible and intangible assets acquired and liabilities assumed using their fair value on the date of acquisition by the major balance sheet caption. Intangible assets that have finite lives will continue to be amortized over their useful lives. However, goodwill and intangible assets that have indefinite useful lives will no longer be amortized. Instead, they will be tested at least annually for any impairments. In the impairment test, goodwill will be impaired if its estimated fair value is lower than the carrying amount, but not vice versa.

Recent studies (e.g., Li and Sloan 2017) find that some managers may have exploited the discretion afforded to delay goodwill impairments, causing earnings and stock prices to be temporarily inflated. Some other studies even go one step earlier in considering the purchase price allocation decisions made by the acquiring firm. For example, Shalev et al. (2013) find evidence suggestive of managers exercising their discretion to over-allocate the purchase price to goodwill and delay goodwill impairment after SFAS 142. Zhang and Zhang (2017) also document significant managerial discretion in purchase price allocation. These findings suggest that the “fair value” allocated to different asset items during purchase price allocation is sometimes not really “fair” due to agency issues such as managerial opportunism.

Due to the often lack of detailed public information on the target, outsiders could find it difficult to assess the fair value of various asset items. Rule 3-05 of Regulation S-X requires registrants to provide the target’s separate audited annual and unaudited interim pre-acquisition financial statements if it satisfies the significance test.[2] While Chen (2019) finds that the disclosure of private targets’ financial statements is associated with better acquisition decisions, most acquisitions do not meet the 20% significance threshold for mandatory disclosures. Some acquirers may voluntarily disclose certain major financial items when they announce the transactions. However, few financial data points on private targets are usually picked up by data vendors.

[2] The significance test concerns income, asset or investment. A 20% significance threshold is generally used to determine whether such financial disclosures are required 75 days after the acquisition is consummated.

In the late 2010s, there were multiple cases of significant goodwill impairments that drew considerable outside scrutiny on several well-known companies.[3] According to Duff & Phelps (2021), goodwill impairment increased by 125 percent to $78.9 billion in 2019 from 2018. Potentially sparked by these cases of significant goodwill write-offs by high-profile companies, goodwill accounting is currently one of the top items on the agenda of accounting standard setters.

### 2.4. Hypotheses

Warren et al. (2015) and Vasarhelyi et al. (2015) conjecture that alternative data can help enhance the measurement and reporting of the fair value of intangible assets. Prior studies also find that there is a positive predictive relationship between social media metrics and firm equity value (e.g., Plangger 2012; Luo et al. 2013). Due to the public nature of most social media interactions, social media platforms may provide valuable alternative data to help us measure firm value, particularly for those components related to intangible assets. In particular, we posit that user engagement metrics on a company's managed social media accounts could serve as useful benchmarking indicators on the value of related intangibles (*intangibles*) consisting of marketing-related intangibles, customer-related intangibles, and goodwill.

Social media users may comprise a company's major stakeholders, such as existing and potential customers (Chung et al. 2020). Prior studies suggest that customer equity can be an important part of firm value (e.g., Ittner and Larcker 1998; Aaker and Jacobson 2001; Anderson et al. 2004; Wiesel et al. 2008).[4] The level of user engagement with the firm on social media

[3] For example, General Electric wrote down at least $23 billion of goodwill in 2018 while Kraft Heinz impaired at least $15.4 billion assets (including at least $7.1 billion goodwill) in 2019.
[4] Ittner and Larcker (1998) suggest that there is generally a positive relationship between customer satisfaction and future accounting performance. Aaker and Jacobson (2001) find that brand attitude has value relevance in high-technology markets. Anderson et al. (2004) develop a model suggesting that customer satisfaction affects future customer behavior and subsequently future cash flows. Wiesel et al. (2008) argue that customer equity is an integral part of financial reporting. They even propose the idea of reporting "customer equity statement" to corporations in order to bridge the gap between financial statement capabilities and objectives.

platforms could thus reflect a firm's brand awareness (Colicev et al. 2018) and dedication to customer service (Mousavi et al. 2019). Active user engagement on social media could also reflect the firm's historical and current investment in marketing and promotion activities as well as resources devoted to building and maintaining customer relationships. These investments are typically expensed immediately and hence not reflected in the firm's balance sheet, although the resulting social media engagement earned from users is known to be beneficial to their financial performance (Tang 2017; Colicev et al. 2018). Therefore, these user engagement metrics could be complementary to accounting metrics in the valuation of related intangibles.

On Twitter, users can engage with corporate tweets through favorites, retweets, and replies. While favorites directly represent positive sentiment toward the firm, retweets could represent the potential network effect for word-of-mouth marketing by the target firm as followers of those retweeters also get to see the corporate tweets (Colicev et al. 2018). On average, retweets are likely from loyal customers who are excited to share the latest updates with their followers. These forms of user engagement may translate into real effects on the target firm by extending the reach of its communication on Twitter because the level of user engagement (e.g., the number of favorites and retweets) is among the key features used in Twitter's timeline ranking algorithm.[5] Some firms also actively monitor social media to gauge customer feedback and brand buzz.

The above arguments support the value relevance of these user engagement metrics with *intangibles*. These metrics could also complement accounting measurement by adding incremental explanatory powers on the value of *intangibles*. However, there are concerns about the reliability of these metrics. For instance, the open nature of social platforms means that these user engagement metrics may be susceptible to manipulation by 'interested' parties (Lee et al. 2018).

[5] https://blog.twitter.com/engineering/en_us/topics/insights/2017/using-deep-learning-at-scale-in-twitters-timelines.html

Teoh (2018) also comments that alternative data may be "redundant, obsolete, trivial, or out of context and therefore just noise". To the extent that the value relevance of these social media metrics outweighs the reliability concerns, we formulate our first hypothesis as follows:

*$H_1$: User engagement metrics from targets' social media accounts reflect information used in the valuation of related intangibles acquired in M&A transactions.*

Intangible assets comprise a massive portion of assets acquired in M&A transactions. Shalev et al. (2013) find that intangible assets (including goodwill) account for 83% of the deal value. Other studies also find that there is a positive predictive relationship between the volume of social media engagement and firm equity value (e.g., Plangger 2012; Colicev et al. 2018). These user engagement metrics on social media should be positively correlated with the scale and publicity of the target firm. Because these user engagement metrics come from third-party sources and are not dependent on the disclosure decision by transacting parties, outside investors may utilize the signal from these metrics to help evaluate the transaction.

We posit that these social media metrics are particularly useful in the valuation process for investors if the targets are private. Public targets are subject to mandatory disclosure requirements and tend to receive more attention from the public. Market participants often pay close attention to the social media accounts of public firms and some even use the information on social media for algorithmic trading (Treleaven et al. 2013). As such, the social media engagement level of public firms' may well have been reflected in their stock prices that are collectively determined by investors. The market price should serve as a more reliable benchmark than social media metrics in deal evaluation involving public targets.

In contrast, private targets do not have an observable market price. The value of *intangibles* of private targets is likely much more difficult to be assessed by the acquirer. The lack of public information on privately-held targets could therefore increase the information asymmetry especially between transacting parties and outsiders. With more discretions in asset valuation, M&A transactions involving private targets may be more susceptible to agency problems, e.g., managers' hubris (e.g., Roll 1986). According to Hansen (1987) and McNichols and Stubben (2015), higher uncertainty about the target firm could be related to overpayment. For outsiders, social media metrics may provide alternative reliable benchmarks to properly assess the transactions when the accounting numbers of private targets are not fully disclosed. Therefore, we formulate our second hypothesis as follows:

*$H_2$: User engagement metrics from private targets' social media accounts provide useful valuation benchmarks for investors in deal evaluation.*

## 3. Research Design

### 3.1. Sample

We obtain the data on M&A transactions announced between 2010 and 2017 from *Capital IQ*. There are a total of 12,759 closed transactions of the type "acquisition of majority stakes" by public acquirers primarily listed in the United States with non-missing total transaction value. To provide a relevant benchmark in assessing the usefulness of social media metrics, we require the target revenue to be disclosed in the transactions and subsequently captured by the database. This data requirement reduces the number of eligible transactions to 2,839.[6] For these 2,839 transactions, we hand-collect the data on purchase price allocation information from the acquirer's 10-K filings within the next three fiscal years after transaction announcements. We identify 1,491 transactions with non-missing data on the total purchase price from the purchase price allocation table disclosed in 10-K filings. After excluding transactions in which the acquisition represents fewer than 100% stake of the target firm, we retain 1,432 transactions.

[6] Disclosed in 2,839 transactions, revenue is most frequently disclosed financial statement item available in the *Capital IQ* database. Net income is the second most frequent item and is disclosed in 1,478 transactions.

Next, we identify the corporate websites of target firms and search for information on their social media platform adoption. Through *Capital IQ* and additional Google searches, we manage to access the corporate websites for a total of 847 transactions. Our manual search on corporate websites and other business information vendors such as Crunchbase identifies the targets' Twitter account handles for 441 transactions. After scraping all the historical tweets from their Twitter accounts[7], we identify 283 transactions in which we can compute trailing Twitter user engagement metrics for the target firm as of transaction announcement dates. With additional data requirements on the target firm's industry classification scheme, our final sample contains 281 transactions. Table 1 provides the outline of the sample selection discussed above.

