The Intangible-adjusted Book-to-market Ratio

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Abstract

The book-to-market ratio has been widely used to explain the cross-sectional variation in stock returns over the past three decades. However, there is growing evidence that the explanatory power of the ratio has become weaker. I argue that the change is related to the growth of intangible assets unrecorded in balance sheets due to the challenges in accounting for intangibles and propose an intangible-adjusted ratio as an alternative by capitalizing prior expenditures to develop the assets and excluding goodwill. I find that the alternative ratio outperforms the original significantly. The cumulative return on the high-minus-low (HML) portfolio formed on the alternative (original) ratio is 910% (316%) during 1976 – 2017.

Keywords: Research and Development (R&D), Intangible Assets, Goodwill, Price-to-book, Value index
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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 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 examples of value indexes and valuation multiples used in the indexes. Successful value investors like Warrant Buffett use B/M when making share repurchase decisions (Buffett, 2017).

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.

Why has the B/M effect become weaker? Park (2017) analyzes the impact of intangible assets and related transformations in accounting standards and finds that the B/M effect is weaker after new standards on intangibles became effective especially in the 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 preparers of financial statements face when they value intangibles, 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

[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).

related, 4) technology related, and 5) other unspecified intangible assets (Castedello and Klingbeil, 2009).

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?

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 of US public companies 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 four 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. 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 by the market, size, profitability, and investment factors as in Fama and French (2015 and 2016), the alpha of the iB/M decile 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 by a momentum factor. In all three models, iHML intercept is larger and more significantly different from zero than 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.

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

To capitalize unrecorded intangibles, I build on prior research to develop guidelines for national economic accounting. Note that the international guidelines for national economic accounting revised in 2008, the *System of National Accounts* (*SNA 2008*), recommend capitalizing R&D expenditures while US GAAP for business accounting adopts more conservative approaches and requires immediate expensing of most intangible-related investments (Rassier, 2014).

The perpetual inventory method is used for estimating the two components of unrecorded intangibles, knowledge capital and organization capital. 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 take neither knowledge capital nor goodwill into consideration 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 present 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 the net income to estimate the value of unrecorded intangible assets while the perpetual inventory method uses previous expenditures to capitalize them. Using the conservatism correction factor (CCF) as in McNichols (2014) is another way to 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 the following three-step procedure to calculate the intangible-adjusted book value of equity of each firm each year. I take accounting data from Compustat and stock market data from the Center for Research in Security Prices (CRSP).

- First, I estimate knowledge capital (Kcap) by capitalizing past R&D expenditures using industry-specific R&D depreciation rates of the US Bureau of Economic Analysis (BEA) as in Li (2012) and Li and Hall (2016). One challenge in this method is to estimate the initial capital stock each company accumulated before its entry into the database as many firms have a founding year (FOY) earlier than the start date of the Compustat data (CBEGDT). To overcome this limitation in data, 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.

- Second, organization capital (Ocap) is estimated by capitalizing 30% of past SG&A. The remaining 70% is expensed as it is assumed to generate net income for the current period. 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 defined as the sum of a firm' actual reported SG&A expenses and R&D expenditures (Compustat item XRD) as explained in Ball et al. (2015 and 2016). Therefore, 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.
- Third, I calculate the book value of common equity adjusted with intangibles (iBE) using the estimates from the previous steps. Equation (1) defines iBE where BE is the book value of common equity, and Gdwl is goodwill.

$$iBE \equiv BE + Kcap + Ocap - Gdwl \tag{1}$$

Following Fama and French (2018), BE is defined as total assets minus total liabilities, plus balance sheet deferred taxes and investment tax credit if available, minus preferred stock liquidating value if available, or redemption value if available, or carrying value.

The total capital (TCap) of a firm is defined in Equation (2), where TA is total assets.

$$\text{TCap} \equiv \text{TA} + \text{Kcap} + \text{Ocap} - \text{Gdwl} \tag{2}$$

Gdwl is the excess purchase price paid over the estimated fair value of the target's identifiable net assets in business combinations.[2] I exclude 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).[3]

The next step is to calculate iB/M using iBE. 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

[2] 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 (2017) for details. FASB standards are now incorporated in the FASB's Accounting Standards Codification (ASC), and 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.

