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Measuring Intangible Capital with Market Prices

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Abstract. Accounting standards prohibit internally created knowledge and organizational capital from being disclosed on firm balance sheets. As a result, balance sheets exhibit downward biases that have become exacerbated by increasing levels of intangible investments. To offset these biases, researchers must estimate the value of these off-balance sheet intangibles by capitalizing prior flows of research and development (R&D) and selling, general, and administrative (SG&A). In doing so, a set of capitalization parameters must be assumed (i.e., the R&D depreciation rate and the fraction of SG&A that represents a long-lived asset). We estimate these parameters using market prices from firm exits and use them to capitalize intangibles for a comprehensive panel of firms from 1978 to 2017. We then use a series of validation tests to examine the performance of our intangible capital stocks versus those developed from commonly used parameters. On average, our estimates of intangible capital are 15% smaller than estimates from status quo parameters while exhibiting larger variation across industry. Intangible capital stocks derived from exit price parameters outperform existing measures when explaining market enterprise values and identifying human capital risk. Adjusting book values with exit-based intangible capital stocks markedly attenuates well-documented biases in market-to-book and return on equity ratios while increasing the precision of the high-minus-low asset pricing factor. We conclude that our capitalization parameters create intangible stocks that perform equal to or better than status quo measures in various applications.

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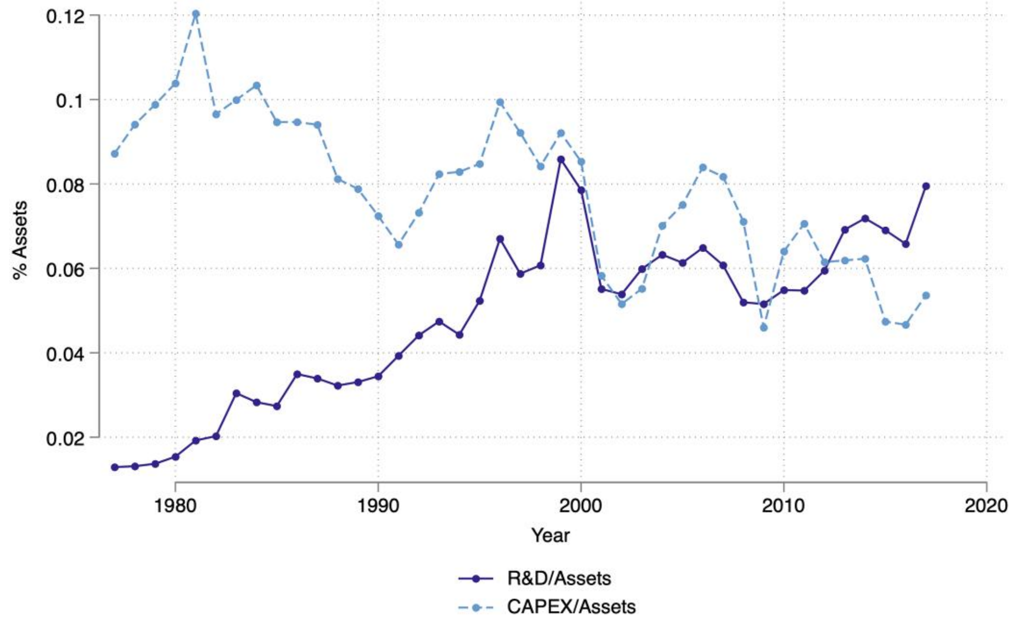
1. Introduction

Corporate investment has transformed over the last few decades, with U.S. firms spending less on tangible assets and more on intangibles related to knowledge and organizational capital (Figure 1). This reduction in physical capital investments, along with the weaker connection between physical capital investments and firm valuation, is described as a broader "investment puzzle" by Gutiérrez and Philippon (2017, p. 90) and Crouzet and Eberly (2019). A shared conclusion of both papers is that standard investment measures on firms' balance sheets fail to capture the growing importance of intangible assets, resulting in a downward bias in the recorded book values of invested capital.[1] This bias has grown over time as evidenced by the dramatic upward trend in market-to-book ratios.

Reliable measures of intangible capital are becoming increasingly important for capital markets and financial managers. For instance, numerous studies have provided evidence of mispriced equity for firms with higher levels of intangible capital, which could lead to suboptimal resource allocation.[2] In debt markets, banks are less willing to lend to firms with higher information asymmetry and more uncertainty about their liquidation values, two primary characteristics of intangible-intensive firms.[3] In corporate finance, financial managers making capital budgeting decisions must estimate book values of intangible capital to calculate returns to intangible capital (Hall et al. 2010). To adjust for the downward bias in invested capital, researchers estimate the off-balance sheet intangible capital with accumulated flows of R&D,[4] SG&A,[5] or both.[6] Such adjustments require assumptions about the capital accumulation process, such as intangible depreciation rates and the fraction of SG&A to be capitalized. Unfortunately, as Corrado et al. (2009) highlight, "relatively little is known about depreciation rates for intangibles" (Corrado et al. 2009, p. 674). Although there is no clear consensus on parameter values, the most recently updated rates for knowledge capital depreciation use Bureau of Economic Analysis

Figure 1. (Color online) Capital Expenditures (CAPEX) and R&D: 1977–2018



Note. This figure reports average R&D expense and CAPEX as a fraction of lagged total assets (without internally generated intangibles) for Compustat firms from 1977 to 2018.

(BEA) data based on multiple data sets, including National Science Foundation (NSF) surveys, where depreciation rates are based on the Li and Hall (2020) forward-looking profit model. Hulten and Hao (2008) (HH) provide the main parameter for organizational capital (hereafter, we refer to the combination of these parameters as "BEA-HH"). These capitalization parameters, however, are limited by gaps in industry coverage.[7]

We propose a capitalization model that uses the market values of intangible assets to estimate a new set of intangible capitalization parameters (hereafter referred to as "exits" or "exit-based" parameters) from a firm's prior flows of intangible investments. Specifically, we obtain market values of intangible assets from firm exits that include acquisitions, liquidations, and bankruptcies. We identify the market prices of identifiable intangible assets (IIAs) and goodwill (GW) from these firms and match these prices to the firm's past spending on R&D and SG&A to estimate parameters that capture (1) the depreciation rate of prior R&D investment in knowledge capital and (2) the fraction of SG&A that represents an investment into organizational capital.

The results of our parameter estimation imply an average 33% annual depreciation rate for R&D versus 23% for BEA R&D depreciation rates where industry coverage is available.[8] Across industries, we find a significantly higher depreciation rate for the two industries with the highest R&D intensity: healthcare (33% versus 17%) and high tech (42% versus 28%). For organizational capital, we find that our 28% estimate of the fraction of SG&A representing invested capital is similar to that used in earlier work (30%). However, although prior studies have assumed this ratio to be constant across industries, this ratio varies dramatically across industries: from 20% (consumer) to 51% (healthcare).

To assess the quality of these parameter estimates versus existing parameters, we develop a series of out-of-sample validation tests where we use our exit-based parameters to measure intangible capital and compare the results of our validation tests with those using estimated values of intangible capital against those derived from BEA-HH parameters. Utilizing a full panel of Compustat firms from 1978 to 2017, our primary validation test asks whether augmenting book values of invested capital with our intangible asset estimates improves their ability to explain market enterprise values. We find that exits-based intangible stocks improve the R^2 in year-by-year cross-sectional regressions in all 39 years (relative to BEA-HH) from 1978 to 2017. This additional explanatory power is statistically significant in all years.

Additional validation tests directly examine the association between economic outcomes and capitalized knowledge and organizational capital stocks. To begin, we examine whether our estimates of organizational capital better capture differences in human capital and brand value versus BEA-HH estimates of organizational capital. We follow Eisfeldt and Papanikolaou (2013) to test whether firms with high organizational capital are more likely to disclose risks regarding the potential loss of key talent in their 10-K filings. To do so, we analyze text from management discussions about risk in over 100,000 10-K filings from 2002 to 2017 and identify whether the firm mentions "personnel" or "key talent." Exits-based organizational capital measures more accurately sort firms into portfolios of high and low human capital risk versus BEA-HH-based sorts. A similar exercise using firms' brand equity rankings corroborates the effectiveness of our measures in identifying organizational capital. Our final validation asks if and how our new estimates of intangible capital can explain previously established measures of patent values and trademark production. We find that exits stocks explain marginally more of the R^2 in patent valuations from Kogan et al. (2017) and the number of new trademarks filed by a firm in a given year (Heath and Mace 2020). Overall, we find that intangible capital stocks created from our exits parameters are better associated with the expected economic outcomes relative to using BEA-HH parameters, with the documented improvements in the quality of our intangible stocks likely coming from industry-level variation in the organizational capital investment rate parameters and broader industry coverage in the knowledge capital depreciation rates.

To illustrate how estimated intangible capital stocks may improve the usefulness of financial statements in empirical research applications, we incorporate our measure of capitalized intangible assets using exits parameter estimates into several commonly used variables in corporate finance and asset pricing applications. Specifically, we calculate intangible adjusted measures of market-to-book ratios, returns on equity, and portfolio returns to the high-minus-low (HML) value premium factor. We find that using exits parameters to adjust these values for intangible capital improves the usefulness of all three variables. First, the impact of incorporating intangibles when calculating market to book is economically large, and the importance of such an adjustment has increased with time. Since 1997, the unadjusted market-to-book ratio drifts have drifted upward by 0.04 per year, with the average book to market recently exceeding two in the 2010s. After adjusting book equity for missing intangible capital, this upward trend falls by 68%, demonstrating that unadjusted book equity measures are systematically understated. Next, we find a similar impact when exploring the effects of adjusting intangible capital on the return on equity (ROE). Adjusted ROEs fall 37% compared with the standard measure, and the final average mirrors the cost of equity capital estimates from the literature (e.g., Graham and Harvey 2018, Damodaran 2020). Finally, we show that adjustments to book equity for missing intangible capital shift 32% of firm-month observations away from their original HML portfolio assignment with unadjusted book equity values (Fama and French 1992, 1993). Returns from an intangible-adjusted HML factor portfolio are higher with lower standard deviations when compared with the standard HML measure, implying that the inclusion of intangible capital increases the precision of HML portfolio sorts.

Given the importance of selection concerns for the representativeness of our parameter estimates, we compare the stocks from our exits price-based estimates with an alternative approach of using trading prices for intangibles' market prices. The parameter estimates we obtain from the publicly traded prices have no sample selection issues. Repeating all the diagnostic tests of the implied stocks from this sample shows that the exits parameters are superior (Online Appendix Section A.5). We also examine the quality of our organizational capital parameters against more granular industry-level estimates based on a profit model from Iqbal et al. (2024). When paired with the standard BEA-based knowledge capital stocks, the exits stocks also outperform the Iqbal et al. (2024) implied organizational stocks. Next, our inability to separately identify parameters requires we assume a fixed depreciation rate used in the literature when estimating the fraction of SG&A that is investment. In a robustness test, we find that other parameter estimates do not depend on this assumption (see Figure 10). Finally, we provide a battery of robustness checks (Section 8) to assess the role of each major assumption with our sample choice and find that our adjustments to reported goodwill and inclusion of liquidations are important for the estimates' superior performance.

