Are the Recorded Values of Acquired Intangible Assets Indicative of Their Future Payoffs?

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Abstract

There is a long-standing debate on the recognition of intangible assets and whether they can be measured reliably. Most recognized intangibles are acquired in business combinations, and estimating their fair value is highly subjective. Using a broad sample of business combinations in the U.S. from 2003 to 2014, we find no significant relation between the recorded value of identifiable intangibles and future operating income. However, in cross-sectional tests we predict and find a positive association between future income and identifiable intangibles arising from deals where measurement uncertainty is lower, indicating that unreliable measurement plays a role in our findings. Additionally, we find some evidence that acquisitions with more recorded identifiable intangibles have worse future stock price performance, suggesting investors may not fully understand the implications of recorded identifiable intangibles for future income.

1. Introduction

We examine whether the recorded amounts of investments in intangible assets are associated with future operating income. We are interested in this question because there is a long-standing debate concerning the recognition of intangible assets (e.g., Lev 2001). While many agree that intangibles like patents, trademarks, and customer relationships likely contribute significantly to value creation, identifying and reliably estimating the value of these intangibles is difficult, and internally-generated intangibles are therefore generally not recognized in U.S. GAAP.

Acquired intangibles are recognized, however, and since the passage of SFAS 141 and 142, U.S. companies have added, in aggregate, billions to their balance sheets in intangible assets, mostly in connection with business combinations. In a business combination, identifiable intangibles like patents and trademarks are recorded at their estimated fair values. Unidentifiable intangibles are recognized as goodwill, which is the residual acquisition price left after valuing identifiable tangible and intangible net assets. Although a number of prior studies examine the recognition and impairment of goodwill, there is much less work on identifiable intangibles, which are the primary focus of this paper.

Since the vast majority of intangibles recorded under U.S. GAAP involve business combinations, we start with a business combination setting (in supplemental tests we examine intangibles acquired outside of business combinations). In the spirit of Richardson, Sloan, Soliman, and Tuna (2005), we view the acquisition price as an investment accrual measured with error since it may not perfectly correspond to the "true" discounted payoffs from the target. Further, in allocating the acquisition price, the fair values of identifiable assets are also likely measured with error, particularly for intangibles since they are rarely traded and must be estimated subjectively. Since goodwill is a residual, it contains typically offsetting measurement error: the misvaluation in the acquisition price less the misvaluation of the identifiable assets.[1]

Overall, if acquisitions yield positive returns and tangibles, intangibles, and goodwill are measured with sufficient reliability, we expect a positive association between these accruals and future incremental operating income. On the other hand, if these measures are sufficiently unreliable, we do not expect them to be useful in predicting future income, and we expect no significant association with future incremental income. In particular, estimating the fair value of identifiable intangibles is highly subjective and arguably represents non-financial firms' most significant exposure to fair value accounting. Given long-standing measurement concerns for these items, it is not clear that the recorded values of identifiable intangibles will be useful for predicting future payoffs, which is a primary goal of financial accounting information. It is therefore important to document whether, when, and to what extent recorded investments in identifiable intangibles correspond to higher future profits.

To examine this issue, we follow prior work (e.g., Lev and Sougiannis 1996; Lys, Vincent, and Yehuda 2012) and calculate the incremental future operating income before depreciation and amortization from the acquisition, which equals average operating income for the combined entity over the one, three, and five years after the acquisition less operating income for the acquirer prior to the acquisition. We then regress future incremental operating income over these three horizons on the recorded amounts of identifiable intangible assets, along with goodwill and tangibles from the acquisition, and other acquirer investments not part of the acquisition.

[1] For example, suppose the "true" value of the target is $100 and the acquisition price is $120. If tangibles are measured correctly, but identifiable intangibles are overvalued by $10, goodwill will be overvalued by $10 ($20 of target overvaluation less $10 of intangibles overvaluation).

We use a unique dataset provided by Houlihan Lokey that contains reported purchase price allocations for 4,166 firm-years involved in business combinations from 2003 to 2014. Overall, using this broad sample, we find a positive relation between the total acquisition price and future income. This implies any measurement error (i.e., under or over-payment for the target) is small enough to result in acquisition prices still being predictive of future profits. We find that each dollar spent by the acquirer is associated with an incremental operating return of between 5 and 11 cents per year, depending on the specification and horizon. These returns are economically similar to acquirers' returns to investments in other assets (e.g., capital expenditures) not part of the acquisition.

Importantly, when we examine the recognized components of the acquisition price, we find no significant association between future income and the estimated fair value of identifiable intangibles. This implies that identifiable intangibles either have no or very low returns or, more likely, are not measured with sufficient reliability to be predictive of future payoffs. In contrast, we find that recorded net tangibles yield an operating return of about 8% per year, and recorded goodwill yields a return of between 9% and 19% per year. This suggests that the net (or offsetting) measurement error in goodwill is small enough to render goodwill a reliable predictor of future income. We find that these results are robust to corrections for survivorship bias, other definitions of profitability, and intra-industry analyses.

Since the insignificance of identifiable intangibles as a predictor of future income is our most surprising finding above, we next investigate the role measurement uncertainty plays. We predict that in settings where the measurement of identifiable intangibles is likely more reliable, there should be a closer correspondence between recorded intangibles and future profits. We examine three settings. First, we expect that larger acquirers will have more expertise in, and devote more resources toward, the identification and valuation of intangibles. Second, we expect that when there is less uncertainty as to the underlying value of the acquirer and target on a combined basis, the value of intangibles to the combined entity can be estimated more reliably. Finally, we expect that when the acquirer has more experience with past acquisitions, it will be more likely to accurately value intangibles and the target as a whole. We find support for these predictions. In contrast to our main findings above, recorded identifiable intangibles *are* positively associated with future operating income for larger acquirers, for combined entities with less valuation uncertainty, and for acquirers that have other acquisitions in the recent past. Thus, we do find evidence of a positive association between recorded intangibles and future profitability in settings with relatively less estimation uncertainty.

We also conduct supplemental tests to extend these main findings. First, we examine the implications of the findings for future stock returns. Some prior studies (e.g., Loughran and Vijh 1997; Rau and Vermaelen 1998; Harford 2005; Rosen 2006) find negative long-run abnormal stock returns after acquisitions, which some interpret as evidence that investors overvalue the combined entity in an acquisition. It is possible that acquired identifiable intangible assets could contribute to or exacerbate this phenomenon. In particular, if investors believe recorded investments in identifiable intangibles, on average, correspond to higher future operating profits, we expect acquisitions involving more intangibles to have worse future stock performance, and we expect this pattern to be the strongest for smaller stocks (where the intangibles/income relation is weakest). We find some evidence consistent with this conjecture. Specifically, while acquirers earn negative average abnormal returns after the acquisition (about 20 to 35 basis points per month over 12 to 36 month horizons), this negative stock price performance is worse in acquisitions with relatively more identifiable intangibles, but only when we equally weight all observations. When we value-weight returns, which down-weights small stocks, these future return patterns disappear, indicating these return patterns are concentrated in smaller acquirers.

Finally, we examine whether recorded investments in identifiable intangibles predict higher future income for firms not involved in a business combination. We select a sample of firms from Compustat from 2003 to 2014 and screen out firms that engaged or likely engaged in an acquisition. We then measure investments in identifiable intangibles using changes in balance sheet intangibles adjusted for amortization. Although we find that capital expenditures and working capital investment in this sample are positively associated with future income, we find no significant association between future income and identifiable intangibles. Thus, our main findings above do not appear to be confined to business combinations. However, we caution that this analysis may lack power given that recorded identifiable intangibles among firms not involved in acquisitions are relatively rare and small in magnitude.

This study makes several contributions to the literature. First, we contribute to the literature on accruals, investment, and future income (e.g., Fairfield, Whisenant, and Yohn 2003; Allen, Larson, and Sloan 2013). This literature suggests there is a lower correspondence between future income and investment accruals when these accruals are less “reliable” (Richardson et al. 2005). Our contribution is to show that a relatively under-studied but important investment accrual – investments in acquired identifiable intangibles – actually has no significant statistical relation with future profits across a broad sample of firms. This has implications for both policy makers and users, as we discuss further below. Second, we contribute to the literature on the usefulness of fair value measurements, and importantly, offer evidence on this issue outside the financial industry, where much of the prior work has focused (e.g., Barth, Beaver, and Landsman 1996; Nelson 1996; Cantrell, McInnis, and Yust 2014).

Thus, our study speaks to the usefulness of fair value measurements in predicting future operating income across a variety of industries. Finally, we contribute to the accounting literature on acquisitions, which has recently focused heavily on goodwill accounting (e.g., Lys and Vincent 1995; Ayers, Lefanowicz, and Robinson 2002; Shalev, Zhang, and Zhang 2013). We add to this literature by examining the reliability of the accounting for acquired identifiable intangibles, which has received much less attention.

Our findings also offer some practical takeaways. For investors interested in forecasting post-acquisition profitability, our results suggest that the amounts recorded as acquired identifiable intangibles are not particularly helpful on average. However, they are helpful for larger acquirers and in other settings with lower measurement uncertainty. For standard setters, our results offer feedback on the usefulness of fair value measurements required by GAAP for intangibles acquired in business combinations. This feedback may be particularly relevant as the FASB considers changes to accounting for intangibles (FASB 2016a, 2016b).

Our findings are subject to an important caveat. While we find no relation between identifiable intangibles and future operating income on average, this does not necessarily imply these assets are poor investments with little to no payoffs. In fact, given that most market-to-book ratios are above one, it seems likely that identifiable intangibles contribute significantly to firm value. Our findings simply suggest that the amounts recorded as the value of acquired identifiable intangibles in the financial statements appear to, on average, bear little relation to future operating returns.

Section 2 discusses prior literature and develops our hypotheses. Section 3 contains the research design and Section 4 describes the data and presents empirical results. Section 5 concludes.

2. Prior Literature and Hypothesis Development

2.1 Prior Literature

To our knowledge, no prior studies directly investigate the relation between recorded investments in identifiable intangibles and future operating income. One possible reason could be data availability. Recognition of internally-generated intangibles in U.S. GAAP is fairly rare. Further, for intangibles acquired in an acquisition, detailed disclosure of purchase price allocations to assets and liabilities acquired was not mandated until 2001 (SFAS 141 – FASB 2001a).

