NBER WORKING PAPER SERIES

ACQUISITION PRICES AND THE MEASUREMENT OF INTANGIBLE CAPITAL

Michael Ewens
Ryan H. Peters
Sean Wang

Working Paper 25960
http://www.nber.org/papers/w25960

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2019

We thank Gordon Phillips for providing data for the SDC-Compustat merge and Shiyu Zhang for research assistance. Jan Bena (discussant), Nagpurnanand Prabhala (discussant), Hila Fogel-Yaari, Arthur Korteweg, Pierre Liang, Song Ma, Tom Ruchti, Luke Taylor and seminar participants at University of Utah, Tulane University, Caltech, Midwest Finance Association, and the Finance, Organizations and Market Conference (2018) provided helpful feedback. Code and data to incorporate the intangible capital stocks can be found at: http://bit.ly/intan_cap. First version: September 2018. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Acquisition Prices and the Measurement of Intangible Capital
Michael Ewens, Ryan H. Peters, and Sean Wang
NBER Working Paper No. 25960
June 2019
JEL No. G30,G32,G34,O3,O34

ABSTRACT

We use 1,521 acquisition purchase price allocations to estimate intangible capital stocks. The estimated depreciation of knowledge capital (R&D) is 32%, some 28% of SG&A represents investment in organizational capital and parameter estimates exhibit significant industry variation. Aggregating these accounts, 75% of intangibles come from organizational capital, and total stocks are 10% smaller versus stocks using prior parameters. Adjusting for intangibles, average market-to-book falls from 1.74 to an average of one. Relative to existing approaches, our stocks improve the explanatory power of enterprise value, human capital and brand rankings, while exhibiting the expected correlations with patent valuations and investment rates.

Michael Ewens
California Institute of Technology
MC 228-77
1200 East California Avenue
Pasadena, CA 91125
and NBER
mewens@caltech.edu

Ryan H. Peters
Tulane University
7 McAlister Dr Suite 365
New Orleans, LA 70118
rpeters4@tulane.edu

Sean Wang
Southern Methodist University
6425 Boaz Lane
Dallas, TX 75205
seanwang@mail.smu.edu

An appendix is available at http://www.nber.org/data-appendix/w25960

> 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. Figure 1 illustrates that U.S. firms spend less on physical capital, and more on intangibles related to knowledge and organizational capital which are recorded as research and development (R&D) and sales, general and administrative (SG&A) expenditures. Such a reduction in physical capital investment, as well as its weaker connection with firm valuation, are described as a "broader investment puzzle" by Gutiérrez and Philippon (2017) and Crouzet and Eberly (2019). A common conclusion of both papers is that standard measures of investment, which focus on physical assets, fail to capture the growing importance of intangible assets. This failure is most evident in Figure 2, which shows a market to book ratio of invested capital as consistently greater than one and increasing over the last 20 years.[2] In fact, as of 2018, 32% of firms in Compustat have a negative tangible net worth based on book values.[3] This paper proposes new measures for intangible investment and its accumulation that are central to capital stock adjustments.

Accounting rules for intangibles originated in 1974 at a time when intangible investments were a small proportion of the economy, and have not changed despite a paradigm shift towards intangibles as economic value drivers. Specifically, a firm's internal R&D and SG&A activities are immediately recorded as expenses, and thus do not appear on its balance sheet. This lack of capitalization inhibits attempts to connect firm value to current accounting statements (e.g. Lev and Zarowin, 1999). In the face of this, researchers in economics and finance estimate the off-balance sheet intangible capital with accumulated flows of R&D (Bernstein and Nadiri, 1988;

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

[2] Neoclassical investment theory theorizes that under perfectly competitive markets with constant returns to scale and perfectly elastic scale, the market value of invested capital equals the replacement cost of invested capital, (i.e. market to book approaches one in long-run equilibrium.)

[3] We measure tangible net worth for Compustat firms as total assets ("at") minus the sum of total liabilities ("lt"), intangible assets ("intan") and preferred stock ("dcpstk").

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 off-balance sheet intangible stocks from R&D and SG&A requires assumptions about the capital accumulation process, i.e. intangible depreciation rates and the fraction of SG&A to be capitalized. Unfortunately, as Corrado, Hulten, and Sichel (2009) highlight, "[r]elatively 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 have gaps in industry coverage or rely on modeling assumptions due to the lack of market prices.[5] The purpose of this paper is to provide capitalization parameters that are informed by market prices. We estimate these parameters, use them to create intangible stocks and then in a series of validation tests show that they perform at least as well or better than stocks using existing parameter estimates.

Beyond improving measures of investment for resolving debates in academic research, reliable measures of intangible stocks are important for capital markets and financial managers. In equity markets, numerous studies have provided evidence of mispriced equity for firms with higher levels of intangible assets, which could lead to suboptimal allocations of capital resources.[6] 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.[7] In theory, the accurate measurement of intangible capital could mitigate potential equity mispricing and lending market frictions for firms that rely heavily on intangibles to create economic value. In corporate finance, compensation committees and financial managers making capital budgeting decisions must accurately estimate book values of intangible capital to calculate returns to intangible capital (Hall, Mairesse, and Mohnen, 2010). Inaccurate measurement of intangible capital could lead to compensation that is poorly tied to value creation and incorrect project

[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.

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

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

selection.

Our parameter estimations exploit prices paid for intangible assets in acquisitions. Acquisitions are an excellent setting to price intangibles because the SEC and GAAP require the acquirer to allocate the price paid for the target's assets across three major categories: physical assets, identifiable intangible assets (IIA), and goodwill (GW). Given that physical assets are directly identified in the purchase price allocation, the sum of IIA and GW represents the total price paid for intangible capital in an acquisition. 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 identifiable intangible asset allocations and goodwill from the purchase price allocation of over 1,500 acquisition events, generally from acquirer 10-K or 8-K filings.[8] Combined with ten years of the target firm's past spending on R&D and SG&A, we follow a capitalization model previously used in existing work such as Corrado and Hulten (2014) and Peters and Taylor (2017) to estimate the depreciation parameter on R&D and the fraction of SG&A that best fits an adjusted market price paid for intangible capital in acquisitions. We then use these parameter estimates to measure the off-balance sheet knowledge and organizational capital across the full sample of firms.

Our estimated parameters imply an average 32% annual depreciation rate for R&D,[9] more than double the 15% benchmark rate commonly used in the literature.[10] Relatedly, our estimates for R&D depreciation rates are close to those estimated by Li and Hall (2016) on a smaller subsample of firms and SIC codes. Our 28% estimate of the fraction of SG&A that represents investments in 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 this ratio varies dramatically across industries from 20% in the consumer industry to 50% in the healthcare industry.

Using these parameters to capitalize the knowledge and organizational capital for the full

[8]We evaluated over 2,000 such acquisitions, but many lacked information for inclusion into the final sample. A few other papers use 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.

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

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

universe of Compustat firms,[11] we find that intangible intensity, measured as the fraction of firms' total capital stock that is intangible, has increased from 37% of total capital in 1980 to 60% by 2016. Over 80% of healthcare firms' assets are intangible in 2016, versus 40% for firms in manufacturing. Our estimation allows us to decompose a firm's total intangible stock into knowledge and organizational capital. Organizational capital comprises the majority (over 80%) of all intangibles across our entire sample. The magnitudes of knowledge and organizational capital stocks exhibit significant time-series variation due to changes in the magnitude of R&D and SG&A expenditures over time. The impact of adjusting book values of invested capital for intangibles has a dramatic effect on the time series of average market-to-book: Figure 3 shows that adjusting the denominator for both intangible capital types results in a ratio centered around the theoretically predicted one in all years.

Relative to previous methods, our parameter estimates imply smaller intangible stocks for firms in the consumer and manufacturing industries and larger stocks in high tech and health firms. These differences demand that we validate the new measure, which we do so in five settings: market enterprise valuations, human capital, brand rankings, patent valuations, and the investment-q relation. The results show that our new parameter estimates used to calculate intangible stocks perform at least as well and often significantly better as those commonly used in these various literatures. The improvement stems from our new industry-level organizational capital investment rate and broader industry coverage in knowledge capital depreciation than previous estimates.

The first test asks whether the incorporation of our intangible capital stocks improves the explanatory power of firm book assets on market enterprise values. We compare total capital stocks implied by our parameter estimates with capital stocks implied by the BEA-HH parameters. Our measures improve the R^2 in the cross-section in all years from 1986 to 2016, and this additional power is statistically significant in all years after 1995. The additional explanatory power demonstrates that our estimated stocks are an improvement over existing methods.

The next two tests verify whether our estimates of organizational capital stocks capture differences in human capital and brand value across firms more effectively than current measures.

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

We follow Eisfeldt and Papanikolaou (2013) in examining whether firms with high organizational capital stocks are relatively more likely to disclose risks regarding the potential loss of key talent in their 10-K filings. To do so, we parse the text files of 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.

Next, we validate whether the new estimates of intangible capital stock 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 valuations on our measures of knowledge and organizational capital stocks 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. However, to our knowledge, this is one of the first direct measurements of returns to intangible investments.

The final validation uses our intangible capital stocks to adjust the firm's total capital and examine how this adjustment affects the strength of the relation between the adjusted Tobin's Q and the firm's investment (Fazzari, Hubbard, and Petersen, 1988, e.g). Peters and Taylor (2017), using intangible capital stocks calculated with the Li and Hall (2016) parameter assumptions, show that incorporating measures of intangible capital strengthens this relation. The incorporation of our measures improves explanatory power in the investment-q relation for R&D and broadly replicates previous results for SG&A and capital expenditures.

We acknowledge two concerns related to our acquisition setting and attempt to address each directly: sample selection and noisy prices. First, although acquisitions provide market prices for a target firm's intangibles, it is possible these targets may not be representative of the full population of firms, e.g., acquisition targets may have more successful prior intangible investments. In response, in the results summarized above, we supplement our acquisitions sample with a set of 479 bankruptcy events of publicly-traded companies over the sample period. For these bankruptcies, we assume a 70% debt recovery rate (Bris, Welch, and Zhu (2006)) and allocate a fraction of this total to all priced intangibles using observed fractions from the acquisition sample. Second, it is possible that the raw price of intangibles may be confounded by merger-specific values (i.e. synergies) and over or underpayment by the acquirer, which would contaminate goodwill, our proxy for unidentifiable intangible assets. We adjust for both synergy and over/underpayment using the change in the target's market valuations around deal announcement, as well as the probability of a failed merger. Together, these adjustments lower the values of intangible stocks by an average of 35%. 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 by both re-estimating the knowledge capital accumulation process using market prices and by extending 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 the price paid for intangible assets of U.S.-based public acquisition targets to estimate parameters for our intangible capitalization model. Below, we discuss the disclosure setting regarding intangibles. Appendix Section A1 provides a history of the accounting rules surrounding the acquisition of physical 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 physical assets.[12] While a firm's capital expenditures on physical 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.[13] Although these intangible expenditures may fulfill GAAP's primary criterion for asset recognition,[14] GAAP's justification for not capitalizing and amortizing these intangibles stems from the uncertainty in measuring their value and estimated useful lives.[15]

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.[16] The criteria for capitalization of intangibles documented in ASC 805 notes

[12] 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

[13] 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 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.

