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MEASURING INTANGIBLE CAPITAL WITH MARKET PRICES

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ABSTRACT

Existing standards prohibit disclosures of internally created intangible capital to firm balance sheets, resulting in a downward bias of reported assets. To characterize off-balance sheet intangible assets, we use transaction prices to estimate this missing intangible capital. On average, our new measure of intangible capital is 10% smaller than prior estimates, while varying more by industry. These estimates better explain market values, increase HML portfolio returns, act as a better proxy for human capital and brand rankings, and exhibit a strong association with patent values.

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> In the early days of Microsoft, I felt like I was explaining something completely foreign to people. Our business plan involved a different way of looking at assets than investors were used to. They couldn't imagine what returns we would generate over the long term. The idea today that anyone would need to be pitched on why software is a legitimate investment seems unimaginable, but a lot has changed since the 1980s. It's time the way we think about the economy does, too.
>
> - Bill Gates (2018)[1]

Corporate investment has changed significantly over the last few decades, with U.S. firms spending less on tangible assets and more on intangibles related to knowledge and organizational capacity (Figure 1). This reduction in tangible capital investment, along with the weaker connection between investment and firm valuation, is described as a "broader investment puzzle" by Gutiérrez and Philippon (2017) and Crouzet and Eberly (2019). A shared conclusion of both papers is that standard investment measures fail to capture the growing importance of intangible assets, resulting in a downward bias in the recorded book values of invested capital. This bias has grown over time, as evidenced by the dramatic upward trend in market-to-book (Figure 2). This paper proposes new measures for intangible investment and its accumulation that are central to capital stock adjustments.

Beyond academia, reliable measures of intangible capital are important for capital markets and financial managers. For instance, numerous studies have provided evidence of mispriced equity for firms with higher levels of intangible capital, which could lead to sub-optimal allocations of resources.[2] In debt markets, research has documented that banks are less willing to lend to firms with higher information asymmetry and less certain liquidation value, two primary characteristics of intangible intensive firms.[3] In corporate finance, fi-

[1] `http://bit.ly/2Xk8qEU`

[2] A partial list of these studies includes Daniel and Titman (2006); Eberhart, Maxwell, and Siddique (2004); Aksoy, Cooil, Groening, Keiningham, and Yalçın (2008); Edmans (2011); Eisfeldt and Papanikolaou (2013).

[3] Williamson (1988); Shleifer and Vishny (1992); Loumioti (2012); Mann (2018)

nancial managers making capital budgeting decisions must accurately estimate book values of intangible capital in order to calculate returns to intangible capital (Hall, Mairesse, and Mohnen, 2010).

Accounting rules for intangibles originated in 1974 at a time when intangible investments were only a small proportion of the economy, and they have not changed, despite a paradigm shift towards intangibles as economic value drivers. Specifically, a firm's internal Research and Development (R&D) costs and Selling, General, and Administrative (SG&A) activities are immediately recorded as expenses and thus do not appear on its balance sheet. This lack of capitalization reduces the informativeness of accounting book values in explaining market values (e.g., Lev and Zarowin, 1999). In an attempt to resolve this problem, researchers in economics and finance estimate the off-balance sheet intangible capital with accumulated flows of R&D (Bernstein and Nadiri, 1988; Chan, Lakonishok, and Sougiannis, 2001; Hirshleifer, Hsu, and Li, 2013), SG&A (Eisfeldt and Papanikolaou, 2013, 2014; Belo, Lin, and Vitorino, 2014), or both (Falato, Kadyrzhanova, and Sim, 2013; Peters and Taylor, 2017). Capitalizing in this way requires assumptions about the capital accumulation process, such as intangible depreciation rates and the fraction of SG&A to be capitalized. Unfortunately, as Corrado, Hulten, and Sichel (2009) highlight, "relatively little is known about depreciation rates for intangibles" (pp 674). The most commonly used rates for knowledge capital originate from Li and Hall (2016) who use BEA data,[4] while Hulten and Hao (2008) provide the main parameter for organizational capital (hereafter, "BEA-HH"). These measures of depreciation rates, however, are limited by gaps in industry coverage or rely on modeling assumptions due to the lack of market prices.[5]

[4]This paper first circulated in 2010.

[5]Less than 15% of 4-digit SIC codes have depreciation rates for knowledge capital. Organizational capital parameters have only been estimated in the pharmaceutical industry.

In this paper, we estimate capitalization parameters for intangible capital and use these estimates to impute values of off-balance sheet intangible capital. We add these values to existing book values of invested capital, thereby creating more accurate capital stock measures for the Compustat universe of firms. Then, in a series of validation tests, we show that these estimates perform at least as well or better than existing parameter estimates.

Our parameter estimation exploits prices paid for intangible assets in acquisitions. Acquisitions provide an excellent setting to price intangibles because the SEC and GAAP mandate the allocation of the purchase price paid for the target's net assets across tangible assets, liabilities, identifiable intangible assets (IIA), and goodwill (GW). Given that tangible assets are marked to market (i.e. stand-alone fair value) in the purchase price allocation, the sum of IIA and GW represents the total price paid for intangible capital in an acquisition. One can view the sum of IIA and GW as the residual after the auditor assigns market values of net tangible assets, which is likely an easier task. Thus, unbiased estimates of total intangible assets follow from unbiased market values of net tangible assets. Our acquisition sample spans the years 1996–2017 and comprises a substantial fraction of U.S. publicly-traded acquirer-target pairs found in SDC's M&A database.

We hand-collect the market prices of identifiable intangible assets and goodwill from over 1,500 acquisition events.[6] We then match these prices to ten years of the target firm's past spending on R&D and SG&A to estimate parameters of a capitalization model used in Corrado and Hulten (2014) and Peters and Taylor (2017). Specifically, we estimate the

[6]Data requirements restrict us to using public-to-public acquisition events. There are just over 2,000 such acquisitions, but many lacked information, generally from acquirer 10-K or 8-K filings, for inclusion into the final sample. Using similar data, Li, Li, Wang, and Zhang (2018) study the acquisition of a target's organizational capital in acquisitions, using the existing depreciation parameters. Potepa and Welch (2018) use the acquired intangibles from M&A to revisit some of the questions about the informativeness of innovation proxies. To our knowledge, we are the first to use these market prices to estimate capitalization parameters.

R&D depreciation rate and the fraction of SG&A that represents an investment.

Our parameter estimates imply an average 33% annual depreciation rate for R&D,[7] more than double the 15% rate commonly used in the literature.[8] Our estimates for R&D depreciation rates are comparable to those from Li and Hall (2016) who use a limited subsample of firms and SIC codes. Our 27% estimate of the fraction of SG&A that represents invested organizational capital is similar to that used in earlier work. However, while prior studies have assumed this ratio to be constant across industries, we find that it varies dramatically across industries, from 19% (consumer) to 49% (healthcare).

We use these parameters to estimate the values of knowledge and organizational capital for Compustat firms from 1975-2016.[9] Under these new parameter estimates, the fraction of firms' total capital stock that is intangible has increased from 37% of total capital in 1975 to 60% by 2016. At the extremes, over 80% of healthcare firms' assets are intangible in 2016, versus 40% for firms in manufacturing. The impact of adjusting the book value of assets for intangibles has a dramatic effect on the time series of average market-to-book. Figure 2 shows that adjusting the denominator for both intangible capital types reduces the magnitude of the upward trend by 70%.

Relative to previous methods, the new parameter estimates imply smaller stocks of intangible capital for firms in the consumer and manufacturing industries and larger stocks in high tech and health industries. We validate these differences in five settings: market enterprise valuations, asset pricing factors, human capital, brand rankings, and patent valuations. The results show that our new parameters perform significantly better than those commonly

[7]Note that these are average depreciation rates, including successful and failed projects.

[8]Griliches and Mairesse (1984); Bernstein and Mamuneas (2006); Corrado, Hulten, and Sichel (2009); Huang and Diewert (2007)

[9]Parameter estimates and firm-year-level measures of intangible capital are available online: `http://bit.ly/intan_cap`

used in prior work. This relative improvement likely stems from our new industry-level organizational capital investment rate and broader industry coverage in knowledge capital.

The first validation test asks whether the incorporation of our intangible capital estimates improves the explanatory power of book capital stock values on market enterprise values. We compare the market enterprise value explained by book values adjusted with our intangible capital estimates with that book values adjusted by BEA-HH intangible capital estimates. Our measures improve the R^2 in the cross-section in all years from 1986 to 2016; this additional power is statistically significant in all years after 1995.

Next, we test whether the inclusion of estimated intangible capital in book equity affects the portfolio returns from the HML factor of Fama and French (1992, 1993). After this adjustment, the value premium (HML) exhibits returns that are 54% larger and a have smaller standard deviation than when constructed using book equity alone, leading to an 87% increase in the Sharpe ratio. This result suggests that our measure of intangible capital has significant implications for empirical asset pricing.

The next two tests verify whether our estimates of organizational capital are better at capturing differences in human capital and brand value versus current measures. We follow Eisfeldt and Papanikolaou (2013) in examining whether firms with high organizational capital are more likely to disclose risks regarding the potential loss of key talent in their 10-K filings. To do so, we analyze text from management discussions about risk in over one hundred thousand 10-K filings from 2002–2017 and identify whether the firm mentions "personnel" or "key talent." Our measure of organizational capital stock outperforms the existing measure in all years: firms in the top quintile of organizational capital stock are significantly more likely to mention these human capital risks than those in the bottom quintile. In contrast, the current method of capitalizing SG&A only produces significant differences across firms in

35% of the sample years. A similar exercise using firms' brand ranking shows that firms in the top (bottom) quintile have higher (lower) brand ranking when using the new organizational capital stock to sort firms.

The final validation asks whether our new estimates of intangible capital can explain previously established measures of patent values. Kogan, Papanikolaou, Seru, and Stoffman (2017) provide a measure of patent valuations from market reactions to patent grants. Regressions of these values on our measures of knowledge and organizational capital significantly increase within-firm R^2, while the estimates imply that an additional dollar of knowledge capital increases patent values 16%. Because these regressions include both firm and year fixed effects, there is little scope for our measure to improve upon earlier estimates. Still, to our knowledge, we offer one of the first direct measurements of returns to intangible investments.

Two concerns related to our acquisition setting are worth acknowledging: sample selection and noisy goodwill. We address each in turn. First, although acquisitions provide market prices of a target firm's intangibles, these targets may not be representative of the full population of firms. For example, acquisition targets may have more successful prior intangible investments. To address this concern, in all results summarized above, we supplement our acquisitions sample with a set of 479 bankruptcy events of publicly-traded companies over the sample period. We use firm-level bankruptcy recovery data (or industry-level averages if unavailable) to allocate a fraction of this total to all priced intangibles. Robustness checks reveal that including these events is important for the new measure's out-performance described above.

Second, the raw price of intangibles may be confounded by merger pair-specific values (i.e., synergies) and over/underpayment by the acquirer. These factors would contaminate goodwill, which is our proxy for unidentifiable intangible assets. To directly address this, we adjust for both synergy and over/underpayment using the change in the target's market valuations around the acquisition announcement along with the probability completion. Together, these adjustments lower the price of target-firm intangibles by an average of 34%. These adjustments are significant to the estimation and important for the improvements discussed above.

One advantage of our approach is that any potential measurement error in the identification of intangible assets is ameliorated by the inclusion of adjusted goodwill, which captures unidentified intangible capital. We alleviate concerns pertaining to acquired intangible prices by repeating the same estimation methodology on the full Compustat sample, replacing acquired intangible prices with market enterprise values less net tangible assets (see Section 7 below). While the resulting parameters are similar to those using acquisition prices, they do not outperform our parameters based on the acquisition sample on the validation tests described above. Finally, we address concerns about time-varying market prices by estimating the model over rolling 10-year observation periods, with no major change in conclusions.

We contribute to three broad literatures. First, we provide parameter estimates to corporate finance researchers that rely on estimates of intangible capital as an input to examine real outcomes in firms (Eisfeldt and Papanikolaou, 2013; Gourio and Rudanko, 2014; Sun and Zhang, 2018). Second, we contribute to a long-standing literature on growth economics that attempts to measure the value of knowledge in the economy. Specifically, our work both re-estimates the knowledge capital accumulation process using market prices and extends these estimates to organizational capital for the first time (Corrado, Hulten, and Sichel, 2009; Corrado and Hulten, 2010; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2013; Hall, Mairesse, and Mohnen, 2010). Finally, we contribute to an active debate surrounding off-balance sheet intangible capital. Lev (2018) suggests that standard-setters' resistance to recognizing intangibles on firm balance sheets has substantial costs to both firms and the broader economy. In addition to confirming the value-relevance of currently included intangible assets such as goodwill, we provide evidence that estimating the value of internally generated intangible capital is feasible and provides meaningful information to financial statement users.

1 Accounting for intangibles

We exploit information about prices paid for intangible assets of U.S.-based public acquisition targets to estimate parameters that allow us to recover off-balance sheet intangible capital. Below, we discuss the disclosure setting regarding intangibles. Internet Appendix Section IA1 provides a history of the accounting rules surrounding the acquisition of tangible and intangible assets.

1.1 Intangibles accounting

For nearly all internally generated intangible assets, such as knowledge and organizational capital, accounting methods differ significantly from tangible assets.[10] While a firm's capital expenditures on tangible assets such as plant, property, and equipment are recorded on the balance sheet at its purchase price and depreciated over its estimated useful life, a firm's R&D, advertising or employee training expenditures are fully expensed in the period incurred.[11] Although these intangible expenditures may fulfill GAAP's primary criterion for

[10]U.S. GAAP treats the development of computer software differently from other R&D costs. Following ASC 985 (formerly FAS 2), once a software developer has reached "technological feasibility," the developer must capitalize and amortize all development costs until the product is available for general release to consumers. `https://asc.fasb.org/link&sourceid=SL2313776-111772&objid=6503587`

[11]For example, although The Coca-Cola Company spends several billion dollars each year to maintain and promote its products, and brand names such as Coca-Cola®and Dasani®are assets to the firm that

asset recognition,[12] GAAP's justification for not capitalizing and amortizing these intangibles stems from uncertainty in measuring their value and estimated useful lives.[13]

In contrast, intangibles acquired via the purchase of a target firm are recorded as either identifiable intangible assets (IIA) or goodwill (GW) and added to the acquirer's balance sheet, following guidance from ASC 350 (formerly FAS 142). If the target's internally created intangible expenditures meet specified criteria, they will be capitalized onto the balance sheet of the acquiring firm at fair market value.[14] The criteria for capitalization of intangibles documented in ASC 805 notes that an intangible asset is identifiable if it meets either the separability criterion, meaning it can be separated from the entity and sold, or the contractual-legal criterion, meaning that the control of the future economic benefits arising from the intangible is warranted by contractual or legal rights.[15] Simply, IIA prices reflect fair or public value, rather than value specific to the post-acquisition firm. Some examples of these identifiable intangible assets include brand names, customer lists, trademarks, Internet domain names, royalty agreements, patented technologies, and trade secrets. Other intangibles with a non-zero market value, such as corporate culture, advertising effectiveness, or management quality, that fail to meet these criteria for identification are captured in the goodwill accounts of the acquirer's balance sheet. The following figure shows an example

create future benefits in the form of higher margins and increased sales volume, The Coca-Cola Company is not permitted to recognize these assets to the balance sheet.

[12] Asset recognition requires that the expenditure in the current period provides economic benefits to the firm in future periods (Corrado, Hulten, and Sichel, 2009, 2005).

[13] `https://asc.fasb.org/section&trid=2127268#topic-730-10-05-subsect-01-108369`

[14] The approach by which intangibles are marked to fair value at the time of acquisition follows ASC 820 (formerly FAS 157). The firm's choice of method is disclosed in the appraisal notes for intangibles in the acquirer's financial statements. Firms have the option to appraise the value of intangibles by either: (1) estimating the replacement cost of the asset, (2) comparing the asset to a similar asset whose price trades on the open market, or (3) using discounted cash-flow valuation models where earnings or free cash flows are discounted by an appropriate discount rate. Because of the unique nature of intangibles, firms frequently use the DCF approach when appraising these assets.

[15] `https://asc.fasb.org/link&sourceid=SL4564427-128468&objid=99405171`

purchase price allocation, details of which are discussed in the Internet Appendix.