This study is closely related to three streams of prior literature, however. The first is the literature initiated by Sloan (1996) on the implications of accruals for future profitability. One takeaway from this literature, highlighted by Richardson et al (2005), is that working capital, investment, and financing accruals with low "reliability" (i.e., those involving high estimation uncertainty) tend to be measured with more error and, all else equal, have a lower association with future profits. We view the purchase price paid by an acquirer for a target as an investment accrual with potentially high measurement uncertainty. The overall price paid, along with the allocation to tangibles, intangibles, and goodwill, may or may not correspond closely to the eventual payoffs accruing to the acquirer's shareholders. We develop this idea more formally in the next sub-section.

The second related stream is the value relevance literature on identifiable intangibles and goodwill. Several studies find that goodwill is positively related to equity values (e.g., Barth and Clinch 1996; Jennings, Robinson, Thompson, and Duvall 1996; Vincent 1997). Aboody and Lev (1998) show that software firms' capitalized software costs are associated with returns and the cumulated software costs are associated with stock price. Barth and Clinch (1998) find that revalued amounts for intangible assets are associated with market value of equity in an Australian setting where historical cost and fair value are both allowable valuation methods. Lev and Sougiannis (1996) demonstrate that prior R&D expenditures both reliably predict future operating income and are associated with future stock returns.

We do not use a value relevance approach using equity values as the dependent variable for two reasons. First, concerns have been raised regarding statistical inferences in price-level regressions due to confounds with scale, omitted variables, and model specification (Brown, Lo, and Lys 1999; Kothari 2001; and Holthousan and Watts 2001). More importantly, several studies in finance find that acquirers earn abnormally low stock returns after the acquisition date, suggesting acquirers may be overvalued prior to and soon after the acquisition (Harford 2005; Betton, Eckbo, and Thorburn 2008). These findings involving potential mis-valuation confound inferences in a regression using equity prices around the acquisition date. As such, we take an ex post approach and examine the relation between realized operating payoffs and recorded intangibles.

The final related stream of literature involves research on mergers and acquisitions and purchase price allocations. In the post SFAS 141/142 era, many studies examine goodwill impairments (e.g., Hayn and Hughes 2006; Li, Shroff, Venkatamaran, and Zhang 2011, Bens, Heltzer, and Segal 2011; Beatty and Webber 2006) and the overall usefulness of goodwill accounting (e.g., Ramanna and Watts 2012; Li and Sloan 2015). Other recent studies involve goodwill and post-acquisition performance (e.g., Shalev 2009; Cedergren, Lev, and Zarowin 2015). Lys, Vincent, and Yehuda (2012) use acquirer announcement returns to split acquisitions into those expected to be profitable versus unprofitable. They find that goodwill is positively related to future performance only in acquisitions expected to be profitable (about 60% of their sample). Shalev, Zhang, and Zhang (2013) find that managers with higher earnings bonuses allocate more of the acquisition price to goodwill—and thus less to tangibles and identifiable intangibles—to avoid future drags on earnings (we discuss the effects of compensation-based incentives on our results in Appendix C).

There has been far less work on other elements of purchase price allocations outside of goodwill. Using market prices and estimated standalone values, Lys and Yehuda (2015) find that private targets yield more deal synergies than public targets, and this effect appears to be related to private targets having more identifiable intangible assets. Interestingly, in one test, Lys and Yehuda (2015) report a positive association between recorded identifiable intangibles and future operating income. Conversely, Lys et al. (2012) use a similar sample to that used in Lys and Yehuda (2015), but find no consistent relation between recorded identifiable intangibles and future operating income. Identifiable intangibles are a control variable in both studies, so neither study discusses the association or attempts to reconcile this difference. In contrast, our primary focus is on the association between identifiable intangible assets and future operating income.

2.2 Hypothesis Development

In this section we formalize the economic intuition behind our hypotheses and establish a framework for our empirical tests that follow. The ideas are similar to those in Section 2.1 of Richardson et al. (2005), except they frame their discussion using a short-term receivable while we focus on a long-term investment.

Suppose a firm spends P dollars at time 0 on a multi-period investment with expected payoffs of Y_t each year. A manager with perfect foresight knows each Y_t and spends $P = P^*$, where P^* is the sum of the discounted future payoffs Y_t, using the firms' expected return on investment projects as the discount rate.[2] Note that P is accrued as an asset in most settings under U.S. GAAP. Let Z_t be a profit measure that equals the realized payoff, which is Y_t plus a random noise term, less an appropriate charge for depreciation. Then in the first year:

$$Z_1 = \beta(P^*) + \varepsilon \tag{1}$$

where $\beta > 0$ is the discount rate applied to payoff Y_1 or, equivalently, the firm's expected return on investment projects. This relation will hold each year using the remaining undepreciated balance of P^*. Importantly for our purpose, there is a positive correspondence between the amount spent on the project, P^*, and future profits Z_t from the project.

Now suppose firms do not have perfect foresight and the amount spent on the project does not perfectly correspond to "true" discounted, expected payoffs. Instead, $P = P^* + U$, where U is zero-mean error term and can be thought of as a firm's overpayment or underpayment for the risky investment. (1) then becomes:

$$Z_1 = \mathrm{b}(P^* + U) + \omega \tag{1a}$$

Where $\omega = \varepsilon - \beta U$ and b is the ols estimate of β. In (1a), P is a noisy measure of the true expected payoffs on the project and if Z_1 were regressed on P, it is well known that b would be attenuated toward zero (i.e., $\mathrm{b} < \beta$). If the variance of U is large enough, b may not be different from zero. In other words, P has no ability to predict future payoffs when it is a sufficiently noisy measure of P^*.

Suppose now that the risky investment is an acquisition of a business. U.S. GAAP requires the acquirer to allocate P to the fair value of the tangible assets acquired (TAN), the fair value of identifiable intangibles ($IDINT$), and the remainder, which is goodwill (GW). All three

[2] We can assume this is the average internal rate of return on the firm's investment projects. In a perfectly competitive environment, this return should be close to the firm's total cost of capital given the riskiness of its investments. However, if the firm has competitive advantages others cannot easily imitate (i.e., earns economic rents), this expected return on investment will be greater than cost of capital.

components are recognized separately as assets. If the acquirer has perfect foresight, then $P = P^* = TAN^* + IDINT^* + GW^*$, and (1) becomes

$$Z_1 = \beta^T(TAN^*) + \beta^I(IDINT^*) + \beta^G(GW^*) + \varepsilon \qquad (2)$$

As before, the βs correspond to the expected returns to each component of P^* but need not be equal across components. They will vary based upon the riskiness and economic rents earned for each component. For example, if acquirers can effectively integrate targets and capture synergies in ways competitors cannot, their expected returns to goodwill (β^G)may be higher than, say, acquired inventory. Most importantly for our purpose, if there is no measurement error in P^* or its components, there will be positive associations between future payoffs and the amounts allocated to tangibles, identifiable intangibles, and goodwill.

As above, estimating the returns to acquisitions is complicated by measurement error in P. For example, suppose there is measurement error and $P = P^* + U$, but tangibles and identifiable intangibles are measured perfectly at their "true" fair values. Since goodwill is a residual calculation, it will absorb all of the measurement error in P, as given by:

$$GW = P - TAN^* - IDINT^* = GW^* + U.$$

If the variance of U is large enough, recorded goodwill will be a poor predictor of future payoffs.

More realistically, assume identifiable intangibles are also measured with error due to the lack of active markets and the subjectivity in estimating their fair values, as discussed in Section 1. For simplicity, assume further that measurement error in tangibles is relatively small and can be ignored.[3] Then $IDINT = IDINT^* + V$, where V is a measurement error term, and

$$GW = (P^* + U) - TAN^* - (IDINT^* + V) = GW^* + U - V.$$

Because goodwill is the residual in the allocation process, any measurement error in

[3] Measurement error in tangibles would simply add another term to (2a) but would not change the intuition behind our hypotheses.

identifiable intangibles offsets or reduces measurement error in goodwill, assuming *U* and *V* are positively correlated, which seems likely (i.e., when acquirers overestimate the expected payoffs from the target as a whole, they also overestimate the payoffs from identifiable intangibles). (2) then becomes:

$$Z_1 = b^T(TAN^*) + b^I(IDINT^* + V) + b^G(GW^* + U - V) + \omega \qquad (2a)$$

Expression (2a) forms the basis for our hypotheses. Although our primary focus is on identifiable intangibles, we also hypothesize about goodwill given its role in absorbing residual measurement error. If identifiable intangibles and goodwill are measured reliably, measurement error from *U* and *V* should be small and these assets will be reliable predictors of future profits: each additional dollar recorded as an asset should yield incremental future operating returns. On the other hand, if measurement error from *U* and *V* is large, both may be poor predictors of future payoffs, resulting in no correspondence between the amounts recorded for these assets and future profits.

Alternatively, there may be differences in relative reliability. If *V* has small variance, most of the measurement error from the acquisition will be concentrated in goodwill, making it a relatively poor predictor of future payoffs. On the other hand, if *V* has large variance, some of the measurement error in goodwill will be mitigated and the overall variance of the measurement error in goodwill, $U - V$, may be small relative to GW^*.[4] This could result in goodwill being a more reliable predictor of future profits than identifiable intangibles. Given this discussion, we state both of our hypotheses in the null:

H1: There is no association between recorded identifiable intangibles and future operating profits

[4] $Var(U\text{-}V)$, the variance of $U - V$, is given by $Var(U) + Var(V) - 2Cov(U,V)$. From this it can be shown that $Var(V)$ will be larger than $Var(U\text{-}V)$ whenever $[\ Var(V) / Var(U)\ ] > [\ 1 / 4\rho^2\ ]$, where ρ is the correlation coefficient between *V* and *U*. If V and U are highly positively correlated (i.e., ρ is close to 1), then $Var(V)$ will be more than $Var(U\text{-}V)$ whenever $Var(V)$ is at least approximately ¼ of $Var(U)$.