[3] 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 outperforms gB/M.

following Peters and Taylor (2017). When calculating iB/M, the numerator is iBE adjusted with net share issuance (NSE), and the denominator is the total market value of equity that is price times shares outstanding from CRSP. I follow Fama and French (2018) and define NSE as in Equation (3).

$$\text{NSE} = \frac{\text{(Ending market cap/beginning market cap)}}{\prod(1+\mathit{monthly\ withoud{-}dividend\ stock\ return\ during\ the\ period})} - 1 \tag{3}$$

The NSE 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 portfolios is important especially in the presence of the momentum factor. Later in this paper, I examine this issue in more detail as a robustness check by defining HML_{AF} and iHML_{AF} as in Asness and Frazzini's paper and comparing them with HML and iHML and present the results in Section 4.4.

I follow Fama and French (2018) to adjust BE and iBE for net share issuance. 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 NSE from the fiscal year-end to the end of December of year t-1 using NSE as in Equation (3).

For example, Firm M's fiscal year ends on September 30, 2010 with an iBE of \$732.14 million and the monthly without-dividend stock returns during October, November, and December 2010 are 1.2%, 0.8%, and -0.6%, respectively. Firm M's stock price is \$26.15 and 59.87 million shares are outstanding on September 30, 2010 and the corresponding numbers on December 31, 2010 are \$26.52 and 60.74 million according to CRSP. NSE of Firm M is $\frac{(26.52*60.74)/(26.15*59.87))}{1.012*1.008*0.994} - 1 = 0.0147$, NSE-adjusted iBE is 1.0147*732.14 = \$742.90 million, and iB/M is $\frac{742.90}{26.52*60.74} = 0.4612$.

In monthly Fama-MacBeth regressions, I update all explanatory variables including B/M and iB/M every month. For example, for the regression using stock returns in July 2011, iB/M is calculated using the iBE adjusted for NSE 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 presents summary statistics. The sample period starts in 1975 because the accounting standard that requires most R&D expenditures to be expensed immediately became effective in 1975.[4] I calculate the descriptive statistics as the time series averages of the percentiles. Following prior research, negative BE stocks are excluded from the analysis. Panel A shows annually observed accounting variables scaled by total capital during 1975 – 2016. The distributions of both recorded intangibles (Gdwl and Roint) and unrecorded intangibles (Kcap and Ocap) are skewed to the right, having an average larger than the median.

[4] In October 1974, FASB 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 (2017) for details. SFAS 2 is now ASC 730.

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 presents outliers: the median is 2.1%, the average is 9.6%, and the 99th percentile is 89.9%. The outliers presented in the table 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. As these are the explanatory variables in Fama-MacBeth Regressions, I explain them 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).

See Panel B of Table 1 for the summary descriptive statistics for the variables. The average log(B/M) is -0.6 and the 1st and 99th percentiles are -3.9 and 1.9, 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.

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 Fama and French (1992), 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 in Panel A and iB/M in Panel B. The sample period is July 1976 – December 2017. The table shows the portfolios' value-weighted average excess returns and the alphas from the regressions of the portfolios' excess returns on the market (MFA), size (SMB), profitability (RMW), and investment (CMA) factors as in Fama and French (2015 and 2016).[5]

Table 3 shows that 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 return but also multi-factor model alphas because a non-zero alpha implies that 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.

[5] The MFA, 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.

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 30th and the 70th NYSE percentiles. The 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 return 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.

Panel A in 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 past two decades when the intangible assets become more important in the economy than in earlier sample periods ($1,010 vs. $416 in December 2017 and $323 vs. $239 in December 1997).

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 (2017) 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.

Panel B in 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. For example, see Fama and French (1993 and 2015), Xing (2008), and Hou et al. (2015) among others. 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-statistic = 2.46 ~ 5.20) while HML's intercept is not significantly different from zero in the five-factor model (t-statistic = -0.17) and the six-factor model (t-statistic = 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).

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.

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 presented 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 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, and 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.

$$BE = CC + RE + AOCI \tag{4}$$

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.

Table 7 presents Fama-MacBeth regressions to compare RE/M, CC/M, and AOCI/M with B/M, iB/M, and the components of 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. Panel A is for ABM and Panel B is for Micro.

Table 7 shows 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. Regressions (5) and (7) in the table are to compare RE/M with all other components of B/M and iB/M. Note that knowledge capital-to-market (KCap/M) has a more significant coefficient than RE/M and other components in both ABM and Micro. Overall the regressions in Table 7 show that the intangible-adjusted book-to-market ratio is a better predictor of stock returns than retained earnings-to-market.