In millions	
Cash and short-term investments	$ 3,034
Accounts receivable	2,549
Property, plant and equipment	3,203
Other tangible assets	3,126
Notes payable and debt	(3,298)
Pension liability (Note 15)	(2,243)
Restructuring liability (Note 8)	(1,515)
Net deferred tax liabilities	(1,427)
Other liabilities assumed	(5,370)
Total net tangible liabilities	$ (1,941)
Amortizable intangible assets:	
Customer contracts and related relationships	3,199
Developed technology and trade name	1,349
Goodwill	10,395
IPR&D	30
Total preliminary estimated purchase price	$13,032

Example purchase price allocation: HP acquires Electronic Data Services

In summary, the purchase and acquisition methods of GAAP accounting require that the target's net assets be marked to market at the time of the acquisition. During this process, any internally developed intangibles by the target firm that meet specified criteria are identified, appraised, and brought onto the acquirer's balance sheet at fair market value. Internally generated intangibles that do not meet such criteria, but are still valued by the acquirer, are not separately identified and are instead recorded as a goodwill asset for the acquirer.[16]

[16]Figures IA1 and IA2 in the Internet Appendix provide basic examples of the differences between the purchase and pooling method. Section IA3 provides several real-world examples found in our data.

2 Literature

Prior research[17] that estimates intangible capital uses the perpetual inventory method, which aggregates net investment flows over the life of the firm. This can be estimated by adding the value of the intangible asset at the beginning of the period, adding any other intangible investment flows and subtracting any depreciation to the beginning of period intangible capital stock as shown below in (1), for capital stock X at the end of year t:

$$X_t = X_{t-1} + Z_t - D_t \tag{1}$$

Z_t represents periodic investment, and D_t represents depreciation during period t of existing stock X_{t-1}. Assuming that X depreciates geometrically at the rate of δ, we have:

$$X_t = X_{t-1}(1-\delta) + Z_t \tag{2}$$

Through iterative substitution, the intangible capital stock becomes the total sum of all undepreciated intangible investments throughout the firm's existence.

$$X_t = \sum_{i=0}^{\infty}(1-\delta)^i Z_{t-i} \tag{3}$$

Due to data limitations on intangible expenditures prior to the firm being publicly-traded, (3) is modified as follows:

$$X_t = (1-\delta)^k X_{t-k} + \sum_{i=0}^{k}(1-\delta)^{k-i} Z_{t-i} \tag{4}$$

[17] e.g., Corrado, Hulten, and Sichel (2009); Corrado and Hulten (2014); Cockburn and Griliches (1988); Eisfeldt and Papanikolaou (2013, 2014); Hall, Mairesse, and Mohnen (2010); Hulten and Hao (2008)

Thus, to estimate a firm's stock of intangible capital via (4), we need periodic measures of investment in knowledge and organizational capital, Z, over k periods, the value of the initial stock X_{t-k}, and the depreciation rate, δ.

The consensus proxy for knowledge capital flows is the firm's annual R&D activities.[18] The proxy for organizational capital, however, is less clear. While R&D is directly defined as a proxy for knowledge capital, recent research capitalizes Sales, General, and Administrative Expenses (SG&A) as a proxy for the firm's organizational capital flows using logical deduction. SG&A is defined by GAAP as a firm's operating expenses unrelated to the cost of goods sold. Some examples include advertising and marketing expenses, provisions for employee bonuses, and bad debt expenses. Because SG&A aggregates items which should be classified as periodic expenses with items that are long-lived assets, this creates an additional parameter to be estimated, γ, which is the fraction of SG&A that represents an organizational capital investment.[19]

To the best of our knowledge, the only estimate of γ comes from Hulten and Hao (2008), who estimate $\gamma = 0.3$, based on data from six pharmaceutical firms in 2006. Conversely, there have been a number of attempts to estimate δ for R&D investments. The main challenges in estimating δ, as stated by Griliches (1996) and Li and Hall (2016), stem from the fact that the majority of firms conduct R&D activities for use within the firm, and thus market prices do not exist for most R&D assets. Thus, most models that estimate R&D depreciation often

[18] ASC 730 (formerly FAS 2) define R&D activities as "the translation of research findings or other knowledge into a plan or design for a new product or process".

[19] For example, in 2017 Coca-Cola Company reports \$12.5 billion in SG&A expenditures. Footnotes reveal that \$4 billion of these costs are incurred to support the advertising and media expenses, while \$1.1 billion of these SG&A costs are related to shipping and handling costs incurred to move furnished goods from sales distribution centers to customer locations. Assuming that advertising expenses incurred in 2017 will continue to enhance the firm's brand equity in future periods, these expenditures represent organizational capital. Conversely, the shipping costs only support operations in the current period, and therefore should be immediately expensed.

require strong identifying assumptions.[20]

Given the lack of estimates for γ, and the wide range of δ, there is little consensus regarding the parameters that are needed to measure intangible capital. For example, Eisfeldt and Papanikolaou (2013) and Li, Qiu, and Shen (2018) estimate organizational capital, and assume γ to be 1 and 0.3, and δ to be 0.15 and 0.2, respectively. Corrado, Hulten, and Sichel (2009) allow δ on R&D investments to vary by industry and assume values between 0.2 and 0.6. Falato, Kadyrzhanova, and Sim (2013) assume δ on R&D equals 0.15, and both δ and γ on SG&A to be 0.20.

3 Data

Data for our public acquisitions comes from Thomson's SDC Merger & Acquisition database. Sample construction starts with all U.S. public acquirer and public targets for deals that closed between 1996 and 2017 with a reported deal size. Our sample begins in 1996 because we require financial statements from the SEC's EDGAR website. We drop deals where the acquirer or target has a financial services, resources, real estate or utility SIC code.[21] As

[20]For example, Pakes and Schankerman (1984) develop a model by which they infer δ of R&D by examining the decline in patent renewals over time. This assumes that valuable R&D must result in patents and that the value of R&D is directly inferable from patent renewal prices. Pakes and Shankerman estimate $\delta = 0.25$. Lev and Sougiannis (1996) use an amortization model in which firms' current period operating income is regressed on lagged values of R&D expenditures and find δ varies between 0.11 and 0.20. They assume that the amortization of R&D capital is responsible for generating earnings, which fully captures the benefits of R&D investments, where R&D investments may benefit the firm's cost of equity or provide strategic real option value. Li and Hall (2016) use a forward-looking profit model approach to estimate R&D depreciation with NSF-BEA data. Their model assumes a concave profit function for R&D investment and that the firm invests optimally in R&D capital to maximize the net present value of its investment. Unlike tangible assets, the model assumes that R&D capital depreciates solely because its contribution to the firm's profit declines over time. Under these conditions, their model produces δ of R&D between 0.12 and 0.38. Their estimates cover 10.5% of 4-digit SIC codes and 28% of firm-year in Compustat, thus requiring other assumptions for firms in SIC codes outside of these estimations.

[21]The excluded SICs are 6000 to 6399, 6700 to 6799, 4900 to 4999, 1000 to 1499.

discussed in Section 1, we exclude all deals that use the pooling method pre-2001.[22] This leaves us with a set of 2,109 acquisitions.

We also require data availability of the acquirer's purchase price allocation of the target's assets in order to collect the prices paid for goodwill and identifiable intangible assets (IIA). When available, these purchase price allocations were found in the acquirer's subsequent 10-K, 10-Q, 8-K or S-4 filing. We found information on the purchase price allocation for 81% (1,719) of all candidate acquisitions.[23] In the final step, we merge the target and acquirer firms to Compustat and CRSP. For each target firm merged to Compustat, we gather up to 10 years of the firm's past R&D and SG&A expenditures along with any pre-acquisition acquired intangibles on its balance sheet.[24,25] The final sample includes 1,521 events (70%). Below we describe how these deals differ from those lost in the data collection process.

3.1 Sample selection

Acquisitions are non-random and often depend on the quality of both the acquirer and the target firm (e.g., Maksimovic and Phillips, 2001) and the innovation needs of the acquirer (e.g., Phillips and Zhdanov, 2013; Bena and Li, 2014)), as well as whether the acquisitions can be predicted by the relative market-to-books of acquirers and potential targets (e.g., Rhodes-Kropf, Robinson, and Viswanathan, 2005).[26] Relatedly, the acquisitions in our sam-

[22]The results presented below for all deals from 1996–2017 are robust to exclusion of pre-2002 deals (see Panel A of Table 8).

[23]Some filings lacked the footnote for the acquisition (e.g., the acquisition was immaterial) or we could not identify any filing for the acquiring firm (e.g., the firm has a unique registration type with the SEC).

[24]If Compustat has less than 10 years of data and the firm is older than 10 years old, then we impute any missing R&D and SG&A using observed growth rates for the same age firms with non-missing data. All results are robust to excluding these imputed data.

[25]We also lose acquisitions because we either failed to find a Compustat identifier or the firm did not have stock price data in CRSP (e.g., it was traded on the OTC markets).

[26]See Betton, Eckbo, and Thorburn (2008) for a survey of the major empirical results in the corporate takeover literature.

ple naturally exclude another exit for target: failures.

Our first attempt to address potential selection issues is to supplement our acquisition sample with other, presumably worse, exit events. We add to the sample 479 CRSP delistings from 1996–2017, which come from a combination of liquidations and bankruptcies.[27] Given the absence of purchase price allocations for these events, we estimate the sum of IIA and goodwill as the percentage of assets recovered during the bankruptcy event,[28,29] multiplied by the ratio of IIA and goodwill to total deal size for the same 4-digit SIC code in the non-bankruptcy acquisitions.[30]

Any remaining selection issues after incorporating bankruptcies take one of two forms. If most acquisition targets are low productivity innovators (e.g., Bena and Li (2014)), then we may estimate too high a depreciation rate and too low a value of γ. Alternatively, acquired firms may on average represent firms with successful innovation projects or that are purchased at the peak of their innovative productivity. In this case, we would estimate too low a depreciation rate and/or too high a fraction of organizational capital investment (γ). It is not clear which source of selection issues dominate, so we use the well-identified parameter estimates from Li and Hall (2016) to help judge our estimates. Since their estimation of depreciation parameters for R&D is derived from a representative set of firms (from a small

[27]CRSP delisting codes of 2 and 3.

[28]Ma, Tong, and Wang (2019) show that assuming a value of zero for intangibles is incorrect because innovation is a crucial asset class in asset allocation in bankruptcy.

[29]We obtain recovery rates via the "Ultimate Recovery" file from Moody's Default and Recovery database. This file covers fully-resolved large public U.S. corporate defaults between 1987 and 2019, and includes the final recovery of total debt, based on 10-K, 10-Q's, press releases and other legal filings. The data field named "FAMILY_RECOVERY" provides the dollar-weighted proportion of debt recovered, after discounting for lost interest. We find exact matches with our sample of CRSP delistings for 95 of 478 events. We use industry (Fama-French five industries) average recovery rates from the same database for the remaining firms (49% across all firms). This recovery rate multiplied by outstanding debt forms our "deal value" for this sample of exit firms.

[30]All results below are robust to setting the fraction to one-half or one-quarter of the acquisition sample fraction.

set of industries), a lack of systematic differences with our estimates would indicate that our sample selection is not severe.[31]

3.2 Synergy and overpayment: adjusting goodwill

Acquisitions may be motivated by pair-specific synergy values, and prior research has documented that managers may overpay for a target due to agency frictions or hubris (e.g., Roll (1986)). These issues could potentially affect the representativeness of our imputed parameter estimates when applied to the full population of firms. Extending our parameter estimates to all publicly listed firms requires that the prices paid for intangible capital in our sample represent a *public* or market value. Fortunately, the purchase price allocation process directly separates intangible assets that can be identified via either a separability criterion or previously established contractual legal criterion. Thus, pair-wise values arising from the acquisition – synergies – will be recorded as goodwill. Because we are interested in the stand-alone value of assets, our analyses adjust goodwill accordingly.

To make these adjustments, we apply the market's assessment of synergy value and under/overpayment of the target firm by using changes in the target and acquirer's market valuation around the acquisition event date. We follow the Bhagat, Dong, Hirshleifer, and Noah (2005) framework for estimation merger value creation as an adjustment to goodwill. Specifically, using this probability scaling method for announcement day returns, we estimate the synergy and over-payment component of the acquisition value and then remove this estimate from goodwill valuations from the purchase price allocation.[32] This estimate is removed from goodwill valuations from the purchase price allocation.[33]

[31]For robustness, we later run all analyses with and without the bankrupt firms and show that the estimates change as predicted.

[32]We cannot easily implement the second "intervention method" with our relatively small sample size.

[33]In cases where the adjustment exceeds goodwill (less than 15% of deals), the remainder is removed from

For each acquisition event, we first calculate the $[-5, 5]$ day change cumulative abnormal return for both the target and acquirer.[34] Multiplying by the pre-deal ($t = -6$) market value of each gives the abnormal change in market valuation at deal announcement. Next, as the market's response incorporates expectations about merger failures, we weight them by the inverse of the probability of acquisition success implied by the end-of-period market price of the target compared to the offer price in the deal.[35] The sum of the target and acquirer's changes – the expected synergy – is subtracted from goodwill.[36] We remove the acquirer's change in valuation as it incorporates under/overpayment. Here, a decline in the acquirer's market value would signal overpayment for the target, leading to goodwill that is abnormally large when compared to payment at fair market value; as such, this overpayment must be removed from goodwill. We find that the goodwill adjustments to be substantial, with the average (median) deal adjustment resulting in a 34% (21%) decline in goodwill.[37]

3.3 Main variables

Figure 3 (a) shows the prevalence of goodwill and IIA for our acquisition sample. It reports the percentage of all deals that have some amount of either asset in the purchase price allocation. We observe an upward trend in these components since the mid-1990s, with over 85% of deals containing goodwill or IIA since 2004. To ensure that our observations are

the IIA valuation.

[34]The estimates below are robust to 2, 4 and 30 day event windows.

[35]That is, the probability of a successful merger is $\frac{P_1 - P_0}{P_{\text{offer}} - P_0}$, where P_1 is the end-of-day target share price, P_0 is the pre-announcement share price and P_{offer} is the original offer price. For example, if the pre-announcement price is 100 and the tender offer is 200, an end-of-day share price of 170 implies a 70% probability of deal completion. When this is unavailable or outside the unit interval, we use the observed success rate in SDC over our sample period (78%).

[36]If the result is negative, then the remainder is subtracted from the identifiable intangible assets.

[37]Internet Appendix Figure IA4 reports the percentage of acquisition deal size allocated to goodwill and IIA after these adjustments. The prevalence of goodwill in deal size falls in all years (see the green arrows), which has an impact on the total intangible value in acquisitions.

not driven by smaller acquisitions, Figure 3 (b) repeats the analysis but replaces the y-axis with a dollar-weighted measure, which is the sum of all IIA and goodwill in the sample, scaled by the sum of all acquisition deal sizes in the sample. The patterns remain. Figure 4 asks how much of the total enterprise value is comprised of goodwill and IIA. The latter represents 25% of total transaction value over the sample period, while the former accounts for approximately 35% of the typical deal size over the full sample period. This suggests that intangibles play a major role in the U.S. acquisition market.

3.4 Summary statistics

Panel A of Table 1 presents summary statistics on deals and the parties. All dollar values are in 2012 dollars. The average deal year is 2005 with an average (median) deal size of \$2.3b (\$426m). Deal size as measured by enterprise value (thus including assumed liabilities) averages \$2.5b. We assign firm industries using the Fama-French 5 industry classification. Consumer firms represent 18% of targets, while the average target has an EBITDA of \$142m. Over one-quarter of the acquirers are headquartered in California, which is slightly above the rate for all public firms. This is likely a consequence of both our focus on acquisitions and our requirements for observability of the purchase price allocation for intangibles. We also see that goodwill is on average \$1.1b with a much lower median of \$159m.[38] IIA comprises 38% of total intangible capital (goodwill plus IIA) on average. Finally, total intangibles represent 75% of enterprise deal size on average. In 281 acquisitions, the total intangible

[38]In a few of our observations, total intangibles (identifiable intangible assets and goodwill) is negative. These instances, while rare, occur because goodwill can take on negative values and in these cases, the negative value is larger than the value of identifiable intangible assets. Since goodwill is the plug variable that equates the balance sheet, negative goodwill occurs when the acquirer is able to purchase the target at a price that is below the fair value of net tangible assets that is measured during the due diligence appraisal. This negative goodwill is immediately recorded to the income statement as an extraordinary gain. See Figure IA3 in the Internet Appendix for an example. We allow goodwill to be negative, but because the estimation is done in logs we bottom code total intangibles to zero.

capital exceeds the enterprise value of the firm. We randomly checked 20 acquisitions in this subsample and verified that this is a result of the target's net tangible assets being less than zero. Correspondingly, we found that these targets tended to be high-tech or healthcare targets with very high R&D and SG&A expenditures and very low levels of PP&E on their balance sheets.