### 3.2. Main Variables

#### 3.2.1. Social Media Metrics

We consider two types of user engagements triggered by corporate tweets on the Twitter platform: favorites (renamed as "likes" in late 2015) and retweets. According to Twitter, favorites (likes) are represented by a small star (heart) and are used to show appreciation for a Tweet. A tweet that one shares publicly with followers to pass along news and interesting discoveries is known as a retweet.[8] We compute the user engagement metrics *favorites* and *retweets* by taking the natural logarithm of the total number of favorites and retweets, respectively, received by the target firm's tweets in the trailing three months before transaction announcements.

#### 3.2.2. Accounting Metrics

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[7] There are a total of 146,230 tweets over the trailing twelve months of the transaction from these 283 targets. Users engage with these tweets with a total of 12,724,968 favorites and 229,587 retweets.

[8] We do not consider "replies" in constructing the social media metrics because replies may not necessarily reflect users' positive sentiment towards the target. For example, replies to corporate tweets may include customer enquiries or even complaints. Therefore, the volume of replies is likely a much noisier benchmark for the value of intangibles.

Because our sample includes both public and private targets, we are limited by the available data on target accounting metrics from *Capital IQ*. As revenue is the most widely available accounting metric of target firms in M&A transactions, we utilize revenue (*revenue*) as the benchmark to compare with Twitter metrics. Given that the data requirements on net income greatly diminish the sample size, we consider net income (*earning*) as an alternative benchmarking metric only in additional analyses.

**3.2.3. Related Intangibles**

We consider three broad categories of intangible asset items that could have relevance to Twitter user engagement metrics. The first category is marketing-related intangibles (*brand*). Common items under this category include trademarks, trade names, and brands. The second category is customer-related intangibles (*customer*). Customer lists, customer relationships, and customer contracts are common items under this category.[9] The third category is accounting goodwill, which represents assets that are not separately identifiable in the acquisition.

According to prior studies, accounting goodwill accounts for the largest component of the total purchase price.[10] However, Shalev et al. (2013) find that CEOs may over-allocate the purchase price to goodwill to maximize their earnings-based bonus as goodwill is not amortized periodically over time. Zhang and Zhang (2017) also document significant managerial discretion in purchase price allocation. Therefore, in our main analyses, we take the summation of marketing-

[9] To provide some structure to the recognition of identifiable intangible assets, the FASB has classified these identifiable intangibles into five categories, including marketing-related intangible assets (e.g., trademarks, tradenames), customer-related intangible assets (e.g., customer lists, customer relationships), artistic-related intangible assets (e.g., books, photographs), contract-based intangible assets (e.g., licensing agreements, franchise agreements), and technology-based intangible assets (e.g., computer software, patented technology). The remaining portion of purchase price after assigning the fair values to all identified tangible and intangible assets and assuming the liabilities is the goodwill. Our classification of identifiable intangibles largely follows the five-category classification by FASB except that we also treat customer contracts as customer-related intangibles.

[10] For example, in the sample used by Shalev et al. (2013), intangible assets including goodwill account for 83% of the deal value while goodwill alone accounts for about 59% of the deal value on average.

related intangibles, customer-related intangibles, and goodwill to create a measure that represents the total amount of related intangibles (*intangibles*) that user engagement metrics on Twitter may have value relevance with.

### 3.2.4. Transaction Price Multiples

While traditional transaction comparables analysis often utilizes accounting-based multiples, we extend the analysis by further incorporating multiples based on social media metrics (e.g., *favorites* and *retweets*). Specifically, we construct two multiples *price/favorites* and *price/retweets* respectively as the ratio of the total purchase price to the volume of favorites and retweets received by the target's Twitter accounts in the trailing three months before transaction announcements. As a benchmark for comparison, we also construct a multiple *price/revenue* by dividing the total purchase price by the target's annual revenue before transaction announcements. This approach implicitly assumes that the average relationship between these metrics and pricing reflects the fair value of underlying assets. Higher transaction price multiples relative to peer firms may represent overvaluation of the target firm's intangible assets with respect to the underlying metrics.

### 3.2.5. Acquirer Announcement Return

To assess how the acquirer's market participants immediately react to the transaction, we calculate the three-day cumulative market-adjusted return of the acquirer *CAR [-1, +1]* in the [-1 day, +1 day] window around the dates of transaction announcement. In computing the adjusted returns, we use the value-weighted return in *CRSP* as the benchmark.

### 3.2.6. Valuation Adjustments

We calculate the extent of purchase price adjustments as the percentage change between the final implied enterprise value of the target at deal closing and the initial implied enterprise value of the target at the initial deal announcement based on the data from *Capital IQ*.

### 3.2.7. Acquirer Goodwill Impairment

We obtain the data on goodwill impairment from *Audit Analytics*. We search for whether both the name of the target and keywords related to goodwill impairment appear in the same sentence in the relevant 10-K filings of the acquirer. We then manually read these filings to ascertain whether the impairment in a particular fiscal year is related to the transaction concerned. We create a variable *impairment* to represent the cumulative amount of goodwill impairment related to the transaction concerned within five years after the transaction, scaled by the total purchase price.

### 3.2.8. Business Models

We classify the business models of target firms into B2B and B2C based on the information presented on their corporate websites. If the products and services of the target firm primarily serve consumers, we define an indicator *b2c* as one to represent firms with a B2C business model. If the target firm primarily targets business customers, the indicator *b2c* is set to zero.

### 3.2.9. Other Deal Characteristics

As our sample includes both private and public targets, we are limited by the information disclosed in the transactions and subsequently captured by *Capital IQ*. Besides deal size, other observable deal characteristics we consider include whether the target firm is private (*private*) as well as whether both the target and acquirer belong to the same industry sector at the 2-digit GIC or 2-digit SIC level (*same industry*). We also consider the form of payment using the percentage of transaction amount paid through cash (*cash%*) and deal attitude represented by whether the transaction is an unsolicited deal (*unsolicited*).

## 3.3. Model Specifications

### 3.3.1 Social Media Metrics and Intangibles

To test *H1*, we examine how well social media metrics reflect information used in intangible valuation through the statistical association between Twitter user engagement metrics and the "fair" market value of *intangibles* as recognized by the acquirer (Model 1). This approach is analogous to the "value relevance" literature which studies the association between accounting items and the market value of equity (e.g., Barth et al. 2001). To aid interpretation regarding the magnitude of the association, we also examine the statistical association between revenue and the "fair" market value of *intangibles* by replacing these Twitter metrics with *revenue* in Model (1). If *intangibles* are on average fairly valued in these acquisitions, higher statistical association ($R^2$) and a higher level of statistical significance of $\beta_1$ represent better capability in using the particular metric to explain the value of recognized *intangibles*. As $R^2$ is not comparable across different samples, Model (1) utilizes the same sample that requires data availability on all three metrics (*revenue*, *favorites*, *retweets*) to facilitate the comparison.

$$intangibles = \alpha + \beta_1\ Twitter\ metrics + \Sigma\ \beta_x control_x + \varepsilon \qquad (1)$$

To investigate whether these Twitter metrics can complement the firm's historical accounting numbers in intangible asset valuation, we additionally examine the explanatory powers of these Twitter metrics that are incremental to accounting-based metrics when they are both used to account for the value of *intangibles* (Model 2). The statistical significance of $\beta_1$ can reflect the explanatory powers of these Twitter metrics that are incremental to revenue.

$$intangibles = \alpha + \beta_1\ Twitter\ metrics + \beta_2\ revenue + \Sigma\ \beta_x control_x + \varepsilon \ (2)$$

In the full specification, Model (1) and Model (2) also control for several major deal-related characteristics that are generally available in the acquisitions of both public and private targets, including private target status (*private*), within-industry transaction (*same industry*), deal type (*unsolicited*), and deal financing (*cash%*). The specification also controls for 2-digit GIC industry fixed effects and transaction year fixed effects.

### 3.3.2 Transaction Price Multiples and Announcement Returns

In testing *H2*, we examine whether market participants impound information consistent with the signals from social media metrics during deal announcements. While deals involving private targets often have scant disclosures on their financial performance[11], market participants can easily look up the level of user engagement at the target firm's Twitter account to gauge its operational scale and deal value. Therefore, transaction announcement returns may incorporate these social media signals that facilitate investors' deal evaluation.

Specifically, we examine the market-adjusted returns of the acquiring firm within the [-1, +1] window around transaction announcements (Model 3). Our main independent variables of interest are *price/favorites* and *price/retweets*. Consistent with *H2*, the coefficients on transaction price multiples based on social media metrics $\beta_1$ should be negative in Model (3) among deals with private targets. In other words, a higher extent of overpayment benchmarked against Twitter metrics concerned should be associated with lower announcement returns for private targets. Additionally, we consider transaction price multiples based on revenue to provide a benchmark against social media metrics.