I next perform portfolio tests based on RE/M and present the results in Table 8 to be compared with the iB/M portfolio results in Table 3. These results confirm that iB/M is superior to 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 to B/M

iB/M is based on two adjustments for book values, adding unrecorded intangibles and subtracting goodwill. i) 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? ii) 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 tangible book equity (tBE) is often used instead of BE by analysts.

tBE is defined in Equation (5) where INTAN is intangible assets from Compustat. Note that tBE contains neither recorded intangibles nor unrecorded intangibles.

$$\text{tBE} \equiv \text{BE} - \text{INTAN} \tag{5}$$

tBE is adjusted for NSE using Equation (3) and then tB/M is calculated by dividing the NSE-adjusted tBE by market equity.

The second alternative, gB/M, uses goodwill-inclusive book equity (gBE) as defined in Equation (6). 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 NSE-adjusted gBE by market equity.

$$gBE \equiv iBE + GDWL \quad (6)$$

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

$$kBE \equiv BE + \text{knowledge capital} - GDWL \quad (7)$$

kB/M is calculated by dividing NSE-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 (8).

$$oBE \equiv BE + \text{organization capital} - GDWL \quad (8)$$

oB/M is calculated by dividing NSE-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.

Table 9 compares B/M and iB/M with tB/M, gB/M, kB/M, and oB/M in Fama-MacBeth regressions. The results confirm 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. Portfolio-level tests in Table 10 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.

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 (0.278% per month and *t*-statistic 1.76 vs. 0.362% per month and *t*-statistic 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.

Table 9 also shows 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 are larger than those of oB/M in both ABM and Micro. The B/M coefficient and *t*-statistic are smaller than those of oB/M and kB/M in both ABM and Micro. Table 10 shows similar results. The four-factor model alpha and *t*-statistic of kB/M are higher than those of oB/M. The four-factor model alpha and *t*-statistic of oB/M are higher than those of B/M.

Overall, these results have three implications. First, taking both recorded and unrecorded intangibles into consideration improves the performance of a 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 a 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 affect the performance of book-to-market measures and iB/M is better than other alternative measures 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 and organization capital, and subtracting goodwill that is subject to the issue of unverifiable fair value estimates.

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 US 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 internally developed intangibles. The main contribution of this paper is to show that an imperfect proxy is better than ignoring unrecorded intangibles when we use a book-to-market measure in asset pricing models.

Appendix A. Examples of value indexes, multiples, and funds

This table presents value index examples, 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 index funds.

Value index	Multiples each index use 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 to explain 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 make 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 exenditure (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 for Estimating Knowledge Capital

Industry	SIC Codes	R&D Depreciation Rate
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 the R&D depreciation rates. For industries not listed in the table, I assume the R&D depreciation rate of 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

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Table 1
Descriptive statistics, 1975 - 2017

This table presents distributions of variables. I calculate the descriptive statistics as the time series averages of the percentiles. Accounting variables in Panel A are scaled by total capital (TCap) and they are annual data. TCap ≡ TA – Gdwl + Kcap + Ocap where TA 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 (Roint) ≡ Intan – Gdwl where Intan is intangibles recorded in balance sheets and thus reported to Compustat. According to the variable definitions of Compustat, Gdwl is a subset 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 natual 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.

Variable	Mean	Standard Deviation	Percentiles				
			1st	25th	50th	75th	99th
Panel A: Accounting variables scaled by total capital (Annual data from 1975 to 2016)							
Recorded intangibles							
Goodwill (Gdwl)	0.096	0.198	0.000	0.000	0.021	0.110	0.899
Recorded other intangibles (Roint)	0.035	0.083	0.000	0.000	0.006	0.034	0.413
Unrecorded intangibles							
Knowledge capital (Kcap)	0.119	0.139	0.000	0.004	0.072	0.181	0.605
Organization capital (Ocap)	0.198	0.129	0.008	0.099	0.177	0.273	0.578
Reported SG&A expenses	0.191	0.130	0.000	0.096	0.171	0.262	0.577
R&D expenses	0.042	0.048	0.000	0.005	0.027	0.063	0.212
Panel B: Market and accounting variables (Monthly data from July 1976 to December 2017)							
log (B/M)	-0.628	1.101	-3.862	-1.209	-0.547	0.040	1.891
log (iB/M)	-0.145	1.093	-3.016	-0.794	-0.122	0.524	2.511
log (Kcap/M)	-2.645	2.210	-10.861	-3.421	-2.279	-1.315	1.010
log (Ocap/M)	-1.522	1.490	-5.550	-2.392	-1.467	-0.574	1.856
log (Gdwl/M)	-2.322	1.710	-6.908	-3.329	-2.191	-1.178	1.447
Cop	0.095	0.263	-0.710	0.037	0.124	0.200	0.510
log (M)	4.837	2.025	0.783	3.385	4.724	6.154	9.958
$r_{1,1}$	0.013	0.168	-0.342	-0.069	0.001	0.076	0.543
$r_{12\text{-}1}$	0.152	0.656	-0.734	-0.197	0.053	0.346	2.411