We contribute to three broad literatures. First, we provide parameter estimates to corporate finance researchers who 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 Xiaolan 2018). Second, we contribute to a long-standing literature on growth economics that attempts to measure the value of knowledge in the economy. Specifically, our work both re-estimates the knowledge capital accumulation process using market prices and extends these estimates to organizational capital for the first time (Corrado et al. 2009, Corrado and Hulten 2010, Hall et al. 2010, Acemoglu et al. 2018). Finally, we contribute to an active debate surrounding off-balance sheet intangible capital. Lev (2019) 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.

2. A Framework for Estimating Intangible Capital

Although book values of physical assets are periodically reported on the balance sheet at the original market price of the purchased investment less the asset's total depreciation (i.e., net book value), the same values for intangible assets typically go unreported. Such exclusions come despite the importance of a firm's intangible capital in generating economic value. We present a methodology motivated by the process for measuring physical asset values to accurately estimate intangible capital stocks for U.S. publicly listed firms.

Physical asset depreciation and the resulting net book value rely on a set of accounting depreciation rates, which are generally industry-level norms (e.g., estimated useful lives for straight-line depreciation). So, we begin by detailing an estimation approach for industry-level intangible depreciation rates (i.e., the fraction of assets depreciated over a year) and combine these parameters with the values of prior intangible investment flows to compute these intangible capital stocks:

$$K_t = K_{t-1} + Z_t - D_t. \tag{1}$$

Here, an asset in the current period t, K_t, evolves by adding current period investment Z_t to the previous period stock K_{t-1}, net of periodic depreciation D_t. Let δ be the periodic depreciation rate for K_{t-1}. Assuming geometric depreciation, (1) can be rewritten as

$$K_t = K_{t-1}(1-\delta) + Z_t. \tag{2}$$

The identity in (2) provides structure for estimating δ. Assuming $K_0 = 0$ and via iterative substitution, we arrive at (3), where the intangible capital stock (i.e., the net book value) is the aggregation of all undepreciated intangible investments since firm birth:[9]

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

To estimate the intangible depreciation rate, δ, in (3), we need data for K_t and Z_{t-k}. Although firms generally report values for Z_{t-k} on the income statement, they do not self-report estimates of K_t. Ideally, a well-functioning marketplace that reports current prices of these depreciated assets would be a data source of net book values K_t. Although some marketplaces like these exist for physical assets, such as Plant, property and equipment (PP&E) and real estate, this is generally not the case for intangible assets. Market prices for intangibles are difficult to obtain because many intangibles are unique and developed for internal use. Furthermore, these investments are generally not divulged to competitors for strategic reasons. Section 3 describes how we infer the prices of intangible assets from the market values of firm exit prices to obtain estimates of K_t.

Motivated by prior research that bifurcates intangible capital into two subcomponents, we express firm i's total intangible capital stock at time t, K_{it}, as the sum of *knowledge* capital, G_{it}, and *organizational* capital, S_{it}. Knowledge capital relates to information learned about processes, plans, or designs that can lead to economic benefits in future periods. Prior literature uses R&D expenses as a proxy for periodic investment in knowledge capital. Although the definition of organizational capital is more vague,[10] the consensus in the literature is to use some fraction (γ_S) (discussed further in Section 4) of SG&A to represent the periodic investment in organizational capital. Total intangible capital can now be written as $K_{it} = G_{it} + S_{it}$. Because both G and S evolve as in Equation (3), we have

$$K_{it} = \sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-\delta_S)^k \gamma_S \text{SG\&A}_{i,t-k}, \tag{4}$$

where δ_G and δ_S are the knowledge and organizational capital depreciation rates, respectively. Recall that if δ_G and δ_S are unbiased measures of economic depreciation for G and S, we can substitute the net book value with its price (i.e., $K_{it} = P_{it}^I$). This step assumes that prices for intangible assets are derived from firms that are price takers with constant returns to scale and thus, that average Q will approach a marginal Q of one (Hayashi 1982). To the extent that there are exceptions, let ξ be the market-to-book ratio. Equation (4) becomes

$$P_{it}^I = \xi\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-\delta_S)^k \gamma_S \text{SG\&A}_{i,t-k}\right). \tag{5}$$

From (5), we see that depreciation rates δ_G and δ_S combine with prior investment flows of R&D and SG&A and the intangible market-to-book ratio to give the total market price of the firm's intangible capital.[11]

Finally, adjustments are required before we take (5) to the price data discussed. To avoid weighting firms by size and without an obvious scaling variable, we take the natural logarithm of (5). Intangible asset prices and investments are likely measured with error, which we capture with the error term ϵ_{it}. The adjustments lead to our baseline estimating equation:

$$\log(P_{it}^I) = \log(\xi) + \log\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-\delta_S)^k \gamma_S \text{SG\&A}_{i,t-k}\right) + \epsilon_{it}. \tag{6}$$

With price (P_{it}^I) data, the values of periodic investment ($\text{R\&D}_{it}$, $\text{SG\&A}_{it}$), and modifications to adapt the model for real-world data, we can estimate parameters using nonlinear least squares. The resulting parameters allow us to recapitalize knowledge and organizational capital over a large panel of firms.[12]

3. Intangible Asset Market Valuations from Exit Prices

We obtain P^I_{it} from a sample of firms whose intangible assets are valued by the market in exits. This sample consists of a set of firms that allow us to derive the market values of intangibles from public firm acquisitions of other public firms and recovery asset values for firms that delisted from publicly traded markets because of bankruptcy. With acquisitions, asset appraisals owing to an acquisition undergo an extensive due diligence process by expert appraisers that result in precise valuations. Accounting regulations (Accounting Standards Codification 350) require that intangibles being purchased by the acquirer are directly recorded at market value on the acquirer's balance sheet as either IIAs or GW. Subsequently, P^I_{it} is calculated as the sum of IIA and GW. Most importantly, because our model relies on the value of total intangibles, we need only trust the valuation of physical assets and liabilities because the sum of IIA and GW equals the difference between the firm's mark-to-market net (physical) assets and the acquisition purchase price. The valuation of these physical assets and liabilities has a long history with standardized practice.[13]

We acknowledge two concerns related to our acquisition setting. The first relates to goodwill. Because our goal is to precisely measure the target firm's stand-alone values of organizational and knowledge capital and because prior studies (e.g., Roll 1986) have shown goodwill to be related to overpayment and acquisition-specific synergy values, we remove these factors from goodwill. What remains is a value that proxies for unidentifiable intangible assets. Specifically, we use the probability scaling method from Bhagat et al. (2005) and apply this to announcement day returns to estimate the synergy and overpayment component of the acquisition. The method—fully detailed in Online Appendix Section A.1.2—uses changes in target and acquirer market valuations in response to the acquisition announcement to estimate synergies. This estimate of acquisition-specific value is subtracted from the goodwill value reported in the purchase price allocation.[14]

The second concern relates to the nonrandom selection of acquired firms; acquisition targets may not be representative of the full population of firms. For example, empirical evidence suggests that acquirers may target firms with better than average innovation efficiency as part of a firm growth strategy (Phillips and Zhdanov 2013, Bena and Li 2014). To address this concern, we expand the sample of acquired firms to include firm exits from bankruptcies and liquidations of publicly traded companies over the sample period. For these exits, we estimate P^I_{it} by collecting recovered asset values from Moody's Default and Recovery Database (DRD) and multiplying by the average ratio of intangibles scaled by total assets, which we calculate from acquisitions in the same four-digit Standard Industrial Classification (SIC) code.[15] When the recovered asset values are not available in the DRD, we estimate recovery rates using the modified Fama–French (FF) 5 industry average recovery rates from the Moody's DRD. This recovery rate, multiplied by the outstanding debt, forms the "deal value" for these firms.

Ultimately, our goal is to improve the measurements of intangible capitalization parameters that allow us to create more accurate measures of intangible capital stocks than existing methods. We acknowledge that it may be difficult to create a sample of intangibles with market prices that perfectly represent the full population of firms. For example, it may be the case that acquisition targets have unsuccessful prior intangible investments, and supplementing the sample with liquidating firms does not remove the sample bias. In such instances, we acknowledge that such bias will be reflected in subpar performance of our exit-based stocks in validation tests that use the full panel of firms. As such, we allow the efficacy of our adjustments to address noisy goodwill and nonrandom selection to be dictated by the empirical results of the validation tests we develop in Section 8. Online Appendix Section A.1 provides more details on the goodwill and selection issues, with summary statistics on the firms in the sample and the role of goodwill in acquisitions.

It is still possible that our proposed adjustments to the exits sample fail to fully address the selection and valuation issues. Therefore, Online Appendix Section A.3 provides nearly all the diagnostic and validation tests using an alternative measure of intangible asset values that we call "trading." Using the universe of Center for Research in Security Prices (CRSP)–Compustat public firms, we take the market enterprise value and subtract an estimate of the market value of tangible assets, leaving us with the market value of intangible assets. Although this approach can apply to all firms with publicly traded prices, it demands that we estimate the markup of each firm's tangible assets (reported to the books at historical cost) to market value. We follow the prior literature from Erickson and Whited (2006, 2012) and Peters and Taylor (2017) and use gross PP&E to proxy for the market value of tangible assets in the estimation. This sample of intangible values removes concerns about sample selection bias, but it comes at the cost of requiring an assumption about the markup. Online Appendix Section A.5 discusses how the intangible stocks built from the estimated parameters from the trading prices underperform our proposed method.

3.1. Data Sources

We obtain data for R&D and SG&A from Compustat. Data on acquisitions, liquidations, and bankruptcies come first from Thomson's SDC Merger & Acquisition Database. We consider all U.S. public acquirers and public targets for deals that closed between 1996 (the year in which the Securities and Exchange Commission required all firms to provide financial statements to Electronic Data Gathering, Analysis, and Retrieval system) and 2017 with a reported deal size. We drop deals where the acquirer or target has a financial services, resources, real estate, or utility SIC code.[16] We also exclude all deals that use the pooling method pre-2001. We also require data on the acquirer's purchase price allocation of the target's assets to collect prices paid for goodwill and IIAs. When available, these purchase price allocations were found in the acquirer's subsequent 10-K, 10-Q, 8-K, or S-4 filing. We found information on the purchase price allocation for 81% (1,719) of all candidate acquisitions. In the final step, we merge the target and acquirer firms to Compustat and CRSP, leaving us with 1,523 acquisition events. We add to this sample a set of 481 bankruptcy events from CRSP firm delistings between 1996 and 2017. We can find direct matches on asset recoveries from Moody's Default and Recovery Database for 95 of these events and use the estimation process described in Section 3 to estimate asset recovery for the remainder. In total, our panel of exit prices consists of 2,004 firm observations.

4. Parameter Estimation

This section details the remaining assumptions and data issues for the baseline estimation.

