An Intangible-adjusted Book-to-market Ratio Still Predicts Stock Returns

Hyuna Park*

October 18, 2019

Abstract

The book-to-market ratio has been widely used to explain the cross-sectional variation in stock returns, but the explanatory power is weaker in recent decades than in the 1970s. I argue that the deterioration is related to the growth of intangible assets unrecorded on balance sheets. An intangible-adjusted ratio, capitalizing prior expenditures to develop intangible assets internally and excluding goodwill, outperforms the original ratio significantly. The average annual return on the intangible-adjusted high-minus-low (iHML) portfolio is 5.9% from July 1976 to December 2017 and 6.2% from July 1997 to December 2017, vs. 3.9% and 3.6% for an equivalent HML portfolio.

Keywords: Research and Development (R&D), Goodwill, Price-to-book Ratio, Value Index Fund
JEL Classification: G12, M41, O3

---

* Hyuna Park is Herb Kurz Chair in Finance and Risk Management at Brooklyn College of the City University of New York; e-mail hyuna.park38@brooklyn.cuny.edu, phone (413) 348-9116. I thank Stephen Brown, Bill Francis, Daniel Giamouridis, Aparna Gupta, Yong Chul Kim, Yoshie Saito Lord, Stanimira Milcheva, Christpher Schwarz, Thomas Shohfi, Daniel Tinkelman, Qiang Wu and participants of the European Financial Management Association 2019 Annual Meeting and the Center for Financial Studies Seminar at Rensselaer Polytechnic Institute for helpful comments and suggestions.

1. Introduction

Does the book value of a company on its balance sheet provide value relevant information for investors? Prior research shows that the book-to-market (B/M) ratio can explain the cross-sectional variation in stock returns (e.g., Rosenberg et al., 1985; Fama and French, 1992, 1993, 2008; Lakonishok et al., 1994; Zhang, 2005; Asness et al., 2013). This finding has had a large impact on both academic research and real-world investing. For example, Vanguard launched a value index fund in 1992 using the B/M ratio as an important input in the index construction. See Appendix A for major value indexes and valuation multiples used in the indexes.

However, recent research shows that B/M is losing explanatory power. Hou et al. (2015) point out many anomalies existing factor models cannot explain and propose a new asset pricing model that does not use B/M. Fama and French (2015) show that the B/M factor becomes redundant for describing stock returns when profitability and investment factors are used along with the market and size factors. Asness et al. (2015) present that the B/M factor premium is more significant in the 1960s and 1970s than in later sample periods. Value investors like Warrant Buffett had used B/M for decades when making important decisions such as share repurchases but abandoned the measure recently (Buffett, 2017, 2018, 2019).

Why has the B/M effect become weaker? Park (2019) analyzes the impact of intangible assets and related transformations in accounting standards and shows that the B/M effect is weaker after new standards on intangibles became effective, especially in firms that have goodwill and impairment risk. McNichols et al. (2014) and Peters and Taylor (2017) examine conservative accounting biases related to intangibles and find that conservatism correction enhances the usefulness of book values in predicting future investments of firms.

This paper builds on these findings and proposes adjustments in intangibles to create a more accurate book-to-market measure to explain the cross-section of stock returns.

Tangible assets like property, plant, and equipment (PP&E) were the most important assets of companies when the B/M measure was developed in the 20th century, but intangibles like technology, innovative business models, and brand names are becoming more important in the 21st century. Nakamura (2001, 2003) of the Federal Reserve Bank of Philadelphia estimates that US firms invest at least $1 trillion in intangibles every year.

However, there are many challenges accountants face when they value intangible assets, leading to the issues of "conservative accounting biases in book value", "unrecorded intangible assets", and "unverifiable fair value estimates" (e.g., Lev and Zarowin 1996, 1999; Beaver and Ryan 2000, 2005; Lev 2001, 2003; Kothari et al. 2002; Penman and Zhang 2002; Roychowdhury and Watts 2007; Ramanna and Watts 2012; McNichols et al. 2014).

For example, under US Generally Accepted Accounting Principles (GAAP), most R&D expenditures are expensed immediately rather than capitalized even though they generate long-term benefits. Therefore, the values of most internally developed technologies are not recorded on balance sheets, resulting in underestimated book values.[1] See Appendix B for a numerical example that illustrates this issue. I use R&D in this example, but many other expenses have similar issues, such as marketing expenses to develop brand names. The categories of intangible assets include 1) marketing-related, 2) customer-related, 3) contract-related, 4) technology-related, and 5) other unspecified intangible assets (Castedello and Klingbeil, 2009).

[1] Kothari et al. (2002) explains that the rationale behind the immediate expensing decision is the high degree of uncertainty about the future benefits of R&D. One exception is software development costs that are allowed to be capitalized in certain circumstances under US GAAP. However, little or none are actually capitalized in practice because of many challenges in assessing feasibility (Paul and Durbin, 2016).

How much intangible assets are unrecorded on the balance sheets of US public firms, and what are the impacts of intangibles on the book-to-market effect? Can historical income statements data be used to adjust book value by capitalizing internally developed intangible assets for improving the B/M measure?

[Figure 1 here]

To answer these questions, I use past R&D expenditures, and selling, general, and administrative (SG&A) expenses data of Compustat firms to estimate unrecorded intangible assets, and find that 23 percent of the total capital is unrecorded intangibles as of December 31, 2016 (3.38 out of 15 trillion USD). As shown in Figure 1, the proportion of tangible assets has been decreasing over time from 81 to 66 percent while the proportions of both recorded and unrecorded intangibles have been increasing significantly during 1975 - 2016. After estimating unrecorded intangibles, I adjust the book values of firms using the estimates to calculate the intangible-adjusted B/M ratio (iB/M). Then I test whether the adjusted ratio performs better than the original and show five primary results.

First, iB/M outperforms B/M in Fama-MacBeth (1973) regressions to explain future stock returns after controlling for the differences in size, profitability, momentum, and short-term reversal. The iB/M coefficient is larger and more significantly different from zero than that of B/M in both large and small stocks.

Second, portfolio-level tests confirm the superior performance of iB/M. The excess return of the high minus low iB/M decile portfolio constructed as in Fama and French (1992) is larger and more significantly different from zero than that of B/M. When the excess returns are regressed on the market, size, profitability, and investment factors as in Fama and French

(2015 and 2016), the alpha of the iB/M portfolio is positive and significantly different from zero while the B/M alpha is not significant (0.362, *t*-value = 2.28 vs. -0.028, *t*-value = -0.17).

Third, when high-minus-low (HML) portfolios are formed as in Fama an French (1993 and 2015), iHML outperforms HML significantly. $100 invested in the HML (iHML) portfolio on June 30, 1976 grows to $416.23 ($1,010.21) on December 31, 2017. To compare the performance of iHML and HML formally, I use spanning regressions and bootstrap methods.

In spanning regressions, iHML (HML) is regressed on the other factors in an asset pricing model. I use the three-factor model of Fama and French (1993), the five-factor model of Fama and French (2015 and 2016), and a six-factor model augmented with the momentum factor. In all three models, the iHML intercept is larger and more significantly different from zero than the HML intercept (0.206, *t*-value = 2.46 vs. -0.017, *t*-value = -0.17 in the five-factor model, for example). I also use the maximum squared Sharpe ratio of the six factors in bootstrap tests to compare iHML with HML. I find that the model with iHML has a higher maximum squared Sharpe ratio than the model with HML in full-sample, in-sample, and out-of-sample tests.

Fourth, I compare iB/M with other variations based on retained earnings, tangible book value, goodwill inclusion, knowledge capital, and organization capital, and find that iB/M is the best alternative to B/M. Therefore, I propose using iB/M instead of B/M in asset pricing research, value indexes, and stock portfolio management.

Fifth, I find that iHML still explains average US stock returns for 1976 – 2017 while HML does not. This finding is consistent with Fama and French (2015) who show that HML is redundant for explaining average US stock returns for 1963-2013.

The paper proceeds as follows. Section 2 describes the procedures to estimate unrecorded intangibles and iB/M, and present summary statistics. Section 3 presents firm-level tests using Fama-MacBeth regressions, and Section 4 explains portfolio-level tests. Section 5 compares iB/M with other alternatives, and Section 6 concludes.

2. How to adjust book value using unrecorded intangibles

Prior research finds that the usefulness of reported earnings, cash flows, and book-values has deteriorated over the past decades (Lev and Zarowin, 1999). There is criticism on US GAAP in that many company's most critical assets are intangible assets, but most of them are not recorded on their balance sheets (Paul and Durbin, 2016). Unrecorded intangibles are attributable to accounting conservatism that requires R&D and other costs to develop intangible assets internally to be expensed immediately instead of capitalizing them even though the benefits last longer than a year.[2] Kothari et al. (2002) argue that the high uncertainty about the future benefits of R&D and other intangibles is the rationale behind the immediate expensing decision.

Rassier (2014) points out that national economic accounting capitalizes R&D expenditures while US GAAP for business accounting adopts more conservative approaches and requires immediate expensing of most intangible-related investments. Therefore, I build on prior research to develop guidelines for national economic accounting and use the perpetual inventory method to estimate the two components of unrecorded intangibles, knowledge capital, and organization capital. Note that the international guidelines for

[2] In October 1974, FASB (Financial Accounting Standards Board) issued SFAS 2 (Accounting for Research and Development Costs) to standardize accounting rules on R&D. In SFAS 2, FASB decided to takes a conservative approach and required R&D costs to be expensed immediately instead of capitalizing them. The rationale behind this decision is the high degree of uncertainty about the future benefits of R&D costs. See Kothari, et al. (2002) and Park (2019) for details. FASB standards are now incorporated in the FASB's Accounting Standards Codification (ASC), and SFAS 2 is now ASC 730.

national economic accounting revised in 2008, the *System of National Accounts* (*SNA 2008*), recommend capitalizing R&D expenditures.

Knowledge capital is from capitalizing past R&D expenditures, and organization capital is from capitalizing a fraction of past selling, general, and administrative (SG&A) expenditures. Peters and Taylor (2017) use a similar method to adjust Tobin's q when they analyze the impact of intangibles on the investment-q relation. However, analyzing the cross-section of stock returns is beyond the scope of their paper. Eisfeldt and Papanikolaou (2013) use the perpetual inventory method to estimate organization capital and find that firms with more organization capital have higher average stock returns than others. However, they examine neither knowledge capital nor goodwill when analyzing stock returns as their main focus is on organization capital.

Prior research examines the relationship between R&D expenditures and future stock returns and presents mixed results. Lev and Sougiannis (1996 and 1999) examine whether R&D expenditures can be used to predict stock returns. They find that low-B/M companies have large amounts of R&D capital, and the R&D capital-to-market variable subsumes the role of the B/M ratio. Chan *et al.* (2001) test whether R&D expenditures can explain stock returns and find that companies with a high ratio of R&D to equity market value tend to have poor past returns and earn large excess returns. Donelson and Resutek (2012) decompose realized stock returns into R&D returns and non-R&D returns to test whether R&D is related to mispricing or shifts in firm risk. They find that stronger future returns of R&D firms are associated with investors incorporating more value-relevant information into stock prices not captured by R&D or other accounting measures of growth.