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

This table reports average Fama and MacMeth (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. 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 (cop), size (log(M)), short-term reversal ($r_{1,1}$), and momentum ($r_{12\text{-}1}$). 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.

Explanatory variable	ABM			Micro		
	(1)	(2)	(3)	(4)	(5)	(6)
log (B/M)	0.248 (3.36)		0.125 (1.41)	0.401 (7.11)		0.347 (3.25)
log (iB/M)		0.325 (5.04)			0.594 (11.12)	
log (KCap/M)			0.051 (3.65)			0.106 (3.53)
log (OCap/M)			0.058 (1.45)			0.135 (1.68)
log (Gdwl/M)			0.012 (0.32)			-0.128 (-3.16)
cop	1.940 (6.22)	1.885 (6.28)	2.091 (4.31)	1.712 (6.31)	1.650 (5.85)	2.856 (5.59)
log (M)	-0.087 (-2.25)	-0.079 (-2.10)	-0.062 (-1.17)	-0.200 (-3.09)	-0.121 (-1.85)	-0.197 (-1.88)
$r_{1,1}$	-2.252 (-4.93)	-2.122 (-4.62)	-2.474 (-4.26)	-3.574 (-9.41)	-3.483 (-9.19)	-3.248 (-5.70)
$r_{12\text{-}1}$	0.771 (4.63)	0.797 (4.81)	0.299 (1.36)	1.033 (8.44)	1.083 (8.83)	0.655 (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

This table presents value-weighted average excess returns and four-factor model alphas for portfolios sorted by B/M (iB/M). The four factors are MFA, SMB, RMW, and CMA as in Fama and French (2015). I sort stocks into deciles based on NYSE breakpoints at the end of each 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.

Panel A: B/M

Portfolio	Excess return	Four-factor model					
		α	β_{mkt}	β_{smb}	β_{rmw}	β_{cma}	Adj-R^2 (%)
Low	0.522	0.047	0.987	-0.043	0.045	-0.596	90.35
	(2.30)	(0.63)	(53.68)	(-1.60)	(1.34)	(-15.20)	
2	0.673	0.030	0.991	0.050	0.088	-0.112	89.73
	(3.24)	(0.43)	(57.20)	(1.96)	(2.78)	(-3.03)	
3	0.727	-0.010	1.004	0.092	0.244	-0.024	88.71
	(3.53)	(-0.14)	(55.82)	(3.50)	(7.39)	(-0.63)	
4	0.661	-0.141	1.035	0.144	0.208	0.148	87.50
	(3.14)	(-1.79)	(53.45)	(5.06)	(5.85)	(3.58)	
5	0.811	-0.004	1.035	0.040	0.172	0.332	83.23
	(3.90)	(-0.05)	(46.72)	(1.23)	(4.22)	(7.04)	
6	0.788	0.080	1.003	0.162	-0.031	0.155	84.25
	(3.65)	(0.89)	(44.96)	(4.96)	(-0.75)	(3.25)	
7	0.711	-0.056	1.013	0.148	0.002	0.325	83.29
	(3.34)	(-0.61)	(44.76)	(4.46)	(0.04)	(6.74)	
8	0.698	-0.187	1.080	0.183	0.074	0.487	83.77
	(3.15)	(-1.98)	(46.44)	(5.35)	(1.73)	(9.82)	
9	0.930	0.024	1.063	0.304	0.137	0.421	76.77
	(3.98)	(0.20)	(36.32)	(7.07)	(2.54)	(6.74)	
High	0.998	0.019	1.115	0.334	0.120	0.565	73.75
	(4.01)	(0.14)	(33.57)	(6.86)	(1.96)	(7.98)	
High - Low	0.476	-0.028	0.128	0.378	0.074	1.161	30.96
	(2.51)	(-0.17)	(3.12)	(6.28)	(0.99)	(13.29)	