4.1. SG&A, Gamma, and Delta

Recall that organizational capital stems from capitalizing SG&A. Because of its broad Generally Accepted Accounting Principles definition, SG&A aggregates a variety of spending for various operating activities. Thus, researchers must assume that some proportion of total SG&A flows represents organizational capital investments.[17] We define this proportion as $\gamma_S \in (0, 1]$. Incorporating γ_S introduces a complication to any estimation of Equation (6). The relative stability of R&D and SG&A within firms over time, along with the multiplicative functional relationship between the parameters, means that we cannot separately identify the parameters γ_S and δ_S in each capital accumulation process.[18] We address this issue by reducing the parameter space by calibrating a subset of parameters. In particular, we estimate the parameter γ_S taking the depreciation of organizational capital δ_S as the standard 20% from the literature.[19] The estimating equation becomes

$$\log(P^I_{it}) = \log(\xi) + \log\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-0.2)^k \gamma_S \text{SG\&A}_{i,t-k}\right) + \epsilon_{it}. \tag{7}$$

4.2. Market-to-Book Parameterization

We aim to improve upon existing parameters that allow us to capitalize off-balance sheet intangibles. In 2013, there was a comprehensive update of the national accounts whereby the BEA now recognizes R&D expenditures as an investment. Thus, the BEA now requires and publishes the estimated R&D depreciation rates used in the intangible capitalization. Using a forward-looking profits model based on Li and Hall (2020), the BEA estimates depreciation rates based on the decay rate at which a firm's prior intangible investments contribute to firm profits. To map the decline in profits to the depreciation of capital, researchers must assume a rate of return on these intangible investments. Li and Hall (2020) assume that the marginal realized rate of return equals the firm's expected return (i.e., they assume zero-excess returns in equilibrium, and this assumption is equivalent to the assumption that marginal Q for knowledge capital equals one).

Because our estimated parameters to allow us to identify the net of depreciation intangible stock and maps them to intangible market prices, we require an assumption about the average Q of our intangible capital stocks. We follow Hall (2005), who assumes that R&D average returns are equal to the cost of capital, tantamount to imposing an average Q of unity. These conditions are identified in Hayashi (1982), where the firm is a price taker with constant returns to scale. We relax the rigidity of this assumption for any particular firm or year, only imposing that average market to book equals one over the full panel. This is done by parameterizing ξ (i.e., industry-year Market to Book ratio (M/B) intangible ratios as industry-year fixed effects). The estimation simply requires that the average of the estimated industry-year fixed effects within each industry be one within the sample (technically, the log of the fixed effects is zero). This approach allows for industry-year exceptions (e.g., high industry growth periods (recessions) where firms within a particular industry have an M/B ratio greater (less) than one within the time series).[20] We acknowledge that to the extent that our assumptions of M/B reflect error for a particular industry-year, such error will be ultimately reflected in poor performance in the validation tests.[21] Defining the industry-year fixed effect parameterization of ξ as ρ_{jt}, where j is industry, we arrive at the following:

$$\log(P^I_{it}) = \log(\rho_{jt}) + \log\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-0.2)^k \gamma_S \text{SG\&A}_{i,t-k}\right) + \epsilon_{it}$$

$$\text{s.t.} \quad \sum_{s=1}^{T}\log(\hat{\rho}_{js}) = 0 \qquad \forall j. \tag{8}$$

Equation (8) is estimated using nonlinear least squares[22] using the intangible prices data (Section 3) and firm-year financial data from Compustat.[23]

4.3. Previous Approaches to Estimation Depreciation Parameters

Before presenting our results, it is important to highlight earlier approaches to this empirical problem. We are not the first to estimate the depreciation parameters in intangible asset capitalization, although we are the first to use market-based prices for the estimation. To our knowledge, the only estimate of γ_S comes from Hulten and Hao (2008). They estimate it based on descriptions of income statement items from six pharmaceutical firms in 2006, applying the investment share of expensed items from Corrado et al. (2006). Conversely, there have been several attempts to estimate the depreciation rate for R&D investments (δ_G). Most models that estimate R&D depreciation propose a channel through which knowledge capital affects firm behavior or outcomes. Pakes and Schankerman (1984), for example, develop a model by which they infer δ_G by examining the decline in patent renewals over time. This assumes that the value from R&D is realized through patents and is directly inferred from patent renewal. Lev and Sougiannis (1996) assume that the depreciation of knowledge capital enters the production function directly and estimate a depreciation model by regressing firms' current period operating income on lagged values of R&D expenditures. The BEA depreciation parameters for knowledge capital are based on a production-function-based model in Li and Hall (2020). Their estimated parameters are based on NSF–BEA data and cover a little over half of firm-years in Compustat, thus requiring other assumptions for firms in SIC codes outside these estimations.

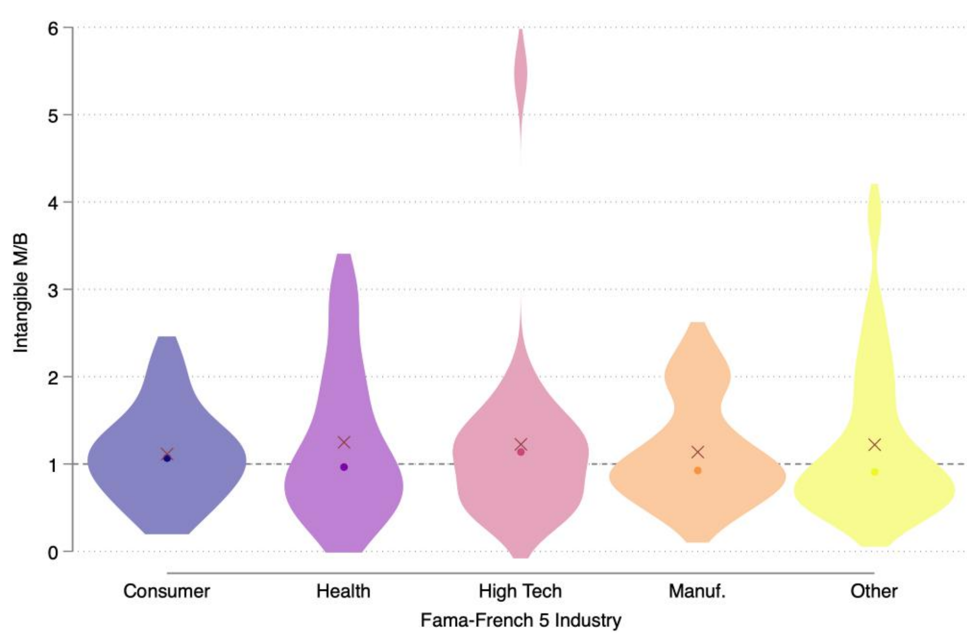
In summary, the lack of a consensus for δ_S and δ_G has led to a wide range of parameters being used to capitalize internally generated intangibles. To benchmark our market price-based capitalization parameters, we use the current set of published BEA knowledge capital depreciation rates for each four-digit SIC code-year where available[24] and 15% otherwise, an approach that has become common in recent years (see Peters and Taylor 2017), while using the estimate that 30% of SG&A represents an investment into organizational capital with a depreciation rate of 20% per year. We refer to this benchmark as "BEA-HH" in subsequent validation tests.

5. Capitalization Parameter Estimates

This section presents the results of our estimation of Equation (8). Before discussing the parameter estimates for δ_G and γ_S, Figure 2 reports the distribution of the estimated industry-year fixed effects across the Fama–French 5 industry classifications.

Each industry "violin" represents a mirrored density plot of all time-series observations for a particular

Figure 2. (Color online) Estimated Industry-Year Fixed Effects



Notes. This figure reports industry-year estimated market-to-book ratios, ρ_{jt}, as the estimated fixed effects from Equation (8). The estimation allows for the market-to-book ratios to vary across industry-years, only requiring that the average of the industry-year fixed effects be one across the entire sample. Each "violin" reports the mirrored distribution of the estimated fixed effects for each year in each Fama–French 5 industry split. The dot indicates the median fixed effect, and the "x" indicates the mean.

industry. The "dot" indicates the median, and the "x" indicates the mean of the estimated fixed effects. Although the median M/B values across all industries approach one, our flexible estimation approach allows for significant variation within industry-year, with roughly 50% of all industry-year intangible market-to-book ratios either exceeding 1.4 or falling below 0.8.

Table 1 reports exits parameter estimates from Equation (8) using exit prices. For comparison, columns (1) and (2) in Table 1 report BEA-HH parameters where δ_G coefficients are equal-weighted averages for each SIC-4 year within the listed FF5 industry classification and γ_S is 0.30 from Hulten and Hao (2008). Column (3) in Table 1 reports the percentage of firms within each sector of the Compustat sample for which BEA depreciation rates are available (i.e., they are not imputed to 0.15). Recall that δ_G represents the depreciation rate of R&D capital, and γ_S represents the proportion of SG&A that is to be classified as a long-lived asset. Thus, Equation (8) tells us that lower (higher) values of δ_G (γ_S) will lead to higher levels of G_{it} (S_{it}).

Consider first γ_S in the "All" row relative to the 30% used in the literature. We estimate a similar but slightly smaller value of 28% using the exits data. Additionally, although prior estimates assume a constant ratio of 30% across all industries, we find a large degree of industry-wide variation in γ_S, the fraction of SG&A representing an investment. For the knowledge capital depreciation parameter, δ_G, the exits estimates for "All" (33%) are significantly higher than the BEA's estimate (23%). Overall, the combination of the exits parameters having a higher δ_G and a lower γ_S relative to BEA-HH indicates that, on average, exits stocks will have smaller levels of intangible capital than BEA-HH stocks. To

Table 1. Parameter Estimates from Nonlinear Least Squares Estimation

	BEA-HH			Exits	
	(1) γ_S	(2) δ_G	(3) $\neq 0.15$, %	(4) γ_S	(5) δ_G
All	0.30	0.23	52	0.28 (0.024)	0.33 (0.034)
Consumer	0.30	0.21	43	0.20 (0.039)	0.43 (0.175)
Manufacturing	0.30	0.19	42	0.21 (0.078)	0.50 (0.162)
High tech	0.30	0.28	62	0.37 (0.084)	0.42 (0.147)
Health	0.30	0.17	80	0.51 (0.221)	0.33 (0.093)
Other	0.30	0.28	49	0.21 (0.077)	0.35 (0.149)
Pseudo-R^2				0.542	
N				2,004	

Notes. Parameter estimates are based on nonlinear least squares regressions of the price of intangible firm assets on accumulated intangible assets:

$$\log(P^I_{it}) = \log(\rho_{jt}) + \log\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-0.2)^k \gamma_S \text{SG\&A}_{i,t-k}\right) + \epsilon_{it},$$

where P^I_{it} is the price of the firm's total intangible capital as discussed in Section 3.1 and I_{it} is the target's externally acquired intangibles reported to the balance sheet. The industry-year fixed effects (ρ_{jt}) are constrained to an average of zero (log of one) across all years within industry. The "All" row reports the pooled sample estimates, whereas all other rows are separate estimations for the modified Fama–French 5 industry classifications. Firms can have up to 10 years of financial data. Columns (1) and (2) summarize the parameters used in the BEA-HH methodology discussed in Section 4.3, whereas column (3) displays the proportion of SIC-4 industry-years for which the BEA publishes the knowledge capital depreciation rate. Columns (4) and (5) summarize the exits-based parameters estimated from market-based exit prices. In each set of columns, the first reports the estimates of γ_S, 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 the R&D depreciation rate. Pseudo-R^2 estimates are calculated as the percentage improvement in the exponentiated root mean squared error relative to a model that includes only a constant. Column (2) reports the average R&D depreciation rates from Li and Hall (2020) for SIC codes in each of the major industry groups (one observation per SIC). Bootstrapped (1,000 replications at the firm level) standard errors are reported in parentheses. N reports the number of unique firms in the estimation.

the extent that the exits parameters developed from market prices more accurately reflect the true values of γ_S and δ_G, intangible stocks developed from exits estimates will outperform the stocks developed by BEA-HH parameters when both sets are subjected to the validation tests in Section 6.