H2: There is no association between recorded goodwill and future operating profits

3. Research design

To test H1 and H2, we regress incremental future operating income before depreciation and amortization on components of the acquisition price. Specifically, we estimate Models (3) and (4), which are similar to 1(a) and 2(a) above, as follows:

$$INOPINC_{t+1(3)[5]} = \beta_0 + \beta_1 P_t + \beta_2 \Delta AcqAssets_t + \varepsilon_{t+1(3)[5]} \quad (3)$$

$$INOPINC_{t+1(3)[5]} = \beta_0 + \beta_1 TAN_t + \beta_2 IDINT_t + \beta_3 GW_t + \beta_4 \Delta AcqAssets_t + \varepsilon_{t+1(3)[5]} \quad (4)$$

where *INOPINC* is the combined firm's incremental operating income before depreciation and amortization over the one, three, or five years following the acquisition. Similar to Lys and Yehuda (2015), this variable is calculated by subtracting operating income for the fiscal year prior to the acquisition from average operating income measured over the one, three, or five years beginning the fiscal year following acquisition consummation. Thus, this variable captures the future operating income of the combined entity (the acquirer and the target) *incremental* to the acquirer's level of operating income just before the acquisition. We use operating income to focus on gross investment payoffs before charges for depreciation and amortization. In theory, this incremental gross income should be a function of the acquirer's investment in the target (which we label *P*), as well as other investments by the acquirer not part of the acquisition (which we label $\Delta AcqAssets$).[5]

P, the purchase price of the acquisition, is made up of three components, all of which are

[5] As an alternative to Models (3) and (4), we also considered an autoregressive model (e.g., future income is regressed on prior income plus investment) more common in the accruals literature. However, given that the combined entity is often significantly larger than the acquirer prior to the acquisition, income is not mean-reverting, and the coefficient on prior income is generally larger than 1. Thus, we use a model more consistent with those used in prior work on acquisitions and intangibles.

included as independent variables in Model (4). The independent variables of interest in Model (4) are *IDINT* and *GW*, the fair value of acquired identifiable intangible assets and the total goodwill from the acquisition, respectively. We also include *TAN*, the fair value of acquired tangible assets. If a firm has multiple acquisition in a year, *P* and its components are summed across all acquisitions in that year. Δ*AcqAssets* is a control variable that captures other acquirer investments not part of the acquisition, and is calculated by subtracting total assets at the end of the fiscal year prior to the acquisition from total assets (excluding *P*) at the end of the year of acquisition consummation. All regression variables are scaled by acquirer's total assets in the year prior to the transaction[6] and winsorized at the 1st and 99th percentiles, and both models are estimated including industry and year fixed effects[7] and with standard errors clustered by acquirer.

We first estimate Model (3) over one-, three-, and five-year horizons to provide a baseline interpretation of the effect of *P* on *INOPINC*. Estimating Model (3) constrains the coefficient on the components of *P* to be equivalent, and provides an estimate of the overall return to acquisitions.

We formally test H1 and H2 by estimating Model (4), which breaks *P* into its components. A non-zero β_2 would indicate a rejection of H1, or that the estimated fair value of *IDINT* is associated with incremental future operating income. Likewise, non-zero β_3 would indicate a rejection of H2. On the other hand, consistent with hypothesis development in Section

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[6] Scaling by prior year's assets avoids having the scaling variable be significantly influenced by the acquisition itself (i.e., since the acquisition increases the combined entity's scale). Thus, for an investment in a target given the scale of the acquirer before the acquisition, Models (3) and (4) tell us the returns to the acquirer to that investment. However, results are inferentially similar when all variables are scaled by total assets in the year of the acquisition or the year following the acquisition.

[7] Industries are consistently defined in the study as the nine industries from Barth, Beaver, Hand, and Landsman (2005) plus financial and regulated firms. Results are robust to alternative industry definitions, including Fama-French 17 and 48 industries. Using the industries from Barth et al. (2005) provides a more uniform distribution of acquisitions across industries with sufficient firms to reliably estimate a fixed effects model.

2.2, if *IDINT* and *GW* are measured with significant error, we expect little to no association between these components of *P* and future operating income (i.e., β_2=0; β_3=0).

We note however that in a multivariate regression, measurement error in one or more variables does not necessarily imply attenuation of the coefficients toward zero (Barth 1994; Nelson 1996). Technically, the bias in the coefficients depends on the values of the "true" coefficients, the variance-covariance matrix of the "true" covariates, and the variance-covariance matrix of the measurement error in those covariates (see Appendix B, where we discuss the econometric implications of measurement error). In fact, it is theoretically possible for measurement error in one or more variables in (4) to actually bias the coefficients on identifiable intangibles and goodwill upward. This possibility seems unlikely for identifiable intangibles in our setting, as we discuss further in Appendix B, but this is ultimately an empirical question.

4. Data and empirical results

4.1 Data and Descriptive Statistics

Data on acquisitions and the purchase price allocations were provided by the investment bank Houlihan Lokey. It collects this data in connection with an annual Purchase Price Allocation study, which provides detailed descriptive statistics on purchase price allocations and acquisition trends in the U.S. We obtained data for business combinations consummated from 2003 through 2014, where the acquirer is a public company on a U.S. stock exchange, the ownership percentage sought by the acquirer was 50% or greater, and the purchase consideration is disclosed. Data on the recorded fair value of tangible assets, identifiable intangible assets, and goodwill acquired are collected by Houlihan Lokey from the annual report disclosures required by ASC 805-20-50 (SFAS 141R – FASB 2001a) and ASC 350-20-50 (SFAS 142 – FASB 2001b). Importantly, all transactions in our study occur in the post-SFAS 141 era. We merge the data with Compustat for financial variables, CRSP for price- and return-related variables, Execucomp for CEO compensation data, and Mergerstat to fill in missing industry data for private targets. After eliminating acquisitions without sufficient post-merger earnings data and where the purchase consideration is greater than two times the acquirer's assets[8] and summing purchase price data for multiple mergers within a year over firm-years, our dataset contains 4,166 firm-years containing at least one acquisition.

Table 1, Panel A provides descriptive statistics for variables used in our hypothesis tests. The mean (median) of *P* indicates that the average purchase consideration for acquisitions in our sample is 29.7% (15.1%) of total acquirer assets. Moving to the components of the purchase consideration, *TAN* is the largest with a mean (median) of 11.8% (4.1%) of acquirer assets; *GW* is next with a mean (median) of 10.4% (3.8%) of acquirer assets; and the mean (median) of *IDINT* is 7.4% (2.5%) of acquirer assets. With respect to the total purchase price, *TAN*, *GW*, and *IDINT* make up on average 39.7%, 35.0%, and 25.3% of *P*, respectively. Our sample of 4,166 business combinations corresponds to total purchase consideration of $5.3 trillion and resulted in identifiable intangible assets and goodwill of $730 billion and $1.02 trillion, respectively, added to firm balance sheets (untabulated).

As discussed in Section 1, we examine certain settings with heightened measurement uncertainty. Variables used to identify these settings (*Size*, *Volatility*, and *Experience*) display predictable patterns. The mean (median) of *Size* indicates acquirers in our sample have total assets of $702.0 ($682.0) million in the year prior to the acquisition. *Volatility* indicates that targets' daily post-acquisition returns have a standard deviation of about 2.7% on average.

Panel B presents detail on the distribution of these acquisitions by year and industry. The

[8] We eliminate these acquisitions to reduce the influence of highly leveraged acquisitions or reverse mergers on our results. Inferences are unchanged when these acquisitions are not eliminated from the sample.

acquisitions in our sample are fairly evenly distributed across years, with an average of about 347 transactions per year. The one exception is 2009, with only 232 acquisitions. This is unsurprising, given the effect of the financial crisis on M&A activity. The distribution across industries is less uniform. The two industries with the most transactions are *Computers, software, and telecom*; and *Durable manufacturers*, with 1,111 (26.67%) and 835 (20.04%) of the sample, respectively. The two industries with the fewest transactions are *Food* and *Chemicals*, each with 75 (1.80%) of the sample. 2,770, or 66.5%, of the firm-years in our sample represent takeovers of private targets (untabulated). This is very similar to 68% of completed mergers reported in the Betton et al. (2008) review.

Table 2 presents univariate Pearson and Spearman correlations among variables in our empirical tests. *P* and two of its components, *TAN* and *GW*, are significantly positively correlated with *INOPINC* on a univariate basis. *IDINT* has a positive correlation as well, but only in the three- and five-year measurement horizon for *INOPINC*. However, *IDINT* is positively correlated with both *TAN* and *GW*, so it is unclear whether the univariate correlation between *IDINT* and *INOPINC* is due to positive returns to *IDINT* or correlation with these other components.

4.2 Empirical Results for H1 and H2

Results from estimating Models (3) and (4) in the full sample of acquisitions are in Table 3. The coefficients on *P* indicate that a dollar spent by an acquirer corresponds to an incremental 5.0 cents, 8.2 cents, and 10.9 cents in operating income from the year prior to the acquisition through the first one, three, and five years following the acquisition, respectively. Disaggregating *P* into its respective components sheds light on the sources of this increased operating performance from acquisitions. Over all three time horizons, the coefficient on *TAN* is significantly positive, with returns of about 8% per year. In addition, the coefficient on acquirer investments in other assets outside the acquisition (Δ*AcqAssets*) is positive and significant as well, with returns of between 5 and 11 cents per year, which is similar to the overall returns to acquisitions in general.

In contrast, *IDINT* has no statistically significant relation with operating income over any time horizon, suggesting the recorded fair values of identifiable intangible assets acquired in a business combination are unassociated with future operating performance. This is consistent with identifiable intangibles being measured with significant error, such that their recorded values are not a reliable predictor of future income. Based on these results, we are unable to reject H1.