Panel B: iB/M

Portfolio	Excess return	Four-factor model					
		α	β_{mkt}	β_{smb}	β_{rmw}	β_{cma}	Adj-R^2 (%)
Low	0.381	-0.072	1.037	0.024	-0.023	-0.772	91.55
	(1.53)	(-0.94)	(54.97)	(0.88)	(-0.66)	(-19.18)	
2	0.616	-0.052	0.979	0.028	0.239	-0.160	89.40
	(3.03)	(-0.74)	(56.85)	(1.11)	(7.57)	(-4.37)	
3	0.731	0.054	0.976	0.008	0.105	0.066	89.03
	(3.71)	(0.78)	(57.43)	(0.33)	(3.35)	(1.83)	
4	0.809	0.104	1.012	0.007	0.123	0.066	86.80
	(3.92)	(1.31)	(51.77)	(0.24)	(3.42)	(1.58)	
5	0.702	-0.014	0.964	0.011	0.019	0.347	86.51
	(3.65)	(-0.19)	(52.47)	(0.42)	(0.56)	(8.87)	
6	0.740	-0.015	0.985	0.134	0.065	0.277	84.04
	(3.62)	(-0.18)	(46.40)	(4.30)	(1.67)	(6.12)	
7	0.918	0.044	1.088	0.140	0.082	0.449	86.95
	(4.21)	(0.53)	(53.10)	(4.65)	(2.17)	(10.28)	
8	0.928	0.108	1.037	0.310	-0.049	0.387	83.07
	(4.09)	(1.09)	(42.63)	(8.70)	(-1.10)	(7.47)	
9	1.045	0.089	1.103	0.524	-0.002	0.497	81.18
	(4.13)	(0.77)	(38.57)	(12.49)	(-0.03)	(8.15)	
High	1.251	0.290	1.074	0.594	0.002	0.517	76.22
	(4.81)	(2.16)	(32.53)	(12.26)	(0.03)	(7.34)	
High - Low	0.870	0.362	0.037	0.570	0.025	1.289	42.73
	(4.39)	(2.28)	(0.95)	(9.93)	(0.35)	(15.46)	

Table 4
Double sorts on size and B/M (or iB/M to) to compare HML with iHML

This table compares B/M with iB/M by constructing value-weighted portfolios double-sorted on size 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 to test whether the other factors span the value factor, HML or iHML. The sample period is July 1976 – December 2017.

Panel A: Risk and return

	B/M high minus low portfolio (HML)	iB/M high minus low portfolio (iHML)
Average	0.322	0.492
Standard deviation	2.662	2.329
t-statistic	2.70	4.72

Panel B: Spanning regressions

	HML	iHML	HML	iHML	HML	iHML
Intercept	0.413	0.539	-0.017	0.206	0.073	0.260
	(3.50)	(5.20)	(-0.17)	(2.46)	(0.78)	(3.13)
MFA	-0.124	-0.106	0.053	0.043	0.036	0.033
	(-4.52)	(-4.38)	(2.25)	(2.09)	(1.61)	(1.62)
SMB	-0.052	0.091	-0.007	0.091	0.021	0.108
	(-1.26)	(2.51)	(-0.21)	(3.00)	(0.64)	(3.61)
RMW			0.231	0.074	0.267	0.096
			(5.30)	(1.95)	(6.39)	(2.56)
CMA			0.856	0.794	0.836	0.782
			(16.93)	(18.01)	(17.32)	(18.09)
UMD					-0.145	-0.087
					(-7.17)	(-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

This table is to compare HML with iHML using 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. "Actual" is for the actual sample during July 1976 – 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 $Sh^2(f)$.

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 (MFA,SMB,***HML***,RMW,CMA,UMD)	0.139	0.158	0.154	0.194	0.185	0.105	0.096
6-factor model using iHML (MFA,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

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.