[14] 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).

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

[16] 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

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.[17] 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 purchase price allocation, details of which are discussed in the 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.[18]

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 most often use the DCF approach when appraising these assets.

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

[18] Figures A2 and A3 in the Appendix provide basic examples of the differences between the purchase and pooling

2 Literature

Given the importance of the book value of invested capital in measuring a firm's investment opportunity set, or assessing managerial performance, much research attempts to measure the value of intellectual and organizational capital that remains hidden from a firm's balance sheet due to accounting regulations. The most common method used in this stream of literature is based on the perpetual inventory method[19] (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), which aggregates the accumulation of flows over the life of the firm to measure the total stock of intangible capital. These flows are then capitalized to the balance sheet.

The calculation of the year-end off-balance sheet value of a firm's internally-generated intangible capital stock can be estimated by summing the estimated value of the intangible at the beginning of the period with the value of other expenditures used in the internal creation of intangibles in the given period, less any depreciation of the asset over the given period. Thus, the value of the capitalized intangible asset at the end of year t, X_t, is as follows:

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

where Z_t are real expenditures towards intangibles at the end of year t, and D_t represents the depreciation or amortization of the intangible during period t. If we assume geometric depreciation of the beginning of period intangible stock at the rate of δ, we have:

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

Continuously substituting for the lag of X, the formula converges to:

method. Section A4 provides several real-world examples found in our data.

[19]The OECD notes that this is also by far the most common method used in measuring the stock of physical assets (OECD Manual 2009, p. 38).

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

In (3), the intangible capital stock is the sum of all unamortized off-balance sheet intangible expenditures. However, because the availability of high-quality accounting data on expenditures is generally scarce prior to the firm becoming publicly-traded, most papers use a modified version of (3):

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

Thus, in order to operationalize (4) and estimate intangible capital stocks, we need proxies over k periods for the intangible expenditures, Z, that give rise to the stock of knowledge and organizational capital, the value of the initial stock of the intangible, X_{t-k}, and parameters for the estimated depreciation rate, δ.

Following ASC 730's (formerly FAS 2) guidance and definition of research activities as development as "the translation of research findings or other knowledge into a plan or design for a new product or process,"[20] 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. The proxy for the flows of a firm's organizational capital is more difficult to precisely measure. Perhaps part of this measurement problem from an accounting perspective is due to the vagueness by which organizational capital is defined. For example, Evenson and Westphal (1995) first define organizational capital as the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products. Eisfeldt and Papanikolaou (2013, 2014) define organizational capital as intangible capital that relies on essential human inputs, i.e. the firm's key employees. Lev and Radhakrishnan (2005) define organizational capital more broadly, as an agglomeration of technologies – such as business practices, processes, and designs that gives a firm a competitive advantage and enables it to extract additional economic rents from its operating activities.

[20] `https://www.fasb.org/resources/ccurl/286/565/fas2.pdf`, page 5.

Current methods of estimating organizational capital rely on Sales, General, and Administrative Expenses (SG&A) as a proxy for the firm's intangible investment flows. Contrary to the strict definition of R&D and its direct justification as a proxy for knowledge capital, the rationale for capitalizing SG&A stems from the lack of more direct measures and logical deduction. SG&A is defined by GAAP as all commercial expenses of operation, i.e. expenses unrelated to the cost of goods sold, that are incurred in the regular course of business pertaining to the securing of operating income. Some examples of expenses categorized as SG&A include advertising and marketing expenses, provisions for employee bonuses and stock options, bad debt expenses, and foreign currency adjustments. SG&A's inclusive categorization of items that should be classified as both expenses and assets[21] create an additional parameter, γ, representing the fraction of SG&A expense that should be capitalized into the stock of organizational capital.

To the best of our knowledge, there are no empirical estimates for the parameter estimates of γ. The value most commonly used in the literature is from Hulten and Hao (2008) who estimate $\gamma = 0.3$ based on composite data of six companies in the pharmaceutical industry in 2006. Conversely, there have been a number of attempts to estimate δ for R&D investments. The main challenges, as stated by Griliches (1996) and Li and Hall (2016), stem from the fact that the majority of firms conduct R&D activities for their own use (and not to sell to third parties), and thus there does not exist a competitive marketplace for most R&D assets. Mead et al. (2007) argues that none of the current methods used to empirically estimate R&D depreciation rates are particularly satisfactory because the existing data at the firm-level has little variation over time, and nearly all of the existing models depend on strong identifying assumptions.[22]

[21] For example, Coca-Cola Company 2017 10-K disclose documents \$12.5 billion in SG&A expenditures. Accompanying notes reveal that \$4 billion of these costs are incurred to support the production costs of print, radio, television and other advertisements, while \$1.1 billion of these SG&A costs are related to shipping and handling costs incurred to move finished goods from sales distribution centers to customer locations. Assuming that the advertising expenses incurred in 2017 continues to enhance the firm's brand equity in future periods, these expenditures represent off-balance sheet intangibles, which should be capitalized. Conversely, the costs related to transporting finished goods to customers only support operations in the current period, and therefore should be immediately expensed.

[22] 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 obtain an estimate of δ of 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. Their model assumes that the amortization of R&D capital is responsible for generating earnings, which fully captures the benefits of R&D investments. Their amortization

Given the lack of parameter estimates for γ, the fraction of SG&A that should be capitalized, and the wide range of δ on R&D across varying model assumptions, a consensus among depreciation parameters used by empirical researchers does not yet exist. Existing studies generally choose a set of parameters for δ and γ when valuing the intangible stocks, then attempt to show that their results are robust to alternate parameter estimates. 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

The main sample of 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. The constraints on years stems from our need to collect 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.[23] As discussed in Section 1, we exclude all deals that use the pooling method pre-2001.[24] This leaves us with a set of 2,109 acquisitions.

We next search for data on purchase price allocations which, if available, are provided in a footnote in the acquirer's subsequent 10-K, 10-Q, 8-K or S-4 filing. From these we collect all components of the deal. Our main analysis uses the goodwill and the "identifiable intangible assets" (IIA) valuations. Given these values may incorporate synergies, over-payment and strategic

model yields depreciation estimates of R&D that vary across industries between 11 and 20%.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 physical 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 12% and 38%. Their estimates cover 10.5% of 4-digit SIC codes and 28% of firm-year in Compustat, thus requiring ad-hoc assumptions for firms not covered by these estimations.

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

[24]The results presented below for all deals from 1996–2017 are robust to exclusion of pre-2002 deals (see Panel A of Table 7).

goals of the acquirer (e.g. Cunningham, Ederer, and Ma, 2018), we adjust them using changes in market valuations (discussed below). Some filings lack 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). We found information on the purchase price allocation for 81% (1,719) of all candidate acquisitions. The last step requires merging the target and acquirer firms to Compustat and CRSP.[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), the innovation needs of the acquirer (e.g. Phillips and Zhdanov, 2013; Bena and Li, 2014) and 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 sample naturally exclude another exit for target: failures.

Our first attempt to address any sample selection from an acquisition-only estimation is to supplement them 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 a purchase price allocation disclosure for these events, we make assumptions about the firm's exit value and the valuation of its intangible capital. Ma, Tong, and Wang (2019) shows that assuming a value of zero for intangibles is incorrect because innovation is a crucial asset class in asset allocation in bankruptcy. As an alternative for zero, we follow the literature on bankruptcies (e.g. Bris, Welch, and Zhu, 2006), who find that creditors receive about 70% of total debt value after liquidation.[28] This forms our "deal value" for failed firms. The intangible capital in this deal value are then assumed to match the ratio of IIA and goodwill to deal value observed

[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.

[27] CRSP delisting codes of 2 and 3.

[28] Bris, Welch, and Zhu (2006) report that secured and unsecured creditors combined mean (median) recovery is 69% (79%) in Chapter 11 reorganizations.

in the same industry as our main acquisition sample. These resulting intangible valuations are on average 60% lower than those observed in the acquisition sample. Finally, including these requires a re-weighting to address the relatively large sample size compared to the acquisition sample (described in Section 4 below).

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 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. As their estimation of depreciation parameters for R&D is from a representative set of firms (from a small set of industries), a lack of systematic differences with our estimates would indicate that our sample selection is not severe. Further, we will run all analyses with and without the bankrupt firms and evaluate whether the estimates change as predicted.

3.2 Synergy and Overpayment: adjusting goodwill

Acquisitions may be motivated by pair-specific value or synergies, 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 bias the parameter estimates for our sample, relative 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, as opposed to an acquirer-specific value. Thus, we make the following adjustments to the goodwill. We follow the Bhagat, Dong, Hirshleifer, and Noah (2005) framework for estimation merger value creation. Specifically, we use their probability scaling method for announcement day returns to estimate the synergy and over-payment component of the acquisition value.[29] This estimate is removed

[29] We cannot easily implement the second “intervention method” with our relatively small sample size.

from goodwill valuations from the purchase price allocation.[30] For each acquisition announcement, we first calculate the two day change cumulative abnormal return for both the target and acquirer.[31] Multiplying by the pre-deal (two days prior) 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 day market price of the target compared to the offer price in the deal.[32] The sum of the target and acquirer's changes – the expected synergy – is subtracted from goodwill. Next, we remove the acquirer's change in valuation as it incorporates overpayment. Here, a decline in the acquirer's market value would signal over-payment and thus must be added back to goodwill. These adjustments are economically large. The average (median) deal sees a 35% (40%) decline in the goodwill.

3.3 Main variables

As discussed in Section 1, the intangible components of acquisitions are identifiable intangible assets (IIA) and goodwill. For each target firm merged to Compustat, we also 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.[33]

Figure 4 (a) shows the prevalence of both goodwill and identified intangible assets for our sample of acquisitions. It reports the percentage of all deals that have some positive amount of either asset in the purchase price allocation. First, it demonstrates a meaningful increase in such deal components since the mid-1990s. Since 2004, over 85% of deals contain goodwill or some intangible assets. Figure 4 (b) repeats the analysis but weights by dollars in the acquisitions. The patterns remain. Next, Figure 5 asks how much of total enterprise value is comprised of goodwill

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

[31] The estimates below are robust to different event windows.

[32] That is, the probability of a successful merger is $\frac{P_1 - P_0}{P_{offer} - P_0}$, where P_1 is the end-of-day target share, P_0 is the pre-announcement share price and P_{offer} is the original offer price. When this is unavailable or outside the unit interval, we use the observed success rate in SDC over our sample period (78%).

[33] 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.

and IIA. The latter represents some 25% of total transaction value over the sample period. On the other hand, goodwill accounts for approximately 35% of the typical deal size over the full sample period. Taken together, the data suggests that intangibles play a major role in the U.S. acquisition market.