Panel B of Table 1 summarizes the acquisitions in the bankrupt firm sample. The average failure date in our sample is earlier than the acquisition date (2002 vs. 2004). In fact, over a quarter of the delistings in our sample occur in years 2000 and 2001, the burst of the e-commerce dot-com bubble. In contrast to acquired firms, These firms are more to be in the consumer industry (34% vs. 18%). Not surprisingly, the average failed firm tends to be small and unprofitable with an average asset size of $252m and net loss of $80m. Total intangibles – which are estimated as a function of the "deal size" defined in the previous section – are small with an average of $35m, keeping in mind that we make no assumption about the breakdown of goodwill or identifiable intangibles, only the total.

3.5 Selection of acquisitions

Our final acquisition sample (excluding delistings from bankruptcies) excludes 588 deals in which an extensive search failed to find the purchase price allocation. Thus, inferences derived using this final acquisition sample should address these potential sample selection issues. Fortunately, Table 2 shows that our sample of acquisitions is reasonably similar to those excluded. The right-most columns present the excluded acquisitions. These acquisitions occurred earlier in the sample, are less likely to be in manufacturing, and have a smaller median deal size ($177 vs. $385m). The smaller size implies these acquisitions are more likely to be immaterial to the acquirer and, consequently, to not have a purchase price allocation in their filings. Reassuringly, the targets are not significantly smaller in the excluded group when measured by pre-acquisition assets or net sales. Overall, Table 2 shows that our acquisition sample likely tilts toward larger deals and more recent events. The inclusion of delisted firms – with low assumed "acquisition" values and no time period constraints – helps to balance many of these differences out.

4 Parameter estimation

We measure the value of the target's intangible capital as the sum of externally acquired and internally generated intangible capital. The target's externally purchased intangibles, I_{it}, are disclosed on the asset side of its balance sheet (Compustat item *intan*). Building on a large empirical literature,[39] we measure the value of internally generated intangible capital as the sum of knowledge and organizational capital over the previous ten years,

$$K_{it}^{int} = G_{it} + S_{it}$$

where G_{it} is the value of knowledge capital, and S_{it} is the value of organizational capital for firm i in year t.

We estimate these capital stocks by accumulating past spending in R&D and a fraction γ of past spending on SG&A[40] using the perpetual inventory method:

$$G_{it} = (1 - \delta_G)G_{i,t-1} + R\&D_{it} \tag{5}$$

[39] Corrado and Hulten (2010, 2014), Corrado, Hulten, and Sichel (2009), Eisfeldt and Papanikolaou (2013, 2014), Falato, Kadyrzhanova, and Sim (2013), Lev and Radhakrishnan (2005), Zhang (2014) and Peters and Taylor (2017).

[40] We measure SG&A net of R&D expense (*xrd*) and Research and Development in Process (*rdip*).

and

$$S_{it} = (1 - \delta_S)S_{i,t-1} + \gamma SG\&A_{it}. \tag{6}$$

For each acquisition, we construct trailing 12-month measures for these two expenditures using the Compustat quarterly database.[41] Therefore, the fully specified capitalization model is:

$$K_{it}^{int} = (1 - \delta_G)G_{i,t-1} + R\&D_{it} + (1 - \delta_S)S_{i,t-1} + \gamma SG\&A_{it} \tag{7}$$

Our ultimate goal is to estimate the structural parameters of the perpetual inventory equation (7), δ_G and γ, by comparing the log of the intangible capital to the log of the allocated market price paid to acquire the firm's intangible capital, P_{it}^I.

The baseline specification estimates P_{it}^I as the sum of identified intangible assets (IIA) and adjusted goodwill (GW) reported in the acquirer's post-acquisition financial statements. Recall from Section 3.2 that adjusted goodwill is the goodwill in the purchase price allocation after removing the inferred synergies and over-(under) payment from market responses to the deal announcement, weighted by the implied probability of deal completion.

We estimate an equation of the form

$$P_{it}^I = f(I_{it}, K_{it}^{int}; \theta_{it}) \tag{8}$$

where θ_{it} is a parameter vector that includes γ, δ, and a general formulation of the market-to-book for intangibles. We start by assuming that the function f is linear and that the market-to-book enters as a multiplicative factor $\xi_{it} \in (0, \infty)$:

[41] This approach ensures that we have financial data on target firms in the quarter immediately before the acquisition. Using annual Compustat data often results in large gaps between financial report and the deal dates.

$$P_{it}^I = \xi_{it}(I_{it} + K_{it}^{int}) \tag{9}$$

Rearranging (9) shows that ξ_{it} is the intangible market-to-book ratio $\left(\xi = \frac{P}{I+K^{int}}\right)$. Our objective of estimating the book value of intangibles $I_{it} + K^{int}$ requires an assumption about ξ_{it}. Theories of firm dynamic investment such as Hayashi (1982) predict that ξ_{it} is one *on average*. Implementing this requires additional assumptions. In the extreme, we would let ξ_{it} be a firm fixed effect constrained to be one on average across all firms. Our cross-sectional data makes this infeasible. Instead, we let ξ_{it} be a function of time through a modified year fixed effect which is assumed to be one on average over time:[42]

$$\xi_{it} = \rho_t$$

where ρ_t is the year of the acquisition or delisting. Estimating (9) proceeds in several steps.

First, to avoid overweighting large firms in our sample, and without an obvious scaling variable, we first take the natural logarithm of each side of equation (9). We add 1 to both sides to avoid dropping acquisitions without any recognized intangibles:

$$log(1 + P_{it}^I) = log(\rho_t) + log(I_{it} + K_{it}^{int} + 1) \tag{10}$$

Next, due to the nature of SG&A spending, in particular that it is very stable within firms over time, the parameters γ and δ_S in the S_{it} term are not separately identifiable.[43] We

[42] It is important to average the year fixed effect over time, rather than across observations, because acquisition and failure events tend to cluster in economic booms and busts, respectively. Averaging the fixed effects in the standard way, across observations, would cause the estimation to overweight these time periods in estimation of the fixed effects. Fortunately our non-linear least squares estimation is flexible enough to easily accommodate this.

[43] To see this, consider the perpetual inventory equation for a firm i: $S_{it} = \sum_k \gamma SG\&A_{i,t-k}(1-\delta_S)^k$. If $SG\&A_{it}$ is constant for firm i, $SG\&A_{it} = SG\&A$, we have

address this issue by estimating the parameter γ and taking the depreciation of organizational capital δ_S as the standard 20% from the literature. We explore the implications of this assumption in Section 5 and the Internet Appendix. Finally, substituting for the G and S in equation (10), we estimate the structural parameters by minimizing the sum of squared errors of the non-linear equation:

$$log(1+P_{it}^I) = log(\rho_t) + log(I_{it} + \sum_{k=1}^{10}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=1}^{10}(1-0.2)^k \gamma \text{SG\&A}_{i,t-k} + 1) \quad (11)$$

4.1 Estimation details

We highlight a few important features of the estimation procedure here. The acquisitions in bankruptcy observations – where we impute P_{it}^I from debt recovery and intangible asset rate assumptions – are weighted to match the unconditional relative frequency of acquisitions and delistings found in Compustat-CRSP. Since the model is in logs, model fit is assessed by comparing the exponent of the root mean standard error generated by the model to the exponentiated root mean squared error of a model that contains only a constant in the estimation. Also, because our model does not contain a constant, a negative pseudo R^2 is possible. We estimate standard errors by bootstrapping, i.e. re-drawing acquisition events and, thus, the full time-series of target investments, with replacement.[44]

$S_t = \sum_k \gamma SG\&A(1-\delta_S)^k = \gamma SG\&A\frac{1}{1-(1-\delta_S)} = \gamma SG\&A\left(\frac{1}{\delta_S}\right) = \frac{\gamma}{\delta_S}SG\&A$

In this case we can only identify the ratio $\frac{\gamma}{\delta_S}$. A similar result holds if SG&A has a constant growth rate.

[44]We run bootstraps with 1,000 replications, re-drawing across all events before weighting to match the unconditional relative frequency of event types.

5 Results

We first estimate the parameters used to accumulate intangible capital for our acquisition sample using the estimation described above, then apply those parameters to a broader universe of firms to investigate the external validity and implications of our parameters.

5.1 Estimating the capital accumulation process

Results from the estimation of equation (11) are reported in Table 3. The "All" row represents the full sample while the other rows show industry estimates using Fama French 5 classifications.[45] The column "$\bar{\delta}_G^{BEA}$" reports the depreciation rate of knowledge capital for the subset of industries used in Li and Hall (2016), averaged within our industry categories. These estimates cover 10.5% of SIC codes and roughly 50% of Compustat firms with R&D, but exploit non-selected data. The column "$\bar{\delta}_G^{lit}$" reports the average depreciation rates where any gaps in Li and Hall (2016) are filled with 0.15.

Based on organizational capital depreciation rates commonly used in the literature (Eisfeldt and Papanikolaou, 2014; Falato, Kadyrzhanova, and Sim, 2013; Peters and Taylor, 2017) of $\delta_{SG\&A} = 0.2$,[46] we find that a significant portion of SG&A represents a long-lived capital investment, $\gamma = 27\%$.[47] This is only slightly less than the commonly used 30%, and to our knowledge is the first direct confirmation of the γ estimate used in the literature. While we report a similar mean estimate of γ, this parameter varies significantly across industries. The fraction of SG&A spending that represents an investment is lowest in the

[45] We make two changes to the FF5 industries, reclassifying SIC codes 8000-8099 (Health Services) as Consumer and Radio/TV broadcasters are Consumer (from High-tech).

[46] Eisfeldt and Papanikolaou (2013) use a value of .15.

[47] In robustness analyses, we examine the sensitivity of our $\delta_S = 0.2$ assumption. Figure 11a (discussed below) shows no major changes in results presented here for δ_S between $[.1, .3]$. We thus maintain the assumption of .2 throughout.

consumer industry at 19%. This is consistent with selling expenses being a large fraction of SG&A for the retail industry, which tends to have less innovation. On the other extreme, the parameter estimate of 0.44 and 0.49 in the high tech and health sectors imply that almost half of SG&A spending in these industries represents an investment. These relatively higher levels of investments in SG&A for high tech and health firms is consistent with their higher levels of employee training, database usage and branding.

The estimates also provide novel insights on knowledge capital depreciation. Table 3 shows an R&D depreciation rate δ_G across all firms of 33% per year, which is significantly greater than the 15% commonly used in the empirical literature on R&D (Griliches and Mairesse, 1984; Bernstein and Mamuneas, 2006; Corrado, Hulten, and Sichel, 2009; Hall, Mairesse, and Mohnen, 2010; Huang and Diewert, 2007; Warusawitharana, 2010). The cross-sectional variation of δ_G is substantial, ranging from a low of 0.30 in the "other" industry to a high of 0.46 in high-tech firms. The second to last column in each panel reports the average knowledge capital depreciation from the Li and Hall (2016) estimates. Recall that their estimates likely suffer from no sample selection issues and thus represent a benchmark for such concerns in our analysis. Reassuringly, for the "All", consumer and high-tech samples, we cannot reject the null that our estimated δ_G differ from those of Li and Hall (where there is overlap in estimation). Moreover, the relative estimated parameters across industries are similar in both estimations. In contrast, our estimates differ significantly from those used in the broader literature (the final column). The differences suggest that the assumption of .15 for any gaps in Li and Hall (2016) may be incorrect.

Patterns in the industry-level parameters reassuringly match some expected features of intangible investments, while revealing whether certain selection concerns discussed earlier emerge. First, Table 3 shows that R&D depreciation is highest in the high tech industry

(46%), which is also the largest in the BEA estimates (though a smaller 32%). These results confirm that the value of knowledge gained in this industry is short-lived, despite the fact that around 82% of high tech targets report R&D expenditures. The estimates of R&D depreciation rates exceed those currently used in the literature. That these differences suggest positive selection issues – e.g., acquisitions are more likely to be successful innovation projects – is not a first-order concern. We discuss any impacts of selection and non-representative pricing in the analysis of intangible capital stocks below.

How do these estimated depreciation rates translate into useful lives often used in straight-line depreciation models? In Figure 5, we report the estimated useful life of knowledge capital for a firm whose δ_G varies between 0.1 and 0.9. Because the time series of perpetual inventory depreciation is a geometric sequence, the initial gross R&D investment will never converge to zero; thus we estimate the useful life by imputing the number of years to depreciate the initial R&D investment to 10% of its gross value, then impose straight-line depreciation for the remaining 10%.[48] Figure 5 shows that knowledge capital investments generally have an implied useful life between 4.1 and 6.4 years, considerably smaller than the implied useful life for a firm's average PP&E investment.[49] The figure also shows that the literature's assumed average depreciation rate of 16.4% for knowledge capital translates to 14.2 years of useful life, much closer to that found for tangible assets.

As noted in Section 4, our estimation includes year fixed effects. These fixed effects act to connect our estimated book value of intangibles to the market values observed in the acquisition. The exponentiated estimated fixed effects ($\log(\rho_t)$) are shown in Internet Ap-

[48]e.g., a firm with δ_G of 0.22 will have depreciated away 90% of its initial R&D investment over a 10-year period, thus resulting in an estimated useful life of 11 years.

[49]As a comparison, we estimated the implied useful life of firms in the DJIA 30 as of December 2018 by the firm's gross PP&E by its annual depreciation expense. On average, the implied useful life was 17.0 years, ranging between 8 (Microsoft = 8.49 years; Apple = 8.29 years) and 20+ years (McDonald's = 28.5 years; Exxon Mobil = 25.5 years).

pendix Figure IA5, along with deviations from trend of the S&P 500 index. The fixed effects can be interpreted as the average market-to-book of intangibles in acquisitions, relative to the market-to-book in the average year. One should expect the market-to-book of acquisition targets to fluctuate with average market prices, which Figure IA5 demonstrates. The correlation coefficient between these two series is 0.61.

5.2 From parameter estimates to intangible capital stocks

We next apply parameter estimates from our base specification in Table 3 to the intangible capital accumulation process (Equation 7) to the broader CRSP-Compustat universe of firms.[50] The knowledge capital stock accumulates R&D spending following (5), while the organizational capital stock represents the accumulation of SG&A following (6). Both sets of intangible capital stocks use our industry-level estimates of γ and δ_G. Total intangible stock is the sum of knowledge capital, organizational capital and externally acquired intangibles on the balance sheet I_{it} (Compustat *intan*).

5.2.1 Intangible capital stocks by industry and time

The growing importance of disclosing capitalized intangibles to firms' balance sheets is based on the idea that such intangibles are becoming an increasingly important component of how today's firms create economic value. Figure 6a presents time series trends of intangible capital for the four industries. Each series plots intangible intensity, calculated as the average ratio of intangible capital K^{int} ($S_{it} + G_{it} + I_{it}$) to total assets, e.g., intangible and tangible assets (Compustat *ppegt*). As expected, intangible intensities are lowest in consumer and manufacturing industries. Firms in these industries have experienced an increase in the role

[50]We follow Peters and Taylor (2017) in the details of the capital accumulation process such as capital stock initialization. For details see Appendix B2 of their paper.

of intangibles in their total assets since only the late 1990s. In contrast, healthcare and high-tech firms have higher intangible intensities that have each grown continually since the 1970s. The patterns in Figure 6a conform to basic predictions about differences across industries and time and provide the first validation that our estimates measure real economic assets.