The perpetual inventory method used in this paper is similar in spirit to Penman (2009) who argues that business accounting is not deficient in omitting internally developed intangible assets from balance sheets because there is also an income statement and the value of intangible assets can be ascertained from income statements. However, the two approaches are different in that Penman (2009) uses net income to estimate the value of unrecorded intangible assets while the perpetual inventory method uses previous expenditures to capitalize on them. Using the conservatism correction factor (CCF) as in McNichols (2014) can also adjust book values with unrecorded intangibles. However, this method requires the cost of equity of each firm as a critical input for estimating CCF and thus is not suitable for an asset pricing study that aims at explaining the cost of equity.

I use a five-step procedure to calculate an intangible-adjusted book-to-market ratio as summarized in the following table, and the first four steps are for estimating the intangible-adjusted book value of each firm every year. I take accounting data from Compustat and stock market data from the Center for Research in Security Prices (CRSP). I exclude financial firms (SIC codes 6,000 – 6,999), regulated utilities (SIC 4,900-4,999), and firms in public service, international affairs, or nonoperating establishments (SIC 9,000 and up) from the sample following Peters and Taylor (2017).

- Step I: Estimating knowledge capital (**Kcap**)

  A firm accumulates its knowledge capital by spending on R&D, which is based on the claim that the outputs of R&D should be treated as capital rather than as intermediate input (Corrado et al., 2009). Equation I in the table shows the accumulation of knowledge capital that parallels the corresponding equation for tangible assets.

Summary of the five steps for calculating intangible-adjusted book-to-market ratio, iB/M			
No	*Equations*	*Compustat mnemonic*	*Description*
I	**Knowledge capital (Kcap)** of firm i at the end of fiscal year t: $Kcap_{i,t} = (1- d_{XRD})* Kcap_{i,t-1} + XRD_{i,t}$ d_{XRD} *is the depreciation rate of the firm's R&D. I use industry-specific R&D depreciation rates of the US Bureau of Economic Analysis (BEA) as in Li (2012) and Li and Hall (2016), and list the data in Appendix C.* $XRD_{i,t}$ is the firm's R&D expenditure in Compustat during the fiscal year t.	XRD	Research and development expense
II	**Organization capital (Ocap)** of firm I at the end of fiscal year t: $Ocap_{i,t} = 0.8* Ocap_{i,t-1} + 0.3*SG\&A_{i,t}$ $SG\&A_{i,t} = XSGA_{i,t} – XRD_{i,t} – RDIP_{i,t}$ if $XSGA_{i,t}$ is greater than $XRD_{i,t}$ because XSGA in Compustat includes both actual reported SG&A expenses and XRD unless XRD is included in cost of goods sold by the company.	XSGA	Selling, general, and administrative expenses
		RDIP	In-process R&D expense
III	**Book value of common equity (BE)**: BE ≡ AT – LT + TXDB + ITCB – Preferred stock Preferred stock is PSTKL if available, or PSTKRV if available, or UPSTK. *For simplicity, I drop subscripts i and t in Equations III – V.*	AT	Total assets
		LT	Total liabilities
		TXDB	Deferred taxes – balance sheet
		ITCB	Investment tax credit – balance sheet
		PSTKL	Preferred stock – liquidating value
		PSTKRV	Preferred stock – redemption value
		UPSTK	Preferred stock at carrying value
IV	**Intangible-adjusted book value of common equity (iBE)**: iBE ≡ BE + Kcap + Ocap – GDWL **Total capital (Tcap)**: Tcap ≡ AT + Kcap + Ocap – GDWL	GDWL	Goodwill
V	**Book-to-market ratio (B/M)**: B/M ≡ BE adjusted with NSI/price times shares outstanding from CRSP **Intangible-adjusted book-to-market ratio (iB/M)**: iB/M ≡ iBE adjusted with NSI/price times shares outstanding from CRSP *Net share issuance (NSI) is zero if there is no change in CRSP's shares outstanding. Otherwise,* $NSI = \frac{(Ending\ market\ cap/beginning\ market\ cap)}{\prod(1+monthly\ withoud-dividend\ stock\ return\ during\ the\ period)} - 1$	PRC from CRSP SHR from CRST	Price Shares outstanding

One challenge is to estimate the initial capital stock each company accumulated before its entry into the database because many firms have a founding year (FOY) earlier than the start date of the Compustat data (CBEGDT). Thus, I assume that R&D expenses grow at 40 percent per year between FOY and CBEGDT and estimate the expenditures before the Compustat record and use the estimates to calculate the initial knowledge capital of each firm. See Appendix C for a numerical example that explains the estimation procedure in detail.

- Step II: Estimating organization capital (**Ocap**)

  A firm accumulates its organization capital by spending on selling, general, and administrative expenses (SG&A). I assume that 30% of past SG&A accumulates to generate long-term benefits such as brand names, business models, and customer relations, and the remaining 70% generates net income for the current period and thus is expensed. Equation II in the table is an accumulation equation for organization capital that parallels the corresponding equations for knowledge capital and tangible assets. I use the SG&A depreciation rate of 20% following Falato et al. (2013) and Peters and Taylor (2017). Note that XSGA in Compustat is the sum of a firm's actual reported SG&A expenses and R&D expenditures unless XRD is included in cost of goods sold by the company (Ball et al., 2015 and 2016). Therefore, if XSGA is greater than XRD, I subtract XRD from XSGA to calculate the actual reported SG&A when estimating organization capital. For companies that report in-process R&D (RDIP), I subtract RDIP and XRD from XSGA to calculate SG&A as Compustat adds to XSGA only the part of R&D not representing acquired in-process R&D and codes RDIP as negative.

- Step III: Defining the book value of equity (**BE**)

Following Fama and French (2018), I define the book value of common equity, BE, as shown in Equation III of the table.

- Step IV: Defining intangible-adjusted book value of equity (**iBE**) and total capital (**Tcap**)

  I define the intangible-adjusted book value of common equity (iBE) and total capital (Tcap) in Equation IV in the table using the estimates in Steps I-III. Goodwill (GDWL in Compustat) is the excess purchase price paid over the estimated fair value of the target's identifiable net assets in business combinations.[3] I subtract GDWL when defining iBE and TCap because of two reasons. First, GDWL is based on fair value accounting, but analyzing the relation between book-to-market ratio and expected stock returns is meaningful only in historical cost accounting because the ratio is supposed to be one in fair value accounting (Penman et al., 2017). Second, prior research points out that there is subjectivity in estimating goodwill's current fair value and there are cases of goodwill impairment that are not backed by economic fundamentals (Ramanna and Watts, 2012; Chen et al., 2014).[4]

- Step V: Calculating an intangible-adjusted book-to-market ratio (**iB/M**)

  I calculate iB/M using iBE to be compared with B/M based on BE.When calculating B/M and iB/M, the numerator is BE or iBE, adjusted with net share issuance (NSI), and the

[3] In 2001, Financial Accounting Standards Board (FASB) issued the Statement of Financial Accounting Standards (SFAS) 141 (Business Combinations) and SFAS 142 (Goodwill and Other Intangible Assets) to improve accounting standards on intangibles. According to SFAS 141, for mergers and acquisitions since 2001, acquirers must allocate the purchase prices they pay for targets to the tangible and identifiable intangible assets they acquire, and the remainder to goodwill. See FASB (2001a 2007), FASB (2001b), Lim et al. (2016) and Park (2019) for details. FASB standards are now incorporated in the FASB's Accounting Standards Codification (ASC). SFAS 141 can be found under ASC 805 and SFAS 142 under ASC 350-20-35. However, to be consistent with prior research, I will refer to SFAS 141 and 142 instead of ASC 805 and ASC 350-20-35.

[4] I test this theoretical reasoning of excluding goodwill empirically in Section 5 by defining an alternative book-to-market ratio that includes Gdwl (gB/M) to be compared with iB/M. I find that iB/M is superior to gB/M in both Fama-MacBeth regressions and portfolio-level tests.

denominator is the total market value of equity that is price times shares outstanding from CRSP. I define NSI following Fama and French (2018) as shown in the table. The NSI adjustment is necessary when calculating B/M and iB/M because of the measurement time gap between the numerator (book value) and the denominator (market value). There are two reasons for the time gap. First, many firms have a fiscal year ending in December, but there are also firms whose fiscal year ending in other months. Second, it takes several months for financial statements data to become publicly available while stock market data become available immediately.

Asness and Frazzini (2013) examine this time gap issue and argue that considering this issue in HML is important, especially in the presence of the momentum factor. In Section 4.4, I will examine this issue in more detail as a robustness check by defining HML_{AF} and $iHML_{AF}$ following Asness and Frazzini (2013) and comparing them with HML and iHML. I find that HML and iHML outperform HML_{AF} and $iHML_{AF,}$ and the superior performance of iHML over HML is robust to the measurement time of market equity.

In portfolio-level tests, B/M portfolios are formed in June of year t using book equity in financial statements ending in any months of year t-1 and market equity of December of year t-1. If a firm's fiscal year ends in a month earlier than December, their BE and iBE are adjusted for NSI from the fiscal year-end to the end of December of year t-1.

In monthly Fama-MacBeth regressions, I update all explanatory variables every month, including the market value of equity and repurchase data to calculate B/M and iB/M, following Ball et al. (2015 and 2016). As in prior research, financial statements data is updated annually in June with a lag of at least six months to make sure the data is publicly available. For example, for the regression using stock returns in July 2011, iB/M is calculated using the iBE adjusted for NSI from the fiscal year-end to June 30, 2011 as the numerator and the market equity (ME) on June 30, 2011, as the denominator.

[Table 1 here]

Table 1 presents summary statistics. The sample period starts in 1975 because SFAS 2 (now ASC 730), the accounting standard that requires most R&D expenditures to be expensed immediately instead of being capitalized, was issued on October 1974. I present the descriptive statistics using the time-series averages of the percentiles. Following the convention in prior research, negative BE stocks are excluded from the analysis. Panel A shows annually observed accounting variables scaled by total capital from 1975 to 2016. The distributions of both recorded intangibles (Gdwl and Intano) and unrecorded intangibles (Kcap and Ocap) are skewed to the right, having an average greater than the median.

For example, the average knowledge capital is 11.9% of the total capital of a firm, but the median is 7.2%, and the 99th percentile is 60.5%. Goodwill's distribution also presents outliers: the median is 2.1%, the average 9.6%, and the 99th percentile 89.9%. The outliers point to the need either to trim these variables in cross-sectional regressions or to base inferences on portfolio sorts.

Panel B of Table 1 reports summary descriptive statistics for the variables that use both market data observed monthly and accounting data observed annually. As the accounting data start in 1975, and at least six months are required to make sure that the data are public information, the sample period for Panel B is July 1976 - December

2017. These are the explanatory variables in the Fama-MacBeth Regressions presented in the next section.

3. Fama-MacBeth Regressions

I test the impact of intangibles on the book-to-market effect at the firm level by comparing Fama–MacBeth regressions of monthly returns on log(B/M) with those on log(iB/M). I include control variables such as size, momentum, short-term reversal, and profitability as commonly used in the literature. log(M) is the natural logarithm of the market value of equity. $r_{12\text{-}1}$ is the prior year's return skipping the last month to consider the momentum effect, and $r_{1,1}$ is the prior month return to control the short-term reversal effect. COP is cash-based operating profitability scaled by the book value of total assets as in Ball et al. (2016).