Recall that the goodwill valuations used in the estimation are adjusted following the methodology summarized in Section 3.2. Figure 6 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) and this has an impact on the total intangible value in acquisitions.

3.4 Summary statistics

Panel A of Table 2 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. 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.[34] 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 capital exceeded the enterprise value of the firm. We randomly checked 20 acquisitions in this subsample and verified that this was 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.

[34] 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 takes on a negative value that 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 physical 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 A4 in the 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.

Panel B of Table 2 summarizes the failed 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. These failed firms are more likely than acquired firms 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. Recall 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 information. Any inferences we make using our estimates of intangible capital depreciation may have to be qualified by sample selection issues. Fortunately, Table 3 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, in turn, 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 3 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,[35] we measure the value of internally generated intangible capital as the sum of knowledge and organizational capital over the previous 10 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[36] using the perpetual inventory method:

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

and

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

For each acquisition, we construct trailing 12-month measures for these two expenditures using the Compustat quarterly database.[37] Therefore, the fully specified capitalization model is:

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

Our ultimate goal is to estimate the structural parameters of the perpetual inventory equation (7), $\delta_{R\&D}$ 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

[35] 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).

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

[37] 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.

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's 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 $\xi_{it} \in (0, \infty)$:

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

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:[38]

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

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

First, in order 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:

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

[38]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.

Next, due to the nature of SG&A spending, in particular the fact that it is very stable within firms over time, the parameters γ and $\delta_{SG\&A}$ in the S_{it} term are not separately identifiable.[39] We 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 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:

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

4.1 Estimation details

We highlight a few important features of the estimation procedure here. The failure observations – where we impute P^I_{it} from debt recovery and intangible asset rate assumptions – are weighted to match the unconditional relative frequency of acquisitions and non-acquisition 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.[40]

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.

[39] 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

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

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.

[40] We run bootstraps with 1,000 replications. In the case of samples which include failed firms, we re-draw across all events before weighting to match the unconditional relative frequency of event types.

5.1 Estimating the capital accumulation process

Results from equation (11) are found in Table 4. In both panels, the "All" row represents the full sample while the other rows show industry estimates using Fama French 5 classifications.[41] 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 about 10% 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 same rates, but where the standard assumption of .15 is used to fill in coverage gaps. Panel A reports results using a sample that includes both acquisitions and failures while panel B reports results only from acquisitions.

The γ estimates in Panel A suggest that a significant portion of SG&A spending represents an investment in long-lived capital. Taking the organizational capital depreciation rates commonly used in the literature (Eisfeldt and Papanikolaou, 2014; Falato, Kadyrzhanova, and Sim, 2013; Peters and Taylor, 2017) of $\delta_{SG\&A} = 0.2$,[42] γ implies that the fraction of $SG\&A$ that represents an investment in the average firm is 28%.[43] This is substantially larger than zero only slightly less than the 30% used in the literature. This is the first direct confirmation of this major assumption used in the literature. Although we nearly match the estimate used in earlier work across all firms, our estimate of γ varies significantly across industries. The fraction of SG&A spending that represents an investment is lowest in the consumer industry at 20%. 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 0.45 and 0.51 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 a new view on the rates of knowledge capital depreciation. Panel

[41] 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).

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

[43] Recall that we assume that the organizational capital depreciation δ_S is .2. Reassuringly, Figure A1 in the Appendix shows no major changes in results presented here for parameter values in $[.1, .3]$. We thus maintain the assumption of .2 throughout.

A shows an average depreciation rate δ_G across all firms of 32% 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 in Panel A is also substantial, ranging from a low of 0.25 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 these estimate likely suffer from no sample selection issues and thus represent a benchmark for such concerns in our analysis. The standard errors for our estimates imply that the δ_G in high-tech and health differs statistically from existing estimates, while consumer and manufacturing do not–likely due to small sample size. Reassuringly, 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.

Panel B repeats the estimations on the sample without failed firms and shows similar patterns across industries. Excluding failed firms from the analysis raises the average fraction (γ) of SG&A that represents an investment in long-lived organizational capital from 25% to 42%, an increase of 68%. The point estimates for δ_G are lower in Panel B than Panel A, with the full sample implying an average depreciation rate of knowledge capital of 26% per year.[44] Panel B of Table 7 repeats the estimation without the adjustment to goodwill discussed in Section 3.2. As expected, the adjustments to goodwill have a large impacts on estimates. R&D depreciation rates are 35% higher and the percentage of SG&A that is investment are 48% 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.[45]

Patterns in the industry-level estimates reassuringly match some expected features of intangible investments, while revealing whether certain selection concerns discussed earlier emerge. First,

[44]The negative depreciation for "Other" suggests that some firms in that industries were acquired for prices that exceeded even the raw sum of prior R&D expenses.

[45]Comfortingly, these estimates change relatively little between Table 4, which includes all targets and failures, and an estimation which includes only firms which report positive R&D (see Panel C of Table 7 for these results).

Table 4 shows that R&D depreciation is highest in the high tech industry (49%), which is also the largest in the BEA estimates (though a smaller 26%). 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 in both specifications exceed those those currently used in the literature. These differences suggest positive selection issues – e.g. acquisitions are more likely to be successful innovation projects – are not a first-order concern. We discuss any impacts of selection and non-representative pricing in the analysis of intangible capital stocks below.

As noted in Section 4, the 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. A plot of the exponentiated estimated fixed effects ($\log(\rho_t)$) are shown in Figure 7, 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 7 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 Panel A of Table 4 to the intangible capital accumulation process (Equation 7) of the broader CRSP-Compustat universe of firms.[46] 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*).

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

5.2.1 Intangible capital stocks by industry and time

The debate surrounding whether intangibles should be recognized as assets, and if so how to measure them, is based on the idea that such assets are increasingly becoming an important part of firms' balance sheets. Figure 8 presents one view on time series trends in intangible capital for the four industries. Each series plots the average ratio of intangible capital K^{int} $(S_{it}+G_{it}+I_{it})$ to total assets, e.g. intangibles and physical assets (Compustat *ppegt*). Reassuringly, intangible intensities are lowest in consumer and manufacturing firms. Firms in these industries have experienced an increase in the role of intangibles in their total assets since the late 1990s. In contrast, both healthcare and high-tech firms have high intensities that have each grown continually since the 1970s. Only since the mid-2000s have the growth rates slowed. The patterns in Figure 8 conform to basic predictions about differences across industries and over time and thus provide the first validation that our estimates measure real economic assets.

We explore the relative importance of knowledge versus organizational capital by plotting the ratio of the former to total intangibles K^{int}. Figure 9 presents the results. 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 1976 – 1996. Since 1996, the growth has either stalled (Healthcare) or the levels have fallen back to 1970's levels. One possible (though yet to be explored) explanation are changes in R&D tax credits. Many of these originated in 1981 (a period of increase in Figure 9) and expired in 1996 (Bloom, Schankerman, and Van Reenen (2013)). Given that the intensities for all industries has not fallen over this sample period, the decline in knowledge capital found here is connected to a shift to investment in organizational capital with SG&A spending.

Next, we take these new capital stocks to the time series of market-to-book ratios discussed earlier. We calculate the average market equity value to book value from the period 1997–2017. Theory would dictate, across the cross-section of firms, that market-to-book should be centered around one, assuming book assets are properly measured. Figure 3 report the averages for the standard ratio (solid time series) and that adjusted using our stocks. Unadjusted, i.e. internal intangibles excluded under measurement rules, the market-to-book ratio has a mean of 1.74

(the solid line). After our adjustments adding intangible capital stocks, we find that our average market-to-book is 0.994, indicating the importance of properly capitalizing intangibles when estimating the market to book ratio.[47] The change in the sample averages – the horizontal lines – make clear that the introduction of intangible assets gets us to the theoretically predicted average of one. We interpret this result as a significant validation of our intangible asset estimates, which we now compare to earlier approaches.

5.2.2 Comparison to existing methods

To explore how our parameter estimates differ from the parameters 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 estimates to the parameters commonly used in the literature, it is instructive to note that the BEA's numbers 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 10 presents the difference between our estimates ("EPW") and the current methods ("Current") and scaled by the latter. All the parameters are time-invariant, so any time-series variation in this percentage stems from changes in the relative use of R&D and SG&A. The differences in our estimated capital stocks relative to those from the literature vary across industries, as might be intuited from our parameter estimates. The "All" line in the figure shows that the new estimate is approximately 10% smaller across all firm-years. Our intangible capital stocks are lower than commonly assumed in both the consumer and manufacturing industries.

In contrast, estimated stocks are larger in all years for hi-tech firms and half the years for

[47] The results are quantitatively similar if we exclude from the sample all firm-years where one of the acquisitions in our analysis occurred (both target and acquirer).

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 (33% vs. 17%), the relatively smaller stocks in healthcare in the 2000s reflects firms switching intangible investments to R&D from organizational capital investments.

6 Do these new intangible capital stocks perform better?

We now perform three cross-sectional analyses that can reveal whether the new stocks of intangible capital proposed here provide additional explanatory power over current methods. Note that the set of analyses where our estimates can improve in this way is limited by the our estimation of time-invariant, industry-level parameters. We also perform two other validation exercises, relating the estimated intangible capital stocks to firms' patent values and demonstrating that the performance of our new measures is similar to those of the existing approach in the context of investment-q regressions. The results demonstrate that the new estimates behave as expected and in many situations out-perform current methods.

6.1 Explaining public firm valuations

Connections between 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 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%. 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 11 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 period, the new measure outperforms the existing BEA-HH approach (red dashed line), and that the estimated capital stocks leave 1-3% less residual variance unexplained. When comparing our estimated capital stocks to firm capital without capitalized intangibles we find an upward trend in the relative explanatory power since 1994, consistent with the fact that the capitalization of intangibles has become increasingly important in explaining valuations as our economy has become more reliant on organizational and knowledge capital when generating economic value. For years after 2006 we find that including capitalized intangibles leaves 13-23% less unexplained variance in firm values.

The second panel of Figure 11 presents the formal test statistic for the null hypothesis that the R^2 from EPW and BEA-HH are identical, equivalent to the ratio above being zero, using influence functions. 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 and 2016 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 4 have the most predictive power for explaining enterprise value.

6.2 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 that is 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, here using overs 120,000 10-K filings from 2002–2016.[48] 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 comparison by year of the existence of these words between these two quintiles reveals that our measure of organizational capital stock captures something real and new. First, the fraction in the top quintile versus the bottom with some reference of personnel risk is 68% and 51%, respectively across all years. This compares to 59% vs. 52% for the quintiles sorted using the current measures. Figure 12 demonstrates that our stock measures significantly outperform on this metric. It 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.[49]

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

[49] 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 Appendix Table A1).

6.3 Organizational capital as brand

Our next exercise asks whether our organizational capital stocks exhibit stronger correlations with firm brand quality than existing measures. To do so, we collect the top 100 global brands according to Interbrand, a brand consultancy, from 2000 to 2018.[50] We extract the ranking and merge each company (or brand) to U.S. public firms in Compustat.[51] As above with the personnel analysis, 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. That 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.