Figure 6b explores the relative importance of knowledge versus organizational capital by plotting the ratio of the former to total intangibles K^{int}. Healthcare has the highest intensity of knowledge capital (and thus the lowest organizational capital intensity). Both healthcare and high-tech firms experienced increases in knowledge capital stocks from 1977 – 1996. Since 1996, growth has either stalled (Healthcare) or the levels have fallen back to 1970's levels.[51]

Next, we re-examine the time series behavior of market-to-book ratios with these new capital stocks and compare them with the time series behavior of unadjusted market-to-book ratios. We calculate the average market equity value to book value from the period 1997–2017 for both sets of capital stocks, and run a simple linear regression of

$$\frac{M}{B}_t = \beta_0 + \beta_1 \text{Year}_t + \epsilon_t$$

Figure 2 reports two time-series plots with best-fit lines for the standard ratio and that adjusted using our stocks. Each series excludes our sample of acquirers and targets. Unadjusted (i.e. internal intangibles excluded from assets), the slope coefficient of 0.041, indicates that, on average, the Market-to-Book ratio is drifting upwards by 0.041 per year. After our adjustments for intangible capital, we find the slope coefficient to be 0.012, a decrease in the upward trend of 70%. We view this basic result as a validation that our measure is able to

[51] One possible (yet to be explored) explanation are changes in R&D tax credits (Bloom, Schankerman, and Van Reenen (2013)). Many of these originated in 1981 (a period of increase in Figure 6b).

significantly attenuate the increasing downward bias that results from increasing intangible investments over time.

5.2.2 Comparison to existing methods

To explore how our parameters differ from those commonly used in the literature, we first construct the intangible capital stocks – knowledge, organizational and existing intangibles on the balance sheet – using the BEA R&D depreciation estimates from Li and Hall (2016) and the literature's accepted parameters for organizational capital accumulation ($\gamma = 0.3$, $\delta_S = 0.2$). Recall that for organizational capital we only estimate γ (not δ_S) and thus have one mechanism for estimates of organizational capital to differ. Since we compare our parameters to those commonly used in the literature, it is worth noting that the BEA R&D depreciation rates cover only 10.5% of 4-digit SIC codes and 28% of firm-years in Compustat. The literature commonly assumes a depreciation rate of 15% for non-covered firms, which are the vast majority. At the firm level, for firms covered by the BEA data, the correlation between our estimates and those of Li and Hall (2016) is 0.44.

Figure 7 presents the difference between our estimates ("EPW") and the current methods ("Current"), scaled by the latter. All parameters are time-invariant, so time-series variation stems from changes in the relative use of R&D and SG&A. The differences in our estimated intangible capital stocks relative to those from the literature vary across industries. The "All" line in the figure shows that the new estimate is approximately 10% smaller across all firm-years. Our intangible capital stocks are smaller than commonly assumed in both the consumer and manufacturing industries.

In contrast, our intangible stocks are larger in all years for hi-tech firms and half the years for healthcare. In both cases, higher estimates of δ_G, which imply smaller knowledge capital stocks, are outweighed by larger implied organizational capital investments. Given the larger estimated depreciation of R&D for healthcare (34% vs. 17%), the relatively smaller stocks in healthcare in the 2000s reflect firms' shift from organizational capital to knowledge capital investments. Overall, we find economically meaningful differences in implied stocks compared to existing methods. Next, we validate whether the differences improve the informativeness of capital stock book values.

6 Validation of parameter estimation

We now perform several cross-sectional analyses that can reveal whether the new stocks of intangible capital proposed here provide additional explanatory power over current methods. Note that our estimation of time-invariant, industry-level parameters limits the set of analyses where our estimates offer improvement in this way.[52] The results below demonstrate that the new estimates behave as expected and in many situations out-perform current methods.

6.1 Explaining public firm valuations

Connections between a firm's book value of capital stock and market valuations is closely tied to the large investment-q literature and asset pricing. One explanation for a separation between market and book values is measurement error in the latter, particularly missing intangibles. Our intangible stocks provide an alternative adjustment to book values and an

[52]For example, Table IA2 in the Internet Appendix reports a replication of the "Total Q" investment regressions from Peters and Taylor (2017). The even columns report the same regressions with our new estimated intangible stocks. Given the firm fixed effect specification, this is not an ideal setting for validation or performance improvement since the firm fixed effects absorb all of the cross-sectional differences in intangible capital stocks induced by our parameter estimates. We find that the new stocks explain slightly more of the within-firm investment variation in R&D, while the results are slightly worse for SG&A in healthcare and high-tech.

opportunity to directly compare the current capitalization approach to ours. Our first test for any improvements investigates the relative explanatory power of book value of capital stock for firm's market valuations. This regression typically uses the standard capital stock variable (total assets):

$$M_{it} = \beta_0 + \beta_1 K_{it} + \rho_t + \epsilon_{it}$$

where M_{it} is end of fiscal year market capitalization of firm i, K_{it} is the standard book value of capital stock and ρ_t are year fixed effects. Running this regression for the full 1986–2016 Compustat sample results in a R^2 of 84.4%.[53] If intangibles are capitalized as proposed, then the asset side of the balance sheet should be adjusted, improving the explanatory power of these regression. Here we simply replace K_{it} with our new $K_{it} + K_{it}^{int}$. Using the existing BEA-HH estimates for K_{it}^{int} increases the R^2 to 85.6%. Reassuringly, the R^2 increases slightly more – to 86.1% – when we use our imputed intangible stocks.

Figure 8 presents a reinterpreted version of these results when the regressions are run on an annual basis. Here we estimate the model without capitalized intangibles ("None"), with the BEA-HH and our stock estimates ("EPW") each year, reporting the additional amount of explanatory power as the percent reduction in the residual sum of squares between the two models. The top panel reports the ratio $\frac{RSS* - RSS^{EPW}}{RSS*}$, where $RSS*$ is the residual sum of squares from either the BEA-HH approach or of ignoring off-balance sheet intangibles ("none"). A value greater than zero indicates improved fit.

In every year of our sample, the new measure outperforms the existing BEA-HH approach (red dashed line), with our estimated capital stock adjustments leaving 1-3% less

[53] The regression considers the shorter sample period because the R&D data is imperfect for years prior to 1975 (e.g. Nix and Nix (1992)). Starting in 1986 ensures that we have stocks computed using post-FAS 2 passage R&D.

residual variance unexplained. When comparing our estimated capital stocks to firm capital without any capitalization of intangibles we find an upward trend in the relative explanatory power since 1994. This trend is consistent with the fact that intangible capital has become increasingly important in explaining market values as our economy has become more reliant on organizational and knowledge capital when generating economic value. For years after 2006 we find that our adjustments for intangibles to existing book values of capital stock leave 13-23% less unexplained variance in firm values.

The second panel of Figure 8 presents the formal test statistic for the null hypothesis that the R^2 from EPW and BEA-HH are identical. The solid blue line shows that incorporating our estimate has a statistically significant improvement in the R^2 since 1994 when compared to the baseline. When comparing the explanatory power of our estimated intangible capital stocks to those calculated using the BEA-HH approach (dashed red) the t-statistic in all years since 1992 excluding 1999 is greater than two, suggesting that the improvements are statistically meaningful. In no years does the current capitalization method exhibit more explanatory power. Overall, these results demonstrate that the capitalized intangibles using the parameter estimates from Table 3 have the most predictive power for explaining enterprise value.

6.2 Asset pricing implications

The multi-factor Fama-French model (e.g., Fama and French, 1992, 1993) is a well-established method used in both academia and industry to calculate expected returns. One key component in the Fama-French model is HML (high-minus-low), the realized returns to a portfolio that is long (short) high (low) book equity-to-market equity firms. Given the potential bias in reported book equity from missing intangible capital, we examine whether our intangible adjustments improve the relation between HML and realized returns.

We adjust GAAP reported book equity values with both our intangible stocks (EPW) and those following the BEA-HH parameters. Table 4 compares the summary statistics of the HML pricing factor using these adjustments with traditional HML summary statistics (without adjustments). The table shows that HML returns adjusted for BEA-HH or EPW intangibles are larger in total magnitude, while exhibiting smaller standard deviations than the unadjusted HML portfolio. The unadjusted HML portfolio has an average (monthly) return of 0.28%, while the BEA-HH and EPW-augmented portfolios have monthly returns of 0.38% and 0.43%, respectively. Only the EPW-augmented portfolio's return is significantly larger at conventional thresholds (column 3). The HML portfolio adjusted for EPW intangible capital has a Sharpe ratio of 0.6, 87% higher than the traditional HML portfolio's Sharpe ratio of 0.32.

While the conclusive mechanism for why HML is associated with future returns is beyond the scope of our paper, at least two potential explanations appear consistent with our finding that intangible capital adjustments increase HML portfolio returns. The first explanation is that firms with larger proportions of intangible capital have greater distress risk (Korteweg, 2010) and the second is that the stock market underreacts more to firms with higher levels of intangible capital (Edmans, 2011). Regardless of the exact mechanism, our intangible adjustments to book equity result in changes to construction of the HML portfolio, pushing firms with higher (lower) intangible firms into the long (short) side of the portfolio and thereby increase the return spreads to the HML factor.

6.3 Organizational capital and personnel risk

We next test our measure of organizational capital stocks. Eisfeldt and Papanikolaou (2013) propose a similar capitalization of SG&A used in other earlier work and validate it using textual analysis on 100 10-K filings' "Managerial Discussion" (MD&A) sections. They seek out references for personnel risk in these filings and argue that any firm sorting by a measure of organizational capital should correlate with such mentions. We follow a similar approach, using over 120,000 10-K filings from 2002–2016.[54] We calculate the fraction of words in the MD&A statement that reference risk of personnel loss (keywords: "personnel" or "talented employee" or "key talent"). Firms are split into quintiles based on their organizational capital stock scaled by assets in each year using our measure and the current approach (i.e. $\gamma = .3$, $\delta_S = .2$).

A time-series comparison of the existence of these words between these two quintiles reveals that our measure of organizational capital stock outperforms prior parameters. First, the fraction with some reference of personnel risk in the top quintile versus the bottom is 66% and 52%, respectively across all years. This compares to 58% vs. 52% for the quintiles sorted using the current measures. Figure 9 reports the t-statistic for the difference in means of personnel risk mentions between the top and bottom quintile of organizational capital stock. In all years of the sample period, the difference between top and bottom quintile is significant. In contrast, in only six of fifteen years is the difference significant for the current stock measure (BEA-HH). We conclude that our new measure of organizational capital stock provides more predictive power for firm's assessment of the risks to their human capital.[55]

[54] See `https://github.com/apodobytko/10K-MDA-Section` for the code to run this search.

[55] Reassuringly, sorting firms by our organizational capital stocks (by year) results in similar patterns of firm productivity, size and executive characteristics as found in Eisfeldt and Papanikolaou (2013) (see Internet Appendix Table IA1).

6.4 Organizational capital as brand and employee satisfaction

Our next exercise asks whether our organizational capital stocks exhibit stronger correlations with firm brand quality and employee satisfaction than existing measures. For the former, we collect the top 100 global brands according to Interbrand, a brand consultancy, from 2000 to 2018.[56] We extract the ranking and merge each company (or brand) to U.S. public firms in Compustat.[57] As above, we rank firms by our measure of organizational capital stock and the stock currently used in the literature. An improvement in the capital stock measure will manifest itself into a sharper separation of brand ranks when we compare the top and bottom quintiles of each sort. This is indeed what we find: firms in the top (bottom) quintiles of our organizational capital stock have a higher (lower) rank in brand than the sort using the current methods.

Next, we collect employee satisfaction data from the online firm Glassdoor. The company reports the "Best Places to Work"[58] using reviews posted by current employees. Their coverage includes public and private firms, with data going back to 2014. We merge the annual rankings collected from their website to Compustat and correlate these firms' estimated organizational capital stock with their ranking. The pairwise correlation is 9.9% using our estimated stock versus 6.7% for the existing methods. Although neither correlation is statistically significant (there are only 84 firms over the 2014-2019 sample), the larger correlation for our new estimated stocks may suggest that it better captures features of organizational capital.

[56] See `https://www.interbrand.com/best-brands/best-global-brands/previous-years/2000/` for the raw data.

[57] If two brands from the same firm are on the list, we take the average rank within-firm.

[58] For example, see their 2019 ranking here `https://www.glassdoor.com/Award/Best-Places-to-Work-LST_KQ0,19.htm`.

6.5 Patent valuations and the returns to knowledge capital

An important and relevant class of identifiable intangible capital is patents, in part because the production of patents requires investments in both knowledge and organizational capital. Thus, if our measures of S and G capture intangible investments, then they should correlate with patent valuations and patent quality. Moreover, connecting capital stocks to patent valuations can reveal the private returns to investments in knowledge capital that has thus far been difficult to estimate. What has historically been missing is the same thing that was missing in our setting of intangible capital stocks: prices. Fortunately, Kogan, Papanikolaou, Seru, and Stoffman (2017) provide a new measure of patents valuation from market reactions to patent grants that can be connected to knowledge and organizational capital stocks.

Table 5 presents a regression analysis relating two measures of patent values – market-based and citation-based – with our disaggregated intangible stocks G_{it} and S_{it}. For all Compustat-CRSP firms that pass the traditional filters, we calculate intangible capital stocks and merge on the Kogan, Papanikolaou, Seru, and Stoffman (2017) measures. Only firm-years with patents are available, and all right-hand side variables are lagged one year. Controls include firm and year fixed effects and all variables are scaled by lagged total assets (not including intangibles) and logged. We are thus asking whether changes in intangible capital stocks correlate with above average changes in firm's patent values. Interestingly, one can also interpret the coefficients as estimates of private returns to investments in knowledge or organizational capital.

Several patterns from the results in Table 5 lead us to conclude that our intangible capital stocks are economically meaningful. Column (1) shows the baseline specification with a traditional size control of log sales. Column (2) adds in our knowledge capital stock. The positive and significant loading is consistent with R&D spending being an important part of patent production. The within-R^2 nearly doubles from (1) to (2), suggesting that knowledge capital stocks can explain changes in firm patent valuations. Column (3) considers organizational capital in isolation. The loading is smaller and R^2 is essentially unchanged. The full specification in column (4) demonstrates that the relationship between intangible stocks and patent value (in dollars) comes primarily through the stock of knowledge capital.

The coefficient estimates from column (4) suggest that a 1% increase in knowledge capital results in a .16% increase in patent valuations. To our knowledge, this is one of the first direct measurements of intangible investment returns and is an interesting area of future research.

The last four columns repeat this exercise with the more traditional citation-weighted patent value (e.g., Hall, Jaffe, and Trajtenberg (2005)). The measure of patent value is only weakly correlated with the market measure (.38) and represents value not completely owned by the firm. The results here are different. First, both stocks G and S have meaningful explanatory power as demonstrated in the increased R^2 in (2) and (3). Moreover, the last column shows that both intangible capital stocks load and explain variation in citation-weighted patent value. This result could be explained by the nature of organizational capital investments as modeled in Eisfeldt and Papanikolaou (2014), where such capital is only "partly firm specific" and tied to key employees.

7 Alternative intangible asset prices: market valuations

We have argued that the revealed prices of intangible assets found in acquisitions provide an excellent setting for us to estimate the capitalization parameters for R&D and SG&A. We now explore an alternative setting for estimating the market value of a firm's intangibles, one that is not limited to acquisition targets.[59] The potential benefit of this method is that it does not rely on a potentially selected sample of acquired firms. The trade-off, however, is that the market value of intangible assets used in the estimation is measured with error when the market value of tangible assets is mis-measured. We estimate parameters in this setting and compare the explanatory power of these intangible stocks with our acquisition sample.

Hall (2001) and Gutiérrez and Philippon (2017) interpret the difference between a firm's market value of total assets and book value of tangible assets as unmeasured intangible assets. Implicitly, this assumes that the book value of tangible assets approaches the market value of tangible assets, and thus:

$$MV_{\text{Intangibles}} = MV_{\text{Assets}} - MV_{\text{Tangible}} \tag{12}$$

Therefore, it is possible to estimate intangible market prices from firms that are not acquisition targets. Because accounting data primarily records tangible assets at historical cost, we must assume a markup of tangible assets that converts book to market values.

For publicly traded firms, we can observe market values of equity, but only book values of the following: total liabilities (L), preferred stock (PS), and total assets (A). We assume that book liabilities and book preferred stock trade at par values and, thus, that book values reflect market values. We estimate the market value of total assets as:

[59]We are also aware of an alternate setting where countries that report their accounting standards under International Financial Reporting Standards (IFRS) capitalize the development portion of R&D expenditures. However, we refrain from performing alternate validation for δ_G for firms in the IFRS regime because cross-country variation in investor protection may affect intangible depreciation rates and because the majority of firms in the Compustat sample do not disclose the breakdown of research versus development expenses.

$$MV_{\text{Assets}} = MV_{\text{Equity}} + MV_{\text{Liabilities}} + MV_{\text{Preferred}}$$

Then, the difference between the market value of the firm and these market values of balance sheet items approximate the market value intangible assets:

$$MV_{\text{Intangibles}} = (MV_{\text{Equity}} + L + PS) - MV_{\text{Tangible}} \tag{13}$$

With these imputed intangible prices, we can re-estimate our model in (11) where $MV_{\text{Intangibles}}$ replaces $IIA + GW$ as the price of intangible assets. The limitation, however, is that we do not directly observe MV_{Tangible}, only book values recorded at historical cost. This approach highlights the primary advantage of our acquisition setting – we observe the allocation of prices paid for tangible and intangible assets and market values and thus do not have to make assumptions about asset markups. In contrast, (13) forces us to estimate a markup that converts book assets, A, to market value, MV_{Tangible}. To the extent that our estimated markup of book assets contains error, this error transfers to our imputed intangible prices. We consider three approaches to estimating the markup of tangible assets.