The specification also includes other known determinants of announcement returns, including the public or private status of the target (e.g., Fuller et al. 2002; Officer 2007; Capron and Shen 2007), the transaction size relative to the size of the acquirer (e.g., Asquith et al. 1983; Fuller et al. 2002), % payment made by cash (e.g., Travlos 1987; Chang 1998), related acquisition (e.g.,

[11] From randomly sampling and manually checking the available disclosures during transaction announcements for 393 private acquisitions from the *Capital IQ* M&A database, we find that there is no disclosure of the target's financial information during transaction announcements in over 70% of the transactions. Only 27% discloses the target's revenue, 6% discloses the target's EBITDA, and 2% discloses the target's earnings when the transaction is announced.

Barney 1988), deal attitude (e.g., Schwert 2000), stock price run-up of the acquirer before the transaction (e.g., Rosen 2006), as well as other common characteristics of the acquirer such as size (e.g., Moeller et al., 2004), growth opportunity (e.g., Servaes 1991), leverage (e.g., Maloney et al. 1993), free cash flow (e.g., Lang et al., 1991), and audit firm status (e.g., Louis 2005). To account for the industry-specific and time-specific patterns in using social media metrics as valuation benchmarks, we also include 2-digit GIC industry fixed effects and transaction year fixed effects.

$$CAR[-1,+1] = \alpha + \beta_1\, price\ multiples + \Sigma\, \beta_x control_x + \varepsilon \quad (3)$$

## 4. Results and Analyses

### 4.1. Descriptive Statistics

In Table 2, we present the summary statistics for the main variables. The median (mean) of the total purchase price is 170 (1,068) million per transaction. On average, 75 percent of the total purchase price is allocated to *intangibles*. Consistent with prior literature (e.g., Shalev et al. 2013), the statistics in our sample show that the valuation of these intangible assets is a highly important consideration in M&A deal evaluation. Our sample covers both public and private targets, with 61 percent of the targets being private.

Table 3 displays the correlation between different metrics and the value of *intangibles*. *Retweets* exhibit the highest correlation of 0.426 with *intangibles*. *Revenue* follows closely with the second-highest correlation of 0.425. *Favorites* have a correlation of 0.271 with *intangibles*. The correlation statistics provide preliminary evidence that these Twitter metrics can be useful for the valuation of *intangibles*. Consistent with the managerial discretion in purchase price allocation documented in the prior literature (e.g., Zhang and Zhang 2017), goodwill displays a high correlation with customer-related intangibles (0.89) and market-related intangibles (0.50). Therefore, our main analyses focus on the summation of these three components as denoted by *intangibles*, which has over 0.6 correlation with any of the three components. The two social media metrics *favorites* and *retweets* are highly correlated, with their correlation coefficient exceeding 0.84. Due to multicollinearity concerns, we do not utilize both social media metrics as the independent variables in the models at the same time.

**4.2. Social Media Metrics and Intangible Asset Valuation**

To test *H1*, we investigate the usefulness of user engagement metrics on Twitter in assessing the value of *intangibles* in M&A transactions. Table 4 Panel A displays the results of Model (1) by directly comparing the univariate association between each metric and the value of *intangibles* on a standalone basis with industry- and year-fixed effects. Columns (1) and (2) show that both Twitter metrics (*favorites* and *retweets*) exhibit a significant positive association with *intangibles* (t-statistics: 3.67 and 3.24). As a comparison, *revenue* also exhibits a significant positive association with *intangibles* with a t-statistic of 2.32 in column (3). In terms of model $R^2$, the model specification that uses *revenue* has the highest $R^2$ of 0.279 among the three columns.

After further expanding the model to control for additional deal characteristics in Panel B, we obtain similar findings compared to the univariate relationships shown in Panel A. Both *favorites* and *retweets* exhibit a significant positive association (t-statistics: 2.67 and 2.79) with the value of *intangibles*. As a comparison, *revenue* has a significant positive association with *intangibles* (t-statistic: 2.06). Among the three metrics, *revenue* provides the highest model $R^2$ of 0.312 while *retweets* trail behind with a model $R^2$ of 0.282. These results suggest that user engagement metrics on Twitter, especially *retweets*, can provide comparable explanatory powers on the value of *intangibles* relative to *revenue* on a standalone basis.

In columns (4) and (5) of Panel B, we run Model (2) by including one of the Twitter metrics in conjunction with *revenue* as the independent variables. Both *favorites* and *retweets* continue to exhibit a significant statistical association with *intangibles*. The coefficients on *favorites* and *retweets* remain similar in magnitude, suggesting that the statistical association is not subsumed by the inclusion of *revenue* in Model 2. Relative to column (3) which uses *revenue* only, adding *favorites* in column (4) and *retweets* in column (5) further increases the model $R^2$ from 0.312 to 0.329 and 0.362, respectively. The increase in the explanatory power suggests that user engagement metrics on Twitter contain signals that are complementary to accounting numbers in explaining the value of acquired intangibles.

### 4.3. Transaction Price Multiples and Announcement Returns

We test *H2* by examining the market-adjusted returns of the acquiring firm within the [-1, +1] window around transaction announcements in Table 5. Columns (1) to (3) show that the coefficients on all transaction price multiples using different benchmarking metrics are generally not significant. Both *price/favorites* and *price/retweets* have a negative association with transaction announcement returns, but the relationship is not statistically significant (t-statistics: -1.18 and -1.26). Columns (4) to (6) further include an interaction term between the indicator for private targets (*private*) and transaction price multiples to examine the potential differences between public and private targets in the informativeness of various metrics for investors. The results show that the coefficients on *price/favorites* and *price/retweets* are insignificantly negative for public targets. However, the interaction term between *private* and *price/retweets* is significantly negative. The sum of the coefficient on *price/retweets* and the interaction term between *private* and *price/retweets* ($\beta_2 + \beta_5$) is significantly negative (p-value: 0.00). In contrast, the coefficient on *price/revenue* is significantly negative for public targets, but not for private targets. Consistent with *H2*, the results suggest that investors are reacting as if *retweets* provide a useful valuation benchmark for private targets, which often only have scarce financial information disclosed by acquirers during transaction announcements.

### 4.4. Transaction Price Multiples and Valuation Adjustments

To verify whether investors' reactions to deal announcements involving private targets are well-informed using the signals from *retweets*, we next explore whether the *price/retweets* multiple is informative on acquirers' subsequent valuation adjustments. Acquirers typically conduct extensive post-announcement due diligence after initial deal announcements and retain certain price adjustment mechanisms to protect themselves against any drops in the value of the target between initial deal announcements and deal closings due to the exposure of issues from due diligence or targets' deteriorating performance.

In Table 6, we examine the association between transaction pricing multiples and valuation adjustments by acquirers, measured using the percentage change in the implied enterprise value of the target from initial deal announcements to deal closings. The results show that the interaction term between *private* and *price/retweets* is significantly negative. The sum of the coefficient on *price/retweets* and the interaction between *private* and *price/retweets* ($\beta_2 + \beta_5$) is also significantly negative (p-value: 0.01). Consistent with investors' reactions during deal announcements, we find that the *price/retweets* multiple is informative of acquirers' subsequent valuation adjustments on private targets. This finding further supports the usefulness of *retweets* in deal evaluation. It also suggests that acquirers may not have fully incorporated the signals from *retweets* in the initial valuation of private targets before deal announcements, but manage to uncover some of these signals at deal closing through post-announcement due diligence or price adjustment mechanisms.

### 4.5. Transaction Price Multiples and Subsequent Goodwill Impairment

Agency problems in M&A transactions may result in overpriced deals, with final transaction pricing not fully incorporating the signals from social media metrics. We next explore whether the transaction price multiples are informative of subsequent goodwill impairments by acquirers. If transaction price multiples using these metrics are found to be significantly positively associated with subsequent goodwill impairment, this would further support the usefulness of these metrics as benchmarks in deal evaluation for investors or even acquirers.[12]

Table 7 examines whether the transaction price multiples are associated with the amount of subsequent related goodwill impairment by acquirers in the next five fiscal years after transaction closings, scaled by the total purchase price (*impairments*). The results show that the sign of the association between transaction price multiples based on social media and accounting metrics and *impairments* is positive. However, the association is only statistically significant for *price/retweets* (t-statistics: 1.82), confirming earlier evidence on the usefulness of *retweets* as valuation benchmarks for the value of *intangibles*.[13] The interaction terms between *private* and transaction price multiples are generally positive but insignificant, suggesting that there are no significant differences across public and private targets on goodwill impairments. Among other independent variables, the indicator *b2c* is consistently positive, suggesting goodwill impairments are more severe for deals involving B2C targets.

## 4.6. Additional Analyses

### 4.6.1. Value of Social Media Metrics by Business Models

[12] The association is a joint test of both the usefulness of these metrics and the inadequate incorporation of these metrics into final transaction pricing.