6.4 Patent valuations and the returns to knowledge capital

One of the more meaningful types of internally-generated intangible capital are patents. 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 patenting and patent valuations. 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

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

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

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. We observe an almost doubling of the within-R^2 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.

6.5 Investment-q regressions

Having demonstrated that our intangible capital stocks vary across industries and time, improve the explanatory power of capital stock to enterprise value, and exhibit expected correlations with output measures of knowledge and organizational capital, we perform one final validation. Specifically, we test whether our intangible capital stocks can improve the explanatory power of the relation between a firm's "total Q" as in Peters and Taylor (2017) and its investment. We use our parameter estimates to construct a new total Q. This analysis compares our intangible capital stocks against the prevailing approach of estimating intangible capital stocks . Here, Total Q is firm value divided by the replacement cost of physical capital (i.e., PPE), book intangibles on the firm's balance sheet and our estimates intangible capital stocks implied by the industry-level parameters in Table 4. The correlation between alternative measures of capitalized R&D and total intangible capital is 90% and 83% across approaches. The high correlations are a function of similar inputs (e.g. past R&D), while indicating that different parameter estimates can still result in similar output. They also follow from the common assumption about time-invariant depreciation parameters.

The OLS regressions relate our total-Q and that of Peters and Taylor (2017) to four measures of investment. Since R&D and SG&A are intangible investments, they are additional dependent variables in our investment-q regressions. Our major goals are to confirm that the coefficient loads as expected (positive and significant) and that we can match or exceed the R^2 found in earlier work. Table 6 presents the results for the four major industries.

The odd columns report the replication of Peters and Taylor (2017) using their intangible capital stocks to create Total Q. The even columns use our accumulations. First, the loadings across investment measures – e.g., column (2) shows R&D investment – are similar in both specifications and across industries. Second, our market-based model motivated by the structure of existing depreciation models explains a similar fraction of the variation measured by within-R^2 in investment when compared to Peters and Taylor (2017). Most striking is the improvement of explanatory power for R&D investment across all industries. These results reassuring because we have not added much modeling complexity, but have brought novel data – acquisition prices – to an old question.

7 Robustness

We perform two major robustness analyses, beyond the ones discussed throughout the results above. In the first, we confirm that our acquisition setting produces superior results compared to one where we impute intangible asset values across a broader Compustat sample. In the second, we examine whether the estimated parameters exhibit a distinct time trend.

7.1 Comparison with a public market estimation

We argue 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. 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. 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. Because accounting data primarily records tangible assets at historical cost, we must assume a markup of tangible assets that converts book to market values. Despite potential measurement issues, we consider this exercise a meaningful validation of our baseline approach because it uses a representative sample of firms and thus is not subject to possible selection issues.

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:

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

Then, the difference between the market value of the firm and these market values of balance sheet items is then our approximation of 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 physical 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 physical assets. We observe targets' pre-acquisition book value of physical assets and the price paid. From this, we can estimate an average (5% tail winsorized) markup from 1997–2016 of physical 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 physical 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 physical assets, as the average firm-year has a ratio of gross to net PPE of approximately two. This approach allows the physical 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, we randomly sample each firm once over its lifetime (after three years of trading) for 1986–2017. We have repeated this exercise with several random samples, and the results are robust.

Panel D of Table 7 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 physical assets, these gammas fall without a major change in the depreciation estimate for knowledge capital. The final row presenting the firm-level markup assumptions exhibits parameters estimates that are quite close to that from the acquisition methods and for δ_G, very close to the BEA estimate. We believe that the estimates demonstrate how important the purchase price allocation is for our proposed method of retrieving depreciation parameters. The assumptions about markups on physical assets in Panel D are ad-hoc, but matter. 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 asset stocks for all Compustat firms. We ask whether these alternative approaches to retrieving intangible asset valuations improve upon our method in market valuation regressions. Note that this method's estimation effectively minimizes the distance between the sum of all types of assets and market valuations, so it has an advantage for this test. Figure 13 presents the relative differences in R^2 for the alternative stocks and the acquisition-based stocks. The intangible stocks developed by parameter estimates from the smaller acquisitions sample outperform the three alternatives that use a broader sample of publicly-traded companies (i.e., the higher the line, the better). We believe this highlights that selection is not a first-order concern when using adjusted-price acquisitions of intangible assets, or at least that the benefits of observing asset allocations outweigh the potential costs of selection relative to estimation on the full Compustat sample.

7.2 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 10-year subsample, estimated for each year using the previous ten years as the sample period. This allows us to investigate the validity of our assumption that γ and δ_G are constant over time, and 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 7, and imposed within the non-linear least squares estimation.[52]

Figure 14 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.

[52]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.

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.

8 Conclusion

We hand-collect market valuations for intangible assets from over 1,500 acquisitions from 1996 to 2017, and use these prices 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.[53] The resulting parameter estimates imply significant cross-sectional variation in capitalization parameters and we show that our new industry-level variation and price data results in a better measure of intangible stocks. The improvements manifest themselves in the stocks' ability to explain market enterprise values, human capital and brand rankings.

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

References

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William R Kerr, 2013, Innovation, reallocation and growth, Discussion paper, National Bureau of Economic Research.

Aksoy, Lerzan, Bruce Cooil, Christopher Groening, Timothy L Keiningham, and Atakan Yalçın, 2008, The long-term stock market valuation of customer satisfaction, *Journal of Marketing* 72, 105–122.

Belo, Frederico, Xiaoji Lin, and Maria Ana Vitorino, 2014, Brand capital and firm value, *Review of Economic Dynamics* 17, 150–169.

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *The Journal of Finance* 69, 1923–1960.

Bernstein, Jeffrey I, and Theofanis P Mamuneas, 2006, R&D depreciation, stocks, user costs and productivity growth for U.S. R&D intensive industries, *Structural Change and Economic Dynamics* 17, 70–98.

Bernstein, Jeffrey I, and M Ishaq Nadiri, 1988, Interindustry r&d spillovers, rates of return, and production in high-tech industries, *The American Economic Review* 78, 429–434.

Betton, Sandra, B Espen Eckbo, and Karin S Thorburn, 2008, Corporate takeovers, in *Handbook of empirical corporate finance* . pp. 291–429 (Elsevier).

Bhagat, Sanjai, Ming Dong, David Hirshleifer, and Robert Noah, 2005, Do tender offers create value? New methods and evidence, *Journal of Financial Economics* 76, 3–60.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013, Identifying technology spillovers and product market rivalry, *Econometrica* 81, 1347–1393.

Bris, Arturo, Ivo Welch, and Ning Zhu, 2006, The costs of bankruptcy: Chapter 7 liquidation versus Chapter 11 reorganization, *The Journal of Finance* 61, 1253–1303.

Chan, Louis KC, Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *The Journal of Finance* 56, 2431–2456.

Cockburn, Iain, and Zvi Griliches, 1988, The estimation and measurement of spillover effects of R&D investment-industry effects and appropriability measures in the stock market's valuation of R&D and patents, *The American Economic Review* 78, 419–423.

Corrado, Carol, Charles Hulten, and Daniel Sichel, 2005, Measuring capital and technology: An expanded framework, in *Measuring capital in the new economy* . pp. 11–46 (University of Chicago Press).

——— , 2009, Intangible capital and US economic growth, *Review of income and wealth* 55, 661–685.

Corrado, Carol A, and Charles R Hulten, 2010, How do you measure a “technological revolution”?, *American Economic Review* 100, 99–104.

——— , 2014, Innovation accounting, in *Measuring Economic Sustainability and Progress* . pp. 595–628 (University of Chicago Press).

Crouzet, Nicolas, and Janice C Eberly, 2019, Understanding weak capital investment: the role of market concentration and intangibles, Working Paper 25869 National Bureau of Economic Research.

Cunningham, Colleen, Florian Ederer, and Song Ma, 2018, Killer acquisitions, *Working paper.*

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *The Journal of Finance* 61, 1605–1643.

Eberhart, Allan C, William F Maxwell, and Akhtar R Siddique, 2004, An examination of long-term abnormal stock returns and operating performance following R&D increases, *The Journal of Finance* 59, 623–650.

Eisfeldt, Andrea L, and Dimitris Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *The Journal of Finance* 68, 1365–1406.

——— , 2014, The value and ownership of intangible capital, *American Economic Review* 104, 189–94.

Evenson, Robert E, and Larry E Westphal, 1995, Technological change and technology strategy, *Handbook of development economics* 3, 2209–2299.

Falato, Antonio, Dalida Kadyrzhanova, and Jae Sim, 2013, Rising intangible capital, shrinking debt capacity, and the US corporate savings glut, *Working paper.*

Fazzari, Steven M, Glenn Hubbard, and Bruce C Petersen, 1988, Financing constraints and corporate investment, *Brookings Papers on Economic Activity* 1988, 141–206.

Gourio, Francois, and Leena Rudanko, 2014, Customer capital, *Review of Economic Studies* 81, 1102–1136.

Griliches, Zvi, 1996, *R&D and Productivity: The Econometric Evidence* (Chicago University Press).

——— , and Jacques Mairesse, 1984, Productivity and R&D at the firm level, in *R&D, patents, and productivity* . pp. 339–374 (University of Chicago Press).

Gutiérrez, Germán, and Thomas Philippon, 2017, Investmentless growth: An empirical investigation, *Brookings Papers on Economic Activity* p. 89.

Hall, Bronwyn H, Adam Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of economics* pp. 16–38.

Hall, Bronwyn H, Jacques Mairesse, and Pierre Mohnen, 2010, Measuring the returns to r&d, in *Handbook of the Economics of Innovation*vol. 2 . pp. 1033–1082 (Elsevier).

Hall, Robert E, 2001, The stock market and capital accumulation, *American Economic Review* 91, 1185–1202.

Hayashi, Fumio, 1982, Tobin's marginal q and average q: A neoclassical interpretation, *Econometrica* 50, 213–224.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632–654.

Huang, N, and E Diewert, 2007, Estimation of R&D depreciation rates for the US manufacturing and four knowledge intensive industries, in *Sixth Annual Ottawa Productivity Workshop Held at the Bank of Canada*.

Hulten, Charles R, and Xiaohui Hao, 2008, What is a company really worth? Intangible capital and the "Market to book value" puzzle, Discussion paper, National Bureau of Economic Research.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *The Quarterly Journal of Economics* 132, 665–712.

Lev, Baruch, 2018, Ending the accounting-for-intangibles status quo, *European Accounting Review* forthcoming.

——— , and Suresh Radhakrishnan, 2005, The valuation of organization capital, in *Measuring capital in the new economy* . pp. 73–110 (University of Chicago Press).

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting and Economics* 21, 107–138.

Lev, Baruch, and Paul Zarowin, 1999, The boundaries of financial reporting and how to extend them, *Journal of Accounting research* 37, 353–385.

Li, Kai, Buhui Qiu, and Rui Shen, 2018, Organization capital and mergers and acquisitions, *Journal of Financial and Quantitative Analysis* pp. 1–39.