Panel B of Table 1 presents the summary descriptive statistics of these variables. The average log(B/M) is -0.63, and the 25th and 75th percentiles are -1.21 and 0.04, respectively. All percentiles of log(iB/M) are higher than those of log(B/M) due to the inclusion of unrecorded intangibles, and both variables exhibit outliers. To make sure that coefficients are comparable across different model specifications, all regressions presented in Table 2 are based on the same observations that are trimmed at the 1st and 99th percentiles of log(B/M), log(iB/M), and all control variables.

Prior research shows that microcap stocks behave differently in the Fama-MacBeth regressions of future stock returns on B/M. Therefore, I divide the sample into two size groups: ABM (All-but-microcaps) and Micro. Following Fama and French (2008), Micro is defined as NYSE, AMEX, and Nasdaq stocks below the 20th percentile of the market capitalization of NYSE stocks and ABM is all else. Consistent with prior research, Table 2 shows that the book-to-market effect is stronger in Micro than in ABM. The B/M and iB/M coefficients and *t*-statistics are larger in Micro than in ABM.

[Table 2 here]

Note that iB/M outperforms B/M in both size groups (0.325, *t*-value = 5.04 vs. 0.248, *t*-value = 3.36 in ABM and 0.594, *t*-value = 11.12 vs. 0.401, *t*-value = 7.11 in Micro). In Table 2, I also test which component of iB/M makes the intangible adjustment significant. Regressions (3) and (6) show that knowledge capital contributes significantly to the improvement in both size groups. Especially log(B/M) is no longer significant in the ABM sample when log(KCap/M) is added to the regression. Note also that the coefficient on log(Gdwl/M) is negative and significant in Micro. That is, we can have a better book-to-market measure by excluding "unverifiable" fair value estimates in goodwill and including unrecorded intangibles. This contribution of each component issue is examined in more detail later in the paper as a robustness check in portfolio-level as well as firm-level tests in Section 5.

Note also that most control variables in Fama-MacBeths regressions are significant and have the expected signs. The profitability measure (cop) and the momentum effect (r_{12-1}) have positive and significant coefficients while the size (log(M)) and short-term reversal ($r_{1,1}$) coefficients are significantly negative in both size groups during July 1976 – December 2017.

4. Portfolio-level Tests

4.1. Decile portfolios formed on B/M or iB/M

Prior research suggests implementing value-weighted portfolio-level tests in addition to Fama-MacBeth regressions because the firm-level regressions are sensitive to outliers, impose a potentially misspecified parametric relation between variables, weigh each firm equally, and thus nano- and micro-cap stocks are overly emphasized. When considering the skewed distributions and extreme observations shown in Table 1, portfolio-level tests potentially provide a robust method to compare B/M with iB/M. The sample is no longer split into ABM and Micro because microcap stocks have only a small effect on value-weighted portfolio returns.

Following the convention in prior research, I form decile portfolios at the end of each June using NYSE breakpoints of B/M or iB/M and the portfolios are rebalanced annually. Table 3 presents the results from univariate sorts on B/M and iB/M and the sample period is July 1976 – December 2017.

[Table 3 here]

The table shows the portfolios' value-weighted average excess returns and the alphas from the regressions of the portfolios' excess returns on the market (XMKT), size (SMB), profitability (RMW), and investment (CMA) factors as in Fama and French (2015 and 2016).[5] Average excess returns of B/M portfolios generally increase with B/M, with the highest ratio portfolio earning 0.48% per month higher average return than the lowest ratio one with a test statistic of 2.51. Note that the difference is larger and more significant for the portfolios formed on iB/M. The high iB/M portfolio earns 0.87% per month higher average return than the low iB/M portfolio, and the *t*-statistic is 4.39.

When comparing B/M with iB/M, it is important for investors to consider not only excess returns but also multi-factor model alphas because a non-zero alpha implies that

[5] The XMKT, SMB, CMA and RMW data used in this paper are from Kenneth French's data library, and I thank him for making the data available for download from the website. In Section 4.2, I construct HML using Fama and French's methodology to make it based on the same firm-year observations as iHML.

the other strategies based on size, profitability, and investments combined with Treasuries cannot generate an efficient portfolio. As shown in Table 3, the outperformance of iB/M over B/M holds after controlling for other risk factors. The iB/M high minus low portfolio alpha is positive and significant (0.36% per month, *t*-value = 2.28) while the corresponding value for B/M is negative and insignificant (-0.03% per month, *t*-value = -0.17).

The significant four-factor model alpha of the iB/M portfolio shows that investors can improve the mean-variance efficiency of their portfolios by including a portfolio formed on iB/M, but the B/M measure does not provide such benefits. After finding that iB/M portfolios perform better than B/M before and after controlling for other risk factors in a univariate sort, I move on to analyze portfolios double sorted on size and B/M (iB/M) in the next sub-section.

4.2. High minus low portfolios and spanning regressions

Following Fama and French (1993 and 2015), I construct six value-weighted portfolios based on size and B/M. The size breakpoint for each year is the median market capitalization of NYSE stocks, and the B/M breakpoints are the 30^{th} and 70^{th} NYSE percentiles. Returns on the high minus low (HML) portfolios are the average returns on the two (small and big) high B/M portfolios minus the average returns on the two low B/M portfolios. Note that this procedure is the same as how Fama and French construct the HML factor. I apply the same method to iB/M and construct the high minus low portfolio based on iB/M and call it iHML.

[Table 4 here]

Panel A of Table 4 shows that iHML outperforms HML. The average return and *t*-value are higher (0.49% per month, *t*-value = 4.72 vs. 0.32% per month, *t*-value = 2.70) and the standard deviation is lower (2.33% vs. 2.66% per month) during July 1976 – December 2017. Figure 2 presents the growth of $100 each invested in HML and iHML on June 30, 1976. The value of the iHML portfolio grows much faster than the HML portfolio especially during the last two decades when the intangible assets become more important in the economy than in earlier sample periods ($1,010 vs. $416 on December 31, 2017 and $323 vs. $239 on December 31, 1997).

[Figure 2 here]

Note also that the cumulative return on iHML rebounds sharply when the stock market recovers from the 2007-2008 financial crisis as well as the 2001 recession, and these recovery patterns are consistent with the time-varying risk premium of Zhang (2005). The recovery pattern in HML is not as clear as in iHML, especially after the recent financial crisis. This result is consistent with Park (2019) who shows that the explanatory power of B/M in the cross-section of stock returns is weaker in the post-SFAS 142 period than in the pre-SFAS 142 sample and the change is related to intangible assets.

Prior research suggests two possibilities for the cause of the BM effect: a risk-based approach and a behavioral explanation. Zhang (2005) explains the BM effect in the neoclassical framework with rational expectations using the costly reversibility and countercyclical price of risk. In contrast to the risk-based approach, Lakonishok *et al.* (1994) argue that investors overextrapolate a firm's past earnings growth when forecasting future earnings. Therefore, the stock prices of firms with poor past earnings are pushed down too far and thus have high BM ratios. Regardless of whether the B/M effect is due to risk or mispricing, reducing biases in book value related to intangibles can improve the B/M measure. That is, the accounting issue related to intangibles can coexist with the risk-based explanation, as well as the mispricing theory.

Panel B of Table 4 compares HML with iHML using spanning regressions. Prior research uses two approaches to compare factor models. One is the left-hand-side (LHS) approach that compares factor models based on the intercepts of time-series regressions of test assets (e.g., Fama and French, 1993, 2015; Xing, 2008; Hou et al., 2015). One drawback of the LHS approach is the fact that results depend strongly on the choice of test assets. In contrast, the right-hand-side (RHS) approach does not require test assets and spanning regressions belong to this category.

In a spanning regression, the factor tested is regressed by the other factors in an asset pricing model in a time-series regression. If the intercept in a spanning regression is positive and significant, the factor contributes to the corresponding model's explanation of average returns during the sample period.

In Panel B of Table 4, I present spanning regressions based on three different factor models: the three-factor model of Fama and French (1993), the five-factor model of Fama and French (2015 and 2016), and a six-factor model augmenting the five-factor model with a momentum factor. I find that iHML has a positive and significant intercept in all models (*t*-value 2.46 ~ 5.20) while HML's intercept is not significantly different from zero in the five-factor model (*t*-value = -0.17) and the six-factor model (*t*-value = 0.78). That is, iHML contributes to the five-factor and the six-factor model's explanation of stock returns during July 1976 – December 2017 while HML does not.

4.3. Bootstrap simulations to compare HML with iHML

Another approach that focuses on RHS factors is to compare competing factors using the maximum squared Sharpe ratio test. This approach is based on two assumptions. First, the left-hand-side returns each factor model is asked to explain include the factors of competing models. The second assumption is that the best factor model produces intercepts that have the smallest maximum squared Sharpe ratio in time-series regressions of the left-hand-side returns on factors.

Under these two assumptions, Barillas and Shanken (2017) show that minimizing the maximum squared Sharpe ratio of the intercepts in the regression of left-hand-side returns on factors is equivalent to finding a factor model whose factors have the highest maximum squared Sharpe ratio ($Sh^2(f)$). $Sh^2(\cdot)$ denotes the maximum squared Sharpe ratio obtainable from portfolios of the given returns.

If we use this approach, we can compare factor models without using test assets because the model with the highest $Sh^2(f)$ is the best. Fama and French (2018) use this method to compare profitability factors and find that the cash-based operating profitability factor is better than the accrual-based factor when combined with their market, size, value, and investment factors.

I use the maximum squared Sharpe ratio test to compare HML with iHML in the six-factor model. First, I test the actual sample of July 1976 – December 2017 (498 months). Table 5 shows that the factor model that uses iHML has a higher $Sh^2(f)$ than the corresponding model that uses HML (0.161 vs. 0.139).

[Table 5 here]

Note that the results of the actual sample may be biased because the inputs for $Sh^2(f)$ are not population parameters but sample estimates. Sample errors in factor means and covariance matrix affect the optimization leading to biased estimates of the actual sample. Following prior research, I use out-of-sample bootstrap simulations to address this issue. I split the 498 months in the actual sample into 249 adjacent pairs. For example, Month 1 and Month 2 are in the first pair, and Month 497 and Month 498 are in the 249th pair.

In each of the 10,000 simulation runs, I draw a random sample of 249 pairs with replacement. Then, I randomly assign one month from each pair to in-sample tests and use that month repeatedly if the pair is drawn multiple times. I use the other month in the pair for out-of-sample tests. As out-of-sample tests use the factor weights estimated during in-sample tests and monthly returns are not serially correlated, the out-of-sample $Sh^2(f)$ estimates are bias-free. I also run full sample simulations by randomly sampling 498 months with replacement 10,000 times to be compared with the actual, in-sample, and out-of-sample results.