[13] The evidence also suggests that the signals from social media metrics are likely not fully incorporated in the final transaction pricing after post-announcement due diligence for some deals. It is possible that some acquisitions are strategically conducted to eliminate competition (Cunningham et al. 2020) while others are subject to various agency issues, e.g., empire building incentives, tunnelling incentives.

Our main analyses focus on the average relationship between social media metrics and the value of acquired intangibles. However, to what extent social media users can proxy for a target firm's client base can vary by business models. We further investigate whether and how the target's business model moderates the explanatory powers of Twitter metrics on the value of *intangibles*. Specifically, we split the business models of target firms into two types: B2B and B2C.

In Table 8, we separately replicate the main analyses in Table 4 among B2B targets and B2C targets. Panel A examines the explanatory power of each metric on a standalone basis. The results show that both *favorites* and *retweets* exhibit a significant positive association among B2B targets (t-statistics: 2.20 and 2.81) and B2C targets (t-statistics: 2.59 and 2.57). However, *revenue* is only significant among B2B targets (t-statistic: 2.75), but not among B2C targets (t-statistic: 1.35). In terms of the model explanatory power, the model that incorporates *revenue* achieves the highest $R^2$ of 0.285 among B2B targets while the model incorporating *retweets* achieves the highest $R^2$ of 0.327 among B2C targets. The results are similar after including additional firm-level controls in Panel B. These findings suggest that the superiority of revenue's explanatory power vs. social media metrics mainly derives from B2B targets while *retweets* is particularly useful in assessing the value of *intangibles* for B2C firms.

#### 4.6.2. Components of Total Purchase Price

In Table 9, we separately examine the association between each metric and various components under total purchase price, including marketing-related intangibles (*brand*) in Panel A, customer-related intangibles (*customer*) in Panel B, accounting goodwill (goodwill) in Panel C, and net tangibles (*tangibles*) in Panel D. Panel E also examines the association with the total purchase price. The results show that social media metrics exhibit significant explanatory powers for each component of *intangibles (*t-statistics: 2.27 between *brand* and *favorites*, 2.17 between *brand* and *retweets*, 2.58 between *customer* and *favorites*, 2.40 between *customer* and *retweets*, 3.11 between *goodwill* and *favorites*, and 2.90 between *goodwill* and *retweets*), but not *tangibles*. As a comparison, revenue exhibits a marginally significant association with *customer*, *goodwill*, and *tangibles*, but the association with *brand* is not significant. These findings suggest that social media metrics are useful for intangible valuation primarily and can complement accounting numbers which work better with tangible assets in deal intelligence.

**4.6.3. Alternative Metrics**

While our main analyses focus on three metrics (*favorites*, *retweets*, *revenue*) to maximize sample size, we extend our analyses to using alternative metrics in Table 10. As the volume of user engagement on social media is a function of both the firm's social media strategy and the scale/loyalty of its customer base on social media, we separate our user engagement metrics into two components: the number of tweets initiated by the firm and the average *favorites*/*retweets* per tweet in Panel A. With less potential for manipulation, we expect that the component determined by user behaviors will provide more reliable benchmarks than the component determined by corporate actions. Consistent with this notion, the results show that the user component, i.e., the average number of favorites/retweets per tweet, is the major contributor to the explanatory powers of our main metrics. While the number of tweets generally exhibits a positive association with *intangibles*, the association is not statistically significant.

Apart from using revenue in the main analyses, Panel B also considers using earnings as an alternative financial metric. After further data requirements on *earning*, the sample is reduced to only 136 observations. Column (1) shows that *earning* only exhibits a marginally significant association with *intangibles* (t-statistic: 1.88) on a standalone basis. In other columns, *earning* loses its statistical significance with the inclusion of *revenue*, *favorites*, or *retweets* in the model.

*Retweets* are the only metric that remains statistically significant, with a t-statistic of 2.12 after adding on top of *earnings* in column (4) and a t-statistic of 2.35 after adding on top of both *earnings* and *revenue* in column (6). The results suggest that *retweets* appear to be the more useful valuation benchmarks for *intangibles* no matter whether it is compared against revenue or earnings on a standalone basis or used in conjunction with these accounting numbers.

Similar to revenue and earnings, our main user engagement metrics are constructed as *flow* measures. In Panel C, we also consider *stock* measures using total assets and the number of followers of the target's corporate Twitter account at the time of transaction announcements.[14] Similar to the *flow* measures, we find that the number of followers generally exhibits a significant positive association with *intangibles* when it is used on a standalone basis (t-statistic: 1.97) or paired with total assets (t-statistic: 2.27). However, total asset only exhibits a relatively weak association with *intangibles* on a standalone basis. When the *flow* measures are used together with the number of followers in columns (4) to (7), they are generally both significant in explaining the value of *intangibles*[15], suggesting that these *flow* and *stock* measures can be complementary in serving as valuation benchmarks for acquired intangibles.

## 5. Concluding Remarks

In this study, we find that the user engagement metrics on corporate Twitter accounts can serve as useful benchmarks for the value of targets' related intangible assets recognized in M&A transactions and can provide useful signals to investors in deal evaluation. When used on a

[14] We manually collect the data on the number of followers around the date of transaction announcements using *WayBack Machine*. Because *WayBack Machine* does not store all webpages, we only manage to find the number of followers of the targets' corporate Twitter accounts for 186 transactions out of the 241 transactions in Table 4 Panel B. Further requiring the availability of total asset, an accounting *stock* measure, diminishes the sample to 106 observations. As the number of observations are quite small, we do not utilize these *stock* metrics in our main analyses. We also believe that the *flow* measures provide more reliable metrics that are less susceptible to manipulation by the target firm as it is much easier for companies to "buy" dormant followers relative to active followers.

[15] Except that the explanatory power of *favorites* appears to be subsumed by the number of followers.

standalone basis, these Twitter metrics display comparable explanatory power to explain the value of intangibles relative to accounting numbers such as revenue. When used in conjunction with accounting numbers, these Twitter metrics also provide incremental explanatory power. These findings suggest that social media metrics can complement accounting numbers in deal intelligence, especially with regard to the valuation of intangible assets.

Our findings also suggest that social media metrics can provide useful inputs for investors in deal evaluation, especially when accounting numbers are not readily available in the case of private targets. In particular, we find that the transaction price multiples based on retweets display a negative association with deal announcement returns if the target is private. Acquirers' valuation adjustments between deal announcements and closings also display a negative association with the transaction price multiples based on retweets if the target is private. There is also some evidence that the transaction price multiple based on retweets is informative of acquirers' subsequent goodwill impairments.

Due to the limited data availability on private targets' historical financial information, our study is only focused on the cross-sectional relationship between Twitter metrics and the value of intangible assets recognized by acquirers in M&A transactions. It is worth noting that one may also utilize the time-series relationship between social media metrics and market prices/accounting numbers to have a better understanding of the business dynamics. For example, acquirers, likely possessing the relevant data through due diligence, can make use of the time-series relationships among different metrics to verify the financial information provided by target firms. Future studies can utilize other settings to explore the usefulness of the time-series relationships between social media metrics and market prices/accounting numbers.

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## APPENDIX
## Variable Definitions

| Variable Name | Description |
|---|---|
| ***total purchase price*** | The total purchase price in USD millions to be allocated in purchase price allocation from the M&A transaction, hand-collected from the 10-K filings of the acquirer |
| ***goodwill*** | The amount of goodwill in USD millions recognized in purchase price allocation from the M&A transaction, hand-collected from the 10-K filings of the acquirer |
| ***brand*** | The amount of marketing-related intangibles consisting of trademarks/ tradenames/ brands in USD millions recognized in purchase price allocation from the M&A transaction, hand-collected from the 10-K filings of the acquirer |
| ***customer*** | The amount of customer-related intangibles consisting of customer relationships/ customer lists/ customer contracts in USD millions recognized in purchase price allocation from the M&A transaction, hand-collected from the 10-K filings of the acquirer |
| ***intangibles*** | The total amount of relevant intangibles from *goodwill*, *brand*, and *customer* in USD millions recognized in purchase price allocation from the M&A transaction, hand-collected from the 10-K filings of the acquirer (when at least one of the three items are disclosed, the other undisclosed items are assumed to be zero when the three components are aggregated to calculate the total amount of relevant intangibles) |
| ***%intangibles*** | The proportion of total purchase price allocated to *intangibles* (denoted in percentages) |
| ***tangibles*** | Net amount of tangible assets in USD millions, calculated as the total purchase price minus the total intangible assets recognized in purchase price allocation from the M&A transaction, hand-collected from the 10-K filings of the acquirer |
| ***favorites*** | Natural logarithm of one plus the total number of favorites or likes drawn by the target company's tweets released within the three calendar months prior to the transaction announcement |
| ***retweets*** | Natural logarithm of one plus the total number of retweets drawn by the target company's tweets released within the three calendar months prior to the transaction announcement |
| ***favorites per tweet*** | Natural logarithm of one plus the average number of favorites or likes per tweet released by the target company within the three calendar months prior to the transaction announcement |
| ***retweets per tweet*** | Natural logarithm of one plus the average number of retweets per tweet released by the target company within the three calendar months prior to the transaction announcement |
| ***# tweets*** | Natural logarithm of one plus the total number of tweets released by the target company within the three calendar months prior to the transaction announcement |
| ***revenue*** | Annual revenue of the target company in USD millions from the prior fiscal year at the time of the transaction from *Capital IQ* |
| ***earning*** | Annual net income of the target company in USD millions from the prior fiscal year at the time of the transaction from *Capital IQ* |