6. Validation Tests

Given our goal of improving upon existing estimates of capitalization parameters, we assess the performance of our exits parameters against BEA-HH by running an array of validation tests on our resulting capital stocks. In designing such tests, we have two goals. First, the estimated intangible capital stocks should proxy for the expected future benefits the intangibles will provide to their owner. Second, applying the stocks to create new total invested capital should strengthen those stocks' relationship with other cross-sectional measures of intangibles. All these validation tests are *out of sample*. That is, to avoid circularity that would result in better validation test performance of our stocks over those using the BEA-HH parameters, we exclude from the analysis any firm-years used in the exits parameter estimation. Using estimates from the industry-level parameters in Table 1, we construct the knowledge and organizational capital stocks G_{it} and S_{it} as well as total invested capital (including intangible capital) K_{it}^{TOT} using 10 years of trailing R&D and SG&A data from 1976 to 2018 for the CRSP–Compustat universe of firms. Our accumulation process for knowledge and organizational capital follows (4). Total invested capital is the sum of knowledge and organizational capital stocks, the book value of externally acquired intangibles, and the book value of physical capital.

The following subsections describe the motivation of each test and report the results when comparing stocks of BEA-HH versus exits parameters. In Section 5.4, we summarize the results of these tests.

6.1. Explaining Market Valuations

The first diagnostic test examines changes in the informativeness of book values of invested capital in explaining market enterprise values when total invested capital is adjusted for off-balance sheet intangibles. Connections between a firm's book invested capital and market enterprise value play important roles in the investment Q and asset pricing literatures. Book values, when properly measured, reflect the firm's capital investments that are available to produce future cash flows. Market values reflect investor expectations of these discounted future cash flows. To the extent that intangible capital stocks have been properly measured and are now reflected in total book invested capital, we expect a stronger association between market enterprise value and book invested capital. We use a simple regression of firm enterprise value on measures of total invested capital to evaluate the new intangible asset estimates:

$$\log(E_{it}) = \alpha + \beta \log(K_{it}^{TOT}) + \epsilon_{it},$$

where E_{it} is i's year t enterprise value (i.e., the sum of the end of fiscal year market capitalization, total debt, and preferred stock) and K_{it}^{TOT} is the book value of the capital stock (Compustat *at*) adjusted for capitalized intangibles. That is, K_{it}^{TOT} is equal to $K_{it}^{Phy} + K_{it}^{Int}$, where K_{it}^{Int} is the sum of externally acquired and internally generated intangibles from exits and BEA-HH capitalization parameters. More precise measures of intangible capital will be reflected in total invested capital measures that have the strongest associations with market enterprise values. The diagnostic test reports the annual ratio $\frac{RSS^{BEA-HH} - RSS^{Exits}}{RSS^{BEA-HH}}$, which reports the degree to which the fit between book invested capital and market enterprise value has improved relative to BEA-HH. Panel (a) in Figure 3 presents the results of the test statistic by year. Panel (b) in Figure 3 reports the t-statistic of the hypothesis test for no difference in R^2 between BEA-HH and exits.

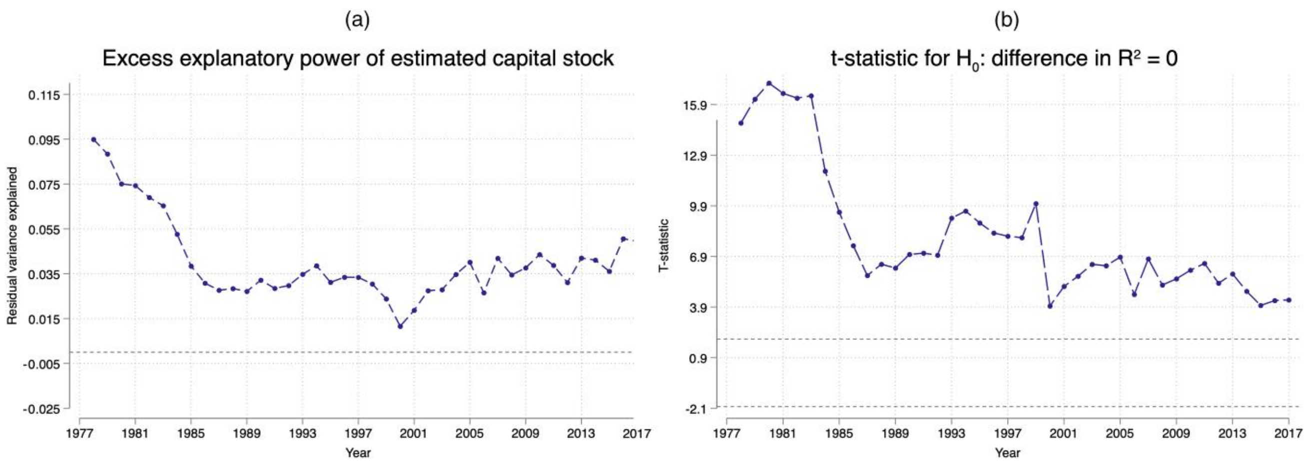
Overall, the exits capital stocks outperform BEA-HH capital stocks in explaining market enterprise values (panel (a) in Figure 3), whereas the t-statistics in panel (b) in Figure 3 show that the R^2 is statistically larger when we use the exits stocks across the entire 39-year sample period. Again, these regressions exclude the companies in the estimation (avoiding circularity). Overall, these results demonstrate that the capitalized intangibles using the parameter estimates from Table 1 have the most predictive power for explaining enterprise value.

6.2. Validation Tests of Organizational Capital

We employ two diagnostic tests to assess the quality of our organizational capital measures: human capital risk and brand quality.

6.2.1. Human Capital Risk. Eisfeldt and Papanikolaou (2013) propose a model whereby organizational capital is a firm-specific investment that has outputs measured by a firm's key talent. Their model shows that the outside option of the firm's key talent determines the share of the firm's cash flows that accrue to shareholders. Thus, shareholders bear more risk for firms with higher levels of organizational capital. They estimate the stock of organizational capital by capitalizing a firm's SG&A expenses and validate their measure by examining the Management discussion and analysis (MD&A) of firms with higher (lower) levels of organizational capital, showing that firms with higher (lower) levels are more (less) likely to disclose the potential for key personnel loss as a significant risk factor to the firm. To do so, they seek out references for personnel risk in 10-K filings and argue that any firm sorting by a measure of

Figure 3. (Color online) Explanatory Power of Assets for Market Enterprise Value



Notes. Panel (a) reports the explanatory power of the estimated capital stock relative to a BEA-HH capital stock measurement in annual regressions of the firm's log market enterprise value (market capitalization plus debt and preferred stock) on the log of book value of capital stock: $\log(E_{it}) = \alpha + \beta \log(K_{it}^{TOT}) + \varepsilon_{it}$, where E_{it} indicates firm i's year t enterprise value and K_{it}^{TOT} is the standard book value of capital stock (Compustat *at*). To avoid mechanical outperformance over BEA-HH, this analysis excludes any firm-years used in the parameter estimation of Equation (8) (i.e., acquisition targets and delisted firms in the exits-based sample and the randomly selected firm-years from the trading sample). Relative explanatory power is plotted by year and calculated as excess residual variance explained: $\frac{RSS^{BEA-HH} - RSS^{Exits}}{RSS^{BEA-HH}}$, where RSS represents the residual sum of squares from the regression models. The baseline (i.e., "RSS^{BEA-HH}") is the benchmark "BEA-HH" model that uses the parameters reported in columns (1) and (2) in Table 1. "RSS^{Exits}" reflects the use of an alternate model based on exit prices. A ratio greater than zero indicates that the market price estimated capital stocks have stronger explanatory power. Using the same regressions described in panel (a), panel (b) reports the t-statistics from the test of the hypothesis that the R^2 using the exits-based capital stock alternative is the same as the R^2 from BEA-HH. The test statistic uses the influence function method (Newey and McFadden 1994) to compare the two separate model statistics. The horizontal lines represent t-statistics of 1.96 and −1.96. (a) Residual sum of squares comparison. (b) The t-test for R^2 differences.

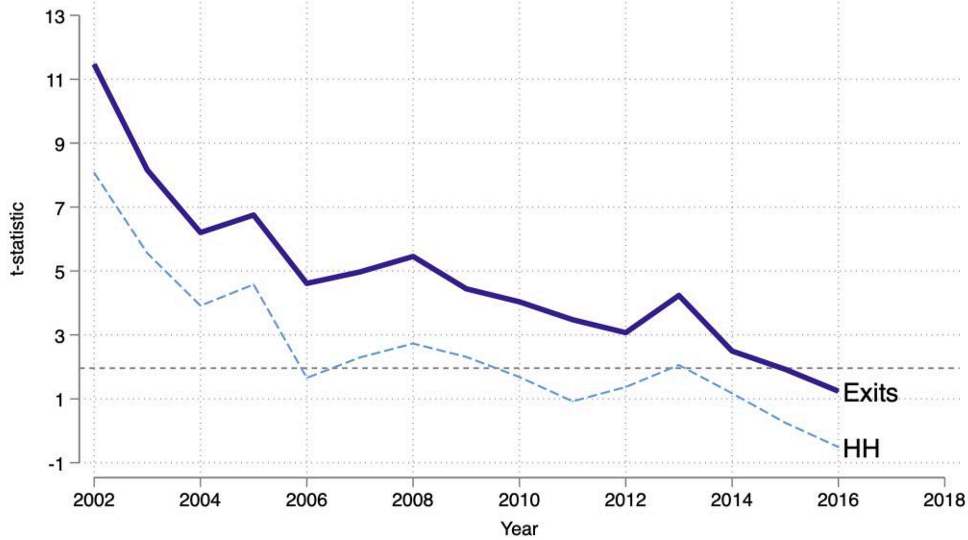
organizational capital should correlate with such mentions. We follow a similar approach using over 120,000 10-K filings from 2002 to 2016. We calculate the fraction of words in the MD&A statement that reference the risk of personnel loss (keywords: "personnel," "talented employee," or "key talent").

Because an improved organizational capital measure will more precisely sort firms into the highest (lowest) quintiles of human capital risk, we expect that such a measure will have more (less) frequent mentions of personnel loss as a risk factor in the firm's MD&A. Thus, our diagnostic test compares the relative performance of exits-based organizational capital stocks with Hulten and Hao (2008)-based organizational capital stocks that use a constant ratio of SG&A investment to be capitalized, $\gamma_s = 0.3$. Both exits and HH organizational capital stocks assume $\delta_S = 0.2$. We sort firms into quintiles based on their estimates of organizational capital stock scaled by assets in each year, and then, we calculate the frequency of mentions between the high and low quintiles by year for both exits and HH measures of organizational capital. Figure 4 reports the t-statistic by year from the difference in frequency means for the top quintile versus the bottom quintile of firms in these sorts.

With exits-based stocks, the fraction with some reference to personnel risk in the top quintile versus the bottom quintile is 65% and 51%, respectively. This compares with 59% and 52% for the quintiles sorted using the HH ($\gamma_S = 0.3$) method from the literature. The difference between top and bottom quintiles for exits is positive in all years of the sample and significant in all but 2 years of the sample, whereas the HH stocks are insignificant in 7 of the 14 years in the time series, indicating that the exits-based measure of organizational capital stock is better able to identify human capital-intensive firms and the subsequent risks associated with these firms.