The first assumption is that the markup on the book value of assets is zero, i.e., that gross assets less depreciation are reflective of current market values. Thus, we have:

$$MV_{\text{Intangibles}} = (MV_{\text{Equity}} + L + PS) - BV_{\text{Tangible}}$$

The second approach exploits the data in our acquisition sample on the purchase price of tangible assets. We observe targets' pre-acquisition book value of tangible assets and the price paid. From this, we can estimate an average (5% tail winsorized) markup from 1997–

2016 of tangible assets of 25% (the median is 41%). Equation (13) becomes

$$MV_{\text{Intangibles}} = (MV_{\text{Equity}} + L + PS) - [(PPE_{\text{net}} \times 1.25)] - CA - IN - OA \tag{14}$$

Here, we markup the net PPE and leave current assets (CA), acquired intangibles (IN) and other assets (OA) at book. The third approach assumes that the tangible assets on a firm's balance sheet are valued at the halfway point between gross (i.e., historical) and net values. This is on average a 50% markup over net tangible assets, as the average firm-year has a ratio of gross to net PPE of approximately two. This approach allows the tangible markup to be firm-specific:

$$MV_{\text{Intangibles}} = (MV_{\text{Equity}} + L + PS) - [(PPE_{\text{net}} + (PPE_{\text{gross}} - PPE_{\text{net}})/2)] - CA - IN - OA \tag{15}$$

Finally, as in our main analysis, our parameter estimates require ten years of past R&D and SG&A spending, backfilling where needed. To avoid overlapping time series from a full Compustat estimation (excluding our acquirer-target deal-years), we randomly sample each firm once over its lifetime (after three years of trading) for 1986–2017. We repeat this exercise with several random samples, and the results are robust.

Our first objective is to determine whether sample selection or contaminated prices from acquisitions lead to fundamentally different parameter estimates when compared to this alternative approach. The results in Table 6 suggest not. The table presents the parameter estimates for intangible values (13)-(15) along with our baseline estimates in the first row. The estimates for the "No markup" method exhibit large gammas and in turn imply large investments in organizational capital. As we introduce markups to the tangible assets, these gammas fall without a major change in the depreciation estimate for knowledge capital. The final row, which presents the firm-level markup assumptions, exhibits parameters estimates that are quite close to that from the acquisition methods and for δ_G, are very close to the BEA estimate. We believe that these estimates demonstrate the importance of the purchase price allocation is for our proposed method of retrieving depreciation parameters. The assumptions about markups on tangible assets are ad-hoc and have real impacts on estimates. The largest mark-up assumption gets closest to those from the acquisition approach. Also, our ability to get relatively close to the acquisition method's estimates with these readily-available public valuations is a validation for the method itself.

As in Section 5, we take these estimated parameters from the above and calculate intangible stocks for all Compustat firms. We ask whether this alternative approach for estimating intangible asset stocks improves the informativeness of book values in explaining market values.[60] Figure 10 presents the relative differences in R^2 for the alternative stocks and our acquisition-based stocks. Intangible stocks developed by our parameter estimates from the acquisition sample outperform the three alternatives that use a broader sample of publicly-traded companies (i.e., the higher the line, the better). Other analyses (untabulated) show similar results. These analyses find that intangible stocks implied by the acquisition sample outperform the public market valuations in the human capital and brand ranking tests, while showing similar performance in the HML predictability and employee satisfaction tests.

Overall, the collective sum of our validation tests that compare the efficacy of acquisition price estimates versus a broader sample (Compustat) and public market-based estimates finds that acquisition-based price estimates perform better. These results are consistent with the additional precision gained from directly observing intangible asset allocations outweighing any potential selection issues. Owing to these analyses, we conclude that selection

[60]Note that the alternative method effectively minimizes the distance between the sum of all types of assets and market valuations, so it has an advantage for this test.

issues are unlikely to be a first-order concern when using acquisition-based parameters in the estimation of intangible capital.

8 Assumption validation and robustness

We perform several robustness analyses, beyond those discussed throughout the results above.

8.1 Inclusion of acquisitions in bankruptcy

Panel A of Table 7 reports the main estimation including only the 1521 non-bankruptcy acquisitions. As expected, excluding failed firms from the analysis raises the average fraction (γ) of SG&A that represents an investment in long-lived organizational capital from 0.27 to 0.43, an increase of 59%. The point estimates for δ_G are lower than those in Table 3, with the full sample implying an average depreciation rate of knowledge capital of 27% per year.[61]

Panel B of Table 7 summarizes the validation tests detailed above when using the stocks implied by the non-bankruptcy sample in Panel A. We compare these stocks to our main specification and BEA-HH. Overall, the original stocks imputed by estimated parameters that include bankruptcies ("Baseline") have a higher R^2 in the model estimation, explain more of firm enterprise value in the cross-section, are better able to capture firms with high personnel risk, have a stronger statistical difference with the traditional HML factor and higher R^2 in the patent valuation regressions. The only case where the sample excluding bankruptcies performs better is in the brand ranking test; however, we cannot reject the null that the rankings are different from the baseline. Overall, the parameters from the full

[61]The negative depreciation for "Other" is mainly driven by one acquisition where the target had less than $30m in annual R&D and had acquired intangibles of over $2b (after adjustments).

sample of acquisitions (Table 3) outperforms those of the non-bankruptcy sample.

8.2 Other robustness

Table 8 presents the main specification under alternative sample or methodological assumptions. First, we use the purchase price allocation information made universally available after 2001 with a change in accounting rules. Acquisitions in the earlier years represent a subset of deals that did not use the pooling of interest method. Panel A estimates the model on the post-2001 sample. The "All" rows exhibits little difference with the main results in Table 3. There are some differences in the knowledge capital depreciation rate for the consumer industry, as well as in the fraction of SG&A that is investment for healthcare. Reassuringly, in unreported results, the estimates in Panel A under-perform all the validations presented above.

Panel B repeats the estimation without the adjustment to goodwill discussed in Section 3.2. As expected, the adjustments to goodwill have a large impact on estimates. R&D depreciation rates are 50% higher and the percentage of SG&A that is investment is 37% lower with the adjusted goodwill. These changes demonstrate that our adjustments are controlling for a large part of the synergies and over-payment found in raw goodwill.[62]

The final panel of Table 8 addresses concerns that firms missing R&D in Compustat should not be treated as zero (Koh and Reeb, 2015), or that R&D is strategically allocated to other expense accounts. Panel C removes firms with zero and missing R&D and considers only the subset of targets in the main sample with at least one year of positive reported R&D in Compustat. Estimates in Panel C find that δ_G, on average, increases from 0.33 to 0.37, and that γ increases from 0.27 to 0.34. These overall changes to parameter estimates

[62] These estimates change relatively little between Table 3, which includes all targets and failures, and an estimation which includes only firms which report positive R&D (see Panel C of Table 8 for these results).

are consistent with the removal of firms who may be shifting R&D expenses into SG&A. Untabulated, we compare the stocks of firms using Table 3 coefficients and Table 8, Panel C coefficients and find the correlation between the two sets of stocks to be 92%, reassuring us that any potential bias in reported R&D is unlikely to affect our broader results.

8.3 Parameter choices

Given the inherent difficulties in separately identifying both the fraction of SG&A that is investment and the rate of depreciation (footnote 42). Figure 11a presents the main estimation under alternative assumptions about the rate of organization capital depreciation rates. We consider a range of $[.1, .3]$ for the δ_S and re-estimate equation 11, reporting both the new parameter estimates for γ and δ_G along with the R^2. We find that Figure 11a shows little variation in the estimate of δ_G. As we increase the δ_S from 0.1 to 0.3, the estimated γ increases from .2 to .4. The R^2 from the model estimation (right axis) remains nearly static across these dynamics, varying by only 2%. We conclude two things from this exercise: (1) that our assumed $\delta_S = .2$ is not driving any of our results, and (2) that the pair of (γ, δ_S) is the key assumption for measuring organization capital.

8.4 Estimation within time-period subsamples

We next analyze whether the baseline parameter estimates vary significantly over time. We estimate γ and δ_G for each year using a ten year rolling window. This allows us to investigate the validity of our assumption that γ and δ_G are constant over time, in addition to whether business cycles or merger waves confound our estimates. The estimation is the same as in Section 4 with one exception: rather than estimate year fixed effects within each time-period, the year fixed effects are instead taken from the full sample estimation, reported in Figure

IA5, and imposed within the non-linear least squares estimation.[63]

Figure 11b reports time varying coefficients: γ (blue solid line) and δ_G (red dashed line). Also reported are full-sample estimates of γ (horizontal blue line) and δ_G (horizontal red line). Parameter estimates are static across subsamples with any time-series variation in γ and δ_G being insignificantly different from their full-sample counterparts. In addition to having only small fluctuations over time, γ and δ_G estimates strongly co-move together ($\rho_{\gamma,\delta_G} = 0.81, p < 0.001$). Because higher levels of γ (δ_G) increase (decrease) the accumulation of intangible capital, γ and δ_G variation will offset each other and total intangible stocks will be even less sensitive to any time-series variation. These results complement a similar exercise in Li and Hall (2016), who present some evidence for declining R&D depreciation rates between 1987 and 2007. The results here do not exhibit such trends, consistent with our baseline assumptions about static depreciation and capitalization parameters over time.

9 Conclusion

We use market valuations of acquired intangible assets from 1996 to 2017 to validate parameter estimates of (1) the depreciation parameters for knowledge capital based on prior R&D spending, and (2) the fraction of SG&A capital that represents investment into long-lived organizational capital.[64] The resulting parameter estimates imply significant cross-sectional variation in capitalization parameters and we show that our new industry-level variation and price data result in a better measure of intangible stocks when compared to existing approaches. The improvements manifest themselves in the stocks' ability to explain market

[63]This leaves in place the identifying assumption from the main estimation that the time-series average market-to-book of intangibles is unity over the entire sample, 1995–2017, rather than within each 10-year window.

[64]Implied stocks and estimation parameters are available for public download and usage at `http://bit.ly/intan_cap`.

enterprise values, expected returns, human capital and brand rankings.

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10 Figures and tables

Figure 1: Capital expenditures, R&D and SG&A: 1977–2017

The figure reports the sum of capital expenditures ('capex'), R&D ('xrd') and SG&A ('xsga') for Compustat firms outside of finance, mining, real estate and utilities, scaled by the total sales in the year (2012 dollars).

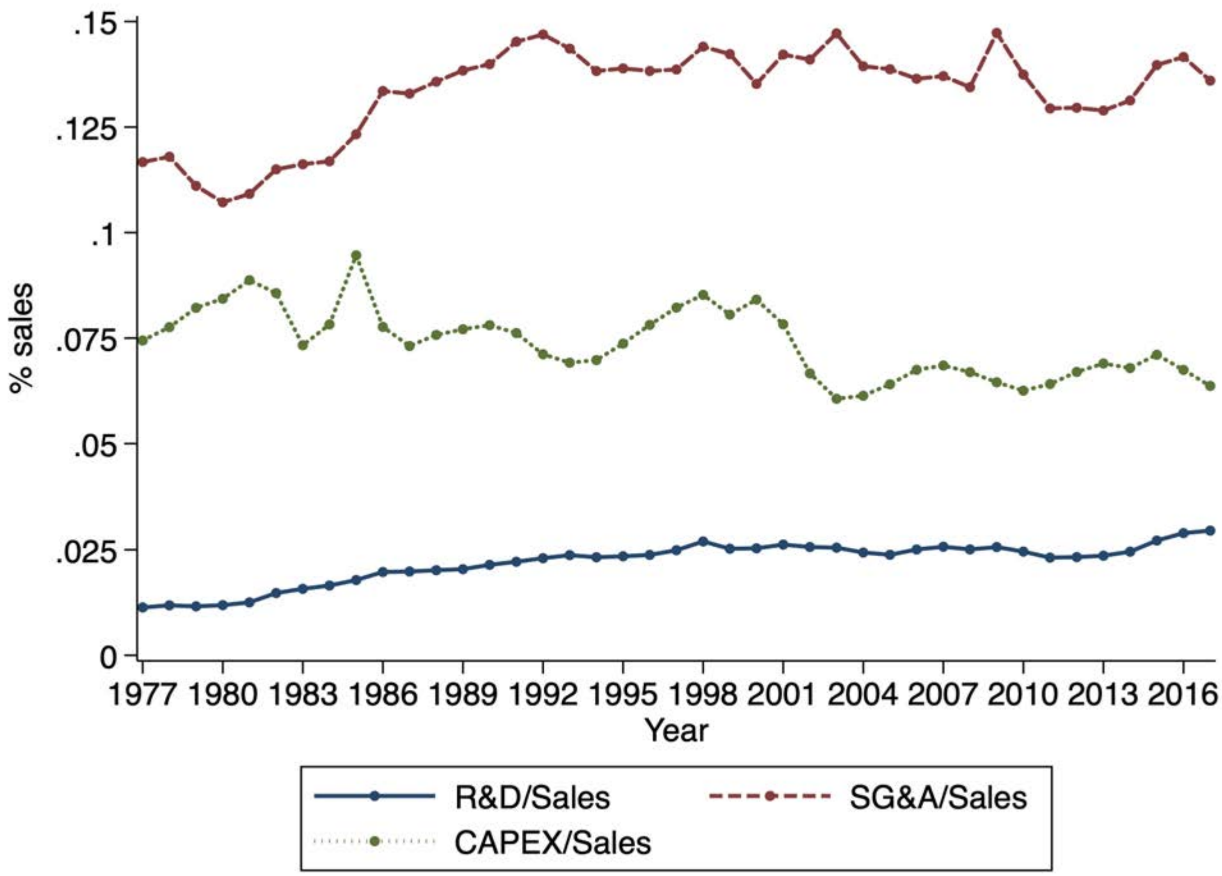


Figure 2: Market-to-book with and without intangibles: 1977–2017

The figure reports the average (2.5% tail winsorized) market-to-book for Compustat firms outside of financials, mining, real estate, utilities and all acquiring firms in our sample. The numerator in both series is the sum of market value of equity at the end of the fiscal year, total liabilities and book preferred stock. For the blue circle series, the denominator is total assets (including acquired intangibles). For the green diamond series, the denominator also includes the knowledge and organizational capital stocks estimated using the parameters in Table 3. The two dotted red lines present the simple linear fit of each series.