However, for *GW*, we do find a significant positive association with future operating income, with returns of about 9% to 19% per year. Thus, we are able to reject H2 and conclude that greater recorded goodwill is associated with higher future income from the target. There are at least two potential explanations for the high and significantly positive coefficient on *GW* compared to *IDINT*. First, goodwill may simply yield higher inherent returns (i.e., rents) than identifiable intangibles if acquirers have skill that competitors cannot easily imitate in leveraging the growth opportunities, future sales, and synergies that comprise goodwill. Second, as discussed in Section 2.2, given the offsetting measurement error in goodwill, the measurement error in identifiable intangibles may be larger (relative to the true value of *IDINT*) than the measurement error in goodwill (relative to the true value of *GW*).[9]

One potential concern with the tests in Table 3 is that results are sensitive to our choice of dependent variable. We use operating income in our main tests (as opposed to net income or pre-tax income, for example) in order to avoid the effects of depreciation, amortization, and

[9] Another possibility, discussed in Appendix B, is that the measurement error in identifiable intangibles (or tangibles) is so large relative goodwill that the coefficient on goodwill is biased upward.

impairments related to acquired assets. While *INOPINC* captures the change in performance most consistent with our research question, one could argue for a measure of profitability that is stripped of the influence of accruals. Thus, as a sensitivity check for our tests of H1 and H2, we also repeat our estimation of Models (3) and (4) using future incremental operating cash flows instead of operating income. These results are tabulated in Table 4.[10]

While the relation between *P* and incremental future cash flows is positive at the $p<0.05$ level in each time horizon, the coefficient on *P* decreases to 0.019, 0.043, and 0.081 over one, three, and five years. The relation between *TAN* and future cash flows is statistically significant only at one- and five-year horizons, with a coefficient of 0.029 (t=1.69) and 0.063 (t=1.66), respectively, which is somewhat weaker than the payoffs observed in Table 3. The increase in incremental operating cash flows to acquisitions is driven mostly by investments in goodwill (*GW*), with coefficients of 0.046, 0.100, and 0.165 over one, three, and five years, respectively. The main pattern for *IDINT* from Table 3 continues to hold. Specifically, the coefficient on *IDINT* is insignificant at all three time horizons: -0.032 (t=-0.758), -0.026 (t=-0.533), and -0.027 (t=-0.469). These results are consistent with results of our primary tests in Table 3.

The results in Table 3 are also robust to corrections for survivorship bias as well as analyses within various industries. We discuss these and other untabulated robustness tests in Appendix C in more detail.

4.3 Cross-sectional Tests of Measurement Error Explanation

[10] To provide additional comfort about the sensitivity of our results to variable construction we estimate Model (4) after 1) scaling all variables by assets of the combined entity rather than by assets in the year prior to acquisition; 2) redefining $\Delta AcqAssets$ after removing the effects of cash acquired in the acquisition; 3) removing year and industry fixed effects; 4) redefining $INOPINC_{t+3}$ and $INOPINC_{t+5}$ to be single-year *OPINC* (as opposed to the average) at three and five years post-acquisition minus *OPINC* in the year prior to the acquisition; and 5) subtracting average pre-acquisition *OPINC* over the three and five years prior to acquisition from average post-acquisition *OPINC* for the same length in calculating $INOPINC_{t+3}$ and $INOPINC_{t+5}$. Results from these sensitivity tests were inferentially similar to our main results in Table 3.

Our results for H2 are consistent with prior value relevance studies finding a positive association between share prices and goodwill (e.g., Jennings et al. 1996). They are also consistent with the findings in Lys et al. (2012), who find a positive association between goodwill and future profits among acquisitions expected to be profitable (about 60% of deals in their sample). The results in Tables 3 and 4 indicate that in our sample there is a positive overall association between goodwill and future payoffs, even without conditioning on expected acquisition profitability.

Our findings for H1 regarding identifiable intangibles are more surprising and interesting. The results in Tables 3 and 4 suggest that measurement uncertainty may impair the ability of recorded identifiable intangibles to predict future payoffs. If so, we would expect to find a positive relation between identifiable intangibles and future payoffs in settings with lower measurement uncertainty. We therefore examine three such settings: when 1) acquirers are larger, 2) there is less valuation uncertainty for the combined entity, and 3) acquirers have more experience with acquisitions. We discuss each setting in turn.

Prior studies suggest that fair values are measured more accurately by large firms or firms with access to more sophisticated external assistance (Barth 1994; Dietrich, Harris, and Muller 2000). We therefore expect larger acquirers are better able to measure acquired intangible assets, since they employ more sophisticated accounting personnel and spend more resources on valuation specialists. Thus, all else equal, we expect larger acquirers to be able to measure acquisition-related identifiable intangibles more reliably than smaller acquirers. We test this by splitting our sample at the median of total acquirer assets in the year prior to acquisition close and then estimating Model (4) in both sub-samples. The results are presented in Panel A of Table 5. We find evidence consistent with our expectations. Specifically, the coefficient on *IDINT* is insignificant for smaller acquirers, yet significantly positive for larger acquirers. This difference is significant at $p<0.05$ for all three horizons.

Second, we consider valuation uncertainty and its effect on fair value estimates. Moeller, Schlingemann, and Stulz (2007) show that measures related to valuation uncertainty and divergence of opinion are negatively associated with acquirer announcement returns. In situations where there is less uncertainty about the underlying value of both the buyer and seller, the value of identifiable intangibles to the combined entity can likely be estimated more reliably. Consequently, when valuation uncertainty of the combined entity is lower (higher), we expect there to be a stronger (weaker or no) correspondence between recorded identifiable intangibles and future profitability.[11]

To test this idea, we measure *Volatility* as the standard deviation of the combined firm's daily stock returns for the six months subsequent to the acquisition close date. We then divide the sample at the median of *Volatility* and estimate Model (4) in each sub-sample. Panel B of Table 5 shows the coefficient on *IDINT* is insignificant when *Volatility* is above the median, yet significantly positive ($p < 0.05$) at the one-year and five-year horizons when *Volatility* is below the median. Further, the differences in coefficients on *IDINT* across the split on *Volatility* are statistically significant ($p < 0.05$) for these horizons.

Finally, we expect that when the acquirer has more experience with past acquisitions, it will be more likely to accurately value intangibles and the target as a whole. We test this by dividing our sample into acquisitions using the indicator variable *Experience*, which is equal to

[11] It is possible that measurement uncertainty of the target is more important for identifying and valuing acquired intangible assets. Thus, we also perform this test with *Volatility* defined as the standard deviation of target stock returns for the six months prior to acquisition announcement. This alternate test restricts our sample to public targets only, which significantly reduces the sample size. However, our empirical results hold under this alternate definition of *Volatility*.

one when the acquirer has completed at least one acquisition in five years leading up to the acquisition, and zero otherwise. We then estimate Model (4) in the two sub-samples. Panel C of Table 5 presents the results. For acquirers with no recent experience making acquisitions, the coefficient on *IDINT* is insignificant for one-year and five-year horizons and significantly negative for the three-year horizon ($p < 0.05$).[12] In contrast, for experienced acquirers, the coefficient on *IDINT* is significantly positive for the three-year ($p < 0.01$) and five-year ($p < 0.05$) horizons and this difference across experienced and inexperienced acquirers is significant over these horizons ($p<0.05$). This suggests that acquirer experience is associated with reduced measurement error for identifiable intangibles and supports the idea that measurement uncertainty contributes to the lack of correspondence between the recorded values of identifiable intangibles and future payoffs.

5. Supplemental tests

5.1 Returns Tests

To supplement our primary tests, we also examine post-acquisition stock returns for acquirers based on the proportion of intangible assets recorded in the business combination. Several studies find some evidence of long-run stock underperformance following an acquisition (e.g., Loughran and Vijh 1997; Rau and Vermaelen 1998; Harford 2005; Rosen 2006). If investors fail to recognize the lack of correspondence between recorded identifiable intangible assets and future operating performance, we would expect the under-performance in acquirer returns to be concentrated in acquisitions with more intangible assets. Further, given the results reported above regarding acquirer size, we expect the under-performance in returns related to identifiable intangibles to be concentrated in smaller acquirers, where the relation between

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[12] A negative coefficient on *IDINT* could result from *non-random* measurement error whereby inexperienced acquirers overvalue identifiable intangibles in the worst acquisitions.

identifiable intangibles and future profitability is non-existent.

To test these conjectures, we use rolling calendar-time regressions, as advocated by Fama (1998) and Betton et al. (2008). The statistical advantages of calendar-time regressions, relative to event-time tests include: a) use of monthly returns, which are less skewed than long-run cumulated returns used in event-time tests, and b) the time-series variation in returns formed in calendar time naturally account for the cross-correlation in merger events (i.e., mergers tend to cluster in time), which standard CARs and BHARs calculated in event time typically ignore. To implement the calendar time tests, we form a portfolio every calendar month from January 2004 to December 2015 of stocks in our sample with an acquisition consummated in the past 12, 24, or 36 months.[13] We then compute the average return for the portfolio each month and run the following time-series regression:

$$R_{pt} - R_{ft} = \alpha + \beta_1[R_{mt} - R_{ft}] + \beta_2 SMB + \beta_3 HML + \varepsilon_{pt} \quad (5)$$

where R_{pt} is the average monthly return for the portfolio, R_{ft} is the one-month Treasury bill rate, R_{mt} is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks, and *SMB* and *HML* are the small-minus-big and high-minus-low factors from Ken French's website. If an acquirer delists during the horizon, we include the delisting return and reinvest the proceeds in the portfolio of matching *SMB* and *HML* quintiles. The α from Model (5) provides an estimate of abnormal returns to acquirers over the various time horizons.

After performing this test for each horizon on the full sample, we repeat the tests described above within two partitions of acquirers divided at the median of *IDINT/P*, which is simply *IDINT* divided by *P* or the proportion of the purchase consideration that was allocated to

[13] Our calendar-time horizons are measured from acquisition *close* date instead of *announcement* date, which is typical in the finance literature. Our research question is focused on the fair value measurement of identifiable intangible assets, which is more likely to be known with certainty at the close date relative to the announcement date.

identifiable intangible assets in the business combination. If the recorded fair value of identifiable intangible assets corresponds to higher (lower) abnormal performance relative to investor beliefs, then the estimated α should be higher (lower) in the partition where intangible assets make up a larger proportion of the purchase consideration. Thus, given our earlier results we expect the negative α for acquirers documented by prior studies to be concentrated in the portion of the sample where recorded identifiable intangibles are higher (above the median).

We perform the tests using equal-weighted (EW) and value-weighted (VW) returns, which is common in portfolio return tests. For VW returns, we use the market value of equity of acquirers in our sample as of the beginning of the fiscal year in which the acquisition closed. While the EW tests weight all observations equally and are most consistent with our main tests, the VW tests down-weight small stocks. Given that the lack of correspondence between *IDINT* and future operating income appears concentrated in smaller acquirers (H3), we expect the differential return patterns for acquisitions with relatively high or low *IDINT* to be concentrated in the EW tests, since the VW tests favor bigger stocks.