Panel A. Risk and return

	HML	HML_{AF}	iHML	$iHML_{AF}$
Average	0.322	0.224	0.492	0.429
Standard deviation	2.662	2.931	2.329	2.632
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	**0.073**	**0.089**	**0.260**	**0.251**	-0.009	0.026	0.043	0.044
	(0.78)	**(0.99)**	**(3.13)**	**(3.15)**	(-0.20)	(0.63)	(0.92)	(0.97)
MFA	0.036	0.014	0.033	0.037	0.024	-0.017	0.001	0.011
	(1.61)	(0.64)	(1.62)	(1.89)	(2.26)	(-1.71)	(0.10)	(0.97)
SMB	0.021	0.029	0.108	0.124	-0.005	0.011	0.002	0.037
	(0.64)	(0.90)	(3.61)	(4.29)	(-0.35)	(0.73)	(0.09)	(2.29)
RMW	0.267	0.265	0.096	0.111	0.025	0.035	0.000	0.035
	(6.39)	(6.53)	(2.56)	(3.09)	(1.23)	(1.79)	(0.01)	(1.72)
CMA	0.836	0.862	0.782	0.901	0.048	0.141	0.005	0.277
	(17.32)	(18.39)	(18.09)	(21.66)	(1.65)	(5.16)	(0.15)	(9.22)
UMD	-0.145	-0.315	-0.087	-0.242	**0.143**	**-0.190**	**0.122**	**-0.173**
	(-7.17)	(-16.06)	(-4.79)	(-13.88)	**(12.48)**	**(-20.04)**	**(10.21)**	**(-17.33)**
HML						0.863		
						(42.78)		
HML_{AF}					0.914			
					(42.78)			
iHML								0.799
								(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%

Table 7
Fama-MacBeth regressions to compare retained earnings-to-market with B/M and iB/M

This table reports average Fama and MacMeth (1973) regression slopes (multiplied by 100) and their *t*-values (in parentheses) to compare log(RE/M) with log(B/M) and log (iB/M). The sample period is from July 1976 to December 2017. RE is retained earnings, CC is contributed capital, and AOCI is accumulated other comprehensive income. KCap is knowledge capital, Ocap is organization capital, and Gdwl is goodwill. Control variables are cash-based operating profitability (cop), size (log(M)), short-term reversal ($r_{1,1}$), and momentum ($r_{12\text{-}1}$). 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.

Panel A. ABM

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log (B/M)	0.248						
	(3.36)						
log (RE/M)		0.163			0.170		0.123
		(3.68)			(3.82)		(2.49)
log (CC/M)			0.060		0.075		0.058
			(2.34)		(2.90)		(1.57)
log (AOCI/M)				0.025	-0.024		0.018
				(0.07)	(-0.07)		(0.66)
log (iB/M)						0.325	
						(5.04)	
log (KCap/M)							0.050
							(3.80)
log (OCap/M)							0.053
							(1.35)
Log (Gdwl/M)							0.008
							(0.22)
Indicator variables		-0.510			-0.599		-0.353
RE ≤ 0		(-2.90)			(-3.35)		(-1.73)
CC ≤ 0			-0.043		-0.251		-0.308
			(-0.38)		(-2.23)		(-1.94)
AOCI ≤ 0				-0.130	0.152		-0.096
				(-0.07)	(0.08)		(-0.72)
cop	1.940	1.596	1.847	1.670	1.792	1.885	2.132
	(6.22)	(6.19)	(6.46)	(5.73)	(6.71)	(6.28)	(4.77)
log (M)	-0.087	-0.103	-0.088	-0.097	-0.086	-0.079	-0.054
	(-2.25)	(-2.85)	(-2.48)	(-2.59)	(-2.44)	(-2.10)	(-1.12)
$r_{1,1}$	-2.252	-2.207	-2.149	-2.145	-2.241	-2.122	-2.458
	(-4.93)	(-4.82)	(-4.61)	(-4.56)	(-4.98)	(-4.62)	(-4.33)
$r_{12\text{-}1}$	0.771	0.707	0.667	0.639	0.743	0.797	0.322
	(4.63)	(4.19)	(3.83)	(3.57)	(4.53)	(4.81)	(1.47)
Adj-R^2	5.02%	5.07%	4.39%	4.14%	5.37%	4.84%	6.13%

Panel B. Micro

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log (B/M)	0.401 (7.11)						
log (RE/M)		0.142 (3.81)			0.165 (4.38)		0.124 (1.76)
log (CC/M)			0.179 (4.34)		0.249 (6.81)		0.195 (2.51)
log (AOCI/M)				-0.127 (-1.18)	-0.139 (-1.30)		-0.002 (-0.05)
log (iB/M)						0.594 (11.12)	
log (KCap/M)							0.099 (3.49)
log (OCap/M)							0.183 (2.39)
Log (Gdwl/M)							-0.112 (-2.73)
Indicator variables RE ≤ 0		-0.364 (-2.66)			-0.659 (-5.09)		-0.292 (-1.37)
CC ≤ 0			0.142 (0.74)		-0.221 (-1.19)		-0.378 (-1.45)
AOCI ≤ 0				0.910 (1.46)	0.993 (1.59)		0.203 (0.79)
cop	1.712 (6.31)	1.812 (7.71)	2.336 (9.20)	2.082 (7.33)	2.010 (8.81)	1.650 (5.85)	3.172 (6.44)
log (M)	-0.200 (-3.09)	-0.278 (-4.44)	-0.211 (-3.36)	-0.281 (-4.43)	-0.203 (-3.23)	-0.121 (-1.85)	-0.168 (-1.69)
$r_{1,1}$	-3.574 (-9.41)	-3.781 (-10.03)	-3.626 (-9.67)	-3.651 (-9.53)	-3.706 (-10.03)	-3.483 (-9.19)	-3.380 (-5.94)
r_{12-1}	1.033 (8.44)	0.859 (6.75)	0.950 (7.55)	0.880 (6.68)	0.971 (8.23)	1.083 (8.83)	0.610 (2.92)
Adj-R^2	2.40%	2.50%	2.27%	2.12%	2.64%	2.37%	3.21%