6.2.2. Brand Quality. Another well-documented subset of firms' organizational capital is brand quality (Mizik and Jacobson 2008, Vomberg et al. 2015). Our second validation test asks whether our organizational capital stocks (and total intangible capital) exhibit stronger associations with brand quality. We collect the top 100 global brands according to Interbrand, a brand consultancy, from 2000 to 2018. We extract the ranking and merge each company (or brand) to U.S. public firms in Compustat.[25] This diagnostic test is a simple fit test where we regress the log of a firm's brand rank on the

Figure 4. (Color online) Human Capital Risk



Notes. In each fiscal year, we sort firms into quintiles based on their estimated organizational capital stock using parameter estimates from Table 1. In each firm-year, we set a variable equal to one if the firm's 10-K mentions "personnel," "key talent," or "talented employee," and we set it equal to zero otherwise. The figure reports the t-statistics (each year) for the difference in mean test for the top vs. bottom quintiles sorted by each estimation of organizational capital. The horizontal line is at $t = 1.96$. "HH" estimates organizational capital using γ_S from column (1) in Table 1. "Exits" estimates organizational capital using γ_S from column (4) in Table 1. All estimates assume $\delta_S = 0.2$.

log of organizational capital (and the log of total intangible capital). Thus, more precise measures of intangible capital will have stronger associations with brand quality, thus leading to higher R^2 in the regression analyses. Table 2 reports the pooled regression results.

Table 2. Brand Ranking Incorporating Intangible Assets

	Log *brand ranking*			
	(1)	(2)	(3)	(4)
Log org. cap. S (HH)	−0.044***			
	(0.0080)			
Log org cap. S (EPW)		−0.052***		
		(0.0084)		
Log total intan. K (BEA-HH)			−0.22***	
			(0.027)	
Log total intan. K (EPW)				−0.23***
				(0.027)
Observations	1,122	1,122	1,122	1,122
R^2	0.014	0.022	0.10	0.12
Year fixed effects?	Yes	Yes	Yes	Yes

Notes. This table reports the Ordinary Least Squares estimates from a regression of the log of brand ranking on measures of intangible capital. Brand rankings are from the Interbrand listings, which are merged with Compustat U.S. public companies. A unit of observation is a firm-year. "Log *org. cap. S (BEA-HH)*" is the log of organizational capital using the BEA-HH parameters from Table 1. "Log *org. cap. S (EPW)*" shows the same estimated stocks using the exits parameter estimates. "Exits" estimates organizational capital using γ_S from column (4) in Table 1. All estimates assume $\delta_S = 0.2$. "Log *total intan. K*" is the sum of externally acquired intangibles, estimated knowledge capital, and estimated organizational capital. "Year fixed effects?" are fixed effects for fiscal year. Robust standard errors are reported in parentheses.

***Significance at the 1% level.

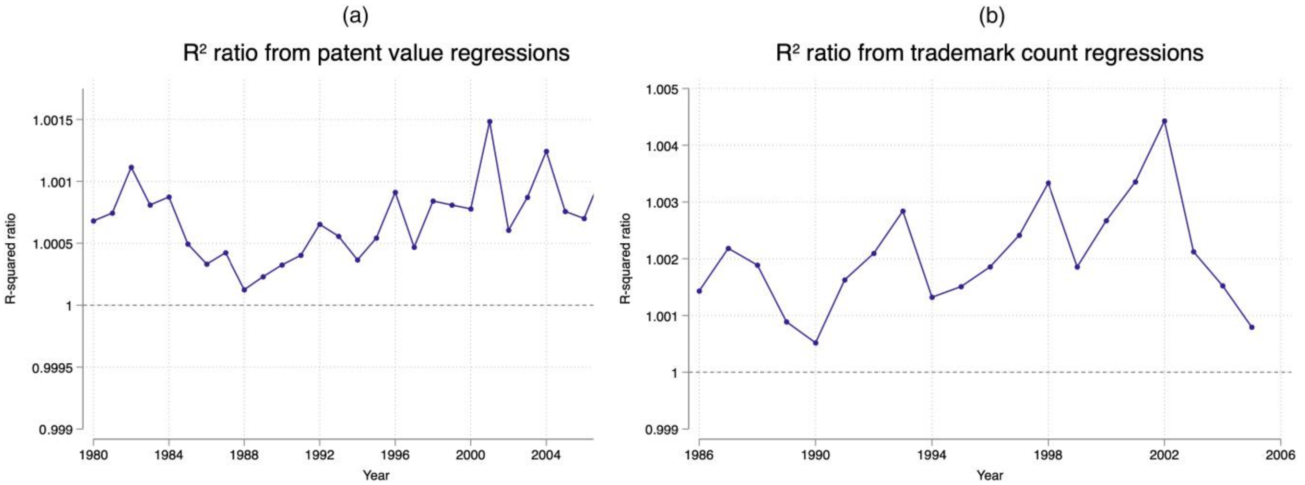
Columns (1) and (2) in Table 2 use the log of organizational capital as the independent variable, whereas columns (3) and (4) in Table 2 use the log of total intangible capital. Results indicate that the coefficients on organizational (total intangible) capital load negatively for both of our price-based stocks as well as stocks based on HH parameters. These findings show that firms with higher organizational capital stocks have higher brand equity. Relative to HH, the exits price-based stocks show the largest improvement for organizational capital (R^2 in column (2) in Table 2) and a more modest improvement when testing total intangible capital (R^2 in column (4) in Table 2).

6.3. Validation Tests of Total Intangible Capital

The final three validation tests evaluate outputs associated with investments in both knowledge and organizational capital.

6.3.1. Patent Valuations. Prior literature (Hall et al. 2000, Dakhli and De Clercq 2004, Subramaniam and Youndt 2005) finds that innovation is related to both knowledge and human capital. We use patent valuations from Kogan et al. (2017) as a measure of innovation quality and examine the association between our total intangible capital measures and innovation. Let the patent valuation for firm i in year t be Patent_{it} (set to zero if missing). The regression takes the following

Figure 5. (Color online) Patent Valuations and Trademark Counts



Notes. This figure reports the ratio of R^2 from the following yearly regressions estimated using the BEA-HH parameters in columns (1) and (2) in Table 1 (denominator) and those from the exits approach (numerator): $\log(Y_{it}) = \beta_0 + \beta_1 X_{it-1} + \beta_2 \log(\hat{G}_{it} + \hat{S}_{it} + I_{it}) + \nu_{it}$, where Y_{it} is either (a) the patent valuation from Kogan et al. (2017) (set to zero if there are no patents in the year) or (b) the log of the number of trademarks (plus one) held by the firm at time t. The sum $\hat{G}_{it} + \hat{S}_{it} + I_{it}$ is the estimated total intangibles, and X_{it} is the lagged stock of the dependent variable. The market price-based alternative to BEA-HH is the exits samples (see Section 3.1) with the organizational capital using γ_S from column (4) in Table 1. All estimates assume $\delta_S = 0.2$. (a) Patent valuations. (b) Trademark counts.

form:

$$\log(\text{Patent}_{it}) = \beta_0 + \beta_1 X_{it-1} + \beta_2 \log(\hat{G}_{it-1} + \hat{S}_{it-1} + I_{it-1}) + \nu_{it}, \quad (9)$$

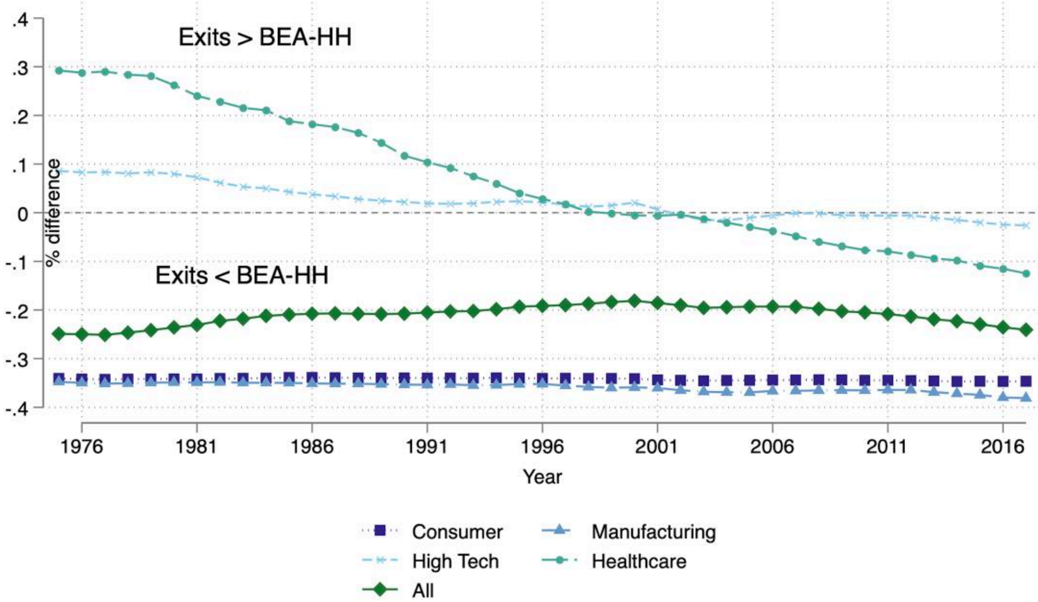
where X_{it-1} is the number of patents held by the firm. This diagnostic test incorporates alternative measures of $\hat{G}_{it-1}$ and $\hat{S}_{it-1}$. Better performance is captured with a higher R^2 from (9).[26] In panel (a) in Figure 5, we report the ratio of two values of R^2, where the benchmark (denominator) is the R^2 using estimated intangible capital stocks from the BEA-HH method and the numerator is the R^2 using the exits-based intangible capital stocks. Results show only a modest increase in explanatory power for exits-based intangible capital stocks, although the improvement appears consistent across our entire time series of patent data.

6.3.2. Trademarks. Similar to the patent analyses in Section 6.3.1, the second validation test examines ratios of R^2 from regressions of newly filed trademarks on total intangible capital. The numerator (denominator) is the R^2 from stocks accumulated by the exits parameters (BEA-HH parameters). The intuition is that firms with higher levels of intangible capital will have, on average, more powerful brands. In order to protect their brand equity, they will file for trademark protection. Using data provided by Heath and Mace (2020), we regress the count of new trademarks on total intangible capital by year. The regression takes the same form as (9), where patents are replaced by a count of trademarks (plus one) and the X_{it-1} is the firm's lagged trademark stock. Panel (b) in Figure 5 reports the results. Overall, results appear similar to those discussed in Section 6.3.1, with exits-based intangible capital demonstrating only a marginal improvement over BEA-HH stocks for all sample years when explaining the number of trademarks held by the firm.