Results of these tests are presented in Table 6, with panel A showing EW results and panel B showing VW results. For the full sample, the results are consistent with prior studies. Specifically, EW results imply average negative abnormal returns of about 36, 25, and 21 basis points per month over the 12, 24, and 36 months after the acquisition. Focusing on recorded intangible assets, these negative abnormal returns to acquirers generally appear concentrated in acquisitions with higher levels of *IDINT/P*. For example, at every horizon, the α for firms with relatively high identifiable intangibles is negative and significant while it is insignificant at every horizon for firms with relatively low identifiable intangibles. One-sided p-values for differences in alphas across acquisitions with high versus low acquisitions are 0.063, 0.034, and 0.114, providing statistical support to the premise that investors do not fully appreciate the effect of acquired intangible assets on future performance.

Moving to VW returns in panel B of Table 6, we find results attenuate significantly. There is no evidence of negative abnormal stock performance for acquirers following the acquisition, either in the overall sample or among acquirers with relatively high recorded identifiable intangibles. Thus, the relatively poor stock performance of acquirers in our sample, particularly those recording high investments in identifiable intangibles, appears concentrated in small stocks. This is consistent with our findings related to firm size in the previous section. Overall, these return tests provide some evidence that for smaller stocks, higher investments in identifiable intangibles are associated with abnormally low stock returns after the acquisition.

5.2 Intangible Assets not from Business Combinations

As an additional test, we use Compustat data to examine the payoffs to intangible assets recorded when there is no indication of a business combination. For intangibles acquired on a standalone basis outside a business combination, the acquirer records the investment at its exchange price, which presumably reflects a market-based expectation of the future payoffs to that investment. Thus, one might expect less measurement error with these investments.

The sample for these tests consists of firm-years from 2003 to 2014 (matching our main sample) from Compustat with non-missing sales (SALE), assets (AT), market value of equity (PRCC_F*CSHO), operating cash flows (OANCF), and operating income before depreciation and amortization (OIBDP) for the current and following year. Compustat does not provide a definitive indicator for whether a given firm-year is impacted by an acquisition, so we then identify firm-years where business combination activity is unlikely by dropping observations with the following characteristics: cash paid for acquisitions (ACQ) is non-zero, sales footnote code indicates acquisition activity (SALE_FN of AA, AB, AR, AS, FA, FB, FD, FE, or FF), acquisition sales contribution (AQS) is non-empty and non-zero, or goodwill (GDWL) increased. Additionally, we drop observations with an absolute value of operating income before depreciation and amortization greater than prior year's assets. This results in a sample of 42,112 firm-years. We then run the following regression:

$$OPINC_{t+1(2)[3]} = \beta_0 + \beta_1 OPINC_t + \beta_2 WCAccruals_t + \beta_3 Capex_t + \beta_4 \Delta IDINT_t + \varepsilon_{t+1(2)[3]} \quad (6)$$

where *OPINC* is equal to operating income before depreciation and amortization, *WCAccruals* are working capital accruals, calculated as operating income before depreciation and amortization (Compustat item OIBDP) minus operating cash flows (OANCF), *Capex* is capital expenditures (CAPX), and $\Delta IDINT$ is the change in identifiable intangible assets, calculated as INTANO minus lagged INTANO plus amortization expense. All regression variables are scaled by lagged assets and winsorized at the 1st and 99th percentiles.[14] Also, all regressions include year and industry fixed effects (using the industries in Barth et al. 2005 plus financials and regulated firms) and have standard errors clustered by firm.

This design is similar to that of the primary tests, except Model (6) models innovations in future income (i.e., instead of utilizing a differences approach) as a function of non-acquisition investments. This autoregressive design is more common in the accruals literature (e.g., Richardson et al. 2005) and tells us how investments in working capital, capital expenditures, and intangible assets predict future income. It is also similar to the design Lev and Sougiannis (1996) use to test a research question similar to ours. We did not use this type of autoregressive model in our main tests because acquisitions frequently change the scale of the combined entity

[14] To eliminate extreme income observations and any potential remaining acquisition years, we additionally drop all firms with operating income before depreciation and amortization that exceeds (in absolute value) prior year's assets. Further, we perform an additional winsorization to ensure *WCAccruals* and *CFO* are between -1 and 1.

so much that autoregressive coefficients are greater than one, which indicates non-stationarity and is very uncommon in the accruals literature.

In Model (6), a positive β_4 would be consistent with investments in intangibles leading to positive future income. Note that β_2 captures the difference in coefficients between working capital accruals and cash flows since *WCAccruals* are included in *OPINC*. We expect this coefficient to be negative since accruals *are* less persistent than cash flows (Sloan 1996, Richardson et al. 2005). We also estimate the following two models, which are similar to Model (6):

$$OPINC_{t+1(2)[3]} = \beta_0 + \beta_1 CFO_t + \beta_2 WCAccruals_t + \beta_3 Capex_t + \beta_4 \Delta IDINT_t + \varepsilon_{t+1(2)[3]} \tag{7}$$

where *CFO*, operating cash flows, is substituted for *OPINC* at time *t*, and

$$OPINC_{t+1(2)[3]} = \beta_0 + \beta_1 OPINC + \beta_2 Capex_t + \beta_3 IDINT_t + \varepsilon_{t+1(2)[3]} \tag{8}$$

where both *CFO* and *WCAccruals* are combined in *OPINC* and constrained to have the same coefficient. Model (8) deemphasizes short-term working capital accruals and focuses more directly on the impact of long-term investments on future income. In Models (7) and (8), a positive β_4 and β_3, respectively, would be consistent with investments in identifiable intangibles be associated with high future operating income.

Evidence from estimating models (6), (7), and (8) is presented in Table 7 and is generally consistent with our primary analysis. Namely, while the coefficients on cash flows, working capital accruals, and capital expenditures are as expected, the coefficient on Δ*IDINT* is insignificant for each model over each time horizon. This suggests there is no reliable relation between increases in identifiable intangibles outside of business combinations and future operating income.

However, we note there are data limitations to these tests and thus some caution is in order in interpreting the results. First, despite our efforts to purge M&A activity from the sample, it is possible that some acquisition-related intangibles remain since there is no foolproof way to do this in Compustat. Second, depending on firms' accounting policies and Compustat data collection, *Capex* could include some investments in intangible assets. Third, we cannot be sure that Δ*IDINT* represents solely external acquisitions of intangibles and not internal cost capitalizations (e.g., computer software). Finally, the tests could also suffer from low power since only 10,167 firm-years (24.14% of this sample) have non-zero Δ*IDINT*.

6. Conclusion

This study explores the ability of fair values allocated to intangible assets acquired in a business combination to predict future operating performance. Using data on purchase price allocations from mergers in 4,166 firm-years from 2003 to 2014, we associate the components of purchase consideration with incremental operating income over the one, three, and five years following transaction consummation. The evidence indicates that while goodwill is associated with future incremental operating income, identifiable intangible assets bear no statistically significant correspondence.

We investigate measurement error in fair value estimates as explanation for the lack of a detectable association between identifiable intangible assets and future income. We find that the relation between identifiable intangibles and future operating income is significantly positive when the acquirer is larger, when there is less valuation uncertainty about the target, and when the buyer has previous acquisition experience. Overall, results of these tests suggest there is a correspondence between the recorded fair values of acquired identifiable intangibles in settings where measurement uncertainty is lower.

Tests of long-term stock returns support the notion that investors may not appreciate the weak or unreliable correspondence between acquired intangibles and future performance, and this result is concentrated among smaller firms. We further examine the effects of acquiring intangibles on future income by isolating non-merger increases in identifiable intangibles. These results support our earlier findings that investments in identifiable intangible assets are not reliably predictive of future operating income.

While the evidence in this study suggests that investments in identifiable intangible assets are not predictive of future operating income, we cannot conclude these assets are poor investments. Rather, measuring fair value of identifiable intangibles is sufficiently subjective and uncertain that detecting a relation can be difficult, especially for smaller firms and firms that lack experience in valuing such acquired assets.

Appendix A

Variable definitions

$INOPINC_{t+\tau}$	Average operating income before depreciation and amortization (Compustat variable OIBDP) over the τ years subsequent to the acquisition close date minus acquirer operating income before depreciation and amortization in the year prior to the acquisition, scaled by the acquirer's assets as of the end of the fiscal year prior to the year of acquisition close date.
$INCFO_{t+\tau}$	Average net cash from operating activities (Compustat variable OANCF) over the τ years subsequent to the acquisition close date minus acquirer operating income before depreciation and amortization in the year prior to the acquisition, scaled by the acquirer's assets as of the end of the fiscal year prior to the year of acquisition close date.
P	Total purchase consideration reported in the acquirer's purchase price allocation disclosure in the 10-K in the year of acquisition consummation, scaled by the acquirer's assets as of the end of the fiscal year prior to the year of acquisition close date.
IDINT	Total identifiable intangible assets reported in the acquirer's purchase price allocation disclosure in the 10-K in the year of acquisition consummation, scaled by the acquirer's assets as of the end of the fiscal year prior to the year of acquisition close date.
GW	Total goodwill reported in the acquirer's purchase price allocation disclosure in the 10-K in the year of acquisition consummation, scaled by the acquirer's assets as of the end of the fiscal year prior to the year of acquisition close date.
TAN	Total tangible assets reported in the acquirer's purchase price allocation disclosure in the 10-K in the year of acquisition consummation, scaled by the acquirer's assets as of the end of the fiscal year prior to the year of acquisition close date.
Δ*AcqAssets*	Change in assets unrelated to the acquisition, measured as total acquisition-year combined assets minus acquirer assets in the year prior to the acquisition minus purchase consideration, all scaled by acquirer's pre-combination assets
Size	The natural log of acquirer assets as of the end of the fiscal year prior to the year of acquisition close date.
Volatility	The standard deviation of the combined firm's daily stock returns over the six months subsequent to acquisition consummation.
Experience	An indicator variable equal to one if the acquirer consummated at least one acquisition in the five years preceding the acquisition, and zero otherwise.
IDINT/P	The proportion of the purchase consideration allocated to intangible assets, calculated as *IDINT* divided by *P*.
WCAccruals	Working capital accruals, calculated as operating income before depreciation and amortization (Compustat item OIBDP) minus operating

	cash flows (OANCF), scaled by prior year's assets.
Capex	Capital expenditures (CAPX), scaled by prior year's assets.
CFO	Operating cash flows (OANCF), scaled by prior year's assets.
Δ*IDINT*	Change in intangible assets, calculated as INTANO minus lagged INTANO plus amortization expense (AM), scaled by prior year's assets.