Table 5 shows that using iHML instead of HML increases the $Sh^2(f)$ in full-sample, in-sample, and out-of-sample simulations as well as in the actual sample. For example, replacing HML by iHML increases the average out-of-sample $Sh^2(f)$ by 19% from 0.105 to 0.125. The model with iHML has a higher $Sh^2(f)$ than the model with HML in 97.3% of the simulation runs in the full sample test. In in-sample and out-of-sample tests, the proportions are lower due to smaller samples, but iHML gives a higher $Sh^2(f)$ than HML in over 85% of the 10,000 simulations.

4.4. Comparing HML with iHML while varying the measurement time of ME

This subsection presents a robustness check to test whether the measurement time of market equity affects the comparison of HML and iHML. Asness and Frazzini (2013) examine this issue and argue for using current market equity instead of lagged one. I construct alternative factors following their suggestions and call them HML_{AF} and $iHML_{AF}$.

In HML and iHML, the measurement time of book equity (BE) and market equity (ME) are as closely aligned as possible as in Fama and French (1993 and 2015). That is, when portfolios are formed in June of year t, BE reported during year t-1 and ME as of the end of year t-1 are used instead of ME in June of year t. However, HML_{AF} and $iHML_{AF}$ use ME as of June of year t.

[Table 6 here]

Panel A of Table 6 shows that HML and iHML outperform HML_{AF} and $iHML_{AF}$ during July 1976 – December 2017. The average return is higher, and the standard deviation is lower when the portfolios are formed using lagged ME as in Fama and French (1993 and 2015) than current ME as in Asness and Frazzini (2013). The results also confirm that the superior performance of iHML over HML is robust to the measurement time of ME. $iHML_{AF}$ has a higher average return and a lower standard deviation than HML_{AF}. iHML has a higher average return and a lower standard deviation than HML.

Spanning regression results are also robust to the measurement time of ME. As shown in Panel B of Table 6, the intercepts of the regressions of iHML and $iHML_{AF}$ on other factors are significant (*t*-statistic = 3.13 for iHML and 3.15 for $iHML_{AF}$) while the intercepts of HML and HML_{AF} regressions are not (*t*-statistic = 0.78 for HML and 0.99 for HML_{AF}).

Panel B of Table 6 also presents regressions to test whether UMD, the momentum factor, interacts differently when concurrent MEs are used as in HML_{AF} and $iHML_{AF}$ instead of lagged MEs as in HML and iHML. That is, when a factor based on lagged ME such as HML is regressed on other factors, the corresponding factor based on concurrent ME such as HML_{AF}, is also added as an explanatory variable, and vice versa. Note that the UMD coefficient is significantly negative for the regressions of HML_{AF} and $iHML_{AF}$ while the coefficient is significantly positive in the regressions of HML and iHML.

This result is consistent with Asness and Frazzini (2013) who show that the value factor becomes more negatively correlated to the momentum factor when the current market value is used instead of lagged market value when measuring the book-to-market ratio. See Asness, Moskowitz, and Pedersen (2013) for more details on the relation between value and momentum factors.

5. Comparing iB/M with other alternatives

Previous sections show that iB/M performs better than B/M in firm-level and portfolio-level tests, and the results are robust to the measurement time of market equity. This section is to test whether there is another alternative of B/M that performs better than iB/M.

5.1. Retained earnings-to-market

The book value of common equity (BE) has three components: contributed capital (CC), retained earnings (RE), and accumulated other comprehensive income (AOCI). CC represents accumulated past equity issuances less past share repurchases. RE is the accumulated total earnings a firm generated since its beginning less accumulated dividend distributions. AOCI is a technical account that represents the unrealized gains and losses related to the long and short positions in financial assets a company holds.

$$BE = CC + RE + AOCI \tag{1}$$

Ball et al. (2018) show that retained earnings-to-market (RE/M) explains the cross-section of stock returns, and argue that book-to-market strategies work because the book value of equity includes retained earnings that measure a firm's *average* earnings power. Therefore, I check whether RE/M is a better alternative to B/M than iB/M.

I use Fama-MacBeth regressions to compare RE/M, CC/M, and AOCI/M with B/M and iB/M. Following prior research, I take the natural logarithm of each ratio and include indicator variables for negative ratios as logarithm cannot be applied to negative numbers. When calculating RE/M, CC/M, and AOCI/M, the numerators are RE, CC, and AOCI adjusted with NSI and the denominators are market equity.

I find that iB/M is better than RE/M in predicting returns of both large and small stocks. The coefficient on log(iB/M) and its *t*-value are greater than those of log(RE/M): 0.325 with *t*-value = 5.04 vs. 0.163 with *t*-value = 3.68 for ABM and 0.594 with *t*-value = 11.12 vs. 0.142 with *t*-value = 3.81for Micro.

I also use portfolio-level tests to compare RE/M with iB/M and find that the portfolio formed on iB/M outperform the corresponding portfolio formed on RE/M. The high-minus-low RE/M portfolio's excess return and four-factor model alpha and their *t*-values are smaller than those of the iB/M portfolio (excess return: RE/M 0.380 with *t*-value = 1.81 vs. iB/M 0.870 with *t*-value = 4.39, four-factor model alpha: RE/M -0.036 with *t*-value = -0.21 vs. iB/M 0.362 with *t*-value = 2.28).

5.2. Other alternatives

iB/M is based on two adjustments for book values, adding unrecorded intangibles and subtracting goodwill. Are these two adjustments the most optimal way to improve the book-to-market measure? Is subtracting goodwill based on theoretical reasoning supported by empirical results? Unrecorded intangibles have two components: knowledge capital from R&D expenditures and organization capital from SG&A expenses. Which component contributes more to the outperformance of iB/M over B/M, knowledge capital or organization capital?

To answer these questions, I test four other variations of B/M and compare them with iB/M. The four variations are tB/M, gB/M, kB/M, and oB/M. The first alternative, **tB/M**, is related to the fact that analysts often use tangible book equity (**tBE**) instead of BE.

tBE is defined in Equation (2) where Intan is intangible assets from Compustat. Note that tBE contains neither recorded intangibles nor unrecorded intangibles. tB/M is calculated by dividing the NSI-adjusted tBE by market equity.

$$tBE \equiv BE - \text{Intangible assets (Intan)} \qquad (2)$$

The second alternative, **gB/M**, uses goodwill-inclusive book equity (**gBE**) as defined in Equation (3). Note that gBE includes everything: tangible assets, all recorded intangibles including goodwill, and unrecorded intangibles such as knowledge capital and organization capital. gB/M is calculated by dividing NSI-adjusted gBE by market equity.

$$gBE \equiv iBE + \text{Goodwill (Gdwl)} \qquad (3)$$

The third alternative, **kB/M**, uses knowledge-capital-based book equity (**kBE**) as defined in the following equation.

$$kBE \equiv BE + Kcap - Goodwill\ (Gdwl) \quad (4)$$

kB/M is calculated by dividing NSI-adjusted kBE by market equity. That is, the difference between iB/M and kB/M is iB/M includes both knowledge capital and organization capital while kB/M includes only knowledge capital, not organization capital.

oB/M is defined similarly. oB/M uses organization-capital-based book equity (**oBE**) as defined in Equation (5).

$$oBE \equiv BE + Ocap - Goodwill\ (Gdwl) \quad (5)$$

oB/M is calculated by dividing NSI-adjusted oBE by market equity. The difference between iB/M and oB/M is iB/M includes both knowledge capital and organization capital while oB/M includes only organization capital, not knowledge capital.

I compare B/M and iB/M with tB/M, gB/M, kB/M, and oB/M in Fama-MacBeth regressions and find that it is important to include intangible assets when constructing a book-to-market measure. tB/M that considers only tangible assets underperform all other alternatives and portfolio-level tests show similar results. The tB/M based high minus low portfolio has a lower average excess return and a lower alpha than corresponding portfolios based on other book-to-market measures: 0.38 vs. 0.70 ~ 0.87 % per month excess return with a *t*-value of 2.11 vs. 3.63 ~ 4.39, and 0.14 vs. 0.28 ~ 0.36 % per month alpha with a *t*-value of 0.80 vs. 1.76 ~ 2.28.

Comparing gB/M with iB/M confirms that subtracting goodwill improves the book-to-market measure. The four-factor model alpha of the gB/M-based high minus low portfolio is lower and less significant than the alpha of the iB/M-based portfolio (0.28%

per month with a *t*-value of 1.76 vs. 0.36% per month with a *t*-value of 2.28). Note that the only difference between gB/M and iB/M is in goodwill; gB/M includes goodwill, and iB/M does not.

I also find that both knowledge capital and organization capital are important to improve the B/M measure, and the contribution of the knowledge capital based on R&D expenditures is larger than that of organization capital based on SG&A expenses. The kB/M coefficient and *t*-statistic in Fama-MacBeth regressions are larger than those of oB/M in both ABM and Micro: 0.30 with a *t*-value of 5.45 vs. 0.26 with a *t*-value of 3.71 in ABM and 0.58 with a *t*-value of 11.77 vs. 0.43 with a *t*-value of 7.83 in Micro. The B/M coefficient and *t*-statistic are smaller than those of oB/M and kB/M in both ABM and Micro. Portfolio level tests show similar results. The four-factor model alpha and *t*-statistic of kB/M are higher than those of oB/M: 0.35 vs. 0.32% per month and *t*-value 2.17 vs. 1.94. The four-factor model alpha and *t*-statistic of oB/M are higher than those of B/M: 0.32 vs. -0.03% per month and *t*-value 1.94 vs. -0.17.[6]

Overall, these results have three implications. First, taking both recorded and unrecorded intangibles into consideration improves the performance of the book-to-market measure significantly. iB/M, kB/M, and gB/M outperform tB/M and B/M by a wide margin. Second, subtracting goodwill from book value improves the performance of the book-to-market measure. Third, the marginal contribution of knowledge capital is larger, but the marginal contribution of organization capital is also significant. In summary, Fama-MacBeth regressions and portfolio level tests show that intangible assets

[6] To save space, I do not include the tables for RE/M, tB/M, gB/M, kB/M, and oB/M in the paper, but the results are available from the author upon request.

affect the performance of book-to-market measures and iB/M is better than other alternatives of B/M.

6. Conclusions

The B/M measure has been widely used in asset pricing studies since the seminal research of Fama and French (1992 and 1993), and value funds are using the measure for stock valuation and index construction. However, there is growing evidence in the literature showing that the B/M measure is losing explanatory power in the cross-section of stock returns.

I argue that the growth of goodwill and unrecorded intangible assets are related to the change, and suggest iB/M, an intangible-adjusted measure, as an alternative. iB/M is based on two adjustments for book values: capitalizing unrecorded knowledge capital (Kcap) and organization capital (Ocap), and subtracting goodwill that is subject to the issue of unverifiable fair value estimates.