6.4. Summary of Validation Tests

Overall, we find that adjusting the firm's invested capital using exits intangible stocks does a better job of explaining the firm's market enterprise value relative to intangible capital adjustments made using the BEA-HH parameters. These improvements are statistically significant ($p < 0.01$) in all of our sample years from 1978 to 2017. In further comparisons of exits intangible capital stocks (relative to BEA-HH) across a wide array of direct outputs from intangible investments, we perform additional validation tests that examine whether exit-based stocks improve explanatory power for human capital risk, patent valuations, trademark counts, and brand equity rankings. In these separate tests, the increase in explanatory power is largest for human capital risk, whereas in other tests, the exits stocks either perform no worse than or show marginal improvement versus those derived from the BEA-HH parameters. Again, we note that any potential concerns for developing parameters from exit prices (i.e., noisy goodwill, bankruptcy recovery rates, or assumptions regarding marginal Q) should not be downplayed, but rather, they should be weighed against the improved performance in this range of out-of-sample tests. In addition, Online Appendix Section A.3 reports an alternative

Figure 6. (Color online) Differences in the Size of Estimated Intangibles vs. BEA-HH



Notes. This figure reports the average percentage difference between the intangible capital stocks constructed using BEA-HH and exits-based (see Section 3.1) parameter estimates across all firms and by industry. A positive percentage difference implies that the alternative measure of intangible stock is larger than BEA-HH. Averages by year and within industry are reported.

priced-based estimation using nonselected traded equities and shows that the exits-based stocks exhibit superior performance.

7. Descriptive Analysis of Exits-Based Intangible Stocks

This section provides the summary statistics of the exits-based intangible asset stocks.

7.1. Comparison with Existing Methods

Figure 6 presents the percentage difference between exits and BEA-HH estimates of capitalized intangible stocks, scaled by the latter. The differences in our estimated intangible capital stocks relative to BEA-HH vary across industries. For example, although the "All" line in the figure shows that the new estimate is approximately between 18% and 25% smaller across all firm-years, our intangible stocks are larger, on average, for high-tech firms, particularly in the earlier part of the sample. Given the larger estimated depreciation of R&D for exits healthcare stocks (33%) versus BEA-HH healthcare stocks (17%), the declining relative size of exits stocks in healthcare across the time series reflects firms' shift from organizational capital to knowledge capital investments. Overall, we document economically meaningful differences in the magnitude of implied stocks across industries compared with BEA-HH.

7.2. Intangible Capital Stocks by Industry and Time

Figure 7 presents time-series trends of intangible capital for the four industries. Each series plots intangible intensity, calculated as the average ratio of intangible capital K_{int} $(S_{it} + G_{it} + I_{it})$ to total assets (e.g., intangible and physical assets (Compustat *ppegt*)). The increasing levels of intangible asset intensity across all industries match the well-documented expanding role of intangibles in the economy. Consistent with our expectations, intangible intensities are lowest in consumer and manufacturing and highest in healthcare and high tech. These patterns conform to basic predictions about differences across industries and time and validate that our estimates measure real economic assets.

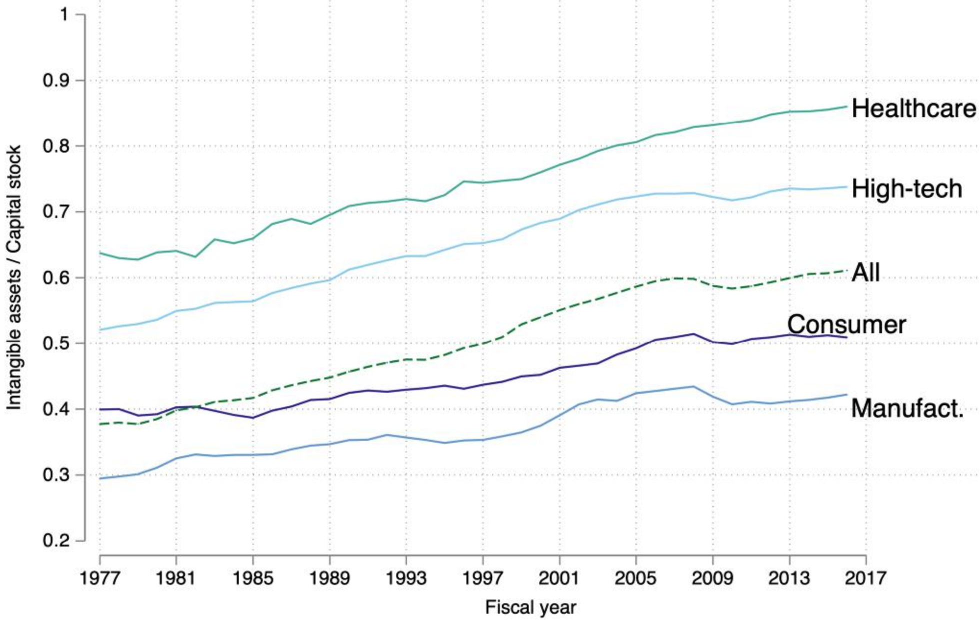
7.3. Intangible Capitalization's Impact on Market to Book and ROE

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

$$\frac{M}{B}_t = \beta_0 + \beta_1 \mathrm{Year}_t + \epsilon_t. \tag{10}$$

Figure 8 reports two time-series plots with best-fit lines for the unadjusted *M/B* and the *M/B* adjusted with the

Figure 7. (Color online) Intangible Asset Intensity



Notes. This figure reports the average ratio of total intangibles—capitalized using the exits parameters (Table 1) and those on the balance sheet—scaled by total capital stock (PPE + intangibles): $\frac{K^{int}}{K^{int}+K^{phy}}$. The averages are calculated across all firms within each industry-year. K^{int} is the sum of knowledge and organizational capital using the estimates from Table 1 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 separately but is included in the "All" series.

exits stocks. When off-balance sheet intangibles are not capitalized in book value, the *M/B* ratio drifts upward by 0.04 per year. After our adjustments for intangible capital, the slope coefficient becomes 0.013, a decrease of 68%.

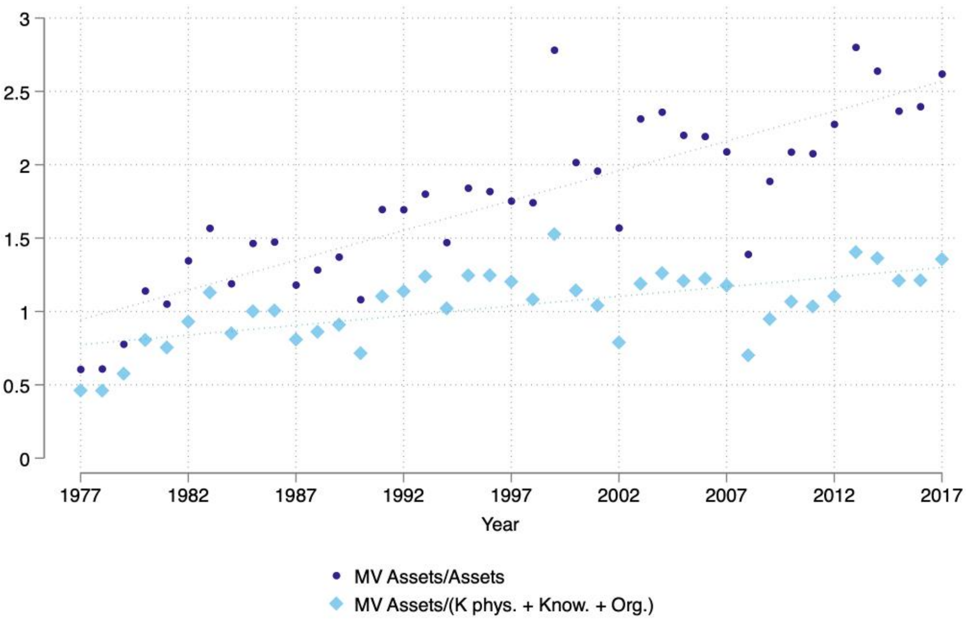
A similar result can be seen when adjusting a firm's ROE, which is calculated as net income scaled by the book value of common equity (start of the year). Because intangible investments are expensed and do not appear on a firm's balance sheet, both the numerator and the denominator of the ratio are biased. The denominator is missing the value of off-balance sheet intangibles, whereas the numerator nets out the current year's intangible investment while ignoring the depreciation of off-balance sheet capital. The downward bias in the book value of equity results in an upward bias in unadjusted ROEs because of the expensing of intangible capital. Assuming competitive markets, long-term averages of ROE should approach the market's cost of equity capital. Although it is beyond the scope of our study to debate the market's cost of equity capital, we rely on some agreement from the literature. Graham and Harvey (2018) surveyed chief financial officers from 2000 to 2017 and found an equity risk premium of 4.42%, whereas Damodaran (2020) finds an implied equity risk premium using a free cash flow to equity model of 4.33% from 1978 to 2017. Adding these values to the 10-year T-bond rate of 6.16% from 1978 to 2017 results in expected market-wide returns on equity of 10.58% and 10.49%, respectively.

Figure 9 displays the impact of incorporating intangibles into the ROE calculation across our panel of firms from 1978 to 2017. It plots the unadjusted average annual ROE across the entire sample (the dashed line) and the average annual ROE (the solid line) after adjusting both the numerator and the denominator for the capitalization of intangibles.[27] These adjustments for intangible capital lower the average annual ROE from 16.82% to 10.53% (untabulated), a decrease of 37%, and they are closely in line with expectations based on Graham and Harvey (2018) and Damodaran (2020). Finally, we note that the degree of ROE bias—the unadjusted ROE less the exits-adjusted ROE (scatter and dotted linear fit)—has steadily risen over time. This rise is consistent with increasing intangible intensity over time and further highlights the importance of capitalizing intangibles.

7.4. Asset Pricing Factors

The multifactor FF model (e.g., Fama and French 1992, 1993) is widely used in calculating expected returns. One key component in the FF model is HML, the realized returns to a portfolio that is long (short) high (low) book equity-to-market equity firms. Given that current accounting standards prohibit the capitalization of internally generated intangible investments,

Figure 8. (Color online) Market-to-Book Ratios with and Without Adjusted Intangibles: 1977–2017



Notes. This figure reports the average (2.5% tail winsorized) market-to-book ratios for Compustat firms outside of financials, mining, real estate, and utilities and all acquiring firms in our sample. To avoid mechanical outperformance over BEA-HH, this analysis also excludes any firm-years used in the parameter estimation of Equation (6) (i.e., acquisition targets and delisted firms in the exits sample). The numerator in both series is the sum of the market value of equity at the end of the fiscal year, total liabilities, and book preferred stock. For the circle series, the denominator is total assets (including acquired intangibles). For the diamond series, the denominator also includes the knowledge and organizational capital stocks estimated using the exits-based parameters in columns (4) and (5) of Table 1. The two dotted lines present the linear fit of each time series. MV Assets is the market value of total assets. Assets is book value of total assets. K phys + Know. + Org. is the sum of physical capital + knowledge capital + organizational capital.

book equity values will be depressed by the amount of intangible capital. As a result, we expect some proportion of firms in a traditional FF HML portfolio sort to be misclassified relative to an HML sort that uses our exit price parameters that adjust for intangible capital. Table 3 documents the consequences of these misclassifications on the observed return.