Appendix B

Potential Effects of Measurement Error on Inferences in Our Setting

We assume that measurement error in intangibles will lead to a lack of association between this variable and future operating income. However, the effect of measurement error on coefficients in a multivariate regression is complex. Below we discuss the econometric details and certain settings where measurement error can actually cause an upward bias in the coefficient of interest.

Suppose a multivariate regression has covariates that are measured with error, such that X = X* + U, where X* is the matrix of the "true" covariates and U is a matrix of measurement error terms. The measurement error may be correlated across elements of U, such that u_1 (error in x^*_1) is correlated with u_2 (error in x^*_2), but we assume U is independent of X* (i.e., u_1 is independent of the value of x^*_1). From 5-30 in Greene (2003), the probability limit of the difference between the estimated coefficient vector (b) and the true coefficient vector (β) is given by:

$$- (Q^* + \Sigma)^{-1} \Sigma \beta \qquad (1B)$$

Where Q* is variance-covariance matrix of the true covariates and Σ is the variance-covariance matrix of the error terms. Thus, bias in b is a function of the variance-covariance matrix of the covariates, the variance-covariance matrix of the measurement error, and the true parameters.

For simplicity, consider a two-variable regression:[15]

$$Y = b_1 x_1 + b_2 x_2 + \varepsilon \qquad (2B)$$

Where both covariates are measured with error (i.e., $x_1 = x^*_1 + u_1$) and have been demeaned to obviate an intercept. Applying (1B) shows that the bias in the estimated coefficient on x_1 equals:

$$b_1 - \beta_1 = -Z \left[\beta_1 \left(\frac{\sigma_{u1}^2}{\sigma_{x1}^2} - \frac{\rho\gamma\sigma_{u1}\sigma_{u2}}{\sigma_{x1}\sigma_{x2}}\right) + \beta_2 \left(\frac{\gamma\sigma_{u1}\sigma_{u2}}{\sigma_{x1}^2} - \frac{\rho\sigma_{u2}^2}{\sigma_{x1}\sigma_{x2}}\right)\right] \qquad (3B)$$

Where ρ is the correlation between x_1 and x_2, γ is the correlation between u_1 and u_2, and $Z = 1/(1-\rho^2)$.

In our setting, where the x's are components of the acquisition price likely measured with error, we assume ρ is positive. That is, when a firm spends a high amount on intangibles, it likely spends a high amount on other components as well. This seems reasonable since all

[15] Our setting actually has three main components of the acquisition price: identifiable intangibles, tangibles, and goodwill. Adding a third covariate to (2B) would complicate the formulas but not change the intuition. Thus, the discussion that follows carries over to a regression with three covariates as well.

components of PC are positively correlated in Table 2.

We conducted a number of untabulated simulations of (2B), varying the relative measurement error in each variable, the correlation structure of the measurement error, the relative variances of x_1 and x_2, as well as whether β_1 and β_2 were equal. Across the vast majority of the simulations, we found that b_1 and b_2 were biased downward relative to β_1 and β_2, with the bias stronger for the variable where there was relatively more measurement error. However, there are settings where b_1 or b_2 can be biased upward. We discuss the two most common settings where this occurs below.

<u>Setting 1: perfect or strong negative correlation in measurement error</u>

If γ equals or is close to -1, then b_1 can be biased upward if $\beta_1 < \beta_2$. To see this, suppose that $u_1 = -u_2$, such that measurement error in x^*_1 is perfectly offset in x^*_2. (3B) then simplifies to:

$$b_1 - \beta_1 = -Z\left[(\beta_1 - \beta_2)\left(\frac{\sigma_u^2}{\sigma_{x1}^2} + \frac{\gamma\sigma_u^2}{\sigma_{x1}\sigma_{x2}}\right)\right] \quad \text{(4B)}$$

which is positive if $\beta_1 < \beta_2$. Likewise, it can be shown that b_2 will be biased *downward* in a similar fashion. Intuitively, given offsetting measurement error in the two variables, the regression pulls the estimated coefficients closer together, similar to what would happen if the two variables with error were simply added together, eliminating the offsetting measurement error and constraining the coefficients on both to be the same.

In our view, this condition (with γ = -1) is not realistic in our setting. From section 2, the measurement error in the variables measured with error is V for identifiable intangibles and (U – V) for goodwill. Since it is highly likely that U and V are strongly positively correlated (i.e., when the target is overvalued, identifiable intangibles will be overvalued), it is very unlikely that γ = corr(V, U-V) is close to -1. In fact, depending on the correlation between U and V and their relative variances, corr(V, U-V) could be positive or close to zero.

<u>Setting 2: relatively low measurement error in the variable of interest and strong positive correlation between the variables</u>

If measurement error for x_1 is very small relative to x_2, b_1 will be biased upward if $\beta_2 > 0$. To see this, note that as σ_{u1}^2 approaches zero, the limit of (3B) approaches:

$$b_1 - \beta_1 = Z\left[\beta_2\left(\frac{\rho\sigma_{u2}^2}{\sigma_{x1}\sigma_{x2}}\right)\right] \quad \text{(5B)}$$

which is positive. Even if σ_{u1}^2 is not close to zero, as long as it small relative to σ_{u1}^2 and ρ is sufficiently high, b_1 can be biased upward if $\beta_2 > 0$. Intuitively, if one variable is strongly positively correlated with another variable that contains significantly more measurement error, the regression will put more weight on the variable with much less measurement error as a proxy for the other. To get significant upward bias in our simulations, this required either very high positive correlations between the variables (e.g., < 0.80) or measurement error as a percentage of a variable's variance that was three to four times larger for one variable relative to the other. Although this may be possible in our setting, it seems likely that measurement error in identifiable intangibles will not be small relative to other components of the acquisition price. Thus, it seems unlikely that measurement error would be small enough for identifiable intangibles (and large enough for other variables) to bias the coefficient on identifiable intangibles upward.

Ultimately, whether potential upward bias in the estimated coefficient on identifiable intangibles threatens inferences for this variable is an empirical question. The overall pattern of results does not suggest that it is. We find a coefficient on identifiable intangibles in our main tests that is insignificantly different zero, but increases in significance in settings where this is likely less measurement error. This suggests that measurement error in identifiable intangibles contributes to an attenuation of its coefficient, which is consistent with the vast majority of simulations we conducted.

Appendix C – Robustness Checks and Other Tests

In this appendix, we discuss additional untabulated robustness or supplemental tests related to our main analysis.

Potential Survivorship Bias

One potential concern with regard to inferences from our main tests in Table 3 is that the sample is reduced from 4,166 firm-years with acquisitions to 2,984, and then to 2,030 as the horizon extends from one to three, and then to five years after the acquisition consummation. This is mostly attributable to acquisitions occurring too late in our sample period for future operating income to be realized. We refer to this issue as one of insufficient "runway." For example, 16.5% (31.1%) of the firms in our one-year (three-year) horizon are too late in the sample period to have later earnings realizations because the acquisitions occurred after 2012 (2010). To address the runway issue, we estimate Models (3) and (4) using only firm-years with acquisitions occurring before 2012 and then before 2010. Results are very similar to those in Table 3 (untabulated).

The remaining portion of firms drop out of the sample due to liquidations, de-lists, or acquisitions of the combined firm, which raises concerns about survivorship bias. It is unclear how this would influence the results. If anything, we would expect factors contributing to firm survival (e.g., stability and profitability) to also be consistent with better identification and measurement of targets and target assets. Thus, the relation between *IDINT* and future operating income should be strongest among survivors, which biases in favor or rejecting H1 (which we do not find). Nevertheless, we conduct two additional tests to assess the impact of survivorship on the results in Table 3.

First, we follow an approach to extend the sample similar to the one used by Kothari et al. (2002) and assume that firms that exit the sample due to non-runway issues would have similar *INOPINC* realizations as firms with the same Altman's (1968) *Z*-score. Specifically, we form decile ranks of acquisition firm-years according to their Z-score in the year prior to the acquisition.[16] We then assign each non-surviving firm the same *INOPINC* as the average *INOPINC* for surviving firms within each Z-score decile. We do this for firms not surviving either three or five years. This increases the sample for testing *INOPINC* over three and five years to 3,481 and 2,872, respectively, essentially leaving only the runway issue as the reason for decreased sample size over estimation periods. Estimating Models (3) and (4) with these extended samples yields very similar (untabulated) results to those in Table 3.

As a second test of the sensitivity of our main results to survivorship, we extend the sample by assuming that non-surviving firms would have maintained similar levels of profitability as they had prior to disappearing from the sample. This is done by taking the average of non-surviving firms' *OPINC* over the maximum number of years available

[16] In an effort to reflect the liquidation risk of the combined firm rather than just the acquirer, we also perform this procedure with the Z-score estimated in the year of acquisition close. Inferences are virtually identical.

subsequent to the acquisition and assigning that value to non-surviving firms' missing years.[17] We then compute $INOPINC_{t+3}$ and $INOPINC_{t+5}$ and run the regressions. Results are very similar to our first sample-extension method, with overall inferences similar to those in Table 3.

Overall, inferences with respect to H1 and H2 are not sensitive to the potential issues of runway and survivorship.

Compensation-related misallocation

We examine an agency cost of purchase price allocation documented by Shalev et al. (2013), who show that managers with higher income-based bonuses tend to allocate more purchase price to goodwill—and thus less to tangible and intangible assets—in order to avoid the amortization expense associated with purchased definite-lived assets. Consistent with intentional mismeasurement of intangible assets, we would expect acquirers with managers having relatively lower income-based bonuses to more accurately measure intangible assets, leading to a higher correspondence between intangibles and future income. To test this, we first follow Shalev et al. (2013) in computing a ratio of the acquirer CEO's bonus over total CEO compensation from Execucomp, averaged over the two-year window before the acquisition consummation year. We then partition the sample at the median of this ratio and estimate Model (4) in each partition.