Li, Peixin, Frank Weikai Li, Baolian Wang, and Zilong Zhang, 2018, Acquiring organizational capital, *Finance Research Letters* 25, 30–35.

Li, Wendy CY, and Bronwyn H Hall, 2016, Depreciation of business r&d capital, *Review of Income and Wealth*.

Loumioti, Maria, 2012, The use of intangible assets as loan collateral, *Available at SSRN 1748675*.

Ma, Song, Joy Tianjiao Tong, and Wei Wang, 2019, Selling innovation in bankruptcy, *Working paper*.

Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains?, *The Journal of Finance* 56, 2019–2065.

Mann, William, 2018, Creditor rights and innovation: Evidence from patent collateral, *Journal of Financial Economics* 130, 25–47.

Mead, Charles Ian, et al., 2007, R&D depreciation rates in the 2007 R&D satellite account, *Bureau of Economic Analysis/National Science Foundation*.

Pakes, Ariel, and Mark Schankerman, 1984, The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources, in *R&D, patents, and productivity* . pp. 73–88 (University of Chicago Press).

Peters, Ryan H, and Lucian A Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.

Phillips, Gordon M, and Alexei Zhdanov, 2013, R&D and the incentives from merger and acquisition activity, *The Review of Financial Studies* 26, 34–78.

Potepa, James, and Kyle T Welch, 2018, Calibrating innovation proxies with an accurate Tobin's Q and appraised innovation value, *Working paper*.

Rhodes-Kropf, Matthew, David T Robinson, and Sean Viswanathan, 2005, Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics* 77, 561–603.

Roll, Richard, 1986, The hubris hypothesis of corporate takeovers, *Journal of business* pp. 197–216.

Shleifer, Andrei, and Robert W Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *The Journal of Finance* 47, 1343–1366.

Sun, Qi, and Mindy X Zhang, 2018, Financing intangible capital, *Journal of Financial Economics* forthcoming.

Warusawitharana, Missaka, 2010, The return to R&D, Discussion paper, Federal Reserve Board Working Paper.

Williamson, Oliver E, 1988, Corporate finance and corporate governance, *The journal of finance* 43, 567–591.

Zhang, Xiaolan, 2014, Who bears firm-level risk? Implications for cash flow volatility, in *2014 Meeting Papers* no. 184. Society for Economic Dynamics.

9 Figures and tables

Figure 1: Capital expenditures, R&D and SG&A: 1977–2018

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).

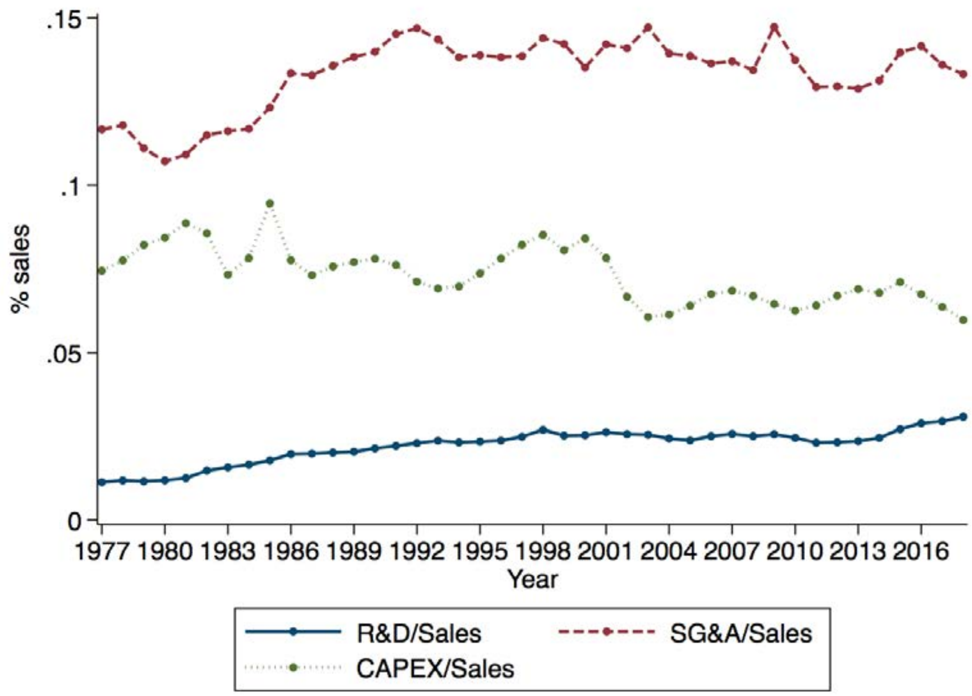


Figure 2: Market-to-book: 1977–2017

The figure reports the average (.025% tail winsorized) market-to-book for Compustat firms outside of financials, mining, real estate and utilities. The numerator is the sum of market value of equity at the end of the fiscal year, total liabilities and book preferred stock. The denominator is total assets (including acquired intangibles). The solid red line is one (theoretical mean) and the dashed horizontal line is the sample average.

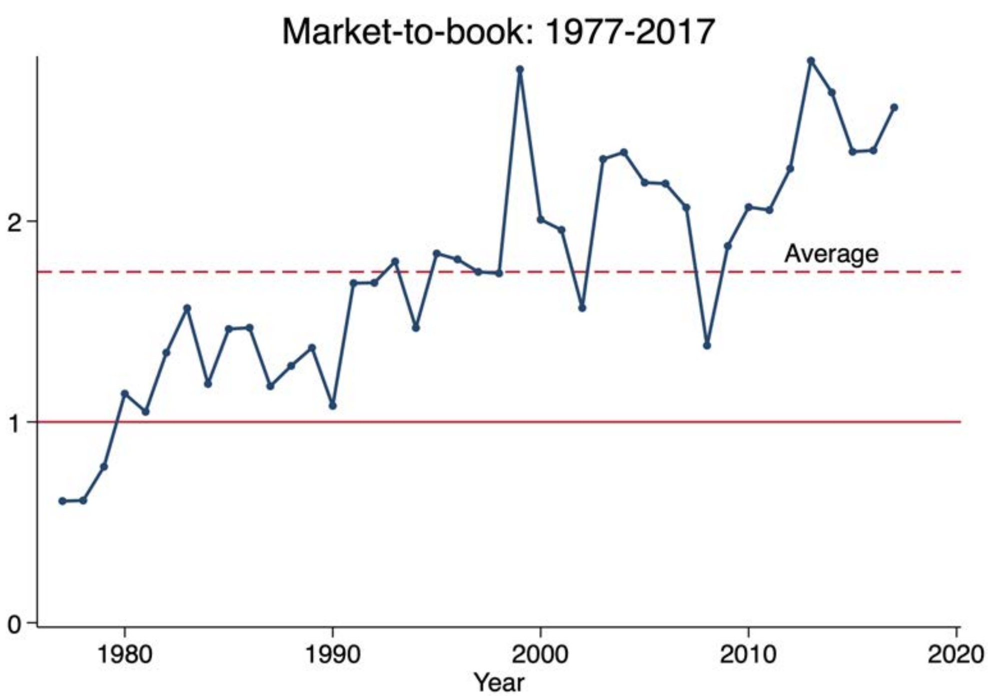


Figure 3: Market-to-book with intangibles: 1977–2017

The figure reports the average (5% tail winsorized) market-to-book for Compustat firms outside of financials, mining, real estate and utilities. 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 solid line time series, the denominator is total assets (including acquired intangibles). For the dashed line time series, the denominator also includes the knowledge and organizational capital stocks estimated using the parameters in Table 4. The two horizontal red lines present the sample averages of each series.

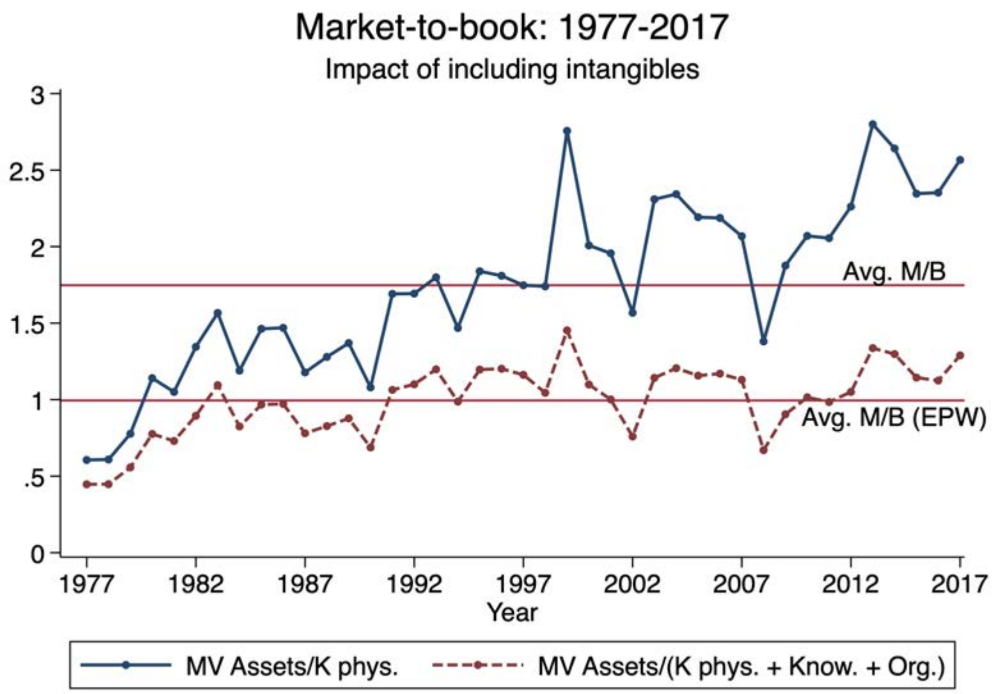
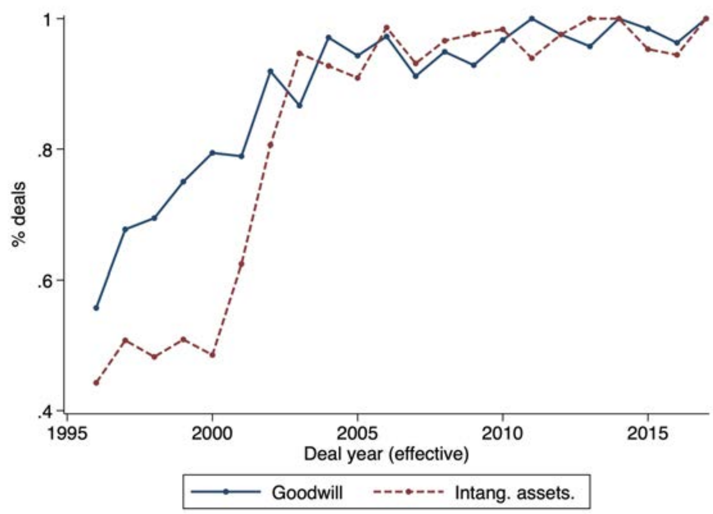


Figure 4: Percentage of acquisition deals with non-zero intangible assets or goodwill

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

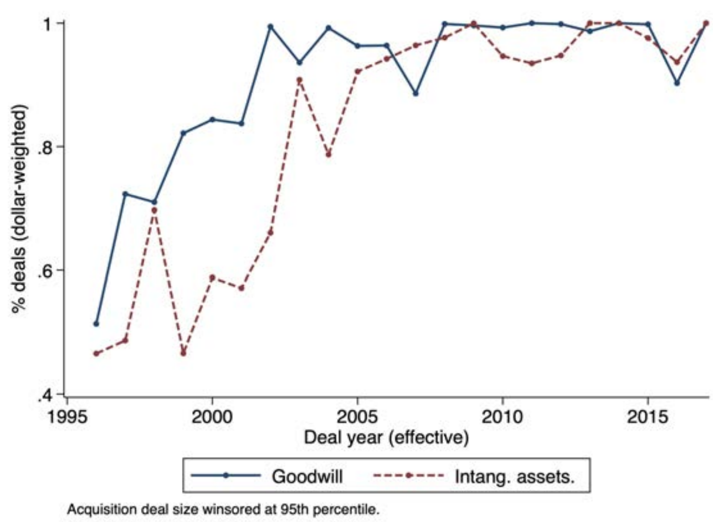


Figure 5: Percentage of acquisition deal size for intangible assets

The figure reports the average percentage of an acquisition deal size (i.e., enterprise value of the deal) that is 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.