Table 8
Portfolios sorted by retained earnings-to-market

This table presents value-weighted average excess returns and four-factor model alphas for portfolios sorted by RE/M. The four factors are MFA, SMB, RMW, and CMA as in Fama and French (2015). I sort stocks into deciles based on NYSE breakpoints at the end of each June and hold the portfolios for the following year. The sample period is July 1976 - December 2017. The numbers in brackets are *t*-statistics.

Portfolio	Excess return	Four-factor model					
		α	β_{mkt}	β_{smb}	β_{rmw}	β_{cma}	Adj-R^2 (%)
Low	0.454	-0.017	1.162	0.464	-0.443	-0.279	88.73
	(1.54)	(-1.62)	(45.03)	(12.26)	(-9.36)	(-5.08)	
2	0.437	0.061	1.043	0.069	-0.361	-0.685	89.43
	(1.66)	(0.67)	(46.69)	(2.11)	(-8.80)	(-14.39)	
3	0.647	0.149	0.937	-0.037	0.011	-0.351	86.39
	(3.07)	(1.82)	(46.31)	(-1.24)	(0.28)	(-8.14)	
4	0.739	0.024	1.013	-0.070	0.265	-0.012	87.71
	(3.63)	(0.32)	(54.46)	(-2.58)	(7.76)	(-0.30)	
5	0.808	0.059	1.008	0.023	0.207	0.117	89.54
	(4.05)	(0.87)	(60.01)	(0.95)	(6.72)	(3.25)	
6	0.740	-0.043	0.957	0.068	0.262	0.259	85.27
	(3.90)	(-0.56)	(50.47)	(2.45)	(7.54)	(6.42)	
7	0.890	-0.028	1.042	0.118	0.392	0.356	85.73
	(4.36)	(-0.34)	(51.91)	(4.02)	(10.65)	(8.32)	
8	0.848	-0.042	0.976	0.072	0.386	0.453	78.46
	(4.32)	(-0.44)	(41.21)	(2.07)	(8.88)	(8.96)	
9	0.965	0.009	1.058	0.207	0.216	0.603	82.57
	(4.52)	(0.10)	(45.54)	(6.07)	(5.07)	(12.17)	
High	0.834	-0.206	1.067	0.350	0.277	0.699	75.12
	(3.62)	(-1.70)	(35.61)	(7.97)	(5.04)	(10.94)	
High - Low	0.380	-0.036	-0.095	-0.114	0.720	0.978	41.14
	(1.81)	(-0.21)	(-2.28)	(-1.86)	(9.37)	(10.95)	

Table 9

Fama-MacBeth regressions to compare iB/M with other alternatives of B/M

This table reports average Fama and MacMeth (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. These regressions are to compare iB/M with other alternatives of B/M. tB/M is based on tangible book value that excludes all intangibles. gB/M is based on book value that includes all intangibles including goodwill. kB/M is based on book value that includes knowledge capital, recorded other intangibles, and tangible assets. oB/M is based on book value that includes organization capital, recorded other intangibles, and tangible assets. Control variables are cash-based operating profitability (cop), size (log(M)), short-term reversal ($r_{1,1}$), and momentum (r_{12-1}). The sample is divided into two size groups: 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.