| | |
|---|---|
| ***asset*** | The total asset of the target company in USD millions from the prior fiscal year at the time of the transaction from *Capital IQ* |
| ***private*** | An indicator for being a private target company |
| ***same industry*** | An indicator for the target company and the acquirer being in the same industry sector (either having the same 2-digit GIC code or 2-digit SIC code) |
| ***cash%*** | Percentage payment through cash from *Capital IQ* |
| ***unsolicited*** | An indicator for being an unsolicited transaction from *Capital IQ* |
| ***CAR[-1,+1]*** | Three-day cumulative market-adjusted return when the acquirer announces the transaction, with the CRSP value-weight return as the market index. |
| ***price/favorites*** | *total purchase price* divided by the total number of favorites or likes (multiplied by 1000) drawn by the target company's tweets released within the three calendar months prior to the transaction announcement |
| ***price/retweets*** | *total purchase price* divided by the total number of retweets (multiplied by 1000) drawn by the target company's tweets released within the three calendar months prior to the transaction announcement |
| ***price/revenue*** | *total purchase price* divided by *revenue* |
| ***target size*** | Natural logarithm of target's annual revenue from Capital IQ |
| ***relative deal size*** | Total purchase price divided by the market value of equity of the acquirer measured at the end of its latest fiscal year-end. |
| ***acquirer stock runup*** | The acquirer's cumulative market-adjusted return during the period (−210, −11) relative to transaction announcement, with the market index represented by the CRSP value-weighted return. |
| ***acquirer size*** | Natural logarithm of the total asset of the acquirer at the time of the transaction, calculated from *Compustat* |
| ***acquirer mb*** | Market-to-book ratio of the acquirer at the time of the transaction, calculated from *Compustat* |
| ***acquirer fcf*** | Free cash flow of the acquirer (operating cash flow – investing cash flow) divided by the total assets of the acquirer |
| ***acquirer leverage*** | Leverage ratio of the acquirer at the time of the transaction, calculated as the ratio of total liability over total assets from *Compustat* |
| ***acquirer big4 auditor*** | An indicator for using a Big 4 auditor by the acquirer |
| ***price adjustment*** | The percentage change in implied enterprise value of the target from initial deal announcements to deal closings |
| ***impairment*** | The sum of each fiscal year's goodwill impairment amount related to the acquisition during the [+1, +5] fiscal years after the transaction, where the amount of goodwill impairment is recorded as a positive number and missing goodwill impairment in a fiscal year is treated as zero. The impairment amount for each fiscal year is based on the data from *Audit Analytics* and is counted only if the impairment is due to the transaction as disclosed by acquirers in their 10-K filings. |
| ***goodwill%*** | The percentage of goodwill in total purchase price from the M&A transaction, hand-collected from the 10-K filings of the acquirer |
| ***acquirer goodwill*** | The amount of goodwill in USD millions on the acquiring firm's balance sheet before the announcement of transactions, extracted from Capital IQ |

## TABLE 1
## Sample Selection

This table presents the steps for constructing our sample. Each row reports an additional data requirement, along with the resulting number of merger transactions from imposing the specific requirement.

| | *Number of Transactions* |
|---|---|
| *Closed transactions of acquisition of majority stakes screened from Capital IQ with the acquirer primarily listed in the United States, non-missing total transaction value, non-missing target company revenue, and transaction announcement dates between January 1, 2010, and December 31, 2017* | 2,839 |
| *Identifying information related to purchase price allocation in the 10-K filings of the acquirer within the next three years and retaining observations with non-missing data on the total purchase price* | 1,491 |
| *Removing observations with <100% equity acquisition* | 1,432 |
| *Retaining observations with non-missing historical Twitter user engagement metrics for target firms* | 283 |
| *Imposing data requirements on relevant intangibles assets* | 241 |

## TABLE 2
## Descriptive Statistics

This table presents the summary statistics for the main variables in the study. Variable definitions are provided in Appendix.

| variable | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| *total purchase price* | 283 | 1068.12 | 2948.48 | 36.18 | 169.60 | 703.21 |
| *intangibles* | 241 | 797.25 | 2176.17 | 20.36 | 128.23 | 583.10 |
| *%intangibles* | 241 | 75.49 | 53.40 | 54.29 | 74.12 | 90.02 |
| *goodwill* | 230 | 612.20 | 1702.86 | 15.11 | 86.70 | 417.31 |
| *brand* | 139 | 165.90 | 671.01 | 1.90 | 13.00 | 60.25 |
| *customer* | 141 | 200.52 | 550.79 | 4.70 | 26.60 | 114.00 |
| *favorites* | 241 | 6.18 | 3.01 | 3.74 | 6.17 | 8.42 |
| *retweets* | 241 | 2.75 | 2.29 | 0.69 | 2.48 | 4.18 |
| *revenue* | 241 | 448.12 | 1115.57 | 27.00 | 81.80 | 357.36 |
| *earning* | 136 | 16.01 | 163.46 | -8.89 | 0.62 | 19.21 |
| *b2c* | 241 | 0.39 | 0.49 | 0.00 | 0.00 | 1.00 |
| *private* | 241 | 0.61 | 0.49 | 0.00 | 1.00 | 1.00 |
| *same industry* | 241 | 0.44 | 0.50 | 0.00 | 0.00 | 1.00 |
| *cash%* | 241 | 83.49 | 31.41 | 83.94 | 100.00 | 100.00 |
| *unsolicited* | 241 | 0.85 | 0.36 | 1.00 | 1.00 | 1.00 |
| *CAR[-1,+1]* | 198 | 0.01 | 0.07 | -0.01 | 0.01 | 0.04 |
| *price/favorites* | 198 | 0.01 | 0.06 | 0.00 | 0.00 | 0.00 |
| *price/retweets* | 198 | 0.08 | 0.24 | 0.00 | 0.01 | 0.03 |
| *price/revenue* | 198 | 4.13 | 9.34 | 0.96 | 1.94 | 3.86 |
| *target size* | 198 | 4.67 | 1.84 | 3.40 | 4.73 | 5.96 |
| *relative deal size* | 198 | 0.17 | 0.31 | 0.02 | 0.05 | 0.19 |
| *acquirer stock runup* | 198 | 0.07 | 0.24 | -0.06 | 0.05 | 0.17 |
| *acquirer size* | 198 | 0.87 | 0.34 | 1.00 | 1.00 | 1.00 |
| *acquirer mb* | 198 | 7.94 | 1.88 | 6.77 | 7.97 | 8.97 |
| *acquirer fcf* | 198 | 4.29 | 4.89 | 2.00 | 2.95 | 4.68 |
| *acquirer leverage* | 198 | 0.19 | 0.13 | 0.12 | 0.18 | 0.25 |
| *acquirer big4 auditor* | 198 | 0.87 | 0.34 | 1.00 | 1.00 | 1.00 |
| *impairment* | 161 | 0.17 | 0.73 | 0.00 | 0.00 | 0.00 |
| *goodwill%* | 161 | 0.56 | 0.26 | 0.39 | 0.56 | 0.67 |
| *acquirer goodwill* | 161 | 0.19 | 0.27 | 0.04 | 0.11 | 0.22 |

**TABLE 3**
**Correlation Table**

This table presents the pairwise correlation matrix for the main variables of interest in the study. Variable definitions are provided in Appendix. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

| Variables | *intangibles* | *goodwill* | *brand* | *customer* | *favorites* | *retweets* | *revenue* |
|---|---|---|---|---|---|---|---|
| *intangibles* | 1.000 | | | | | | |
| *goodwill* | 0.982*** | 1.000 | | | | | |
| *brand* | 0.606*** | 0.497*** | 1.000 | | | | |
| *customer* | 0.885*** | 0.887*** | 0.465*** | 1.000 | | | |
| *favorites* | 0.271*** | 0.248*** | 0.227*** | 0.257*** | 1.000 | | |
| *retweets* | 0.363*** | 0.348*** | 0.264*** | 0.313*** | 0.844*** | 1.000 | |
| *revenue* | 0.425*** | 0.452*** | 0.271*** | 0.510*** | 0.141** | 0.174*** | 1.000 |

## TABLE 4
## Acquired Intangibles and Social Media Metrics

This table displays the results examining the association between the value of the target firm's relevant intangible assets as recognized by acquirers and Twitter metrics. Panel A focuses on the univariate associations. Panel B focuses on the multivariate associations controlling for deal characteristics. Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