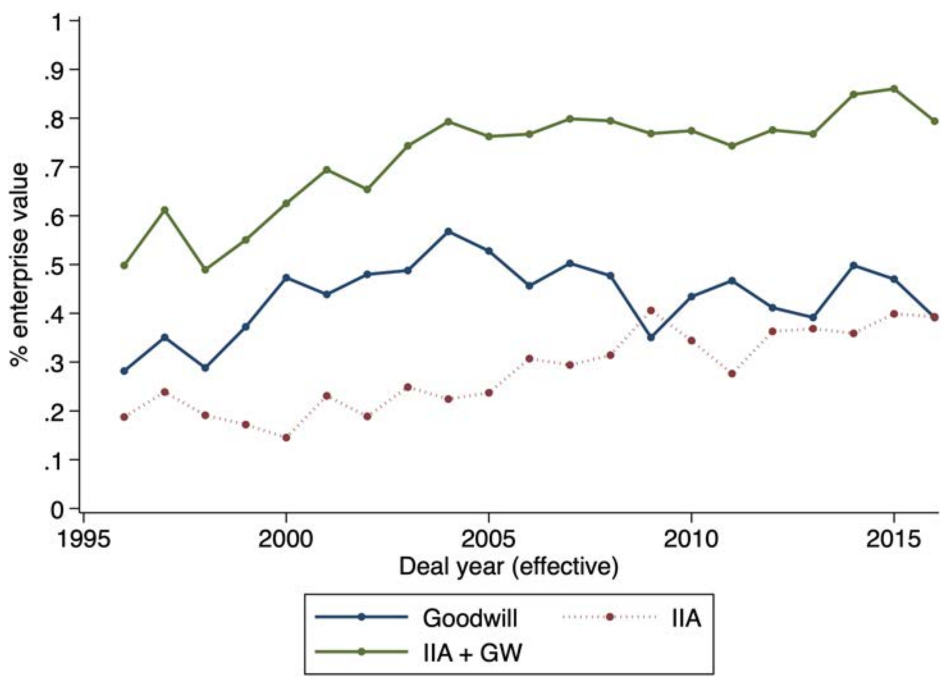


Figure 6: Percentage of acquisition deal size for intangible assets: post-goodwill adjustment

The figure reports the average percentage of an acquisition deal size (i.e., enterprise value of the deal) that is attributed to goodwill after synergy or over-payment adjustment and its sum with IIA. The adjustment detailed in Section 3.2 uses the market reaction to the acquisition announcement for both the target and acquirer. The sample is the subset of acquisitions (see Section 3) associated with deals that have non-zero goodwill or intangible assets acquired.

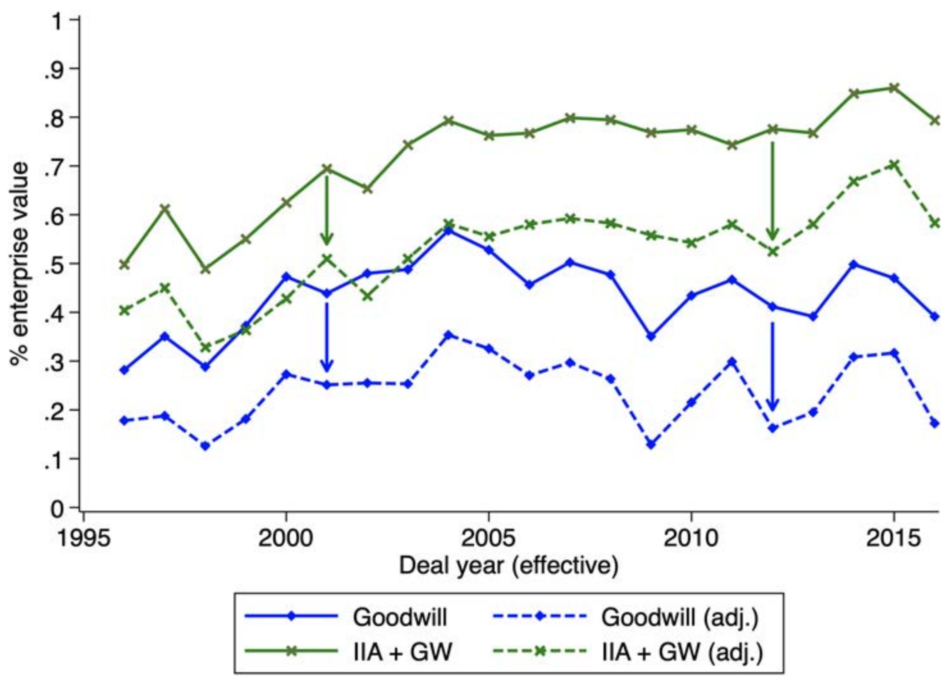


Figure 7: Estimated year fixed effects and S&P 500 index

The figure reports the exponentiated year fixed effects ρ_t from the non-linear least squares estimation of equation (11):

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

along with de-meaned, de-trended levels of the S&P 500 index at the end of the 2nd quarter of each year. The year fixed effects are estimated in logs and constrained such that they average zero over all years.

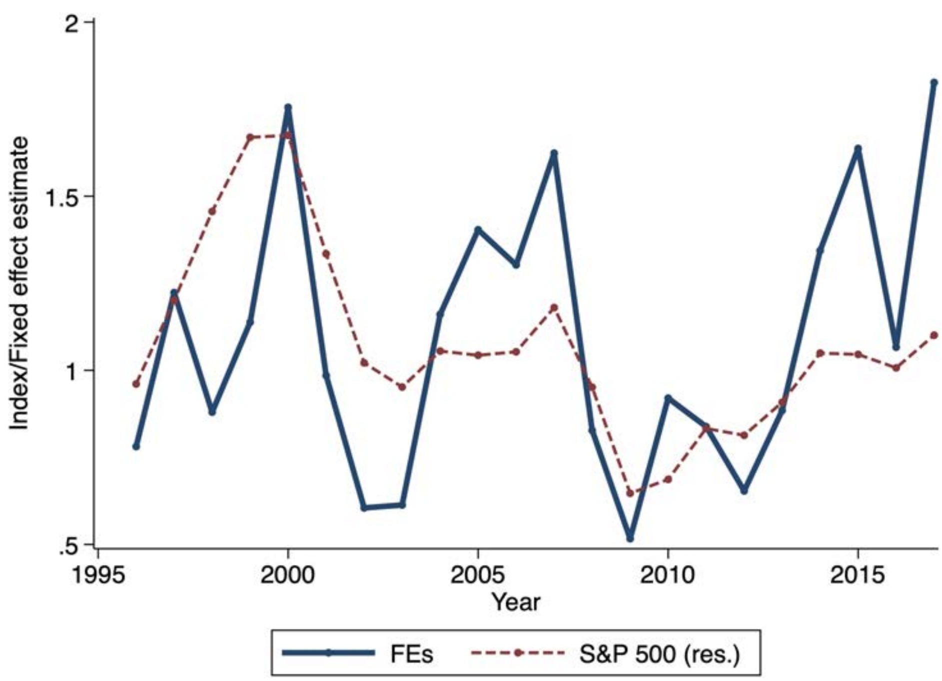


Figure 8: Intangible asset intensity

The figure reports of 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 estimnates from Table 4 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.

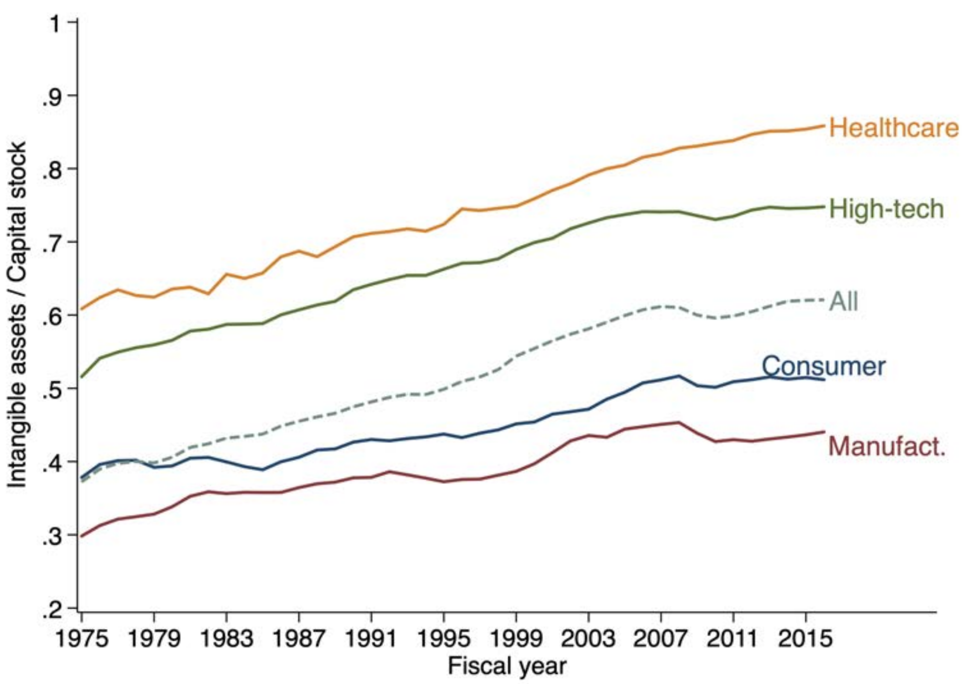


Figure 9: Knowledge capital as a fraction of total intangible capital

The figure reports of the ratio of knowledge capital – the accumulated R&D using the estimates from Panel A of Table 4 – to total intangibles (sum of knowledge and organizational capital) averaged across all firms in each industry-year.