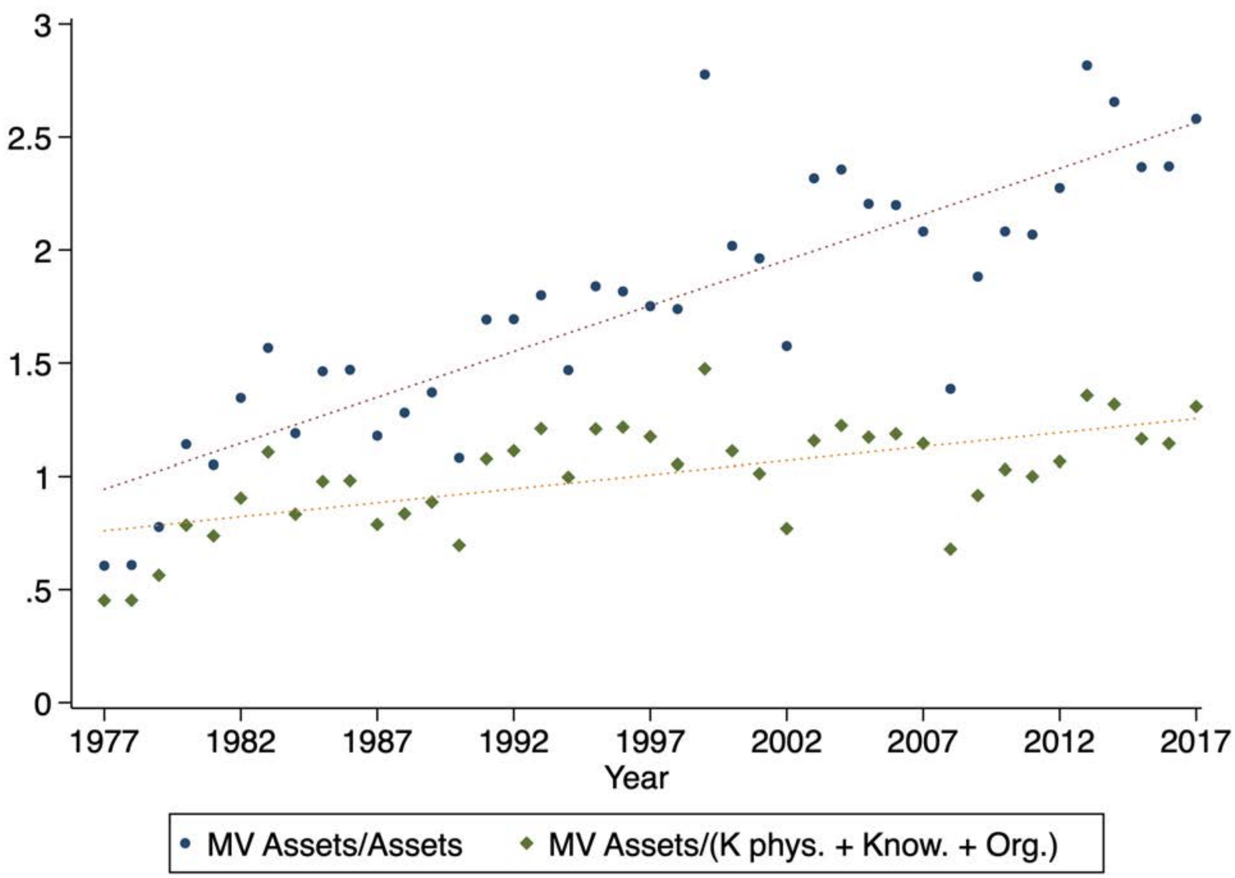
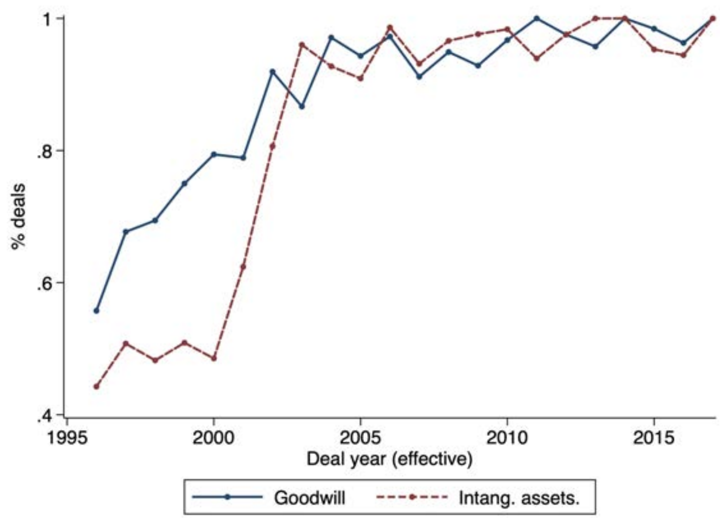


Figure 3: Percentage of acquisition deals with non-zero intangible assets or goodwill

The figure in Panel A reports the percentage of all acquisitions in the sample (see Section 3) that have non-zero intangible assets or goodwill acquired. The deals included are those where we could find a purchase price allocation in the target's 10-K, 10-Q, S-4 or 8-K. Panel B reports the percentage of all deal dollars in our sample of acquisitions (see Section 3) associated with deals that have non-zero goodwill or intangible assets acquired. So the "Goodwill" figure is the annual sum of transactions with some positive goodwill divided by the total amount of transaction dollars in that year.

(a) Prevalence of IIA and goodwill



(b) Deal-weighted

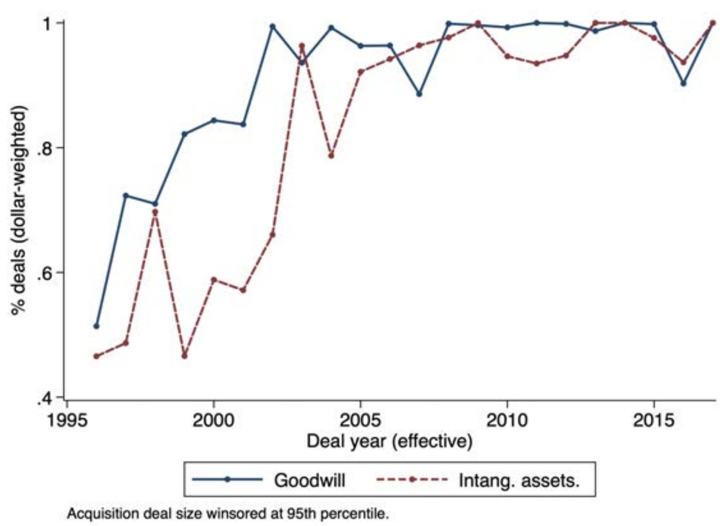


Figure 4: Percentage of acquisition deal size for intangible assets

The figure reports the average percentage of an acquisition deal size (i.e., enterprise value of the deal) attributed to goodwill, intangible assets (IIA) and their sum. The sample is the subset of acquisitions (see Section 3) associated with deals that have non-zero goodwill or intangible assets acquired.

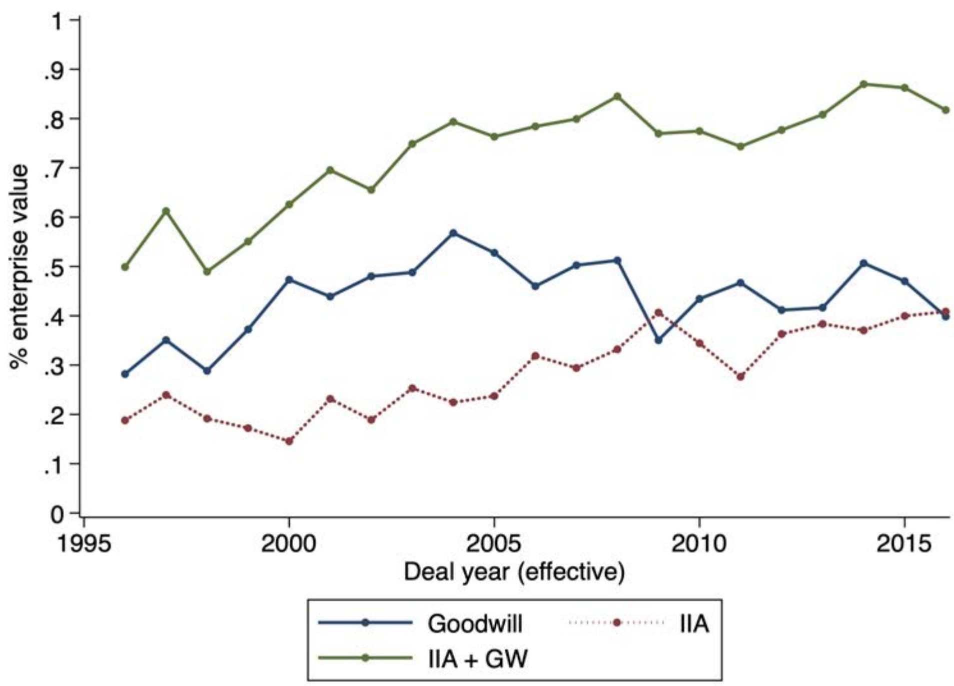


Figure 5: Implied useful lives: knowledge capital depreciation rates

The figure reports the implied useful life based on δ_G estimates in Table 3. The implied useful life is estimated by imputing the number of years to depreciate the initial R&D investment to 10% of its gross value, then assuming straight-line depreciation at a rate equal to the average depreciation rate used over the initial 90% of the firm's depreciation. Industry classifications are identical to those used in Table 3. "Literature" represents the useful life for $\delta_G = 0.164$, the average of all parameter assumptions used in most prior studies.

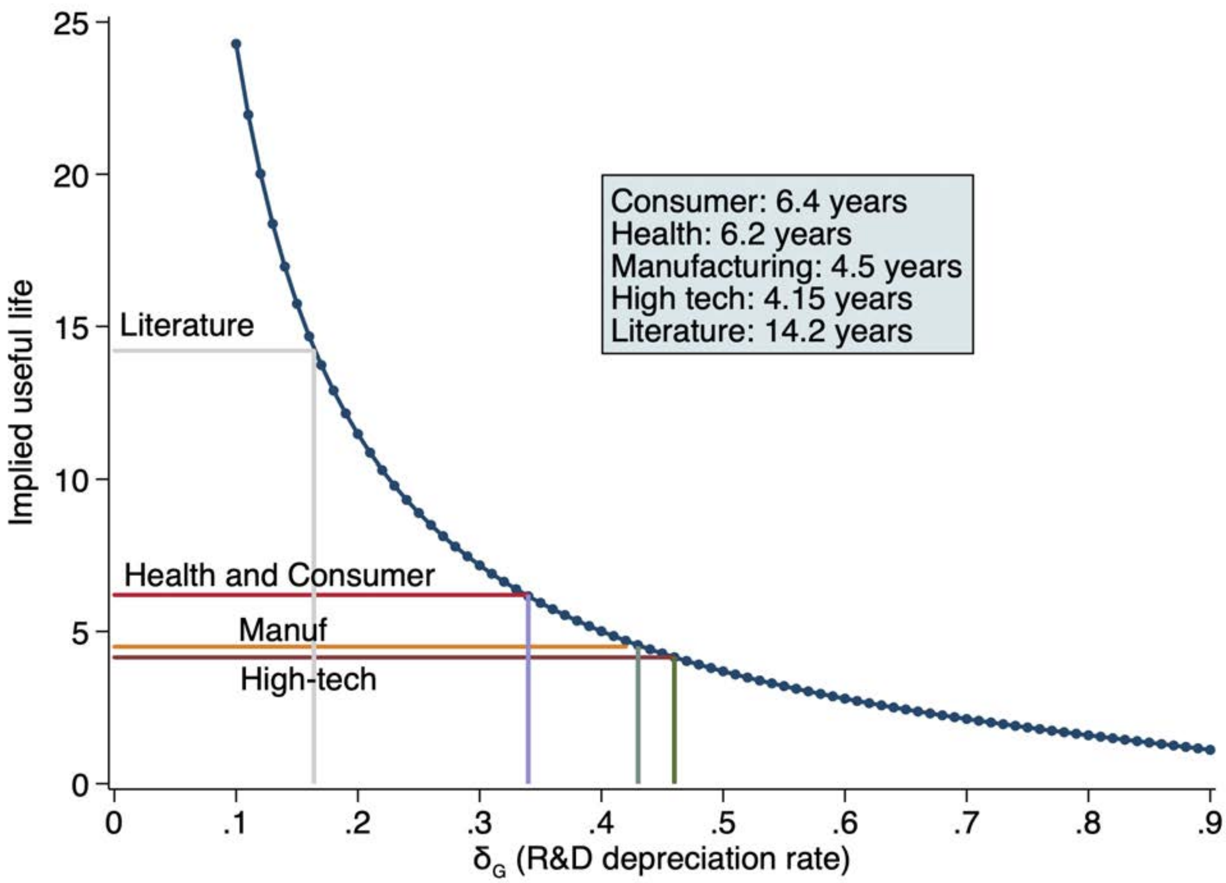
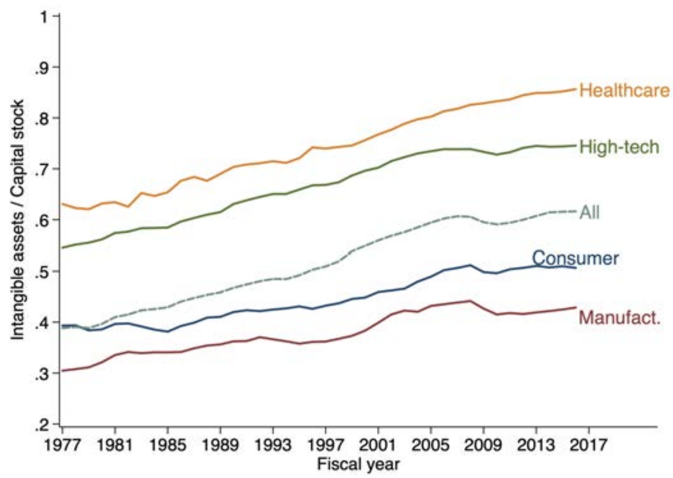


Figure 6: Intangible assets intensities

(a) Intangible asset intensity

The figure reports the ratio of total intangibles – capitalized using our method and those on the balance sheet – scaled by total capital stock (PPE + intangibles): $\frac{K^{int}}{K^{int}+K^{phy}}$. across all (mean) firms within each industry-year. K^{int} is the sum of knowledge and organizational capital using the estimates from Table 3 and a firm's previous 10 years of R&D and SG&A expenditures and its externally acquired goodwill and intangibles. K^{phy} is the firm's PPE (gross). The "All" line reports the mean across all firms. The "Other" industry is not reported separated, but included in the "All" series.



(b) Knowledge capital as a fraction of total intangible capital

The figure reports of the ratio of knowledge capital – the accumulated R&D using the estimates from Panel A of Table 3 – to total intangibles (sum of knowledge and organizational capital) averaged across all firms in each industry-year.

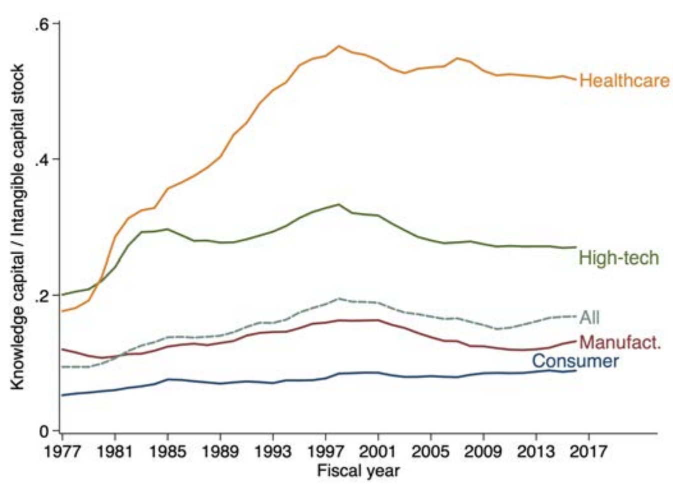


Figure 7: Comparing intangible stocks: new methods versus existing BEA-HH/Literature

The figure reports percent difference between the stocks constructed using the current capitalization method (i.e., BEA-HH and existing literature) and that proposed in this paper ("EPW"). A positive percentage difference implies that the proposed alternative implies a larger intangible capital stock than current methods. Averages by year and within-industry are reported.