Untabulated results weakly support this notion, but we fail to find any difference in coefficients on *IDINT*. Specifically, *IDINT* is statistically associated with *INOPINC* in both partitions over all three time horizons. The coefficient on *IDINT* is more economically significant for lower-bonus acquirers at only the three-year horizon, but the standard errors on this coefficient for lower-bonus acquirers are lower over all three time horizons, suggesting a stronger statistical relation. This pattern of results (consistent significance on *IDINT* with only minor differences across partitions) is likely due to a substantial sample size reduction that occurs from intersecting our sample with Execucomp, along with the preponderance of larger firms (where the relation between *IDINT* and future payoffs is strongest) in the Execucomp.

Intra-industry analysis

Prior studies indicate that acquisition returns are partly a function of industry characteristics (e.g., Shahrur 2005; Akdogu 2009). To investigate the possibility that the same factors leading to differential acquisition returns could also impact acquirers' abilities to accurately measure intangible assets, we estimate Model (4) separately within each of the 11 industries from Barth et al. (2005). Results for industries *Computers, software, and telecom; Retail;* and *Services* largely mirror our earlier findings of strong correspondence between *INOPINC* and both *GW* and *TAN* and no correspondence for *IDINT*. This could be due to characteristics of these industries, or could be a result of their being the most populated in our sample and the resulting increase in statistical power. Interestingly, estimating Model (4) for *Durable manufacturers*, the second most populated industry in our sample, shows no statistical relation between components of *P* and *INOPINC*. We do not explore this further, but rather leave an explanation for the lack of results for this industry to future research.

[17] For example, a firm surviving two years after completing an acquisition and having *OPINC* in those years of 20 and 30, respectively, is assigned annual *OPINC* of 25 for years three through five.

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Table 1—Descriptive statistics

Panel A: Variables

	N	Mean	Std. Dev	25%	50%	75%
$INOPINC_{t+1}$	4,166	0.035	0.144	-0.006	0.026	0.079
$INOPINC_{t+3}$	2,984	0.081	0.162	0.003	0.051	0.124
$INOPINC_{t+5}$	2,030	0.115	0.191	0.009	0.064	0.164
P	4,166	0.297	0.372	0.055	0.151	0.379
TAN	4,166	0.118	0.198	0.008	0.041	0.138
IDINT	4,166	0.075	0.134	0.006	0.025	0.084
GW	4,166	0.104	0.167	0.010	0.038	0.123
$\Delta AcqAssets$	4,166	0.058	0.369	-0.078	0.021	0.126
Size	4,166	6.554	1.924	5.267	6.525	7.778
Volatility	4,059	0.027	0.015	0.017	0.024	0.032
Experience	4,166	0.548	0.498	0.000	1.000	1.000

Panel B: Acquisitions by year and industry

Year	N	Percentage	Industry	N	Percentage
2003	334	8.02%	Food	75	1.80%
2004	395	9.48	Textiles, printing and publishing	131	3.14
2005	352	8.45	Chemicals	75	1.8
2006	432	10.37	Pharmaceuticals	189	4.54
2007	381	9.15	Extractive industries	90	2.16
2008	307	7.37	Durable manufacturers	835	20.04
2009	232	5.57	Computers, software, and telecom	1,111	26.67
2010	350	8.40	Retail	292	7.01
2011	323	7.75	Financial	612	14.69
2012	385	9.24	Services	386	9.27
2013	319	7.66	Regulated and other	370	8.88
2014	356	8.55			
Totals:	4,166	100.0		4,166	100.0

Table 1 provides descriptive statistics for the variables and acquisitions used in this study. Panel A presents descriptive statistics for variables used in hypothesis tests and cross-sectional partitions, and Panel B presents distributional data about acquisitions across years and industries. All variables are defined in Appendix A.

Table 2—Correlation table (Pearson below, Spearman above)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$INOPINC_{t+1}$ (1)	1	0.769*	0.649*	0.201*	0.149*	0.153*	0.180*	0.194*	-0.0108	-0.042*	0.0605*
$INOPINC_{t+3}$ (2)	0.764*	1	0.895*	0.191*	0.0726*	0.200*	0.215*	0.216*	-0.0698*	0.0124	0.0720*
$INOPINC_{t+5}$ (3)	0.626*	0.906*	1	0.200*	0.0681*	0.216*	0.234*	0.223*	-0.0910*	0.0267	0.119*
P (4)	0.130*	0.212*	0.268*	1	0.806*	0.651*	0.723*	-0.171*	-0.291*	0.144*	-0.0870*
TAN (5)	0.135*	0.106*	0.141*	0.737*	1	0.267*	0.397*	-0.128*	-0.107*	-0.085*	-0.129*
IDINT (6)	0.0222	*0.150**	0.173*	0.699*	0.203*	1	0.606*	-0.209*	-0.350*	-0.552*	0.0522*
GW (7)	0.117*	0.231*	0.290*	0.787*	0.293*	0.502*	1	-0.127*	-0.235*	-0.042*	0.0424*
ΔAcqAssets (8)	0.135*	0.237*	0.198*	-0.072*	-0.0594*	-0.0679*	-0.0358*	1	0.0390*	0.0124	-0.0405*
Size (9)	0.0323*	-0.112*	-0.175*	-0.240*	-0.0607*	-0.272*	-0.240*	-0.0832*	1	0.0267	0.0898*
Volatility (10)	-0.066*	-0.007	0.011	0.111*	0.021	0.128*	0.121*	0.021	-0.436*	1	0.0618
Experience (11)	0.0276	0.0383*	0.0746*	-0.075*	-0.147*	-0.0249	0.0266	-0.0871*	0.0854*	0.0448	1

Table 2 presents univariate Pearson (below the diagonal) and Spearman (above) correlations between the variables used in hypothesis tests in this study. * indicates statistical significance at $p<0.10$. All variables are defined in Appendix A.

Table 3—The association between intangible assets and operating income

Model:	(1)	(2)	(1)	(2)	(1)	(2)
Dependent variable:	$INOPINC_{t+1}$	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$	$INOPINC_{t+5}$
P	0.050***		0.082***		0.109***	
	(4.848)		(6.793)		(6.043)	
TAN		0.080***		0.073***		0.081**
		(4.467)		(2.748)		(1.970)
IDINT		-0.044		0.013		0.021
		(-0.814)		(0.250)		(0.309)
GW		0.086***		0.137***		0.190***
		(2.605)		(3.622)		(3.442)
$\Delta AcqAssets$	0.053***	0.053***	0.111***	0.110***	0.113***	0.110***
	(3.225)	(3.239)	(5.930)	(5.858)	(4.507)	(4.380)
Constant	0.025	0.023	0.042**	0.042*	0.075**	0.077**
	(1.330)	(1.263)	(2.026)	(1.883)	(2.148)	(2.249)
Observations	4,166	4,166	2,984	2,984	2,030	2,030
Adjusted R-squared	0.064	0.071	0.123	0.125	0.116	0.120
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 presents results of regressing *INOPINC* over horizons of one, three, and five years on components of the purchase consideration (*P*, *TAN*, *IDINT*, and *GW*) from mergers between 2003 and 2014 and $\Delta AcqAssets$, a control variable for other investments not part of the acquisition. Robust t-statistics clustered by acquirer in parentheses. ***, **, and * indicate a difference from zero with statistical significance of $p<0.01$, $p<0.05$, and $p<0.10$, respectively. Variables defined in Appendix A.

Table 4—The association between intangible assets and operating cash flows

Model:	(1)	(2)	(1)	(2)	(1)	(2)
Dependent variable:	$INCFO_{t+1}$	$INCFO_{t+1}$	$INCFO_{t+3}$	$INCFO_{t+3}$	$INCFO_{t+5}$	$INCFO_{t+5}$
P	0.019**		0.043***		0.081***	
	(2.160)		(3.619)		(5.135)	
TAN		0.029*		0.032		0.063*
		(1.686)		(1.197)		(1.664)
IDINT		-0.032		-0.026		-0.027
		(-0.758)		(-0.533)		(-0.469)
GW		0.046*		0.100***		0.165***
		(1.728)		(2.742)		(3.470)
Δ*AcqAssets*	0.027**	0.027*	0.076***	0.074***	0.094***	0.091***
	(1.972)	(1.959)	(4.427)	(4.344)	(4.345)	(4.243)
Constant	-0.058	-0.059	-0.004	-0.004	-0.008	-0.007
	(-1.348)	(-1.323)	(-0.177)	(-0.189)	(-0.310)	(-0.277)
Observations	4,166	4,166	2,984	2,984	2,030	2,030
Adjusted R-squared	0.032	0.035	0.087	0.090	0.120	0.125
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 presents results of regressing *INCFO* over horizons of one, three, and five years on components of the purchase consideration (*P*, *TAN*, *IDINT*, and *GW*) from mergers between 2003 and 2014 and Δ*AcqAssets,* a control variable for other investments not part of the acquisition. Robust t-statistics clustered by acquirer in parentheses. ***, **, and * indicate a difference from zero with statistical significance of $p<0.01$, $p<0.05$, and $p<0.10$, respectively. Variables defined in Appendix A.