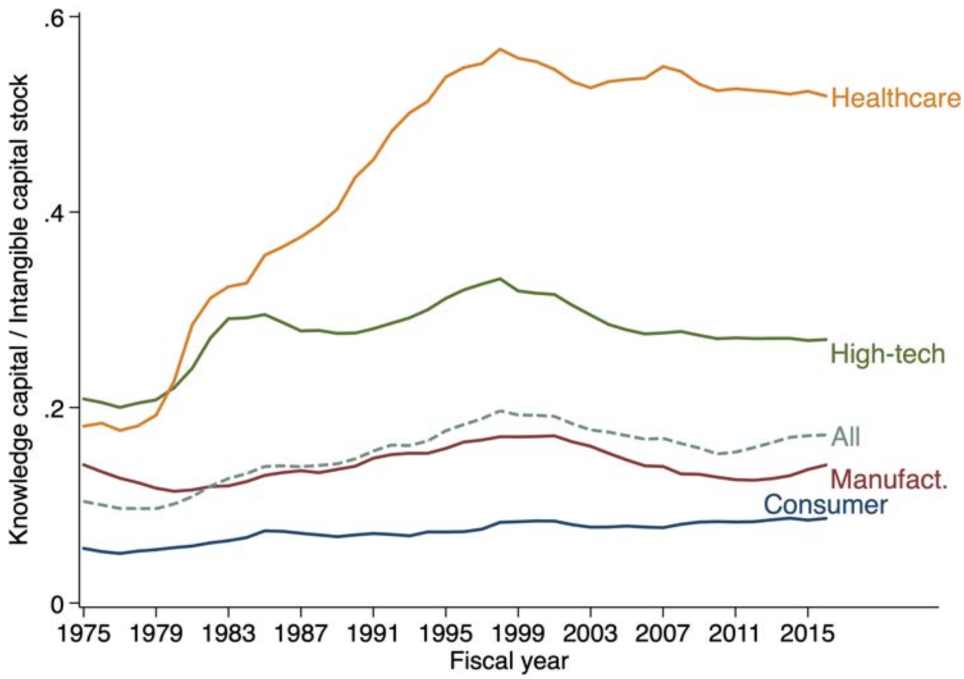


Figure 10: Comparing intangible stocks: new methods versus existing BEA-HH/Literature

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.

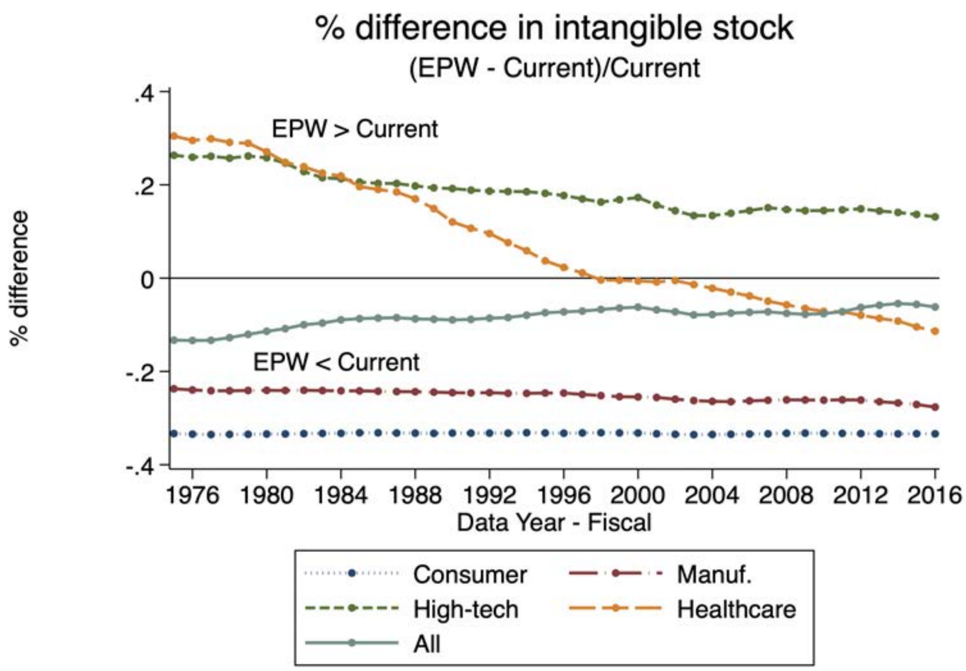


Figure 11: Comparing model fit of intangible capital stock measures

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.

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 instead 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.

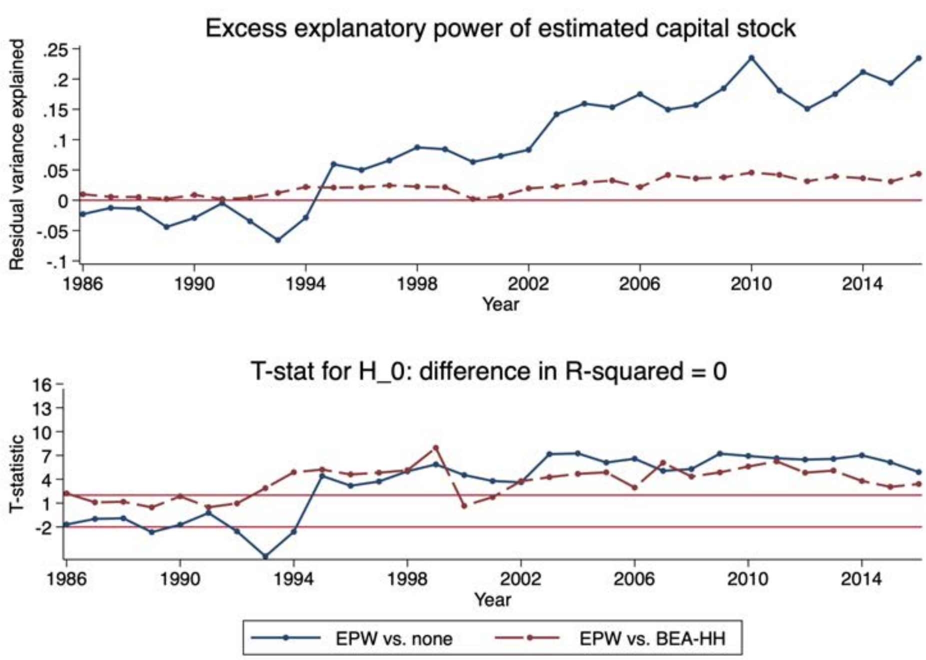


Figure 12: Testing differences in rates of 10-K mentions of "personnel" or "key talent"

In each fiscal year, we sort firms into quintiles based on their organizational capital stock using our depreciation rates (see Table 4) 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 at $t = 1.96$.

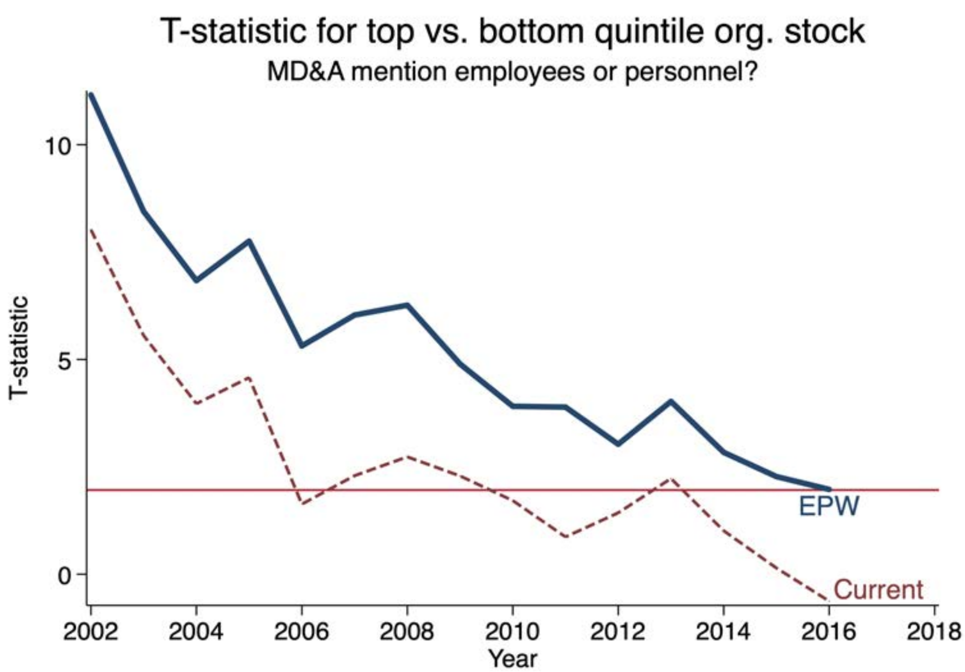


Figure 13: Comparison to an estimation using public market prices

The figure reports the additional explanatory power of the estimated capital stock using our measure ("EPW") over other those from the estimation using the public market estimation detailed in Section 7.1. 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 physical assets 25% for the public market estimation. "EPW vs. firm-level markup" uses physical 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.

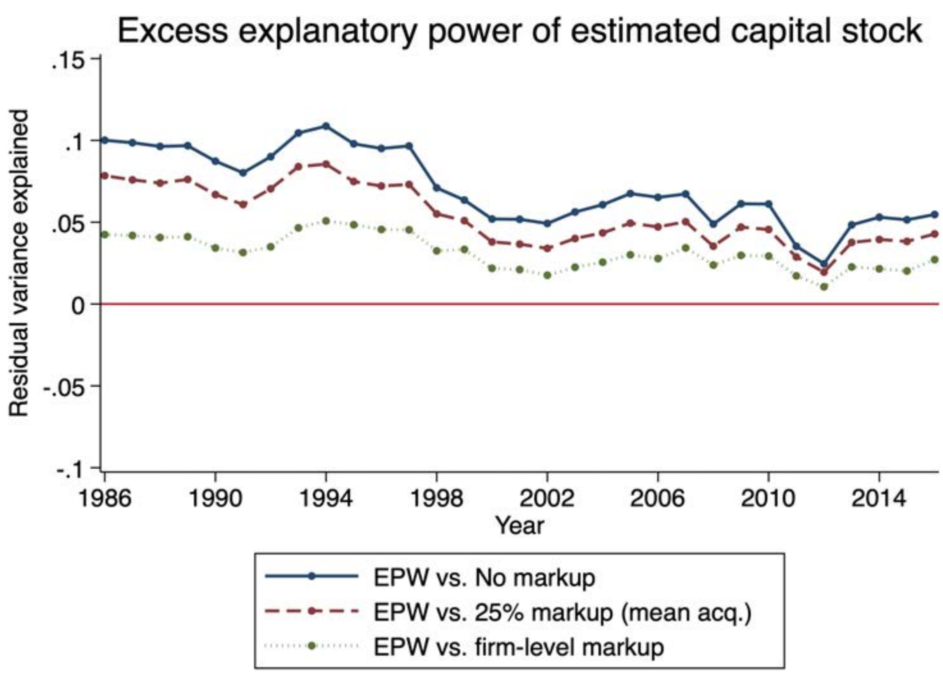


Figure 14: Rolling Estimates of Parameter Values in 10-Year Windows

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 4.