> iB/M ≡ iBE adjusted with net share issuance /price times shares outstanding from CRSP
> iBE ≡ BE + Kcap + Ocap – Goodwill (Gdwl)
> = Total assets (AT) – Total liabilities (LT) + Deferred taxes (TXDB) + Investment tax credits (ITCB) – Preferred stock (PSTKL, PSTKRV, or UPSTK) + Kcap + Ocap – Goodwill (Gdwl)
> **Note that Compustat mnemonics are in parentheses in these equations.*

Portfolio-level and firm-level tests show that adjusting book value with unrecorded intangibles and goodwill improves the explanatory power of the book-to-market ratio in the cross-section of stock returns. Based on these results, I suggest that value index providers and asset pricing researchers adjust book values by adding unrecorded intangibles and subtracting goodwill when they estimate valuation ratios of companies. Future research may find a better methodology to capitalize on internally developed intangibles. The main contribution of this paper is to show that an imperfect proxy is better than ignoring unrecorded intangible assets when we use the book-to-market measure for asset pricing research and stock valuation.

References

Asness, C. & Frazzini, A. (2013). The devil in HML's details. Journal of Portfolio Management, 39(4), 49-68.

Asness, C., Frazzini, A., Israel, R., & Moskowitz, T. (2015). Fact, fiction, and value investing. Journal of Portfolio Management, 42, 75-92.

Asness, C., Moskowitz, T., & Pedersen, L. (2013). Value and momentum everywhere. *Journal of Finance*, 68, 929–985.

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. V. (2015). Deflating profitability. *Journal of Financial Economics*, 117, 225-248.

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. V. (2016). Accruals, cash flows, and operating profitability in the cross-section of stock returns. *Journal of Financial Economics*, 121, 28-45.

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. V. (2018). Earnings, retained earnings, and book-to-market in the cross-section of expected returns. *Journal of Financial Economics*, forthcoming.

Barillas, F., Shanken, J. (2017). Which alpha? *Review of Financial Studies*, 30(4), 1316-1338.

Beatty, A., & Weber, J. (2006). Accounting discretion in fair value estimates: An examination of SFAS 142 Goodwill Impairments. *Journal of Accounting Research,* 44(2), 257–288.

Beaver, W., & Ryan, S. (2000). Biases and lags in book value and their effects on the ability of the book-to-market ratio to predict book return on equity. *Journal of Accounting Research*, 38, 127–148.

Beaver, W., & Ryan, S. (2005). Conditional and unconditional conservatism: concepts and modeling. *Review of Accounting Studies*, 10, 269-309.

Buffett, W. (2017). Chairman's letter in the *2016 Annual Report* of Berkshire Hathaway, INC.

Buffett, W. (2018). Chairman's letter in the *2017 Annual Report* of Berkshire Hathaway, INC.

Buffett, W. (2019). Chairman's letter in the *2018 Annual Report* of Berkshire Hathaway, INC.

Castedello, M., & Klingbeil, C. (2009). Intangible assets and goodwill in the context of business combinations: An industry study. KPMG.

Chan, L. K. C., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *Journal of Finance,* 56(6), 2431–2456.

Chen, W., Shroff, P. K., & Zhang, I. (2014). Fair value accounting: Consequences of booking market-driven goodwill impairment. Working Paper, University of Minnesota.

Corrado, C. & Hulten, C. (2010). How do you measure a technological revolution? *American Economic Review,* 100, 99-104.

Corrado, C. Hulten, C. & Sichel, D. (2009). Intangible capital and U.S. economic growth. *The Review of Income and Wealth*, 55(3), 661-685.

Daniel, K., & Titman, S. (2006). Market reactions to tangible and intangible information. *Journal of Finance*, 61(4), 1605–1643.

Donelson, D., & Resutek, R. (2012). The effect of R&D on future returns and earnings forecasts. *Review of Accounting Studies*, 17(4), 848–876.

Dontoh, A., Radhakrishnan S., & Ronen, J. (2004). The declining value-relevance of accounting information and non-information-based trading: an empirical analysis. *Contemporary Accounting*, 21(4), 795-812.

Eisfeldt, A. L. & Papanikolaou, D. (2013). Organization Capital and the Cross-Section of Expected Returns. *Journal of Finance*, 68(4), 1365 - 1406.

Eisfeldt, A. L. & Papanikolaou, D. (2014). The value and ownership of intangible capital. *American Economic Review*: Papers and Proceedings, 104, 189-194.

Falato, A., Kadyrzhanova, D. & Sim, J.W. (2013). Rising intangible capital, shrinking debt capacity, and the US corporate savings glut. Finance and economics discussions series 2013-67. Divisions of Research & Statistics and Monetary Affairs, Board of Governors of the Federal Reserve System, Washington, DC.

Fama, E., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47, 427-465.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3–56.

Fama, E., & French, K. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105, 457–472.

Fama, E., & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116, 1–22.

Fama, E., & French, K. (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, 29(1), 69-103.

Fama, E., & French, K. (2018). Choosing factors. *Journal of Financial Economics*, 128, 234-252.

Fama, E., & MacBeth, J. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81, 607–636.

Financial Accounting Standards Board (1974). Statement of Financial Accounting Standards No. 2 Accounting for Research and Development Costs. Financial Accounting Standards Board (FASB), Norwalk, CT.

Financial Accounting Standards Board (2001a). Statement of Financial Accounting Standards (SFAS) No. 141 Business Combinations. FASB, Norwalk, CT.

Financial Accounting Standards Board (2001b). Statement of Financial Accounting Standards (SFAS) No. 142 Goodwill and Other Intangible Assets. FASB, Norwalk, CT.

Financial Accounting Standards Board (2007). Statement of Financial Accounting Standards (SFAS) No. 141 Business Combinations (Revised). FASB, Norwalk, CT.

Francis, J., & Schipper, K. (1999). Have financial statements lost their relevance? *Journal of Accounting Research*, 37(2), 319–352.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28, 650–705.

Israel, R. & Moskowitz, T. (2013). The role of shorting, firm size, and time on market anomalies. *Journal of Financial Economics*, 108, 275-301.

Kim, M., & Kross, W. (2005). The ability of earnings to predict future operating cash flows has been increasing – not decreasing. *Journal of Accounting Research*, 43(5), 753-780.

Kothari, S. P., Laguerre, T. E., & Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies*, 7, 355–382.

Lev, B. (2001). Intangibles: Management, measurement, and reporting. Brookings Institution Press.

Lev, B. (2003). Remarks on the measurement, valuation, and reporting of intangible assets. *Federal Reserve Bank of New York Economic Policy Review*, September, 17–22.

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics*, 21, 107-138.

Lev, B., & Sougiannis, T. (1999). Penetrating the book-to-market black box: The R&D effect. *Journal of Business, Finance and Accounting*, 26, 419–449.

Lev, B., & Zarowin, P. (1999). The boundaries of financial reporting and how to extend them. *Journal of Accounting Research*, 37(2), 353–385.

Li, W. C. Y. (2012). Depreciation of business R&D capital. US Bureau of Economic Analysis/ National Science Foundation R&D Satellite Account Paper US Department of Commerce downloaded from https://www.bea.gov/national/pdf/WendyLiDepreciationBusinessR&DCapital20130314BEAwebversion.pdf

Li, W. C. Y. & Hall, B. W. (2016). Depreciation of business R&D capital. U.S. Bureau of Economic Analysis/ University of California at Berkeley and NBER, working paper downloaded from https://www.bea.gov/papers/pdf/BEAworkingpaperLiHallDepreciationofBusinessRDCapital.pdf

Li, Z., Shroff, P., Venkataraman, R., & Zhang, I. (2011). Causes and consequences of goodwill impairment losses. *Review of Accounting Studies*, 16, 745–778.

Lim, S., Macias, A., & Moeller, T. (2016). Intangible assets and capital structure. Working paper, Baylor University.

McNichols, M., Rajan, M. V. & Reichelstein, S. (2014). Conservatism correction for the market-to-book ratio and Torbin's q. *Review of Accounting Studies*, 19, 1393-1435.

Nakamura, L. (2001). What is the US gross investment in intangibles? At least one trillion dollars a year. Federal Reserve Bank of Philadelphia Working Paper No. 01-15.

Nakamura, L. (2003). A trillion dollars a year in intangible investment and the new economy. In *Intangible assets*, J. Hand and B. Lev (eds.). Oxford University Press.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108, 1-28.

Park, H. (2019). Intangible assets and the book-to-market effect. *European Financial Management*, 25, 207-236.

Paul, B., & Durbin, P. (2016). Revisiting accounting for software development costs: An ideal first step. *Point of View*, PricewaterhouseCoopers (PwC), October.

Penman, S. H. (2009). Accounting for intangible assets: There is also an income statement. *Abacus: a journal of accounting, finance and business studies*, 45(3), 358-371.

Penman, S. H., Reggiani, F., Richardson, S. A. & Tuna, I. (2017). A Framework for identifying accounting characteristics for asset pricing models, with an evaluation of book-to-price. Working paper, Columbia Business School.

Penman, S. H., & Zhang, X. (2002). Accounting conservatism, the quality of earnings and stock returns. *The Accounting Review*, 77, 237-264.

Peters, R. H. & Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123, 251-272.

Ramanna, K. (2008). The implications of unverifiable fair-value accounting: Evidence from the political economy of goodwill accounting. *Journal of Accounting and Economics*, 45, 253–281.

Ramanna, K., & Watts, R. (2012). Evidence on the use of unverifiable estimates in required goodwill impairment. *Review of Accounting Studies*, 17, 749–780.

Rassier, D. G. (2014). Treatment of research and development in economic accounts and in business accounts. *BEA Briefings*, March 1-8., Bureau of Economic Analysis (BEA), US Department of Commerce.

Roychowdhury, M., & Watts, R. (2007). Asymmetric timeliness of earnings, market-to-book and conservatism in financial reporting, *Journal of Accounting and Economics,* 44, 2–31.

Ryan, S.G.,& Zarowin, P. A. (2003). Why has the contemporaneous liner returns-earnings relation declined? *The Accounting Review*, 78(2), 523-553.

Snider, B., Kostin, D. J., Sanchez, B., Menon, A., Hammond, R., & Hunter, C. (2017). The death of value? *Goldman Sachs Portfolio Strategy Research*

Turner, L. (1999). Initiatives for improving the quality of financial reporting. Remarks of the Chief Accountant to the New York Society of Security Analysts. US Securities and Exchange Commission (SEC), http://www.sec.gov/news/speech/speecharchive/1999/spch252.htm.

US House (2000). Accounting for business combinations: Should pooling be eliminated? Hearing before the Subcommittee on Finance and Hazardous Materials of the Committee on Commerce, Serial No. 106-100. US Government Publishing Office, Washington, DC.

US Senate (2000). Pooling accounting. Hearing before the Committee on Banking, Housing and Urban Affairs. S. Hrg. 106-1035. US Government Publishing Office, Washington, DC.

Xing, U. (2008). Interpreting the value effect through the Q-theory: an empirical investigation. *The Review of Financial Studies*, 21, 1767-1795.

Zhang, L. (2005). The value premium. *Journal of Finance,* 60, 67–103.