Table 5—The effect of measurement uncertainty on the association between intangible assets and operating income

Panel A: Sample split at median of *Size*

Model:	(2)	(2)	(2)	(2)	(2)	(2)
Dependent variable:	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$
	$Size_{it} \leq Median$			$Size_{it} > Median$		
TAN	0.090***†	0.090**	0.111*	0.056***†	0.043**	0.033
	(2.981)	(2.187)	(1.736)	(4.290)	(2.010)	(1.096)
IDINT	-0.073†	-0.045†	-0.079†	0.094***†	0.201***†	0.220***†
	(-1.077)	(-0.675)	(-0.836)	(3.167)	(3.653)	(3.693)
GW	0.084**	0.155***	0.218***	0.094***	0.078**	0.105*
	(2.018)	(3.220)	(3.113)	(3.848)	(1.975)	(1.896)
Δ*AcqAssets*	0.049**	0.102***	0.101***	0.081***	0.130***	0.116***
	(2.504)	(4.547)	(3.244)	(3.717)	(7.051)	(5.689)
Constant	-0.004	0.033	0.088**	0.031***	0.040*	0.064
	(-0.109)	(0.905)	(1.991)	(2.655)	(1.701)	(1.354)
Observations	2,083	1,483	1,018	2,083	1,504	1,012
Adjusted R-squared	0.061	0.113	0.099	0.206	0.229	0.169
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Sample split at median of *Volatility*

Model:	(2)	(2)	(2)	(2)	(2)	(2)
Dependent variable:	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$
	$Volatility_{it} \leq Median$			$Volatility_{it} > Median$		
TAN	0.080***	0.100***	0.074	0.083***	0.076**	0.114*
	(4.015)	(2.673)	(1.376)	(2.861)	(2.064)	(1.820)
IDINT	0.102**†	0.127	0.249***†	-0.024†	-0.022	-0.073†
	(2.570)	(1.469)	(3.529)	(-0.352)	(-0.350)	(-0.708)
GW	0.091***	0.131**	0.124*	0.067*	0.130***	0.186**
	(2.692)	(2.526)	(1.921)	(1.656)	(2.717)	(2.569)
Δ*AcqAssets*	0.121***†	0.161***†	0.152***	0.051**†	0.108***†	0.108***
	(7.618)	(7.193)	(4.570)	(2.477)	(4.512)	(3.221)
Constant	0.013	0.009	-0.006	0.028	0.077	0.147*
	(1.184)	(0.299)	(-0.135)	(0.644)	(1.605)	(1.930)
Observations	2,030	1,393	946	2,029	1,524	1,039
Adjusted R-squared	0.287	0.291	0.226	0.057	0.100	0.096
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5, cont.—The effect of measurement uncertainty on the association between intangible assets and operating income

Panel C: Sample split based on whether buyer is experienced acquirer

Model:	(2)	(2)	(2)	(2)	(2)	(2)
Dependent variable:	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$	$INOPINC_{t+1}$	$INOPINC_{t+3}$	$INOPINC_{t+5}$
	Experience = 0			*Experience = 1*		
TAN	0.084***	0.070*	0.062	0.083***	0.106***	0.118**
	(3.492)	(1.917)	(1.121)	(3.354)	(3.019)	(1.994)
IDINT	-0.059	-0.135**†	-0.118†	-0.019	0.183***†	0.165**†
	(-0.764)	(-2.016)	(-1.305)	(-0.264)	(3.158)	(2.209)
GW	0.040	0.198***†	0.246**	0.120***	0.060†	0.122**
	(0.680)	(3.002)	(2.389)	(3.305)	(1.513)	(2.421)
Δ*AcqAssets*	0.038†	0.082***†	0.078**	0.092***†	0.165***†	0.147***
	(1.627)	(3.173)	(2.089)	(5.243)	(6.812)	(4.835)
Constant	0.010	0.025	0.096**	0.032*	0.059	0.071
	(0.261)	(0.575)	(2.504)	(1.726)	(1.625)	(1.077)
Observations	1,875	1,306	884	2,283	1,671	1,141
Adjusted R-squared	0.057	0.121	0.097	0.117	0.178	0.157
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 presents results of regressing *INOPINC* over horizons of one, three, and five years on components of the purchase consideration from mergers between 2003 and 2014 and Δ*AcqAssets,* a control variable for other investments not part of the acquisition, after splitting the sample on variables representing characteristics of the acquisition in which measurement uncertainty likely varies. Panels A through C present results of regressions run after splitting the sample at the median of *Size, Volatility,* and *Experience*. Robust t-statistics clustered by acquirer in parentheses. ***, **, and * indicate a difference from zero with statistical significance of $p<0.01$, $p<0.05$, and $p<0.10$, respectively. † indicates a coefficient estimate that is statistically different across sub-samples at $p<0.05$. Variables defined in Appendix A.

Table 6—Calendar-time returns, measured from close date

Panel A: Equal-weighted returns, split at median of *IDINT/P*

	12 months from close			*24 months from close*			*36 months from close*		
	Full	*IDINT/P* < *Median*	*IDINT/P* ≥ *Median*	*Full*	*IDINT/P* < *Median*	*IDINT/P* ≥ *Median*	*Full*	*IDINT/P* < *Median*	*IDINT/P* ≥ *Median*
α	-0.36***	-0.25**	-0.47***	-0.25**	-0.12	-0.38**	-0.21*	-0.13	-0.30**
	(-3.38)	(-2.3)	(-3.2)	(-2.27)	(-1.11)	(-2.56)	(-1.97)	(-1.21)	(-2.05)
MKT	1.12***	1.10***	1.13***	1.12***	1.09***	1.15***	1.11***	1.09***	1.14***
	(32.02)	(28.52)	(27.13)	(26.21)	(22.66)	(22.92)	(26.15)	(23.91)	(22.92)
SMB	0.73***	0.72***	0.73***	0.72***	0.68***	0.77***	0.73***	0.68***	0.77***
	(13.97)	(12.11)	(11.03)	(13.47)	(10.89)	(11.59)	(13.88)	(11.35)	(12.05)
HML	-0.03	0.14**	-0.19	0.00	0.17**	-0.18	0.05	0.23***	-0.14
	(-0.34)	(2.12)	(-1.8)	(-0.05)	(2.6)	(-1.64)	(0.61)	(3.74)	(-1.3)
R-squared	0.945	0.941	0.907	0.944	0.927	0.916	0.945	0.936	0.919
Difference in *α* p-value (one-sided)		0.063			0.034			0.114	
Panel B: Value-weighted returns, split at median of *IDINT/P*									
	12 months from close			*24 months from close*			*36 months from close*		
	Full	*IDINT/P* < *Median*	*IDINT/P* ≥ *Median*	*Full*	*IDINT/P* < *Median*	*IDINT/P* ≥ *Median*	*Full*	*IDINT/P* < *Median*	*IDINT/P* ≥ *Median*
α	-0.03	-0.12	0.04	0.01	0.01	0.01	0.04	-0.01	0.07
	(-0.22)	(-0.48)	(0.28)	(0.10)	(0.03)	(0.11)	(0.41)	(-0.04)	(0.55)
MKT	1.12***	1.10***	1.02***	1.01***	1.14***	1.01***	1.02***	1.09***	0.98***
	(32.02)	(28.52)	(24.20)	(32.08)	(10.65)	(31.81)	(34.63)	(16.16)	(31.73)
SMB	0.73***	0.72***	-0.11	-0.07	-0.03	-0.07	0.02	0.06	-0.02
	(13.97)	(12.11)	(-1.51)	(-1.04)	(-0.35)	(-1.02)	(0.52)	(0.97)	(-0.39)
HML	-0.03	0.14**	-0.41***	-0.35***	0.01	-0.35***	-0.17***	-0.07	-0.25
	(-0.34)	(2.12)	(-5.82)	(-4.94)	(0.11)	(-4.96)	(-3.44)	(-0.98)	(-4.1)
R-squared	0.946	0.941	0.814	0.939	0.913	0.894	0.925	0.884	0.874
Difference in *α* p-value (one-sided)		0.321			0.483			0.343	

Table 6 presents alpha and factor loadings for portfolios formed between 2003 and 2014, where an acquiring firm is added to the portfolio in the month following acquisition consummation date and is held for 12, 24, or 36 months. The first column for each portfolio time horizon is estimated for the full sample of acquirers, and the second two columns are estimated in portfolios consisting only of firms in a lower/upper partition of *IDINT/P*, which is the intensity of investment in identifiable intangibles calculated as *IDINT* divided by P. α is estimated using OLS for Model (4). Panel A presents results using equal-weighted returns, while Panel B uses value-weighted returns. T-statistics in parentheses. ***, **, and * indicate a difference from zero with statistical significance of $p<0.01$, $p<0.05$, and $p<0.10$, respectively.

Table 7—Non-M&A intangible assets and operating income

Panel A: Lagged income and accruals

Model:	(5)	(5)	(5)
Dependent Variable:	$OPINC_{t+1}$	$OPINC_{t+2}$	$OPINC_{t+3}$
OPINC	0.747***	0.703***	0.673***
	(89.31)	(72.95)	(61.96)
WCAccruals	-0.134***	-0.131***	-0.132***
	(-10.43)	(-9.65)	(-8.98)
Capex	0.048***	0.046***	0.044***
	(5.54)	(4.68)	(3.89)
$\Delta IDINT$	0.011	-0.021	-0.021
	(0.17)	(-0.3)	(-0.28)
Constant	-0.046***	-0.047***	-0.052***
	(-11.58)	(-10.29)	(-9.87)
Observations	42,112	34,914	28,959
Adjusted R-squared	0.58	0.57	0.55
Industry and Year FE	Yes	Yes	Yes

Panel B: Accruals and cash flows

Model:	(6)	(6)	(6)
Dependent Variable:	$OPINC_{t+1}$	$OPINC_{t+2}$	$OPINC_{t+3}$
CFO	0.756***	0.709***	0.678***
	(92.86)	(73.76)	(62.32)
WCAccruals	0.599***	0.559***	0.523***
	(53.74)	(46.02)	(39.06)
Capex	0.055***	0.051***	0.050***
	(6.33)	(5.05)	(4.33)
$\Delta IDINT$	0.038	0.008	-0.006
	(0.55)	(0.10)	(-0.07)
Constant	-0.048***	-0.048***	-0.055***
	(-11.95)	(-10.58)	(-10.23)
Observations	42,112	34,914	28,959
Adjusted R-squared	0.58	0.57	0.55
Industry and Year FE	Yes	Yes	Yes

Table 7, cont.—Non-M&A intangible assets and operating income

Panel C: Lagged income without accruals

Model:	(7)	(7)	(7)
Dependent Variable:	$OPINC_{t+1}$	$OPINC_{t+2}$	$OPINC_{t+3}$
OPINC	0.756***	0.709***	0.678***
	(92.86)	(73.76)	(62.32)
Capex	0.055***	0.051***	0.050***
	(6.33)	(5.05)	(4.33)
Δ*IDINT*	0.038	0.008	-0.006
	(0.55)	(0.1)	(-0.07)
Constant	-0.048***	-0.048***	-0.055***
	(-11.95)	(-10.58)	(-10.23)
Observations	42,112	34,914	28,959
Adjusted R-squared	0.58	0.56	0.55
Industry and Year FE	Yes	Yes	Yes

Table 7 presents results of regressing future operating income before depreciation and amortization on measures of prior profitability and investments in working capital, capital expenditures, and intangible assets as in Models (6) through (8). The sample excludes acquisitions in order to examine the effect of intangible assets outside of business combinations. Robust t-statistics clustered by acquirer in parentheses. ***, **, and * indicate a difference from zero with statistical significance of p<0.01, p<0.05, and p<0.10, respectively.