**Panel A: Univariate Relationship with Related Intangible Assets**

| SAMPLES | Requiring the Presence of Target Revenue and Twitter Metrics | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| VARIABLES | *intangibles* | *intangibles* | *intangibles* |
| *favorites* | 169.574*** | | |
| | (3.67) | | |
| *retweets* | | 320.040*** | |
| | | (3.24) | |
| *revenue* | | | 0.823** |
| | | | (2.32) |
| *Industry F.E.* | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes |
| *Observations* | 241 | 241 | 241 |
| $R^2$ | 0.174 | 0.228 | 0.279 |

**TABLE 4 (Cont'd)**
**Acquired Intangibles and Social Media Metrics**

**Panel B: Multivariate Association with Relevant Intangible Assets**

| SAMPLES | | | Requiring the Presence of Target Revenue and Twitter Metrics | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| VARIABLES | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* |
| *favorites* | 144.134*** | | | 121.819*** | |
| | (2.84) | | | (2.70) | |
| *retweets* | | 288.990*** | | | 251.196*** |
| | | (2.89) | | | (3.04) |
| *revenue* | | | 0.728** | 0.702** | 0.666** |
| | | | (2.11) | (2.08) | (2.09) |
| *b2c* | -0.188 | -127.338 | 37.976 | -176.774 | -282.420 |
| | (-0.00) | (-0.48) | (0.15) | (-0.65) | (-1.13) |
| *private* | -982.339*** | -847.910*** | -601.017** | -505.901** | -411.472* |
| | (-4.03) | (-4.43) | (-2.42) | (-2.03) | (-1.77) |
| *same industry* | 213.203 | 256.605 | 226.725 | 288.388 | 323.469 |
| | (0.66) | (0.78) | (0.74) | (0.95) | (1.05) |
| *cash%* | 1.556 | 0.868 | 1.895 | 1.549 | 0.944 |
| | (0.32) | (0.18) | (0.44) | (0.34) | (0.21) |
| *unsolicited* | -341.007 | -312.318 | -375.120 | -393.906 | -366.637 |
| | (-0.70) | (-0.66) | (-0.86) | (-0.93) | (-0.89) |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 241 | 241 | 241 | 241 | 241 |
| $R^2$ | 0.231 | 0.274 | 0.306 | 0.325 | 0.358 |

**TABLE 5**
**Market Reactions to Transaction Announcements**

This table examines how the market reactions to transaction announcements vary with transaction pricing multiples based on Twitter metrics and revenue. The dependent variable *CAR[-1,+1]* is the three-day abnormal announcement return based on the market model. Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

| VARIABLES | (1)<br>*CAR*<br>*[-1,+1]* | (2)<br>*CAR*<br>*[-1,+1]* | (3)<br>*CAR*<br>*[-1,+1]* | (4)<br>*CAR*<br>*[-1,+1]* | (5)<br>*CAR*<br>*[-1,+1]* | (6)<br>*CAR*<br>*[-1,+1]* |
|---|---|---|---|---|---|---|
| *price/favorites* ($\beta_1$) | -0.057 | | | -0.058 | | |
| | (-1.18) | | | (-1.18) | | |
| *price/retweets* ($\beta_2$) | | -0.027 | | | -0.012 | |
| | | (-1.26) | | | (-0.51) | |
| *price/revenue* ($\beta_3$) | | | -0.000 | | | -0.003* |
| | | | (-0.09) | | | (-1.94) |
| *price/favorites* private* ($\beta_4$) | | | | 0.265 | | |
| | | | | (0.64) | | |
| *price/retweets* private* ($\beta_5$) | | | | | -0.112** | |
| | | | | | (-2.43) | |
| *price/revenue* private* ($\beta_6$) | | | | | | 0.003** |
| | | | | | | (2.04) |
| *b2c* | 0.007 | 0.006 | 0.007 | 0.007 | 0.005 | 0.006 |
| | (0.62) | (0.53) | (0.60) | (0.64) | (0.41) | (0.51) |
| *private* | -0.008 | -0.009 | -0.007 | -0.009 | -0.002 | -0.018 |
| | (-0.61) | (-0.68) | (-0.56) | (-0.65) | (-0.18) | (-1.21) |
| *relative deal size* | -0.025 | -0.022 | -0.025 | -0.025 | -0.015 | -0.023 |
| | (-1.31) | (-1.17) | (-1.36) | (-1.31) | (-0.76) | (-1.25) |
| *same industry* | 0.010 | 0.011 | 0.010 | 0.010 | 0.010 | 0.010 |
| | (1.13) | (1.23) | (1.15) | (1.13) | (1.09) | (1.20) |
| *cash%* | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000** | 0.000*** |
| | (3.02) | (3.00) | (2.97) | (3.01) | (2.27) | (2.80) |
| *unsolicited* | -0.004 | -0.005 | -0.004 | -0.005 | -0.004 | -0.002 |
| | (-0.27) | (-0.29) | (-0.28) | (-0.29) | (-0.23) | (-0.14) |
| *acquirer stock runup* | -0.002 | -0.000 | -0.001 | -0.001 | 0.001 | -0.005 |
| | (-0.07) | (-0.01) | (-0.06) | (-0.04) | (0.06) | (-0.23) |
| *acquirer big4 auditor* | -0.006 | -0.006 | -0.006 | -0.006 | -0.004 | -0.005 |
| | (-0.38) | (-0.37) | (-0.35) | (-0.35) | (-0.21) | (-0.31) |
| *acquirer size* | -0.006* | -0.006* | -0.007* | -0.006* | -0.005 | -0.006 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-1.72) | (-1.73) | (-1.87) | (-1.75) | (-1.50) | (-1.59) |
| *acquirer mb* | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (-1.19) | (-1.16) | (-1.27) | (-1.18) | (-1.23) | (-0.89) |
| *acquirer fcf* | 0.046 | 0.039 | 0.044 | 0.046 | 0.040 | 0.049 |
| | (1.14) | (0.99) | (1.12) | (1.14) | (0.96) | (1.18) |
| *acquirer leverage* | 0.023 | 0.022 | 0.025 | 0.023 | 0.018 | 0.019 |
| | (0.56) | (0.55) | (0.62) | (0.56) | (0.43) | (0.44) |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| $Pr(\beta_{1+}\ \beta_4=0)$ | | | | 0.61 | | |
| $Pr(\beta_{2+}\ \beta_5=0)$ | | | | | 0.00 | |
| $Pr(\beta_{1+}\ \beta_6=0)$ | | | | | | 0.66 |
| *Observations* | 198 | 198 | 198 | 198 | 198 | 198 |
| $R^2$ | 0.178 | 0.183 | 0.176 | 0.178 | 0.197 | 0.197 |

## TABLE 6
## Valuation Adjustments by Acquirers

The table displays the regression results on the informativeness of the transaction pricing multiples using Twitter metrics and revenue on purchase price adjustments by acquirers from the initial deal announcement to the closing of the deal. The dependent variable is the sum of announced goodwill impairment amounts related to the transaction in the five years after transaction consummation scaled by the total purchase price. Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | *price adjustment* | *price adjustment* | *price adjustment* | *price adjustment* | *price adjustment* | *price adjustment* |
| *price/favorites* ($\beta_1$) | -0.012 | | | -0.011 | | |
| | (-0.19) | | | (-0.17) | | |
| *price/retweets* ($\beta_2$) | | -0.001 | | | 0.015 | |
| | | (-0.04) | | | (1.05) | |
| *price/revenue* ($\beta_3$) | | | 0.002*** | | | 0.006*** |
| | | | (2.77) | | | (3.12) |
| *price/favorites* private* ($\beta_4$) | | | | -0.557 | | |
| | | | | (-1.02) | | |
| *price/retweets* private* ($\beta_5$) | | | | | -0.122*** | |
| | | | | | (-3.43) | |
| *price/revenue* private* ($\beta_6$) | | | | | | -0.003 |
| | | | | | | (-1.63) |
| *b2c* | 0.006 | 0.006 | 0.002 | 0.005 | 0.005 | 0.002 |
| | (0.52) | (0.50) | (0.14) | (0.44) | (0.38) | (0.21) |
| *private* | 0.006 | 0.006 | 0.006 | 0.007 | 0.014 | 0.019 |
| | (0.50) | (0.49) | (0.54) | (0.60) | (1.13) | (1.46) |
| *target size* | -0.009 | -0.009 | -0.001 | -0.009 | -0.009 | 0.001 |
| | (-1.60) | (-1.58) | (-0.32) | (-1.54) | (-1.52) | (0.28) |
| *relative deal size* | 0.001 | 0.001 | -0.008 | 0.001 | 0.009 | -0.013 |
| | (0.11) | (0.11) | (-0.58) | (0.11) | (0.73) | (-0.95) |
| *same industry* | -0.001 | -0.001 | -0.004 | -0.001 | -0.002 | -0.005 |
| | (-0.15) | (-0.14) | (-0.47) | (-0.16) | (-0.24) | (-0.58) |
| *cash%* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.40) | (0.40) | (0.85) | (0.41) | (0.18) | (1.11) |
| *unsolicited* | 0.021 | 0.021 | 0.017 | 0.022 | 0.022 | 0.015 |
| | (1.45) | (1.46) | (1.30) | (1.50) | (1.55) | (1.28) |
| *acquirer goodwill* | -0.012 | -0.012 | -0.006 | -0.013 | -0.010 | -0.003 |
| | (-0.43) | (-0.41) | (-0.21) | (-0.47) | (-0.35) | (-0.10) |
| *acquirer big4 auditor* | -0.018 | -0.018 | -0.007 | -0.019 | -0.015 | -0.007 |
| | (-1.07) | (-1.06) | (-0.39) | (-1.08) | (-0.90) | (-0.41) |