Table 1: Descriptive statistics, 1975 – 2017

Description: This table presents distributions of variables calculated as the time-series averages of the percentiles. Annual accounting variables in Panel A are scaled by total capital (Tcap). Tcap ≡ AT – Gdwl + Kcap + Ocap where AT is total assets, Gdwl is goodwill, Kcap is unrecorded knowledge capital, and Ocap is unrecorded organization capital. B/M is the book-to-market ratio, and iB/M is the intangible-adjusted B/M. When calculating iB/M, book equity (BE) is adjusted by adding unrecorded intangibles and subtracting goodwill: iBE (intangible-adjusted BE) ≡ BE + Kcap + Ocap – Gdwl. Recorded other intangibles (Intano) = Intan – Gdwl where Intan is intangibles recorded on balance sheets and thus reported to Compustat. According to the variable definitions of Compustat, Gdwl is a component of Intan. Panel B presents distributions for the variables used in monthly Fama-MacBeth regressions. Both accounting and market data are used in Panel B. COP is cash-based operating profitability scaled by book value of total assets as in Ball et al. (2016). Log(M) is the natural logarithm of the market value of equity. $r_{1,1}$ is the prior month return to control the short-term reversal effect, and $r_{12\text{-}1}$ is the prior year's return skipping the last month to consider the momentum effect.
Interpretation: There are more unrecorded intangibles than recorded intangible assets on average. The means are higher than the medians in all categories of intangible assets meaning that the distributions are skewed to the right. Extreme observations point to the need to control outliers either by trimming variables in cross-sectional regressions or base inferences on portfolio sorts.

Panel A: Accounting variables scaled by total capital (Annual data from 1975 to 2016)

Variable	Mean	Standard Deviation	Percentiles		
			25th	Median	75th
Recorded intangibles					
Goodwill (Gdwl)	0.10	0.20	0.00	0.02	0.11
Recorded other intangibles (Intano)	0.04	0.08	0.00	0.01	0.03
Unrecorded intangibles					
Knowledge capital (Kcap)	0.12	0.14	0.00	0.07	0.18
Organization capital (Ocap)	0.20	0.13	0.10	0.18	0.27
Reported SG&A expenses	0.19	0.13	0.10	0.17	0.26
R&D expenses	0.04	0.05	0.01	0.03	0.06

Panel B: Market and accounting variables (Monthly data from July 1976 to December 2017)

Variable	Mean	Standard Deviation	Percentiles		
			25th	Median	75th
log(B/M)	-0.63	1.10	-1.21	-0.55	0.04
log(iB/M)	-0.15	1.09	-0.79	-0.12	0.52
log(Kcap/M)	-2.65	2.21	-3.42	-2.28	-1.32
log(Ocap/M)	-1.52	1.49	-2.39	-1.47	-0.57
log(Gdwl/M)	-2.32	1.71	-3.33	-2.19	-1.18
Cop	0.10	0.26	0.04	0.12	0.20
log(M)	4.84	2.03	3.39	4.72	6.15
$r_{1,1}$	0.01	0.17	-0.07	0.00	0.08
$r_{12\text{-}1}$	0.15	0.66	-0.20	0.05	0.35

Table 2: Fama-MacBeth regressions to compare B/M with iB/M

Description: This table reports average Fama and MacBeth (1973) regression slopes (multiplied by 100) and their *t*-values (in parentheses) from cross-sectional regressions that predict monthly stock returns. The sample period for the monthly regressions is from July 1976 to December 2017 (498 months). There are 14,540 firms and 1,473,950 firm-year observations in the sample, 612,280 in ABM and 861,670 in Micro. These regressions are to test whether iB/M or its components are superior to B/M in predicting stock returns. Kcap is knowledge capital, Ocap is organization capital, and Gdwl is goodwill. Control variables are cash-based operating profitability scaled by total assets (cop), size (log(M)), short-term reversal ($r_{1,1}$), and momentum (r_{12-1}). The sample is divided into two size groups: All-but-microcaps (ABM) and Micro. Micro is for stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. ABM includes all other stocks.

Interpretation: iB/M's explanatory power of stock returns is greater than B/M's in both large and small stocks. iB/M's superior explanatory power is attributable to knowledge capital, especially in large stocks. Small stocks with higher ratios of goodwill to market have lower future returns.

Explanatory variable	ABM			Micro		
	(1)	(2)	(3)	(4)	(5)	(6)
log (B/M)	0.25 (3.36)		0.13 (1.41)	0.40 (7.11)		0.35 (3.25)
log (iB/M)		0.33 (5.04)			0.59 (11.12)	
log (Kcap/M)			0.05 (3.65)			0.11 (3.53)
log (Ocap/M)			0.06 (1.45)			0.14 (1.68)
log (Gdwl/M)			0.01 (0.32)			-0.13 (-3.16)
cop	1.94 (6.22)	1.89 (6.28)	2.09 (4.31)	1.71 (6.31)	1.65 (5.85)	2.86 (5.59)
log (M)	-0.09 (-2.25)	-0.08 (-2.10)	-0.06 (-1.17)	-0.20 (-3.09)	-0.12 (-1.85)	-0.20 (-1.88)
$r_{1,1}$	-2.25 (-4.93)	-2.12 (-4.62)	-2.47 (-4.26)	-3.57 (-9.41)	-3.48 (-9.19)	-3.25 (-5.70)
r_{12-1}	0.77 (4.63)	0.80 (4.81)	0.30 (1.36)	1.03 (8.44)	1.08 (8.83)	0.66 (3.05)
Adj-R^2	5.02%	4.84%	5.63%	2.40%	2.37%	3.15%

Table 3: Portfolios sorted by B/M vs. iB/M

Description: This table presents value-weighted average excess returns and four-factor model alphas in % per month for portfolios sorted by B/M (iB/M). The four factors are XMKT, SMB, RMW, and CMA as in Fama and French (2015). I sort stocks into deciles based on NYSE breakpoints at the end of June and hold the portfolios for the following year. Panel A shows results for B/M deciles and Panel B is for iB/M deciles. The sample period is July 1976 - December 2017. The numbers in brackets are *t*-statistics.
Interpretation: iB/M high minus low portfolio's alpha is significantly positive, but B/M portfolio's alpha is not.

Portfolio	B/M		iB/M	
	Excess Return	Four-factor model alpha	Excess Return	Four-factor model alpha
Low	0.52 (2.30)	0.05 (0.63)	0.38 (1.53)	-0.07 (-0.94)
2	0.67 (3.24)	0.03 (0.43)	0.62 (3.03)	-0.05 (-0.74)
3	0.73 (3.53)	-0.01 (-0.14)	0.73 (3.71)	0.05 (0.78)
4	0.66 (3.14)	-0.14 (-1.79)	0.81 (3.92)	0.10 (1.31)
5	0.81 (3.90)	0.00 (0.05)	0.70 (3.65)	-0.01 (-0.19)
6	0.79 (3.65)	0.08 (0.89)	0.74 (3.62)	-0.02 (-0.18)
7	0.71 (3.34)	-0.06 (-0.61)	0.92 (4.21)	0.04 (0.53)
8	0.70 (3.15)	-0.19 (-1.98)	0.93 (4.09)	0.11 (1.09)
9	0.93 (3.98)	0.02 (0.20)	1.05 (4.13)	0.09 (0.77)
High	1.00 (4.01)	0.02 (0.14)	1.25 (4.81)	0.29 (2.16)
High - Low	0.48 (2.51)	-0.03 (-0.17)	0.87 (4.39)	0.36 (2.28)

Table 4: Portfolios formed on size and B/M (or iB/M to) to compare HML with iHML

Description: This table compares B/M with iB/M by constructing value-weighted portfolios formed on market capitalization and B/M or iB/M. Portfolios are formed at the end of June in each year *t* using NYSE median market capitalization and 30th and 70th percentiles of B/M or iB/M. HML (High Minus Low) is the average return on the two (small and big) high B/M portfolios minus the average return on the two low B/M portfolios as in Fama and French (1993 and 2015) HML ≡ ½ (Small high B/M + Big high B/M) – ½ (Small low B/M + Big low B/M). iHML is defined in the same way but using iB/M instead of B/M. iHML ≡ ½ (Small high iB/M + Big high iB/M) – ½ (Small low iB/M + Big low iB/M). Panel A compares the average return, standard deviation, and *t*-statistic of the HML and iHML portfolios. Panel B compares HML with iHML using spanning regressions based on the three-factor model of Fama and French (1993), the five-factor model of Fama and French (2015), and the six-factor model that includes the momentum factor as in Fama and French (2018). In spanning regressions, the independent variable is HML or iHML and the other factors are explanatory variables. Spanning regressions are for testing whether the other factors span the value factor, HML or iHML. The sample period is July 1976 – December 2017.

Interpretation: iHML has a higher average return and lower risk than HML. Unlike HML's intercept, iHML's intercept is positive and significant in all spanning regressions. This means, adding iHML increases the mean-variance efficiency of portfolios formed on the market, size, profitability, investments, and momentum factors, but the same argument does not hold for HML.

Panel A: Risk and return

	B/M high minus low portfolio (HML)	iB/M high minus low portfolio (iHML)
Average	0.32	0.49
Standard deviation	2.66	2.33
t-statistic	2.70	4.72

Panel B: Spanning regressions

	HML	iHML	HML	iHML	HML	iHML
Intercept	0.41 (3.50)	0.54 (5.20)	-0.02 (-0.17)	0.21 (2.46)	0.07 (0.78)	0.26 (3.13)
XMKT	-0.12 (-4.52)	-0.11 (-4.38)	0.05 (2.25)	0.04 (2.09)	0.04 (1.61)	0.03 (1.62)
SMB	-0.05 (-1.26)	0.09 (2.51)	-0.01 (-0.21)	0.09 (3.00)	0.02 (0.64)	0.11 (3.61)
RMW			0.23 (5.30)	0.07 (1.95)	0.27 (6.39)	0.10 (2.56)
CMA			0.86 (16.93)	0.79 (18.01)	0.84 (17.32)	0.78 (18.09)
UMD					-0.15 (-7.17)	-0.09 (-4.79)
Adj-R^2	4.59%	3.80%	41.65%	42.07%	47.06%	44.53%

Table 5: Bootstrap simulations to compare HML with iHML

Description: This table is to compare HML with iHML using the maximum squared Sharpe ratio ($Sh^2(f)$) of a six-factor model that includes the five factors of Fama and French (2015) and a momentum factor as in Fama and French (2018). "Actual" is for the actual sample from July 1976 to December 2017 (498 months). "Full-sample" is from 10,000 bootstrap simulations, and each simulation draws a random sample of 498 months with replacement. In the 10,000 bootstrap simulations of "In-sample" and "Out-of-sample" tests, the 498 months are split to 249 adjacent pairs as in months (1,2), (3,4),…, (497,498). In each of the 10,000 simulations, a random sample of 249 pairs is drawn with replacement. Then a month from each pair is randomly assigned to "In-sample" using that month repeatedly if the pair is drawn more than once. The "In-sample" months in each run are used to compute the run's values of In-sample $Sh^2(f)$ for all factor models. In-sample $Sh^2(f)$ identifies weights for factors in its In-sample tangency portfolio for each simulation run. These weights are combined with the unused months of the chosen pairs to compute the simulation run's Out-of-sample $Sh^2(f)$.