Columns (1) and (2) in Table 3 show that monthly return spreads are 90% larger (37.3 versus 19.6 basis points ($p = 0.02$)) upon the adjustment for intangible capital to the numerator. Upon further exploration, we find that 68% of firms are correctly sorted to the proper (low, mid, high) Book-to-Market ratio (B/M) portfolio (i.e., they do not move across portfolios after intangible capitalization) and that the return spreads are nearly identical (37.3 versus 38.6 basis points) between the adjusted portfolio and the FF portfolio using only properly sorted firms. Thus, the large difference in observed return spreads must be driven by the missorted firms. Column (5) in Table 3 shows that 30% (22%) of firm-month observations in the traditional FF sort have substantially high (low) intangible capital such that they transition out of the short (long) sides of the portfolio. Column (6) in Table 3 shows the returns in each B/M portfolio for these misclassifications and finds that the well-documented HML relationship not only disappears but also exhibits negative return spreads (−21 basis points). Although the conclusive mechanism of why HML is predictive of future returns is beyond the scope of our paper, Korteweg (2010) has shown that higher-intangible firms have greater distress risk, whereas Edmans (2011) has documented that the stock market underreacts to the value of intangible capital. Our empirical results are consistent with such possibilities and highlight the importance of capitalizing intangibles when HML is used in asset pricing tests.

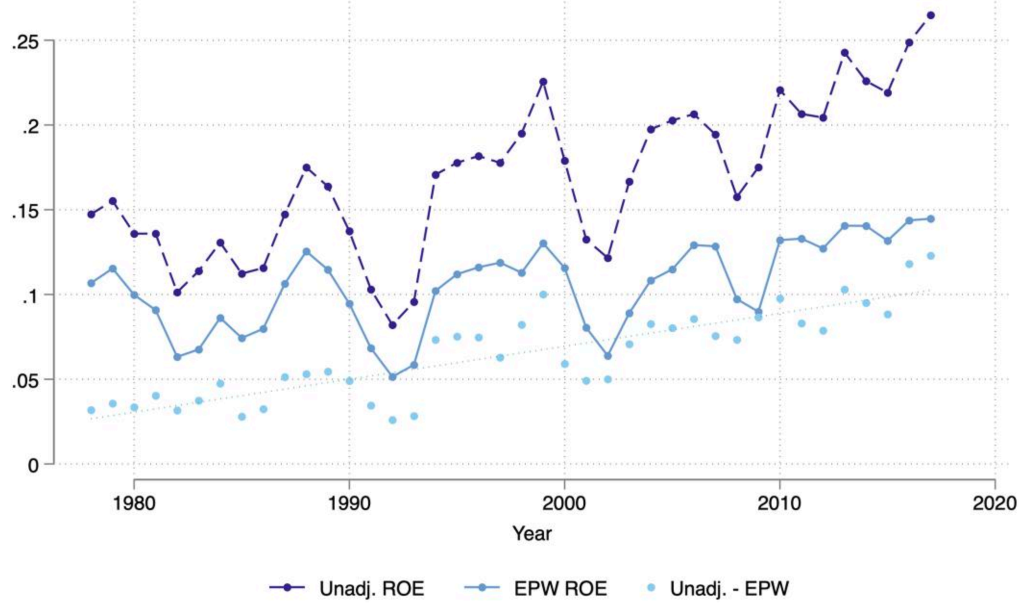
8. Assumption Validation and Robustness

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

8.1. Parameter Calibration

Given the inherent difficulties in separately identifying both the fraction of SG&A that is an investment (γ_S) and the rate of depreciation (δ_S) discussed in Section 4.1, Figure 10 presents the main estimation in the exits sample under alternative assumptions about the rate of organization capital depreciation rates. We consider a range of $[0.1, 0.3]$ for the δ_S and re-estimate Equation (7), reporting the new parameter estimates for γ_S and

Figure 9. (Color online) ROE with Intangibles Adjustment



Notes. This figure reports the average ROE using two alternative measures for public firms in the S&P 500. "Unadjusted" uses the standard ROE definition of net income scaled by lagged book equity. The "exits" time series adjusts book equity for knowledge and organizational capital using the exits parameter estimates. The scatterplot reports the average of the difference between the two measures (with its linear fit). EPW, Ewens, Peters and Wang; S&P, Standard and Poor's.

δ_G along with the R^2. The figure shows little variation in the estimate of δ_G. As we increase the δ_S from 0.1 to 0.3, the estimated γ_S increases from 0.18 to 0.4. The R^2 from the model estimation (the right axis) remains nearly static across these dynamics, varying by only 2%. We conclude two things from this exercise: (1) that our assumed $\delta_S = 0.2$ is not driving any of our results and (2) that the *pair* of (γ_S, δ_S) is the key assumption for measuring organization capital.

8.2. Estimation Within Time-Period Subsamples

We next analyze whether the baseline parameter estimates vary significantly over different estimation windows, estimating γ_S^t and δ_G^t for each year using a 10-year rolling window of price data. This allows us to investigate the validity of our assumption that γ_S and δ_G are constant over time in addition to whether business cycles or merger waves confound our estimates. The estimation is the same as in Section 4 with one exception; rather than estimate industry-year fixed effects within each time period, the industry-year fixed effects are instead taken from the full-sample estimation, reported in Figure 2, and imposed within the nonlinear least squares estimation.[28]

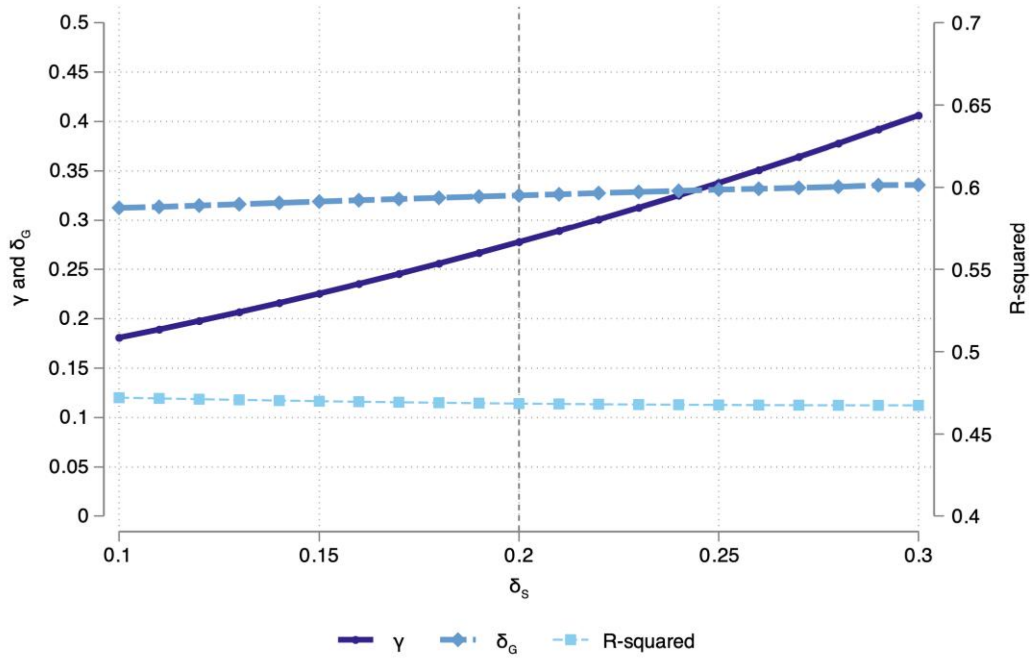
Online Appendix Figure A.3 reports the coefficients of γ_S^t and δ_G^t as estimated over the different time-period

Table 3. The Value Premium: Including Intangibles in Book Value

	(1) Unadjusted portfolios	(2) Adjusted portfolios	(3) Correctly sorted (%)	(4) Return correctly sorted	(5) Missorted (%)	(6) Return missorted
Low B/M	0.876	0.839		0.829		1.105
(# firm-months)	730,696	640,171	70	512,574	30	218,122
Mid B/M	0.969	0.999		0.952		1.000
(# firm-months)	710,488	706,404	55	391,751	45	318,737
High B/M	1.072	1.212		1.215		0.892
(# firm-months)	714,267	808,876	78	559,934	22	154,333
High − low	**0.196**	**0.373**		**0.386**		**−0.2139**
Total firm-month observations			2,155,451			

Notes. The table reports summary statistics for HML portfolio returns from 1976 through 2017. The unadjusted portfolios are constructed as in Fama and French (1992). The adjusted portfolios are constructed similarly, with the measure of book equity augmented by the intangible capital stocks implied by the parameters in Table 1, columns (4) and (5). Returns are reported in percentage points per month.

Figure 10. (Color online) Estimation Sensitivity Under Different Organizational Stock Depreciation Assumptions



Notes. This figure reports the results of re-estimating the main model for different values of the organizational stock depreciation parameter δ_S. Recall that our main results assume that $\delta_S = 0.2$. Here, we vary this parameter and present the estimated γ_S (the fraction of SG&A that is investment), δ_G (the knowledge capital depreciation rate), and R^2 from the estimation. The vertical line indicates the main model assumption. The left y axis reports the parameter estimates, and the right y axis reports the R^2.

subsamples along with 95% confidence interval bounds and the full-sample "All" estimates from Table 1. The figure shows that for both parameters, the subsample estimates are not statistically distinguishable from their full-sample counterparts in all years and are uncorrelated with each other. Although panel (a) in Online Appendix Figure A.3 shows that the γ_S estimates are relatively static over time, panel (b) in Online Appendix Figure A.3 hints at a (perhaps marginally significant) increase in the δ_G estimates in the early 2000s.

These results complement a similar exercise by Li and Hall (2020), who present some evidence for declining R&D depreciation rates between 1987 and 2007. Our results do not exhibit such trends and thus, are consistent with our baseline assumptions about static depreciation and capitalization parameters over time. Additional research is warranted for this critical assumption.

8.3. Unadjusted Goodwill and Exclusion of Bankruptcies

Two assumptions in the use of exit prices are the adjustment to reported goodwill and the use of delisted firms. Recall that the former adjustment attempts to remove acquisition or the pair-specific value embedded in goodwill using market reactions to the merger announcement. Columns (5) and (6) in Table 4 report the main estimation, including only the 1,523 nonbankruptcy acquisitions. As expected, excluding failed firms from the analysis raises the average fraction (γ) of SG&A that represents an investment in long-lived organizational capital from 0.28 to 0.44, an increase of 57%. The point estimates for δ_G are lower than those in Table 1, with the full sample implying an average depreciation rate of knowledge capital of 26% per year. Reassuringly, when we repeat each validation test from Section 6 (unreported), the stocks implied by these alternative parameters underperform those when delistings are included.

Columns (7) and (8) in Table 4 report the main estimation excluding goodwill to examine the impact of unidentifiable intangible assets on our estimation. Results indicate that although δ_G increases moderately (from 0.33 to 0.38), γ_S falls drastically by nearly 90% (from 0.28 to 0.03), indicating that only a tiny fraction of SG&A produces identifiable intangible assets, whereas the majority of SG&A results in higher goodwill or unidentifiable intangible assets. When we re-estimate these stocks and subject them to the full array of validations, they perform worse than the current price that uses identifiable intangible assets and goodwill. Although this may seem intuitive (as the majority of SG&A likely results in assets such as human capital, employee culture, and brand equity, many of which cannot be separated from the firm and sold to a third party), it underscores the importance of our inclusion of goodwill in our parameter estimation.