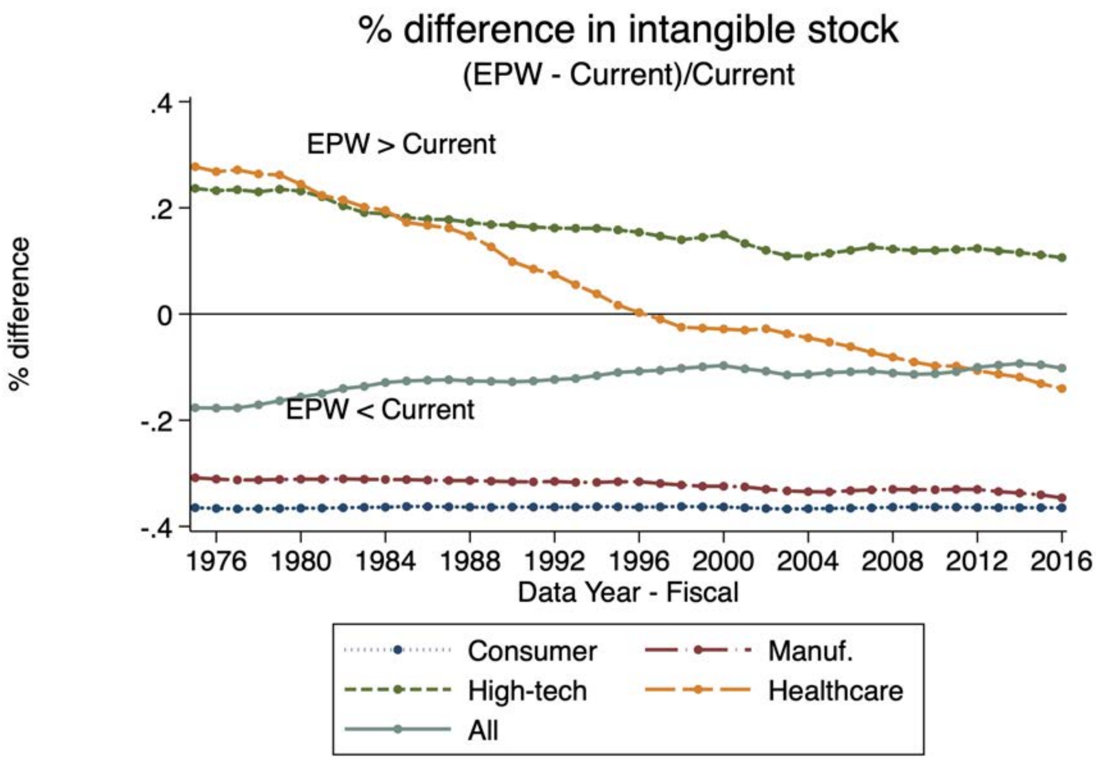


Figure 8: Comparing model fit of intangible capital stock measures

The figure reports the additional explanatory power of the estimated capital stock over other commonly used capital stocks in annual regressions of the log firm enterprise value (market capitalization plus debt) on the log of capital stock, calculated as

$$\frac{RSS* - RSS^{EPW}}{RSS*}$$

where RSS represents the residual sum of squares from the regression models. The underlying regression is:

$$M_{it} = \beta_0 + \beta_1 K_{it} + \rho_t + \epsilon_{it}$$

where M_{it} is end of fiscal year market capitalization of firm i,K_{it} is the standard book value of capital stock and ρ_t are year fixed effects. The sample excludes all company-years associated with the acquisitions or bankruptcies in the estimation.

Capital stocks for "none" use the traditional total asset measure (Compustat 'at'). The "EPW" model adds to this asset the intangible stocks using our parameter estimates. The "BEA-HH" model uses the existing estimates of intangible stocks and the Hulten and Hao (2008) γ of 0.3. A number greater than zero indicates that estimated capital stocks have stronger explanatory power. The solid line compares the EPW model to the model without capitalized intangibles. The dashed line compares our method to that of using the existing BEA estimates. The second panel reports the t-statistics from the test of the hypothesis that the R^2 using EPW is the same as the R^2 from BEA-HH. The test statistic uses the influence function method to compare the two separate model statistics. In the second panel, the horizontal lines represent t-statistics of 1.96 and -1.96.

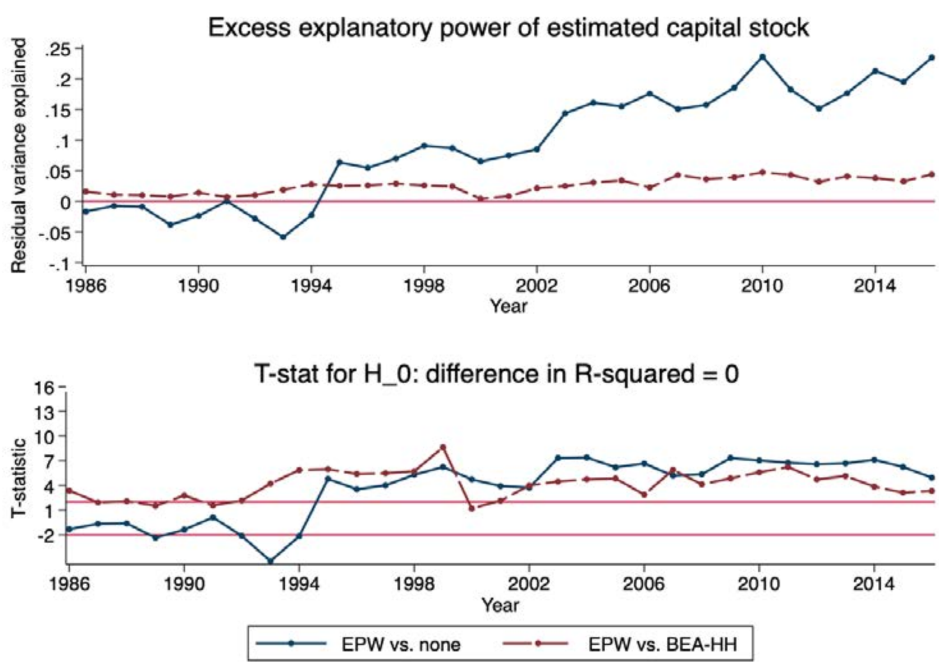


Figure 9: Testing differences in rates of 10-K mentions of "personnel" or "key talent"

In each fiscal year, we sort firms into quintiles based on their organizational capital stock using our depreciation rates (see Table 3) and those currently ("Current") used in the literature ($\gamma = .3$ and $\delta_S = .2$). In each year, consider the firm-level variable that is one if the firm's 10-K mentions "personnel", "key talent" or "talented employee," zero otherwise. The figure report the t-statistics (each year) for the difference in mean test for the top vs. bottom quintiles. "EPW" are the t-statistics from our measure and "Current" are from the sorts using existing depreciation rates. The red horizontal line is at $t = 1.96$.

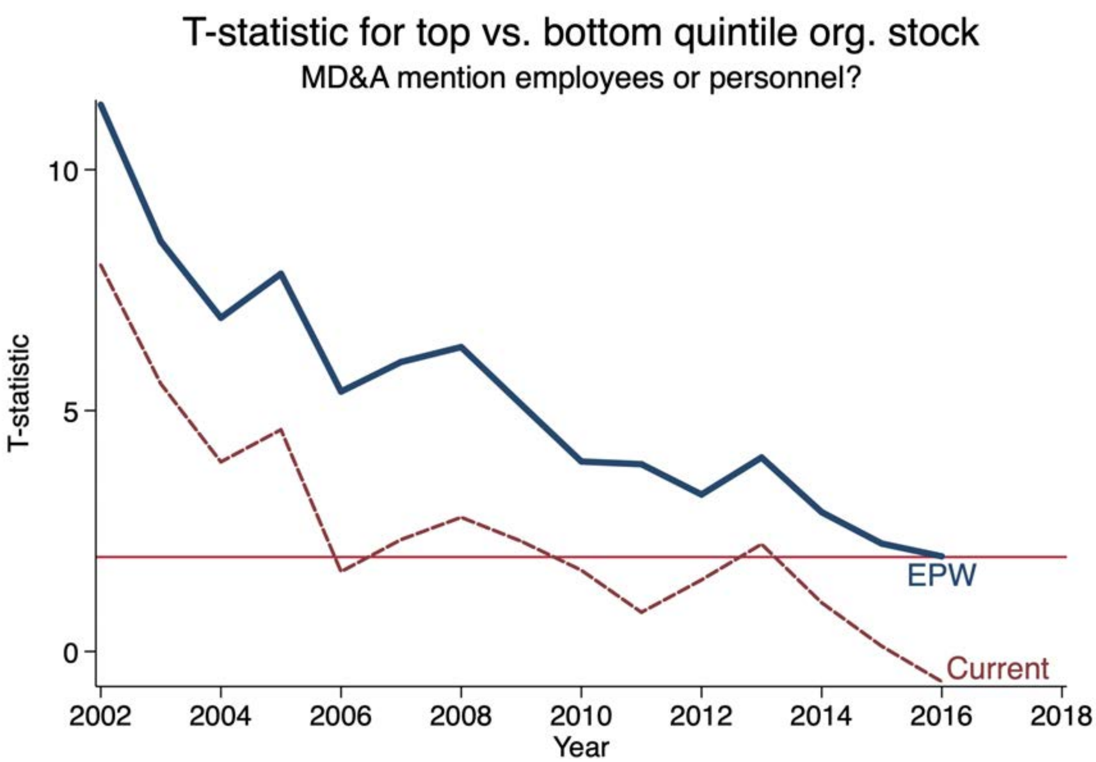


Figure 10: Comparison to an estimation using public market prices

The figure reports the additional explanatory power of the estimated capital stock using our measure ("EPW") over those from the estimation using the public market estimation detailed in Section 7. The difference is calculated as

$$\frac{RSS * - RSS^{EPW}}{RSS*}$$

where RSS represents the residual sum of squares from the regression models. The underlying regression is:

$$M_{it} = \beta_0 + \beta_1 K_{it} + \rho_t + \epsilon_{it}$$

where M_{it} is end of fiscal year market capitalization of firm i, K_{it} is the standard book value of capital stock and ρ_t are year fixed effects. Capital stocks for "none" use the traditional total asset measure (Compustat 'at'). "EPW vs. No markup" compares our measure to the intangible asset value implied by assets without markup. "EPW vs. 25% markup (mean acq.)" reports the same but after marking up tangible assets 25% for the public market estimation. "EPW vs. firm-level markup" uses tangible asset markets that are the average of a firm's current year gross vs. net PPE. A number greater than zero implies that EPW explains more of the variation in market valuations in the year.

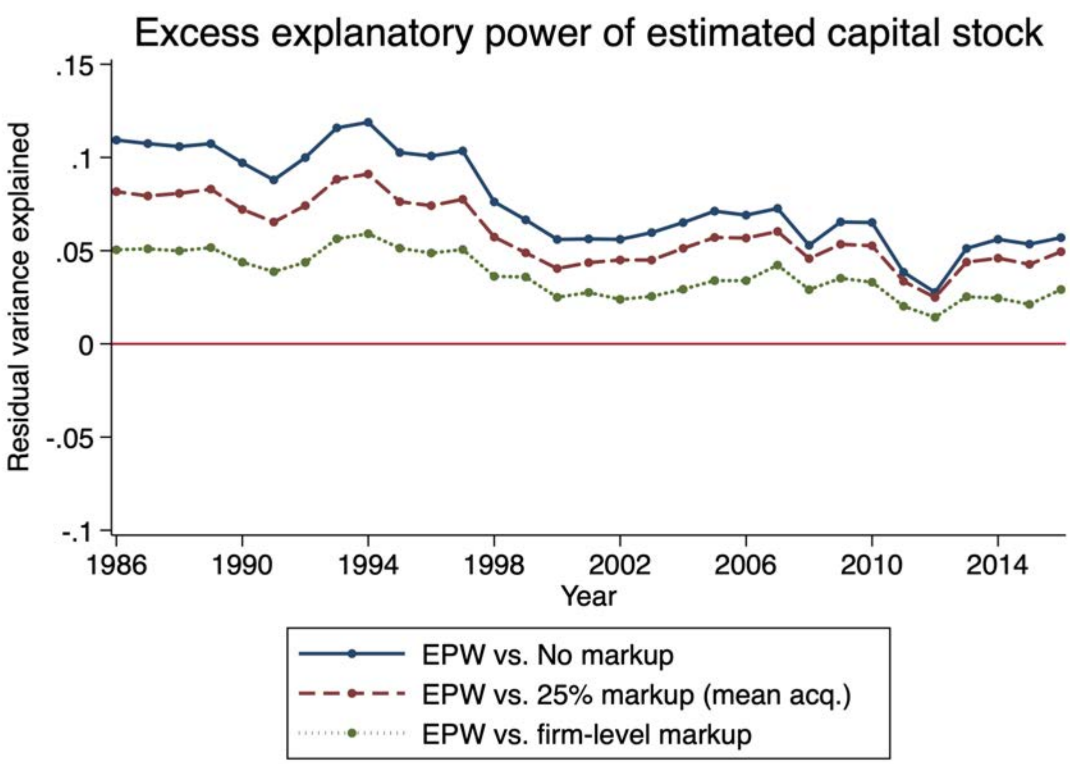
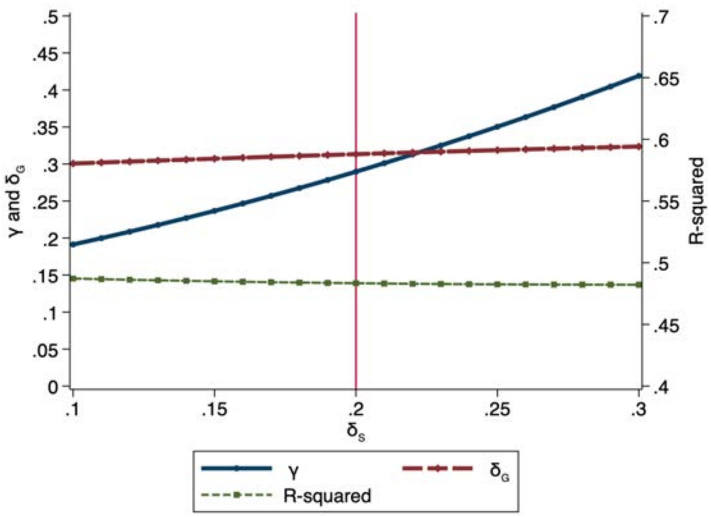


Figure 11: Robustness: organizational stock assumption and time-varying parameters

(a) Estimation sensitivity under different organizational stock depreciation assumptions

The figure reports the results of re-estimating the main model for different values of the organizational stock depreciation parameter δ_S. Recall that our main results assume that $\delta_S = .2$. Here we vary this parameter and present the estimated γ (fraction of SG&A that is investment), δ_G (the knowledge capital depreciation rate) and the R^2 from the estimation. The vertical red line indicates the main model assumption. The left y-axis reports the parameter estimates and the right y-axis reports the R^2.



(b) Rolling Estimates of Parameter Values in 10-Year Windows

The figure reports estimates of γ (the fraction of SG&A which represents investment in long-lived organizational capital; blue, solid line) and δ_G (the depreciation rate of knowledge capital; red, dashed line) from the non-linear least squares estimation of equation (11) run on rolling 10-year windows of events. The horizontal axis reports the first year of the subsample window. The blue and red horizontal lines represent the full-sample point estimates of γ and δ_G, respectively, from Table 3.

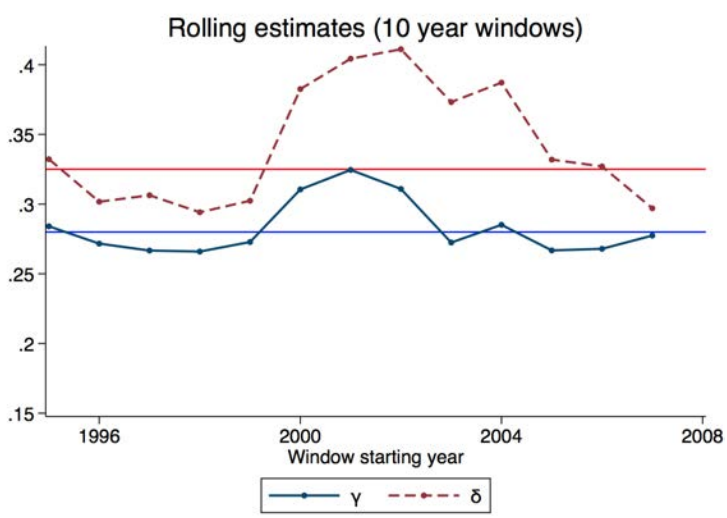


Table 1: Summary statistics for sample of found deals in model estimation.

Summary statistics for observable characteristics of deals, targets and acquirers for the sample of acquisitions in the main estimation. Panel A reports the characteristics of the acquisition sample and Panel B reports the characteristics of the failure sample. Variable definitions found in Appendix Table A1.