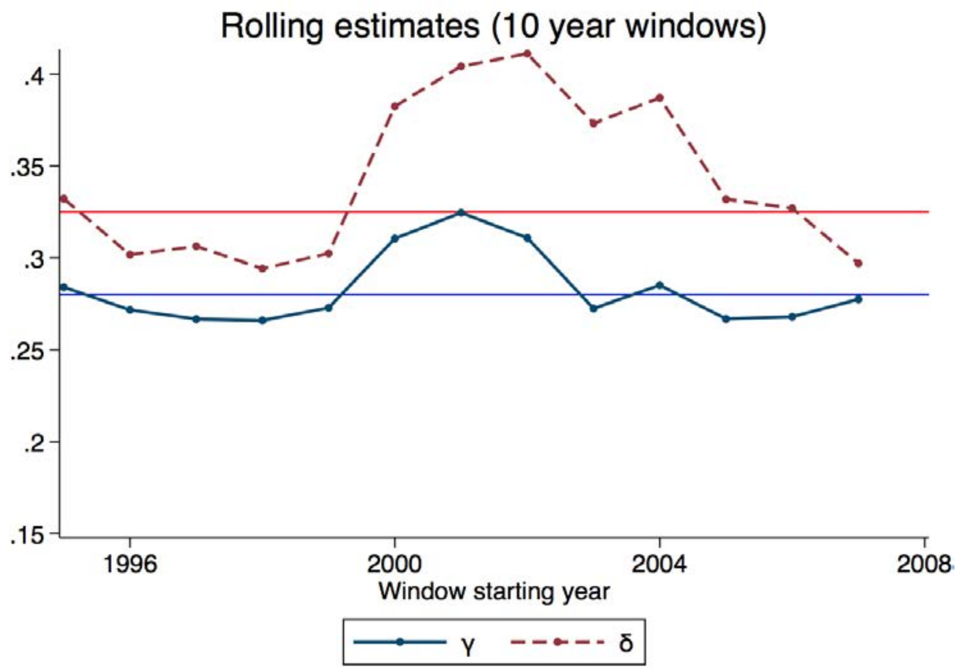


Table 1: Variables and definitions of terms

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

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 physical 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 acroynm 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).

Table 2: 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 Table 1.

	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	2521.68	0.80	444.28	235456.36	9583.26
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	1106.53	-5.54	159.10	52730.25	3475.09
Adjusted goodwill (mil)	1,521	781.26	-2099.53	67.26	37450.17	2863.58
Total intangibles (IIA + GW, mil)	1,521	2002.38	-5.54	266.84	170875.33	7981.41
Total intangibles (IIA + Adj. HW, mil)	1,521	1677.12	-2081.13	174.11	168775.80	7565.14
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	1.30	-0.11	0.84	411.69	11.09
Total intangibles / Total deal size (< 1)	1,056	0.63	-0.11	0.72	1.00	0.29
Total intangibles / Total ent. value (all)	1,521	0.75	-0.10	0.77	35.41	0.97
Total intangibles / Total ent. value (< 1)	1,248	0.63	-0.10	0.70	1.00	0.29

	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	31.92	0.00	2.47	1566.04	117.12

Table 3: 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	2521.68	444.28	9583.26	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 4: Parameter Estimates from Non-linear Least Squares Estimation

Parameter estimates are based on non-linear least squares regressions of the price of non-physical 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 (70%) 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 panel contains all firms, while panels B reports the estimates excluding failed firms. 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`).

Panel A: All firms

	γ	δ_S	δ_G	N	$\bar{\delta}^{BEA}_G$	$\bar{\delta}^{lit}_G$
All	0.28	0.20	0.32	2000	0.28	0.164
	(0.025)		(0.037)			
Consumer	0.20	0.20	0.30	511	0.31	0.153
	(0.029)		(0.304)			
Manufacturing	0.23	0.20	0.34	233	0.25	0.156
	(0.063)		(0.130)			
High Tech	0.45	0.20	0.46	715	0.315	0.255
	(0.057)		(0.076)			
Health	0.51	0.20	0.34	245	0.181	0.172
	(0.159)		(0.073)			
Other	0.35	0.20	0.25	296	N/A	0.15
	(0.067)		(0.183)			

Pseudo-R^2: .504

Panel B: Excluding failed firms

	γ	δ_S	δ_G	N	$\bar{\delta}^{BEA}_G$	$\bar{\delta}^{lit}_G$
All	0.42	0.20	0.26	1521	0.28	0.164
	(0.040)		(0.037)			
Consumer	0.36	0.20	0.28	335	0.31	0.153
	(0.053)		(0.313)			
Manufacturing	0.24	0.20	0.15	186	0.25	0.156
	(0.081)		(0.139)			
High Tech	0.57	0.20	0.38	612	0.315	0.255
	(0.072)		(0.078)			
Health	0.63	0.20	0.24	218	0.181	0.172
	(0.208)		(0.065)			
Other	0.49	0.20	-0.21	170	N/A	0.15
	(0.111)		(0.142)			

Pseudo-R^2: .406

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 market valuation of granted patents in the firm-year, while the columns under the "Citation-weighted" present values of patents measured as the sum of citations received in that year scaled by citations received by patents in the same industry-year. The control "Log knowledge K" is the log (plus 1) of the estimated knowledge capital from the parameter estimates in Table 4 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 4. 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: OLS Results from an Investment-q Relation: By industry

Results are from OLS panel regressions of investment on lagged Tobin's q and firm and year fixed effects. A unit of observation is a firm-year for public firms from 1996–2016. We follow the Peters and Taylor (2017) method to construct both a new total capital that incorporates intangibles and a modified investment rate for $SG\&A$. Each column uses a different investment measure noted in the top rows

$$I_{it} = \beta Q_{it} + \mu_i + \eta_t + \varepsilon_{it}$$

"Total Q (PT)" is the Q_{it} from Peters and Taylor (2017) that uses the BEA-HH depreciation rates. The row "Total Q (EPW)" presents an alternative total Q that uses the depreciation and investment fractions from Table 4 to calculate total intangible stock. Because our main parameters in Table 4 are estimated by industry, each panel here is an industry sub-sample. The "Within-R2" are the within-firm and -year R^2. Standard errors clustered at the firm-year reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R&D		SG&A		CAPX		CAPX+R&D+SG&A	
				Consumer				
Total Q (PT)	0.0016***		0.0075***		0.0079***		0.017***	
	(0.00034)		(0.00078)		(0.00093)		(0.0014)	
Total Q (EPW)		0.0018***		0.0073***		0.0083***		0.017***
		(0.00035)		(0.00074)		(0.00089)		(0.0013)
Observations	29435	29435	29442	29442	29462	29462	29435	29435
R^2	0.57	0.58	0.64	0.63	0.38	0.38	0.50	0.49
Within-R^2	0.047	0.049	0.13	0.16	0.077	0.084	0.16	0.18
				Manufacturing				
Total Q (PT)	0.0026***		0.0057***		0.0059***		0.014***	
	(0.00055)		(0.00077)		(0.0011)		(0.0018)	
Total Q (EPW)		0.0029***		0.0054***		0.0060***		0.014***
		(0.00058)		(0.00074)		(0.0010)		(0.0017)
Observations	18467	18467	18469	18469	18476	18476	18467	18467
R^2	0.56	0.61	0.59	0.57	0.30	0.29	0.43	0.44
Within-R^2	0.057	0.059	0.11	0.11	0.050	0.053	0.13	0.13
				High Tech				
Total Q (PT)	0.0046***		0.0060***		0.0071***		0.018***	
	(0.00035)		(0.00037)		(0.00052)		(0.0010)	
Total Q (EPW)		0.0051***		0.0071***		0.0071***		0.019***
		(0.00039)		(0.00045)		(0.00051)		(0.0011)
Observations	28783	28783	28784	28784	28795	28795	28783	28783
R^2	0.61	0.62	0.53	0.51	0.42	0.42	0.56	0.55
Within-R^2	0.12	0.13	0.17	0.15	0.17	0.16	0.29	0.28
				Healthcare				
Total Q (PT)	0.0060***		0.0060***		0.0048***		0.017***	
	(0.00070)		(0.00049)		(0.00070)		(0.0014)	
Total Q (EPW)		0.0073***		0.0058***		0.0043***		0.017***
		(0.00074)		(0.00070)		(0.00067)		(0.0015)
Observations	13519	13519	13519	13519	13524	13524	13519	13519
R^2	0.54	0.61	0.56	0.48	0.28	0.26	0.47	0.44
Within-R^2	0.066	0.077	0.14	0.078	0.077	0.068	0.18	0.16
Year / Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 7: Parameter Estimates: Robustness tests

Panel A of the table reports the parameter estimates as found in Table 4 for the set of companies acquired after 2001. Panel B of the table reports the parameter estimates as found in Table 4 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 D of 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 4. The last three rows present the estimates for three different markup assumption for physical assets when computing the implied intangible values from traded firms. See Section 7.1 for details.

Panel A: Post-2001 acquisitions and failures						
	γ	δ_S	δ_G	N	$\bar{\delta}_G^{BEA}$	$\bar{\delta}_G^{lit}$
All	0.27	0.20	0.32	1152	0.28	0.164
Consumer	0.16	0.20	0.15	217	0.31	0.153
Manufacturing	0.19	0.20	0.30	122	0.25	0.156
High Tech	0.47	0.20	0.49	450	0.315	0.255
Health	0.83	0.20	0.39	181	0.181	0.172
Panel B: Unadjusted goodwill prices						
	γ	δ_S	δ_G	N	$\bar{\delta}_G^{BEA}$	$\bar{\delta}_G^{lit}$
All	0.43	0.20	0.22	2000	0.28	0.164
Consumer	0.27	0.20	0.09	511	0.31	0.153
Manufacturing	0.45	0.20	0.32	233	0.25	0.156
High Tech	0.71	0.20	0.38	715	0.315	0.255
Health	0.74	0.20	0.21	245	0.181	0.172
Panel C: Targets with positive R&D						
	γ	δ_S	δ_G	N	$\bar{\delta}_G^{BEA}$	$\bar{\delta}_G^{lit}$
All	0.36	0.20	0.37	1208	0.28	0.183
Consumer	0.28	0.20	0.41	96	0.31	0.154
Manufacturing	0.24	0.20	0.31	170	0.238	0.157
High Tech	0.42	0.20	0.45	641	0.315	0.292
Health	0.61	0.20	0.35	239	0.181	0.172
Panel D: Public market estimation						
	γ	δ_S	δ_G	N	$\bar{\delta}_G^{BEA}$	$\bar{\delta}_G^{lit}$
Baseline	0.29	0.20	0.31	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