| | | | | | | |
|---|---|---|---|---|---|---|
| *acquirer size* | 0.008 | 0.008 | 0.001 | 0.008 | 0.009* | -0.002 |
| | (1.62) | (1.63) | (0.11) | (1.62) | (1.80) | (-0.41) |
| *acquirer mb* | -0.000 | -0.000 | -0.001 | -0.000 | -0.000 | -0.002 |
| | (-0.49) | (-0.50) | (-1.23) | (-0.52) | (-0.60) | (-1.39) |
| *acquirer fcf* | 0.013 | 0.012 | 0.022 | 0.013 | 0.013 | 0.018 |
| | (0.43) | (0.40) | (0.72) | (0.43) | (0.43) | (0.56) |
| *acquirer leverage* | 0.001 | 0.001 | 0.030 | 0.001 | -0.004 | 0.037 |
| | (0.01) | (0.02) | (0.54) | (0.02) | (-0.08) | (0.73) |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| $Pr(\beta_{1+}\ \beta_4=0)$ | | | | 0.31 | | |
| $Pr(\beta_{2+}\ \beta_5=0)$ | | | | | **0.01** | |
| $Pr(\beta_{1+}\ \beta_6=0)$ | | | | | | 0.02 |
| *Observations* | 198 | 198 | 198 | 198 | 198 | 198 |
| $R^2$ | 0.179 | 0.179 | 0.259 | 0.181 | 0.198 | 0.281 |

**TABLE 7**
**Goodwill Impairment by Acquirers**

The table displays the regression results on the informativeness of the transaction pricing multiples using Twitter metrics and revenue on subsequent goodwill impairments by acquirers. The dependent variable is the sum of announced goodwill impairment amounts related to the transaction in the five years after transaction consummation scaled by the total purchase price. Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

| VARIABLES | (1)<br>*impairment* | (2)<br>*impairment* | (3)<br>*impairment* | (4)<br>*impairment* | (5)<br>*impairment* | (6)<br>*impairment* |
|---|---|---|---|---|---|---|
| *price/favorites* ($\beta_1$) | 0.494 | | | 0.490 | | |
| | (0.96) | | | (0.95) | | |
| *price/retweets* ($\beta_2$) | | 0.241* | | | 0.184 | |
| | | (1.82) | | | (1.33) | |
| *price/revenue* ($\beta_3$) | | | 0.026 | | | -0.004 |
| | | | (1.23) | | | (-0.29) |
| *price/favorites* private* ($\beta_4$) | | | | 5.448 | | |
| | | | | (0.79) | | |
| *price/retweets* private* ($\beta_5$) | | | | | 0.420 | |
| | | | | | (0.94) | |
| *price/revenue* private* ($\beta_6$) | | | | | | 0.031 |
| | | | | | | (1.35) |
| *b2c* | 0.270*** | 0.288*** | 0.204** | 0.276*** | 0.295*** | 0.204** |
| | (2.71) | (2.70) | (2.18) | (2.73) | (2.70) | (2.22) |
| *private* | 0.007 | 0.001 | 0.032 | -0.003 | -0.030 | -0.085 |
| | (0.03) | (0.00) | (0.16) | (-0.02) | (-0.14) | (-0.47) |
| *target size* | -0.043 | -0.046 | 0.060 | -0.043 | -0.048 | 0.036 |
| | (-0.58) | (-0.62) | (1.28) | (-0.59) | (-0.65) | (0.92) |
| *relative deal size* | -0.317 | -0.341 | -0.452** | -0.318 | -0.378 | -0.419** |
| | (-1.30) | (-1.38) | (-2.26) | (-1.29) | (-1.51) | (-2.03) |
| *goodwill%* | 0.501 | 0.509 | 0.421 | 0.507 | 0.502 | 0.356 |
| | (0.98) | (1.00) | (0.83) | (0.98) | (0.99) | (0.69) |
| *CAR[-1,+1]* | -1.317 | -1.227 | -1.652* | -1.304 | -1.117 | -1.831* |
| | (-1.60) | (-1.52) | (-1.84) | (-1.58) | (-1.48) | (-1.89) |
| *same industry* | 0.136 | 0.125 | 0.126 | 0.134 | 0.129 | 0.134 |
| | (0.97) | (0.90) | (1.17) | (0.95) | (0.92) | (1.26) |
| *cash%* | -0.001 | -0.001 | 0.001 | -0.001 | -0.001 | 0.000 |
| | (-0.31) | (-0.34) | (0.35) | (-0.31) | (-0.22) | (0.09) |
| *unsolicited* | 0.072 | 0.085 | -0.004 | 0.066 | 0.078 | 0.008 |
| | (0.91) | (1.07) | (-0.05) | (0.84) | (0.97) | (0.10) |
| *acquirer goodwill* | 0.907 | 0.917 | 1.061** | 0.913 | 0.944 | 1.042* |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (1.58) | (1.60) | (2.04) | (1.58) | (1.64) | (2.01) |
| *acquirer big4 auditor* | 0.103 | 0.100 | 0.250* | 0.104 | 0.092 | 0.252* |
| | (0.77) | (0.74) | (1.75) | (0.77) | (0.66) | (1.78) |
| *acquirer size* | -0.007 | -0.011 | -0.096 | -0.007 | -0.012 | -0.064 |
| | (-0.06) | (-0.10) | (-1.43) | (-0.06) | (-0.11) | (-0.91) |
| *acquirer mb* | 0.006 | 0.006 | -0.003 | 0.006 | 0.007 | 0.001 |
| | (0.62) | (0.65) | (-0.25) | (0.63) | (0.73) | (0.07) |
| *acquirer fcf* | -0.408 | -0.350 | -0.160 | -0.413 | -0.361 | -0.163 |
| | (-0.77) | (-0.68) | (-0.48) | (-0.78) | (-0.70) | (-0.49) |
| *acquirer leverage* | -0.390 | -0.382 | -0.152 | -0.396 | -0.377 | -0.222 |
| | (-1.06) | (-1.04) | (-0.63) | (-1.07) | (-1.01) | (-0.84) |
| | | | | | | |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| $Pr(\beta_{1+}\ \beta_4=0)$ | | | | 0.42 | | |
| $Pr(\beta_{2+}\ \beta_5=0)$ | | | | | 0.18 | |
| $Pr(\beta_{1+}\ \beta_6=0)$ | | | | | | 0.22 |
| *Observations* | 161 | 161 | 161 | 161 | 161 | 161 |
| $R^2$ | 0.364 | 0.367 | 0.436 | 0.364 | 0.369 | 0.449 |

## TABLE 8
## Additional Analyses: B2B vs. B2C

This table examines how the business models of target firms (B2B vs. B2C) moderate the association between the recognized value of the target firm's related intangible assets and Twitter metrics. Panel A focuses on the univariate associations. Panel B focuses on the multivariate associations controlling for deal characteristics. Columns (1) to (3) display the results among transactions that involve targets with B2B business while columns (4) to (6) display the results among transactions that involve targets with B2C business. Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

**Panel A: Univariate Relationship with Relevant Intangible Assets**

| SAMPLES | | B2B | | | B2C | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* |
| *favorites* | 116.752** | | | 267.341** | | |
| | (2.20) | | | (2.59) | | |
| *retweets* | | 192.770*** | | | 451.521** | |
| | | (2.81) | | | (2.57) | |
| *revenue* | | | 0.816*** | | | 0.838 |
| | | | (2.75) | | | (1.35) |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 147 | 147 | 147 | 94 | 94 | 94 |
| $R^2$ | 0.126 | 0.137 | 0.285 | 0.244 | 0.327 | 0.309 |

**Panel B: Multivariate Association with Relevant Intangible Assets**

| SAMPLES | | B2B | | | B2C | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* |
| *favorites* | 89.226* | | | 225.686* | | |
| | (1.81) | | | (1.99) | | |
| *retweets* | | 157.559** | | | 418.152** | |
| | | (2.49) | | | (2.11) | |
| *revenue* | | | 0.711** | | | 0.692 |
| | | | (2.56) | | | (1.18) |
| *private* | -1,073.882*** | -1,041.824*** | -731.540*** | -809.296* | -515.053 | -422.163 |
| | (-4.77) | (-4.57) | (-4.46) | (-1.70) | (-1.39) | (-0.83) |
| *same industry* | -76.206 | -74.566 | 55.859 | 1,030.170 | 1,114.568 | 835.600 |
| | (-0.26) | (-0.25) | (0.19) | (1.35) | (1.39) | (1.31) |
| *cash%* | 0.118 | -0.980 | 1.095 | 3.409 | 7.562 | 2.011 |
| | (0.05) | (-0.36) | (0.60) | (0.24) | (0.51) | (0.16) |
| *unsolicited* | -280.205 | -296.084 | -335.173 | -767.673 | -573.579 | -785.815 |
| | (-0.72) | (-0.76) | (-1.01) | (-0.64) | (-0.45) | (-0.69) |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 147 | 147 | 147 | 94 | 94 | 94 |
| $R^2$ | 0.224 | 0.234 | 0.336 | 0.308 | 0.380 | 0.342 |