	Panel A: Deals in model sample (acquisitions)					
	Obs	Mean	Min.	Median	Max	Std dev
Deal effective year	1,521	2005.02	1996.00	2004.00	2017.00	6.02
Year announced	1,521	2004.72	1995.00	2004.00	2017.00	6.02
Manufacturing firm (target)	1,521	0.11	0.00	0.00	1.00	0.31
Consumer firm (target)	1,521	0.23	0.00	0.00	1.00	0.42
High-tech firm (target)	1,521	0.40	0.00	0.00	1.00	0.49
Enterprise value of transaction (mil)	1,521	2522.25	0.80	444.28	235456.36	9583.32
Value of Transaction (mil)	1,521	2145.85	0.59	385.22	213641.79	8329.79
Target EBITDA LTM (mil)	1,457	142.92	-7430.77	13.78	14080.53	718.85
Target Total Assets (mil)	1,503	1205.32	0.43	200.76	66446.13	4359.60
Target Net Sales LTM (mil)	1,489	1113.10	-35.17	193.75	67343.40	3763.57
CA HQ (target)	1,521	0.28	0.00	0.00	1.00	0.45
NY HQ (target)	1,521	0.06	0.00	0.00	1.00	0.24
CA HQ (acq.)	1,521	0.24	0.00	0.00	1.00	0.43
NY HQ (acq.)	1,521	0.10	0.00	0.00	1.00	0.29
Goodwill (mil)	1,521	1119.79	-5.54	161.11	52730.25	3479.91
Adjusted goodwill (mil)	1,521	772.04	-2985.72	67.21	36460.48	2807.19
Total intangibles (IIA + GW, mil)	1,521	2035.27	-5.54	272.78	170875.33	7999.14
Total intangibles (IIA + Adj. HW, mil)	1,521	1687.52	-1231.19	175.81	167889.61	7527.35
IIA / IIA + GW (if positive)	1,466	0.38	0.00	0.34	1.00	0.32
Total intangibles / Total deal size (all)	1,521	1.31	-0.11	0.85	411.69	11.09
Total intangibles / Total deal size (< 1)	1,051	0.64	-0.11	0.72	1.00	0.29
Total intangibles / Total ent. value (all)	1,521	0.75	-0.10	0.77	35.41	0.96
Total intangibles / Total ent. value (< 1)	1,244	0.63	-0.10	0.70	1.00	0.28

	Panel B: Deals in model sample (failures)					
	Obs	Mean	Min.	Median	Max	Std dev
Year failed	479	2002.99	1996.00	2001.00	2017.00	5.50
Manufacturing firm	479	0.10	0.00	0.00	1.00	0.30
Consumer firm	479	0.37	0.00	0.00	1.00	0.48
High-tech firm	479	0.22	0.00	0.00	1.00	0.41
Total assets (2012 USD)	469	253.29	0.31	67.28	6562.80	628.68
Net income (2012 USD)	444	-80.64	-9919.58	-10.49	95.52	537.74
Total intangibles	452	19.75	0.00	1.57	661.05	58.26

Table 2: Summary statistics for sample of acquisitions in and out of sample.

Summary statistics of deal characteristics of deals in our main sample and those that were excluded. Excluded deals are described in Section 3 and are generally those acquisitions where we could not find the purchase price allocation in the acquirer's financial statements. The starting sample of potential acquisitions were all U.S.-based public firm acquisitions or public targets outside of finance, mining, real estate and utilities from 1996–2017 where we could match both firm's to Compustat.

	Included acquisitions				Excluded acquisitions			
	Obs	Mean	Median	Std dev	Obs	Mean	Median	Std dev
Deal effective year	1,521	2005.02	2004.00	6.02	588	2002.63	2001.00	5.62
Year announced	1,521	2004.72	2004.00	6.02	588	2002.30	2001.00	5.66
Manufacturing firm (target)	1,521	0.11	0.00	0.31	588	0.12	0.00	0.33
Consumer firm (target)	1,521	0.23	0.00	0.42	588	0.28	0.00	0.45
High-tech firm (target)	1,521	0.40	0.00	0.49	588	0.33	0.00	0.47
Enterprise value of transaction (mil)	1,521	2522.25	444.28	9583.32	588	1941.54	226.19	6838.77
Value of Transaction (mil)	1,521	2145.85	385.22	8329.79	588	1586.12	177.82	6013.43
Target EBITDA LTM (mil)	1,457	142.92	13.78	718.85	526	207.39	10.12	1602.82
Target Total Assets (mil)	1,503	1205.32	200.76	4359.60	555	1246.84	148.93	4199.13
Target Net Sales LTM (mil)	1,489	1113.10	193.75	3763.57	542	1012.73	124.34	3513.33
CA HQ (target)	1,521	0.28	0.00	0.45	588	0.21	0.00	0.41
NY HQ (target)	1,521	0.06	0.00	0.24	588	0.09	0.00	0.28
CA HQ (acq.)	1,521	0.24	0.00	0.43	588	0.16	0.00	0.37
NY HQ (acq.)	1,521	0.10	0.00	0.29	588	0.13	0.00	0.33

Table 3: Parameter Estimates from Non-linear Least Squares Estimation

Parameter estimates are based on non-linear least squares regressions of the price of intangible target firm assets, as reported on acquiring firm financial disclosures, on cumulated intangible assets:

$$log(1+P^I_{it}) = log(\rho_t) + log(I_{it} + \sum_{k=1}^{10}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=1}^{10}(1-0.2)^k \gamma \text{SG\&A}_{i,t-k} + 1)$$

where P^I_{it} is the price paid for IIA and goodwill (adjusted) and I_{it} are the target's pre-acquisition balance sheet intangibles. Th year fixed effects (ρ_t) are constrained to an average of 0 (log of 1) across all years. In the case of firm failures, acquisition prices are the average debt-holder recovery from bankruptcy available from Moody's analytics or the average recovery by four-digit SIC code where using the book value of debt prior to the failure. To get total intangibles for failures, we use the average fraction of acquired intangibles to total deal size in the same industry from the acquisition sample.

The first column reports the estimates of γ, the fraction of SG&A that is investment. The δ_S is assumed to be 0.2 (i.e., not estimated). The δ_G column reports the estimate of R&D depreciation rate. Pseudo R^2 estimates are calculated as the percent improvement in the exponentiated root mean squared error relative to a model which includes only a constant. As a comparison, the column with the header "$\bar{\delta}^{BEA}_G$" reports the average R&D depreciation rates from Li and Hall (2016) for SIC codes in each of the major industry groups (one obs. per SIC). The column "$\bar{\delta}^{lit}_G$" reports the same average where we follow the literature and replace missing parameters with 0.15. Bootstrapped (1000 replications at the firm-level) standard errors reported in parentheses. N reports the number of unique firms in the estimation. Firms can have up to ten years of financial data. The "All" row reports the pooled sample estimates, while all other rows are separate estimations for the Fama-French 5 industry classifications adjusted as discussed in Section 5 (code available `http://bit.ly/intan_cap`).

	Estimates				Previous estimates	
	γ	δ_S	δ_G	N	$\bar{\delta}^{BEA}_G$	$\bar{\delta}^{lit}_G$
All	0.27	0.20	0.33	2000	0.28	0.164
	(0.024)		(0.037)			
Consumer	0.19	0.20	0.33	511	0.31	0.153
	(0.026)		(0.29)			
Manufacturing	0.22	0.20	0.42	233	0.25	0.156
	(0.056)		(0.168)			
High Tech	0.44	0.20	0.46	715	0.315	0.255
	(0.055)		(0.072)			
Health	0.49	0.20	0.34	245	0.181	0.172
	(0.135)		(0.065)			
Other	0.34	0.20	0.30	296	N/A	0.15
	(0.064)		(0.195)			

Pseudo-R^2: .515

Table 4: The value premium: including intangibles in book value

The table reports summary statistics for HML portfolio returns for three measures of book equity from 1976 through 2017. The Fama-French HML is constructed as in Fama and French (1992). The BEA-HH HML is similarly constructed, but augmented with the BEA-HH measure of internally generated intangible assets. The EPW HML is instead augmented with the intangible capital stocks implied by the parameters in table 3. Returns are reported in percentage points per month. The column "P(=FF)" reports the p-value of the t-test with the null hypothesis that the mean of the monthly returns is equal to that of the traditional HML measure. The Sharpe ratio is annualized.

HML	Obs	Mean	P(=FF)	St. Dev.	Sharpe
Fama-French	498	0.28		2.96	0.32
BEA-HH	498	0.38	0.12	2.46	0.53
EPW	498	0.43	0.05	2.49	0.60

Table 5: Relationship between firm patent valuations and firm intangible assets

The table reports regressions of patent value from Kogan, Papanikolaou, Seru, and Stoffman (2017) using two alternative measures. A unit of observation is a firm-year where the patent valuation variables are available (i.e., the firm had a granted patent(s) to measure). The columns headed "Market-weighted" use the log of market valuation of granted patents in the firm-year, while the columns under the "Citation-weighted" present values of patents measured as the log ((sum of citations received in that year scaled by citations received by patents in the same industry-year)/(lagged total assets)). The control "Log knowledge K" is the log (plus 1) of the estimated knowledge capital from the parameter estimates in Table 3 concerning R&D (e.g. δ_G). The control "Log org. K" presents the same measure, but using past SG&A and the parameters γ and .2 in Table 3. The variable "Balance sheet intan." is the total identifiable intangibles (including goodwill) on the firm's balance sheet. All measures are scaled by previous year total assets (Compustat "at") and all balance sheet items are lagged one year. All specifications include firm and year fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Market-weighted				Citation-weighted			
Log knowledge K		0.17***		0.16***		0.39***		0.34***
		(0.019)		(0.022)		(0.026)		(0.026)
Log org. K			0.061***	0.010			0.29***	0.19***
			(0.022)	(0.024)			(0.031)	(0.028)
Balance sheet intan.	-0.00099	-0.0040	-0.0021	-0.0045	0.037***	0.030***	0.034***	0.029***
	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0071)	(0.0068)	(0.0072)	(0.0069)
Log sales	0.25***	0.19***	0.21***	0.19***	0.34***	0.20***	0.16***	0.10***
	(0.021)	(0.021)	(0.024)	(0.024)	(0.024)	(0.024)	(0.028)	(0.025)
Observations	39848	39848	39675	39675	39848	39848	39675	39675
R^2	0.76	0.76	0.76	0.76	0.82	0.84	0.83	0.84
Within-R^2	0.013	0.025	0.014	0.025	0.028	0.10	0.063	0.11
Firm FE?	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y

Table 6: Parameter Estimates: Public market valuations

The table reports the parameter estimates for the alternative model using public market valuations of Compustat firms for intangible assets. The first row "Baseline" reports the original estimates using acquired intangible valuations from Table 3. The last three rows present the estimates for three different markup assumption for tangible assets when computing the implied intangible values from traded firms. See Section 7 for details.

	γ	δ_S	δ_G	N	$\bar{\delta}_G^{BEA}$	$\bar{\delta}_G^{lit}$
Baseline	0.27	0.20	0.33	2000	0.28	0.164
No Markup	0.53	0.20	0.24	15,054	0.28	0.164
25% markup	0.45	0.20	0.23	15,054	0.28	0.164
Firm-level markup	0.39	0.20	0.27	15,054	0.28	0.164

Table 7: Parameter estimates and validation tests: excluding acquisitions in bankruptcy

The table reports the main estimation found in Table 3 after excluding the sample of acquisitions in bankruptcy. Panel A reports the parameter estimates and bootstrap standard errors. Panel B summarizes the validation or fit tests. "Pseudo-R^2 from estimation" is the fit statistic from the model estimation. For the BEA-HH column, we report the fit from the estimation where we plug in the BEA-HH parameters and use the estimated fixed effects from the main specification. "Market reg. RSS increase vs. BEA" reports the average increase (or decrease) in the additional explanatory power in the regression presented in Figure 8 compared to the BEA-HH parameters. "Personnel risk" reports the fraction of years from 2002–2018 where the t-statistic from the test of organizational stock sorts for personnel risk (see Section 6.3). "Adjusting book value" reports the p-value of the t-test with the null hypothesis that the mean of the monthly returns is equal to that of the traditional HML measure. "Market value of patent regression R^2 " is the within-R^2 from column 4 of Table 5. "Brand ranking" reports the average brand ranking for firms in the top vs. bottom quartile of firms sorted by the estimated organizational capital stocks (scaled by total assets).

Panel A: Excluding acquisitions through bankruptcies

	γ	δ_S	δ_G	N
All	0.43	0.20	0.27	1521
	(0.039)		(0.041)	
Consumer	0.38	0.20	0.31	335
	(0.061)		(0.331)	
Manufacturing	0.24	0.20	0.23	186
	(0.074)		(0.194)	
High Tech	0.58	0.20	0.39	612
	(0.073)		(0.067)	
Health	0.62	0.20	0.23	218
	(0.204)		(0.081)	
Other	0.52	0.20	-0.14	170
	(0.119)		(0.221)	
	Pseudo-R^2: .423			

Panel B: Comparing results

Test / Validation	Exc. bank.	Baseline	BEA-HH
Pseudo-R^2 from estimation	.423	.515	.48
Market reg. RSS increase vs. BEA (Figure 8, Panel A)	-.097	.025	N/A
Personnel risk: % years with org. stock sort t-statistic > 1.96	86%	100%	53%
Adjusting book value: H_0: monthly ret. different from FF (Table 4 column 3, p-value)	.08	.05	.12
Market value of patent regression R^2 (Table 5, column 4)	.02	.025	.023
Brand ranking: top quartile vs. bottom quartile rank	34 vs. 52	36 vs. 51	42 vs. 49

Table 8: Parameter Estimates: Robustness tests

Panel A of the table reports the parameter estimates as found in Table 3 for the set of companies acquired after 2001. Panel B of the table reports the parameter estimates as found in Table 3 where we do not adjust the goodwill for synergies and over-payment (see Section 3.2). Panel C reports the parameter estimates after excluding all targets with zero R&D over their pre-acquisition period.

Panel A: Post-2001 deals				
	γ	δ_S	δ_G	N
All	0.25	0.20	0.31	1152
Consumer	0.13	0.20	0.07	217
Manufacturing	0.20	0.20	0.41	122
High Tech	0.46	0.20	0.49	450
Health	0.80	0.20	0.38	181
	Pseudo-R^2: 0.632			

Panel B: Unadjusted goodwill prices				
	γ	δ_S	δ_G	N
All	0.43	0.20	0.22	2000
Consumer	0.27	0.20	0.05	511
Manufacturing	0.46	0.20	0.31	233
High Tech	0.71	0.20	0.38	715
Health	0.71	0.20	0.21	245
	Pseudo-R^2: 0.53			

Panel C: Targets with positive R&D				
	γ	δ_S	δ_G	N
All	0.34	0.20	0.37	1208
Consumer	0.29	0.20	0.46	96
Manufacturing	0.22	0.20	0.38	170
High Tech	0.39	0.20	0.45	641
Health	0.57	0.20	0.35	239
	Pseudo-R^2: 0.533			

Appendix

Table A1: Variables and definitions of terms

The table presents variable and term definitions used throughout the paper.

Variable/Term	Definition
Variable/Term	**Definition**
Deal effective year	Year the acquisition was completed.
Year announced	The year that the acquisition was announced to the public.
Services firm (target)	An indicator equal to one if the acquisition target is in the services sector.
Value of transaction (mil)	The total value of the acquisitions (in 2012, USD millions) as reported in SDC.
Target Net Sales LTM (mil)	The last twelve month net sales for the target firm at the time of acquisition (2012 USD).
Target EBITDA LTM (mil)	The last twelve month EBITDA for the target firm at the time of acquisition (2012 USD).
Target total assets	Total assets of the acquired firm at the time of acquisition (2012 USD).
CA HQ (acq.)	An indicator variable that is equal to one if the firm is headquartered in California.
NY HQ	An indicator variable that is equal to one if the firm is headquartered in New York state.
Intangible assets (IIA)	The total identified intangible assets from the acquisition revealed through the purchase price allocation. Reported in millions (2012 USD).
Goodwill (mil)	The total goodwill allocated in the acquisition (2012 USD).
Goodwill (adj., mil)	The total goodwill net of an estimate of synergy and any over/under-payment of the target by the acquirer. The former is approximated by the sum of the product of 2-day window cumulative abnormal (CAR) and pre-deal market value for both target and acquirer, while the latter is the negative of the acquirer's CAR times the pre-deal market valuation.
All stock	An indicator variable equal to one if the acquisition was an all-stock deal.
All cash	An indicator variable equal to one if the acquisition was an all-cash deal.
Balance sheet intan.	The total intangible assets already on the balance sheet of the firm, typically from past acquisitions of intangibles and goodwill.
Organizational capital	The capitalization of some fraction γ of SG&A expenditures by a firm. It is meant to capture the knowledge used to combine human skills and tangible capital into systems for producing and delivering want-satisfying products. See Section 2 for a collection of papers with related definitions.
Knowledge capital	The consensus proxy for the flows of a firm's knowledge capital in the intangibles literature is its periodic disclosure of research and development expenditures.
BEA-HH	The acronym for the depreciation parameter assumptions from Li and Hall (2016) for knowledge capital and the fraction of SG&A that is investment from Hulten and Hao (2008).