Table 4. Parameter Estimates from Nonlinear Least Squares Estimation: Alternative Assumptions

	BEA-HH		Exits		Excl. liquid.		No goodwill		Unadjusted goodwill	
	(1) γ_S	(2) δ_G	(3) γ_S	(4) δ_G	(5) γ_S	(6) δ_G	(7) γ_S	(8) δ_G	(9) γ_S	(10) δ_G
All	0.30	0.23	0.28	0.33	0.44	0.26	0.03	0.38	0.44	0.22
			(0.024)	(0.034)	(0.040)	(0.036)	(0.005)	(0.021)	(0.035)	(0.029)
Consumer	0.30	0.21	0.20	0.43	0.37	0.43	0.03	0.25	0.26	0.10
			(0.039)	(0.175)	(0.077)	(0.187)	(0.014)	(0.133)	(0.044)	(0.149)
Manufacturing	0.30	0.19	0.21	0.50	0.31	0.19	0.05	0.37	0.57	0.33
			(0.078)	(0.165)	(0.093)	(0.204)	(0.024)	(0.148)	(0.108)	(0.167)
High tech	0.30	0.28	0.37	0.42	0.55	0.41	0.16	0.50	0.73	0.38
			(0.084)	(0.147)	(0.095)	(0.109)	(0.065)	(0.135)	(0.102)	(0.119)
Health	0.30	0.17	0.51	0.33	0.96	0.38	0.14	0.27	0.72	0.19
			(0.221)	(0.093)	(0.264)	(0.095)	(0.133)	(0.089)	(0.228)	(0.079)
Other	0.30	0.28	0.21	0.35	0.43	0.04	0.04	0.24	0.43	0.25
			(0.077)	(0.149)	(0.24)	(0.178)	(0.026)	(0.088)	(0.107)	(0.166)
Pseudo-R^2			0.542		0.461		0.536		0.557	
N			2,004		1,523		2,004		2,004	

Notes. Parameter estimates are based on nonlinear least squares regressions of the price of intangible firm assets on accumulated intangible assets:

$$\log(P^I_{it}) = \log(\rho_{jt}) + \log\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \text{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-0.2)^k \gamma_S \text{SG\&A}_{i,t-k}\right) + \epsilon_{it},$$

where P^I_{it} is the price of the firm's total intangible capital as discussed in Section 3.1 and I_{it} is the target's externally acquired intangibles reported to the balance sheet. The industry-year fixed effects (ρ_{jt}) are constrained to an average of zero (log of one) across all years within industry. The sample is as described in Table 1 but adjusted in three ways. Columns (1) and (2) report the main BEA-HH parameters, whereas columns (3) and (4) report the baseline estimates from Table 1. Columns (5) and (6) present the estimates from a sample without liquidations, columns (7) and (8) consider all exits but exclude goodwill from prices, and columns (9) and (10) report the full-sample estimate without the adjustment to goodwill for synergies or overpayment.

Finally, the last two columns in Table 4 repeat the exits-based parameter estimation without the adjustment to goodwill as discussed in Online Appendix Section A.1.2. That is, we include goodwill as reported in the 10-K filing. As expected, the adjustments to goodwill have a large impact on estimates. R&D depreciation rates are 50% higher, and the percentage of SG&A that is investment is 36% lower, with the adjusted goodwill. These changes demonstrate that our adjustments are controlling for a large part of the synergies and overpayment found in raw goodwill. In the unreported results, the stocks implied by these parameters underperform the main exits stocks in all validations.

8.4. Trading Prices and Alternative Parameters

As discussed in Section 3, the exits sample may suffer from selection issues that could limit the generalizability of the results. As an alternative, we collect a set of intangible asset prices that suffer from no sample selection. These prices compare the publicly traded equity valuations of firms with their physical assets that have been capitalized to the balance sheet, subject to a markup assumption to adjust them from historical cost. The difference between the firm's market capitalization and physical assets thus provides an approximation of the intangible assets of the firm. The approach is described in Online Appendix Section A.3. We estimate Equation (6) using these intangible prices and repeat the intangible asset stock creation with the estimated parameters (see Online Appendix Section A.4 and Table A.4). Although the estimation sample suffers from no sample selection, Online Appendix Section A.5 shows that the resulting stocks from the estimation underperform the exit-based stocks. This outperformance does not prove that selection is not a concern; however, it shows that we must weigh potential selection issues against empirical performance.

Finally, recent work by Iqbal et al. (2024) provides a set of γ_S parameters with finer industry granularity. We build organizational stocks with their parameters and combine them with the BEA stocks to create an alternative benchmark. In unreported results, we repeat the main diagnostics using the their stocks where organizational capital is an input. Our stocks outperform in nearly all cases. The Iqbal stocks provide weakly more explanatory power for brand equity and patents in the pre-2000 sample, but they have relatively worse explanatory power for human capital risk, do not improve on ROE estimates, and underperform BEA in the market valuation regressions after 2000. Overall, this evidence suggests that our organizational capital stocks have better performance than those in Iqbal et al. (2024).

9. Conclusion

Despite the growing importance of intangible capital in today's economy, the literature lacks consensus about the parameters governing intangible assets' capitalization. We develop and test a model that uses market prices to estimate parameters from firm exits, allowing us to estimate off-balance sheet intangible capital from prior R&D and SG&A spending. We compare the quality of these parameter estimates against commonly used BEA-HH parameters by creating two sets of capitalized intangible stocks and putting them through validation tests. Exit-based capital stocks outperform BEA-HH stocks. We document significant performance improvements in the stocks' ability to explain market enterprise values and human capital risk while showing similar or marginal improvements in explanatory power for brand rankings, patent values, and trademarks. Incorporating these new intangible asset stocks into firms' balance sheets lowers values of market to book and return on equity, which conform better with expectations from extant theory.[29]

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Endnotes

1 Accounting rules for intangibles originated in 1974 when intangibles were a small proportion of the economy, and they have not changed, despite a fundamental change toward intangibles as economic value drivers. Specifically, internal research and development (R&D) costs and selling, general, and administrative (SG&A) activities are expensed, and thus, intangible values do not appear on the balance sheet. Such expensing has been shown to reduce the overall usefulness of accounting statements (Lev and Zarowin 1999).

2 A partial list of these studies includes Eberhart et al. (2004), Daniel and Titman (2006), Aksoy et al. (2008), Edmans (2011), and Eisfeldt and Papanikolaou (2013).

3 See the works by Williamson (1988), Shleifer and Vishny (1992), Loumioti (2012), and Mann (2018).

4 See Bernstein and Nadiri (1988), Chan et al. (2001), and Hirshleifer et al. (2013).

5 See Eisfeldt and Papanikolaou (2013, 2014) and Belo et al. (2014).

6 See Peters and Taylor (2017) and Falato et al. (2022).

7 Approximately 46% of four-digit SIC codes for public firms have depreciation rates for knowledge capital using BEA parameters, which can be found at https://apps.bea.gov/national/FA2004/Details/xls/DetailNonres_rate.xlsx. Organizational capital parameters have only been estimated in the pharmaceutical industry.

8 Some 53% of four-digit SIC codes are missing depreciation rates for R&D, and a depreciation rate of 15% is generally assumed by prior papers when a depreciation rate is unavailable for the given industry.

9 Because of data limitations on intangible expenditures, such as unobservable accounting expenditures prior to the firm being publicly traded, (3) is often modified as follows:

$$K_t = (1-\delta)^s K_{t-s} + \sum_{k=0}^{s} (1-\delta)^{s-k} Z_{t-k},$$

where K_{t-k} is an initial intangible capital stock.

10 Evenson and Westphal (1995) define organizational capital as knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products. Lev and Radhakrishnan (2005) define organizational capital as technologies, such as business practices, processes, and designs, that give a firm a competitive advantage.

11 Firms may have zero intangibles and/or zero R&D and SG&A. So, we add one both to the left-hand side and to the term in the parentheses in (5).

12 Because the model is in logs, model fit is assessed by comparing the exponent of the error term generated by the model with the exponentiated error term of a model that uses only a constant in the estimation. Because the model does not contain a constant, a negative pseudo-R^2 is possible. We calculate standard errors by bootstrap, redrawing price observations, and thus, the full time series of company investments, with replacement.

13 Online Appendix Section A.2 provides several real-world examples found in our data.

14 In 15% of cases where the adjustment exceeds goodwill, the remainder is removed from the IIA valuation.

15 This file covers large public U.S. corporate defaults from 1987 to 2019, and it includes the final recovery of total debt based on 10-K, 10-Q, press releases, and other legal filings. The data field named "FAMILY RECOVERY" provides the dollar-weighted proportion of debt recovered. We use FF5 industry average recovery rates from the same database for the remaining firms (49% across all firms). This recovery rate multiplied by outstanding debt forms our "deal value" for this sample of firms.

16 The excluded SICs are 6000–6399, 6700–6799, 4900–4999, and 1000–1499.

17 For example, employee training and advertising expenses should be capitalized because their economic benefits extend beyond the current period, whereas others, such as rent and wage expenses, should not be capitalized because they represent payments for services rendered for a specific period.

18 For example, for SG&A, consider the perpetual inventory equation for a firm i: $S_{it} = \sum_k \gamma SG\&A_{i,t-k}(1-\delta_S)^k$. In the extreme, if $SG\&A_{it}$ is

constant for firm i, $SG\&A_{it} = SG\&A$, we have

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

Whether within-firm variation in SG&A or R&D is enough to separately identify γ_S and δ_S is an empirical question. We find that it is not and that any estimate of, for example, γ_S is ultimately tied to its calibrated counterpart.

[19] We explore the implications of this assumption by running a sensitivity analysis on varying values of δ_S on changes in the magnitudes of intangible capital stocks in Section 8.1 and find that changes in the calibration of δ_S are largely offset by changes in the estimated γ_S, leaving the resulting model fit and capital stock relatively unchanged.

[20] For example, the distribution of M/B within year and across firms is fully flexible. We only require that the mean of these distributions' means is one across years. In fact, no firms could have $M/B = 1$, and the average could be one. We also estimate the parameters and all validation tests imposing year fixed effects for ρ_t, with little quantitative change in the results.

[21] For example, if our M/B assumptions were too low, then parameter estimates of δ_G (γ_S) would be biased downward (upward).

[22] The estimation minimizes the sum of squared deviations (ϵ_{it}) while enforcing the constraint by adding to this objective function the sum (across industries) of the squares of the mean (across years) of the industry-year fixed effects multiplied by a very large number (100,000).

[23] If a firm has any acquired intangible assets at the time of acquisition, bankruptcy, or calculation of intangible value from trading prices, then we add it as I_{it} to the second term on the right-hand side of (8).

[24] BEA knowledge capital depreciation rates are listed as Asset Code IP00, Intellectual Property Products, and they are available at https://apps.bea.gov/national/FA2004/Details/xls/DetailNonres_rate.xlsx.

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

[26] Untabulated, we find that β_2 is positive and significant with all capital stocks.

[27] Our adjustment to net income is $NI_{it}^{adj} = NI_{it} + (\mathrm{RD}_{it} + \gamma_s \mathrm{SGA}_{it} - G_{it}\delta_G - S_{it}\delta_S)(1-0.35)$. The adjustment adds back the capitalized portion of the knowledge and organizational capital investment and subtracts the current year's depreciation of the capitalized asset. Because all the investment flows are before tax, we multiply by $1-0.35$, where 0.35 is an estimated tax rate for our sample.

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

[29] This paper previously circulated under the title "Acquisition Prices and the Measurement of Intangible Capital." (https://www.nber.org/papers/w25960).

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