Interpretation: iHML provides a greater maximum squared Sharpe ratio than HML in portfolios formed with the market, size, profitability, investments, and momentum factor returns from July 1976 to December 2017, and this result is robust to full-sample, in-sample, and out-of-sample simulations.

Panel A: Levels of $Sh^2(f)$

		Full-sample		In-sample		Out-of-sample	
	Actual	Average	Median	Average	Median	Average	Median
6-factor model using HML (XMKT,SMB,***HML***,RMW,CMA,UMD)	0.139	0.158	0.154	0.194	0.185	0.105	0.096
6-factor model using iHML (XMKT,SMB,***iHML***,RMW,CMA,UMD)	0.161	0.179	0.176	0.216	0.206	0.125	0.116

Panel B: Differences between $Sh^2(f)$ for iHML and HML

iHML - HML		Full-sample			In-sample			Out-of-sample		
Model	Actual	Average	Median	%<0	Average	Median	%<0	Average	Median	%<0
6 factor	0.022	0.021	0.020	2.7	0.022	0.017	14.07	0.020	0.017	12.60

Table 6: Comparing HML with iHML while varying the measurement time of market equity

Description: As it takes months for book equity data to become publicly available unlike market equity data, two versions of HML and iHML are presented depending on whether to use lagged market equity data to align them with book equity data or to use most recent market equity data when portfolios are formed in June of each year. HML and iHML use lagged market equity data as in Fama and French (1993 and 2015) while HML_{AF} and $iHML_{AF}$ use June market equity data as in Asness and Frazzini (2013). Panel A compares the risk and return of HML and iHML using the two methods. Panel B presents spanning regressions and other regressions of HML and iHML from each method on six factors including the momentum factor and the HML and iHML factor from the other method. The numbers in parentheses are *t*-statistics. The sample period is July 1976 – December 2017.

Interpretation: The superior performance of iHML over HML is robust to the measurement time of market equity. $iHML_{AF}$ outperforms HML_{AF} and iHML outperforms HML. The adjustments for intangibles do not alter the interaction between book-to-market and momentum factors.

Panel A. Risk and return

	HML	HML_{AF}	iHML	$iHML_{AF}$
Average	0.32	0.22	0.49	0.43
Standard deviation	2.66	2.93	2.33	2.63
t-statistic	2.70	1.71	4.72	3.64

Panel B. Regressions

	Spanning regressions to compare intercepts				Regressions to compare UMD coefficients			
	HML	HML_{AF}	iHML	$iHML_{AF}$	HML	HML_{AF}	iHML	$iHML_{AF}$
Intercept	**0.07** **(0.78)**	**0.09** **(0.99)**	**0.26** **(3.13)**	**0.25** **(3.15)**	-0.01 (-0.20)	0.03 (0.63)	0.04 (0.92)	0.04 (0.97)
XMKT	0.04 (1.61)	0.01 (0.64)	0.03 (1.62)	0.04 (1.89)	0.02 (2.26)	-0.02 (-1.71)	0.00 (0.10)	0.01 (0.97)
SMB	0.02 (0.64)	0.03 (0.90)	0.11 (3.61)	0.12 (4.29)	-0.01 (-0.35)	0.01 (0.73)	0.00 (0.09)	0.04 (2.29)
RMW	0.27 (6.39)	0.27 (6.53)	0.10 (2.56)	0.11 (3.09)	0.03 (1.23)	0.04 (1.79)	0.00 (0.01)	0.04 (1.72)
CMA	0.84 (17.32)	0.86 (18.39)	0.78 (18.09)	0.90 (21.66)	0.05 (1.65)	0.14 (5.16)	0.01 (0.15)	0.28 (9.22)
UMD	-0.15 (-7.17)	-0.32 (-16.06)	-0.09 (-4.79)	-0.24 (-13.88)	**0.14** **(12.48)**	**-0.19** **(-20.04)**	**0.12** **(10.21)**	**-0.17** **(-17.33)**
HML						0.86 (42.78)		
HML_{AF}					0.91 (42.78)			
iHML								0.80 (32.94)
$iHML_{AF}$							0.862 (32.94)	
Adj-R^2	47.06%	58.76%	44.53%	59.74%	88.78%	91.26%	82.69%	87.43%

Figure 1. Tangible Assets, Recorded Other Intangibles, and Unrecorded Intangibles

Description: This figure presents how the proportions of tangible and intangible assets in total capital (Tcap) have changed over time using the total amounts in the sample each year from 1975 to 2016. Tangibles are total assets (AT) minus recorded intangible assets (Intan) in Compustat. Intano is recorded other intangibles in Compustat. Kcap is unrecorded knowledge capital. Ocap is unrecorded organization capital. Since tangible assets, Intano, Kcap, and Ocap are the components of Tcap, they are presented as percentages of Tcap in the primary axis. Gdwl in Compustat scaled by Tcap is presented in the secondary axis.

Interpretation: The proportion of tangible assets in US firms' total capital has decreased overtime during the last four decades, and the proportions of both recorded and unrecorded intangible assets have increased.

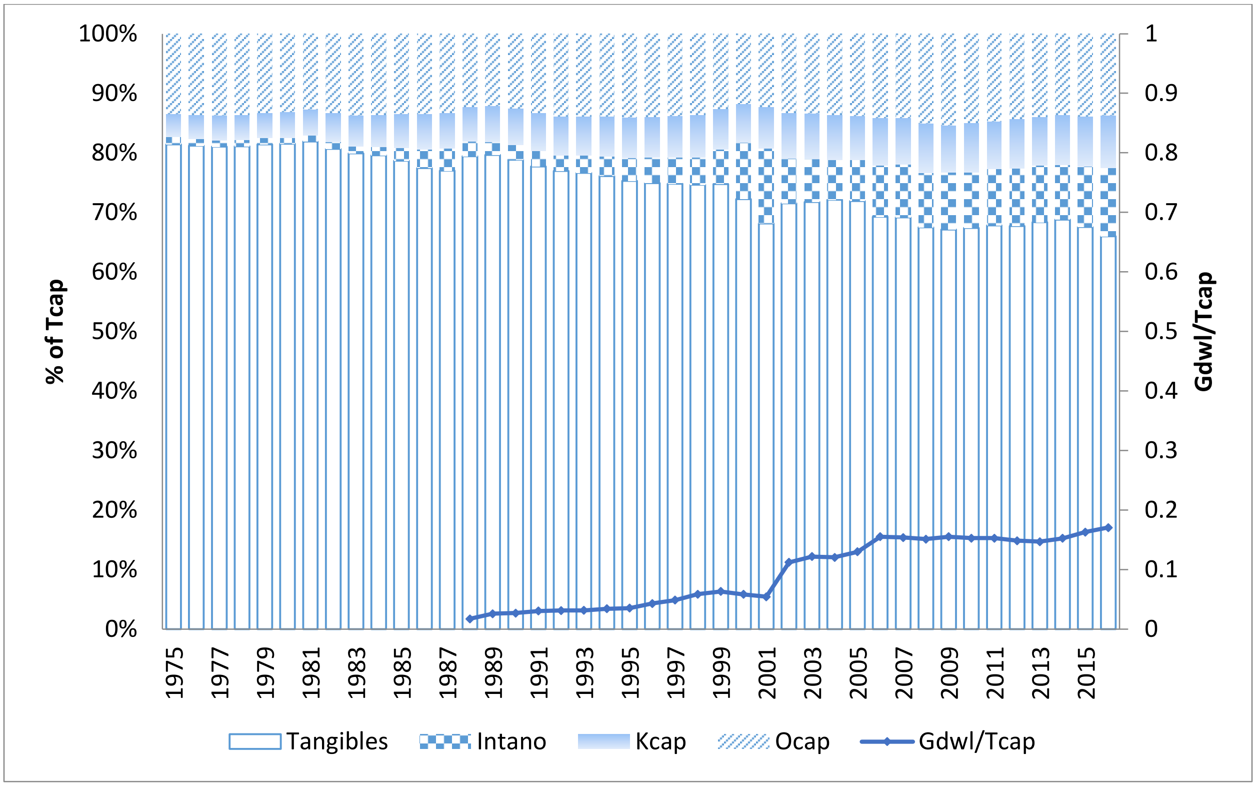
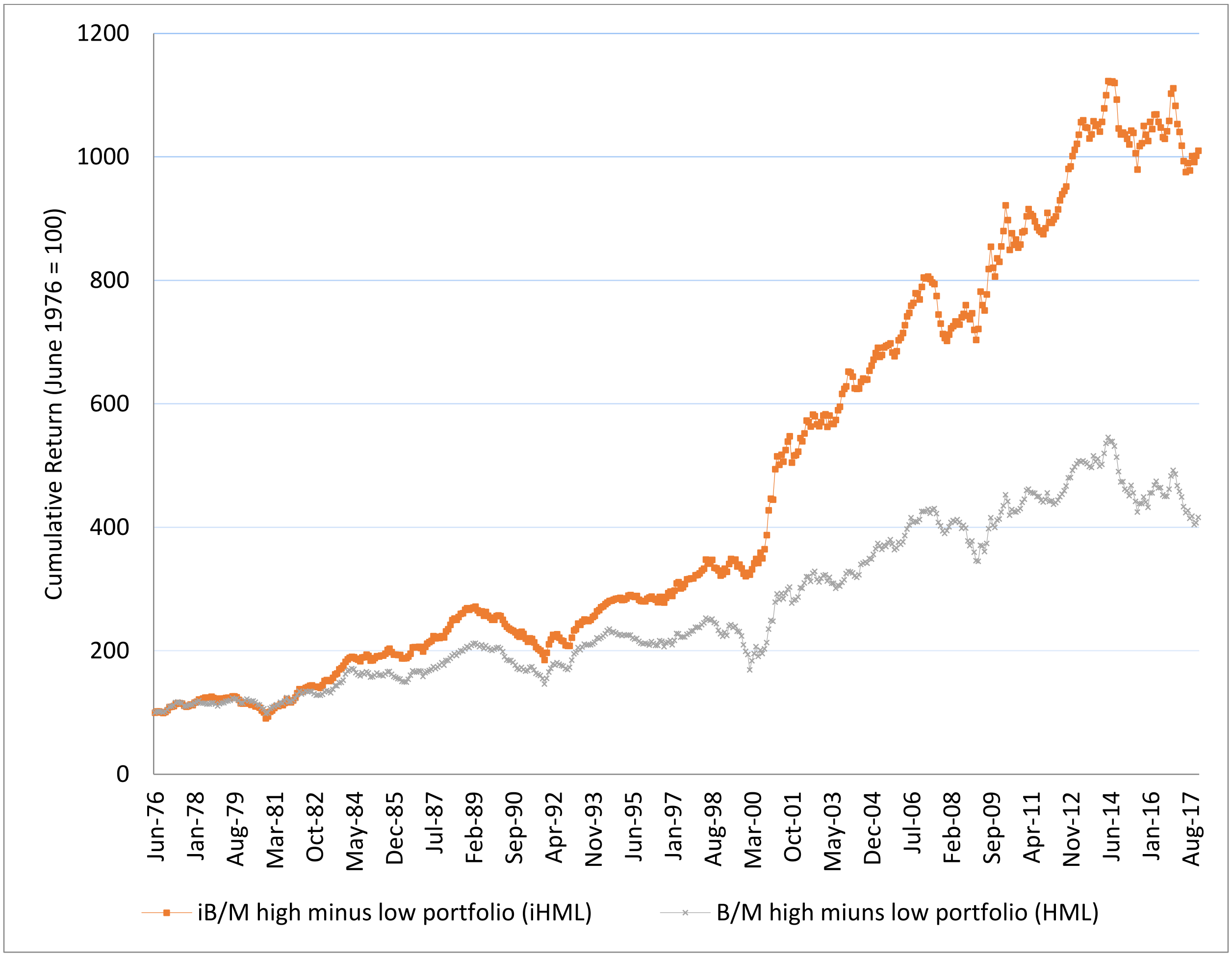


Figure 2. Cumulative returns on HML vs. iHML

Description: This figure shows the growth of B/M (iB/M) high minus low HML (iHML) portfolios from June 30, 1976 to December 31, 2017. The HML (iHML) portfolios are constructed using the NYSE median size and the 30th and 70th percentiles of B/E (iB/E) as in Fama and French (1993 and 2015) and have a starting value of 100 on June 30, 1976.