## TABLE 9
## Additional Analyses: Components of Total Purchase Price

This table displays the results on the association between different components of the total purchase price and Twitter metrics following specifications in Table 4. Panel A examines the component of marketing-related intangible assets (*brand*). Panel B examines the component of customer-related intangible assets (*customer*). Panel C examines the component of goodwill (*goodwill*). Panel D examines the remaining component of the tangible part of the total purchase price (*tangible*). Panel E examines the total purchase price as the dependent variable. Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

**Panel A: Relationship with Marketing-Related Intangible Assets**

| VARIABLES | (1) *brand* | (2) *brand* | (3) *brand* | (4) *brand* | (5) *brand* | (6) *brand* |
|---|---|---|---|---|---|---|
| *favorites* | 52.866** | | | 51.130** | | |
| | (2.27) | | | (2.23) | | |
| *retweets* | | 78.119** | | | 70.397** | |
| | | (2.17) | | | (2.26) | |
| *revenue* | | | 0.160 | | | 0.131 |
| | | | (1.12) | | | (1.04) |
| *Controls* | Not Included | Not Included | Not Included | Included | Included | Included |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 139 | 139 | 139 | 139 | 139 | 139 |
| $R^2$ | 0.142 | 0.161 | 0.157 | 0.257 | 0.266 | 0.256 |

**Panel B: Relationship with Customer-Related Intangible Assets**

| VARIABLES | (1) *customer* | (2) *customer* | (3) *customer* | (4) *customer* | (5) *customer* | (6) *customer* |
|---|---|---|---|---|---|---|
| *favorites* | 35.107** | | | 28.579 | | |
| | (2.58) | | | (1.65) | | |
| *retweets* | | 59.314** | | | 49.305* | |
| | | (2.40) | | | (1.89) | |
| *revenue* | | | 0.220* | | | 0.195* |
| | | | (1.92) | | | (1.78) |
| *Controls* | Not Included | Not Included | Not Included | Included | Included | Included |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 141 | 141 | 141 | 141 | 141 | 141 |
| $R^2$ | 0.194 | 0.217 | 0.342 | 0.270 | 0.284 | 0.379 |

**Panel C: Relationship with Goodwill**

| VARIABLES | (1) *goodwill* | (2) *goodwill* | (3) *goodwill* | (4) *goodwill* | (5) *goodwill* | (6) *goodwill* |
|---|---|---|---|---|---|---|
| *favorites* | 117.304*** | | | 97.021** | | |
| | (3.11) | | | (2.41) | | |
| *retweets* | | 234.431*** | | | 211.197** | |
| | | (2.90) | | | (2.57) | |
| *revenue* | | | 0.756* | | | 0.675* |
| | | | (2.00) | | | (1.80) |
| *Controls* | Not Included | Not Included | Not Included | Included | Included | Included |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Year F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 230 | 230 | 230 | 230 | 230 | 230 |
| $R^2$ | 0.190 | 0.244 | 0.313 | 0.243 | 0.285 | 0.332 |

**Panel D: Relationship with Net Tangibles**

| VARIABLES | (1) *tangible* | (2) *tangible* | (3) *tangible* | (4) *tangible* | (5) *tangible* | (6) *tangible* |
|---|---|---|---|---|---|---|
| *favorites* | -17.635 | | | -19.914 | | |
| | (-0.54) | | | (-0.62) | | |
| *retweets* | | -33.185 | | | -46.538 | |
| | | (-0.80) | | | (-1.09) | |
| *revenue* | | | 0.284* | | | 0.283* |
| | | | (1.93) | | | (1.90) |
| *Controls* | Not Included | Not Included | Not Included | Included | Included | Included |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 240 | 240 | 240 | 240 | 240 | 240 |
| $R^2$ | 0.130 | 0.131 | 0.161 | 0.168 | 0.170 | 0.195 |

**Panel E: Relationship with Total Purchase Price**

| VARIABLES | (1) *total purchase price* | (2) *total purchase price* | (3) *total purchase price* | (4) *total purchase price* | (5) *total purchase price* | (6) *total purchase price* |
|---|---|---|---|---|---|---|
| *favorites* | 160.257** | | | 112.926* | | |
| | (2.65) | | | (1.84) | | |
| *retweets* | | 291.877** | | | 236.793** | |
| | | (2.45) | | | (2.01) | |
| *revenue* | | | 1.379*** | | | 1.283*** |
| | | | (2.90) | | | (2.69) |
| *Controls* | Not Included | Not Included | Not Included | Included | Included | Included |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 282 | 282 | 282 | 282 | 282 | 282 |
| $R^2$ | 0.112 | 0.135 | 0.294 | 0.168 | 0.185 | 0.316 |

## TABLE 10
## Additional Analyses: Metrics

This table examines the association between the recognized value of the relevant intangible assets of target firms and their social media and financial metrics. Panel A decomposes the Twitter metrics in the main analyses into a component determined by user behaviors (*favorites per tweet* and *retweets per tweet*) and a component determined by corporate actions (*#tweets*). Panel B examines a subsample that requires the availability of earnings of target firms and examines the explanatory powers of social media metrics vis-à-vis earnings in this subsample. Panel C examines alternative stock metrics using the number of followers (*follower*) and total assets (*asset*) vs. flow metrics used in the main analyses (*favorites*, *retweets*, *revenue*). Variable definitions are provided in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by industry-year. ***, **, and * denote statistical significance of differences at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

**Panel A: User and Corporate Components of Twitter Metrics**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* |
| *favorites per tweet* | 276.277** | | | 257.382** | |
| | (2.65) | | | (2.57) | |
| *retweets per tweet* | | 1,379.429** | | | 1,294.769** |
| | | (2.43) | | | (2.53) |
| *#tweets* | 46.805 | 76.239 | 59.227 | 17.466 | 47.561 |
| | (0.87) | (1.25) | (1.17) | (0.31) | (0.82) |
| *revenue* | | | 0.721** | 0.706** | 0.645** |
| | | | (2.08) | (2.14) | (2.41) |
| | | | | | |
| *Controls* | Included | Included | Included | Included | Included |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 241 | 241 | 241 | 241 | 241 |
| $R^2$ | 0.241 | 0.371 | 0.308 | 0.336 | 0.450 |

**Panel B: Net Income**

| VARIABLES | (1)<br>*intangibles* | (2)<br>*intangibles* | (3)<br>*intangibles* | (4)<br>*intangibles* | (5)<br>*intangibles* | (6)<br>*intangibles* |
|---|---|---|---|---|---|---|
| *earning* | 6.636* | 4.757 | 6.111 | 5.696 | 4.245 | 4.021 |
| | (1.88) | (1.34) | (1.67) | (1.54) | (1.16) | (1.10) |
| *revenue* | | 0.754 | | | 0.752 | 0.705 |
| | | (1.64) | | | (1.64) | (1.66) |
| *favorites* | | | 146.750 | | 144.550* | |
| | | | (1.60) | | (1.71) | |
| *retweets* | | | | 354.074** | | 323.117** |
| | | | | (2.12) | | (2.35) |
| *Controls* | Included | Included | Included | Included | Included | Included |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 136 | 136 | 136 | 136 | 136 | 136 |
| $R^2$ | 0.289 | 0.374 | 0.305 | 0.354 | 0.390 | 0.430 |

**Panel C: Stock vs. Flow Measurement**

| | Requiring the Presence of Target Asset and Twitter Follower Metrics | | | Requiring the Presence of Target Revenue and Twitter Follower and Engagement Metrics | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| VARIABLES | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* | *intangibles* |
| *follower* | 496.506* | | 362.204** | 253.205* | 187.169* | 229.961** | 173.103** |
| | (1.97) | | (2.27) | (1.94) | (1.89) | (2.12) | (2.05) |
| *asset* | | 0.925 | 0.835 | | | | |
| | | (1.68) | (1.66) | | | | |
| *favorites* | | | | 68.664 | | 40.722 | |
| | | | | (1.34) | | (0.76) | |
| *retweets* | | | | | 212.326*** | | 165.611** |
| | | | | | (2.72) | | (2.45) |
| *revenue* | | | | | | 0.714* | 0.686* |
| | | | | | | (1.86) | (1.85) |
| *Industry F.E.* | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year F.E.* | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 106 | 106 | 106 | 187 | 187 | 187 | 187 |
| $R^2$ | 0.283 | 0.434 | 0.495 | 0.241 | 0.262 | 0.330 | 0.343 |