Interpretation: iHML has higher returns than HML, and the difference is larger during the recent two decades when intangible assets such as technology and innovative business models play more important role in the economy.



Appendix A. How do value index funds define value stocks?

Description: This table presents examples of value indexes, valuation multiples each index uses to identify value stocks, and a sample fund for each index. The data source is the websites of index providers and funds.

Interpretation: All value indexes use the ratio of book value to market value as a tool to identify value stocks.

Value index	The multiples used to identify value stocks	User: one example for each index+		
		Fund Name	Inception date	Net assets ($ billion)
CRSP US Large Cap Value Index	***Book-to-price ratio***, Future Earnings-to-Price ratio, Historical Earnings-to-Price ratio, Dividend-to-Price ratio, and Sales-to-Price ratio	Vanguard Value Index Fund (VIVAX)	11/02/92	56.9
S&P 500 Value Index	***Book-to-price ratio***, Earnings-to-Price ratio, and Sales-to-Price ratio	iShares S&P 500 Value ETF (IVE)	05/22/00	13.4
Russell 1000 Value Index	***Price-to-book ratio,*** Dividend yield, Price to earnings ratio, 5-year Earnings per share growth	Fidelity Large Cap Value Enhanced Index Fund (FLVEX)	04/19/07	2.9
MSCI USA Enhanced Value Index	Forward price to earnings ratio, Enterprise value to operating cash flow ratio, ***Price-to-book ratio***	iShares Edge MSCI USA Value Factor ETF (VLUE)	04/16/13	2.5

+ VIVAX used S&P 500 Value Index (formerly known as the S&P 500/ Barra Value Index) through May 16, 2003, MSCI US Prime Market Value Index through April 16, 2013, and CRSP US Large Cap Value Index thereafter. Net assets of VIVAX are as of June 30, 2017, and it includes the net assets of all Vanguard Value Index Fund shares: Investor Shares (VIVAX), ETF Shares (VTV), Admiral Shares (VVIAX), and Institutional Shares (VIVIX). Net assets of IVE and VLUE are as of August 25, 2017. Net assets of FLVEX are as of July 31, 2017.

Appendix B. A numerical example showing why we need to adjust B/M with intangibles

Suppose Company T incurs $400 million in R&D expenses while developing a new electronics technology, spends $0.5 million in legal expenses to apply for patents of the technology, and the news about the technology makes the stock price jump increasing the market capitalization of the company by $800 million. What is the value of the new technology recorded on Company T's balance sheet? It is $0.5 million under US GAAP.

The book value of the internally developed technology will change precipitously if it is sold to another company. For example, if Company O offers to pay $600 million for this technology and Company T accepts the offer, $600 million will be the book value of this technology on Company O's balance sheet even though the same technology's book value was $0.5 million on Company T's balance sheet.

What if Company T rejects Company O's offer but Company M offers to acquire Company T at a premium of 10 percent, and Company T accepts Company M's offer? After the business combination, Company T's new technology will make the book value of Company M increase by $880 million, consisting of two parts: $280 million in goodwill and $600 million in identifiable intangibles. That is, the same technology's book value in this example varies from 0.5 to 880 million USD under US GAAP.

There is another issue on intangibles and B/M this acquisition example can show. What if there is a financial crisis after the acquisition causing investors to become more risk averse and thus Company M's stock price decreases by 20 percent? Company M is required to do goodwill impairments tests using "fair value" estimates even though many intangibles usually do not have actively traded market prices. All or part of the $280 million goodwill may be written off from Company M's balance sheet permanently during the financial crisis.

That is, even if Company M's stock price recovers completely when the economy recovers from recession, the impaired goodwill is not allowed to be restored under US GAAP. Note that revaluation is allowed in International Financial Reporting Standards (IFRS) unlike in US GAAP. Paragraphs 85 and 86 of International Accounting Standards (IAS) 38 state that revaluation increases and decreases are recognized either in equity or in profit or loss.

Prior research in the accounting literature points out that the subjectivity in estimating goodwill's current fair value is greater than that in most other asset classes, making the goodwill impairment test particularly unreliable (Ramanna and Watts (2012)). Prior research also shows that there are cases of goodwill impairment that are not backed by economic fundamentals and these firms experience a stock price reversal in the subsequent year (Chen et al. (2014)). This is one of the reasons why I exclude goodwill when defining the intangible adjusted book-to-market ratio.

I use R&D in this example, but a similar problem occurs in many other expenses such as costs to develop brand names and business models. For example, the most valuable assets of Amazon are not tangible assets like its headquarter buildings, but the business model and other intangible assets that are unrecorded on the balance sheet because those intangibles were developed internally and the company has never been acquired by another firm. The unrecorded intangibles can explain why there is a huge gap between Amazon's book value and market value, 27.7 vs. 387.3 billion USD as of December 31, 2017.

Appendix C. A numerical example that illustrates the procedures of estimating knowledge capital and organization capital

We need prior expenditures on R&D and SG&A data to estimate knowledge capital and organization capital. As many firms have a founding year earlier than the starting date of their Compustat record, I first compare each firm's founding year (FOY) available in Jay Ritter's website (https://site.warrington.ufl.edu/ritter/ipo-data/), and compare it with the start date of the firm's data in Compustat (CBEGDT). I thank Jay Ritter for making the founding year data available for download.

If the FOY of a firm is missing but its IPO date is available in Compustat, I assume that the FOY is minimum (IPO year - 8, the year of CBEGDT). For example, if a firm's CBEGDT is 19920101, IPO date is 19940305, and the FOY is not known, I assume the FOY is 1986. If both FOY and IPO date are missing for a firm, I set the firm's FOY equal to the CBEGDT.

If a firm's FOY is earlier than the CBEGDT, I assume that the R&D & SG&A expenditures grow at 40 percent per year between FOY and CBEGDT. For example, Firm P (SIC code 2834) was founded in 1975, but its Compustat records start in 1983 with the R&D expenditure (XRD) of $0.48 million and XSGA of $12.24 million. There was no in-process R&D (RDIPA). The capitalizable SG&A is (12.24-0.48-0)*0.3 = $3.528 million because I assume that 30% of SG&A generates long-term benefits.

When calculating capitalizable SG&A, I subtract XRD and RDIPA from XSGA because the XSGA of most firms in Compustat includes XRD and RDIPA according to the variable definition of the database and RDIPA is recorded as a negative number in Compustat. If a firm's XRD is larger than its XSGA, its capitalizable SG&A is equal to XSGA*0.3 as these firms allocate R&D expenditure to Costs of Goods Sold (COGS), not to XSGA. If a firm's XSGA is missing, its capitalizable SG&A is set to zero.

The estimated R&Ds of Firm P during 1975-1982 (when the firm is in operation with financial data not available for us) are 0.48/1.40 = 0.48*0.7143=0.3429 in 1982, $0.48*(0.7143)^2=0.2449$ in 1981,…, $0.48*(0.7143)^8=0.0325$ in 1975. The R&D depreciation rate for the SIC code 2834 (Pharmaceuticals) is 10 percent according to Li(2012) and Li and Hall (2016) as summarized in the following table. Therefore, the estimated knowledge capital of Firm P in 1983

$$= 0.48 + 0.48*0.7143*0.9 + 0.48*0.7143^2*0.9^2 + \ldots + 0.48*0.7143^8*0.9^8$$

$$= 0.48(1+0.6429+0.6429^2+\ldots+0.6429^8) = \$1.3189 \text{ million}$$

R&D Depreciate Rate (d_{XRD}) for Estimating Knowledge Capital (Kcap)

Industry	SIC Codes	d_{XRD}
Computers and peripheral equipment	3570-3579, 3680-3689 and 3695	40%
Software	7372	22%
Pharmaceuticals	2830, 2831 and 2833 - 2836	10%
Semiconductor	3661-3666 and 3669-3679	25%
Aerospace product and parts	3720, 3721, 3724, 3728 and 3760	22%
Communication equipment	3576, 3661, 3663, 3669 and 3679	27%
Computer system design	7370, 7371 and 7373	36%
Motor vehicles, bodies, trailers, and parts	3585, 3711, 3713 and 3716	31%
Navigational, measuring, electromedical, and control instruments	3812, 3822, 3823, 3825, 3826, 3829, 3842, 3844 and 3845	29%
Scientific research and development	8731	16%

Source: Li and Hall (2016) Table 1 for SIC Codes and Li (2012) Table 4 for d_{XRD}. For industries not listed in the table, I assume that the d_{XRD} is 15 percent.

Similarly the capitalizable SG&As during 1975-1982 are $3.528/1.40 = 3.528*0.7143$ in 1982, $3.528*(0.7143)^2$ in 1981,…, $3.528*(0.7143)^8$ in 1975. I assume that the depreciation rate of the organization capital is 20 percent for all firms.

Therefore, the estimated organization capital of Firm P in 1983

$= 3.528 + 3.528*0.7143*0.8 + 3.528*0.7143^2*0.8^2 + \ldots + 3.528*0.7143^8*0.8^8$

$= 3.528(1+0.5714+0.5714^2+\ldots+0.5714^8) = \$8.178$ million

Once the first-year values are estimated, calculating the values for the subsequent years is simpler as we have XRD and XSGA reported to Compustat and thus do not need to estimate the expenditures. For example, Compustat data show that Firm P has XRD of $0.69 million, no in-process R&D (RDIPA), and XSGA of $16.05 million in 1984. The capitalizable SG&A is (16.05-0.69-0)*0.3 = $4.608 million.

Therefore, the knowledge capital in 1984= 0.69 + 0.9*1.3189 = $1.8770 million

The organization capital in 1984 = 4.608 + 0.8*8.178 = $11.1504 million