Panel A. ABM

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
log (B/M)	0.248 (3.36)					
log (iB/M)		0.325 (5.04)				
log (tB/M)			0.187 (3.46)			
log (gB/M)				0.330 (4.46)		
log (kB/M)					0.303 (5.45)	
log (oB/M)						0.256 (3.71)
cop	1.940 (6.22)	1.885 (6.28)	1.786 (5.74)	1.915 (6.27)	1.972 (6.56)	1.850 (6.16)
log (M)	-0.087 (-2.25)	-0.079 (-2.10)	-0.084 (-2.17)	-0.079 (-2.07)	-0.082 (-2.23)	-0.085 (-2.21)
$r_{1,1}$	-2.252 (-4.93)	-2.122 (-4.62)	-2.185 (-4.62)	-2.169 (-4.74)	-2.094 (-4.53)	-2.228 (-4.89)
r_{12-1}	0.771 (4.63)	0.797 (4.81)	0.735 (4.30)	0.804 (4.95)	0.810 (4.83)	0.753 (4.53)
Adj-R^2	5.02%	4.84%	4.85%	4.96%	4.70%	4.99%

Panel B. Micro

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
log (B/M)	0.401 (7.11)					
log (iB/M)		0.594 (11.12)				
log (tB/M)			0.382 (8.06)			
log (gB/M)				0.579 (10.02)		
Log(kB/M)					0.579 (11.77)	
log (oB/M)						0.434 (7.83)
cop	1.712 (6.31)	1.650 (5.85)	1.652 (5.96)	1.644 (5.83)	1.769 (6.29)	1.582 (5.87)
log (M)	-0.200 (-3.09)	-0.121 (-1.85)	-0.210 (-3.21)	-0.131 (-2.00)	-0.161 (-2.51)	-0.159 (-2.40)
$r_{1,1}$	-3.574 (-9.41)	-3.483 (-9.19)	-3.671 (-9.51)	-3.493 (-9.24)	-3.449 (-9.07)	-3.583 (-9.45)
r_{12-1}	1.033 (8.44)	1.083 (8.83)	0.985 (7.75)	1.082 (8.95)	1.121 (9.03)	1.006 (8.19)
Adj-R^2	2.40%	2.37%	2.43%	2.38%	2.36%	2.39%

Table 10
Portfolio-level tests to compare iB/M with other alternatives of B/M

This table reports value-weighted average excess returns and four-factor model alphas for portfolios sorted by B/M or its alternatives (iB/M tB/M, gB/M, kB/M and oB/M). The four factors are MFA, SMB, RMW, and CMA as in Fama and French (2015). I sort stocks into deciles based on NYSE breakpoints at the end of each June and hold the portfolios for the following year. The sample starts in July 1976 and ends in December 2017. The numbers in parentheses are *t*-statistics.

Panel A: Excess return

Portfolio	B/M	iB/M	tB/M	gB/M	kB/M	oB/M
Low	0.522 (2.30)	0.381 (1.53)	0.687 (2.99)	0.445 (1.86)	0.468 (1.91)	0.445 (1.85)
2	0.673 (3.24)	0.616 (3.03)	0.550 (2.69)	0.643 (3.19)	0.522 (2.58)	0.666 (3.27)
3	0.727 (3.53)	0.731 (3.71)	0.559 (2.64)	0.776 (3.93)	0.712 (3.44)	0.684 (3.33)
4	0.661 (3.14)	0.809 (3.92)	0.753 (3.49)	0.752 (3.67)	0.755 (3.60)	0.646 (3.23)
5	0.811 (3.90)	0.702 (3.65)	0.772 (3.47)	0.690 (3.61)	0.766 (3.69)	0.762 (3.81)
6	0.788 (3.65)	0.740 (3.62)	0.667 (3.17)	0.791 (3.83)	0.772 (3.70)	0.862 (4.31)
7	0.711 (3.34)	0.918 (4.21)	0.802 (3.77)	0.930 (4.18)	0.758 (3.63)	0.842 (3.85)
8	0.698 (3.15)	0.928 (4.09)	0.861 (4.00)	0.990 (4.12)	0.806 (3.63)	0.858 (3.77)
9	0.930 (3.98)	1.045 (4.13)	0.894 (3.85)	0.938 (3.71)	0.892 (3.68)	0.938 (3.77)
High	0.998 (4.01)	1.251 (4.81)	1.070 (4.17)	1.204 (4.76)	1.170 (4.52)	1.259 (5.01)
High – Low	0.476 (2.51)	0.870 (4.39)	0.383 (2.11)	0.759 (3.94)	0.702 (3.63)	0.814 (4.20)

Panel B: Four-factor model alpha

Portfolio	B/M	iB/M	tB/M	gB/M	kB/M	oB/M
Low	0.047 (0.63)	-0.072 (-0.94)	-0.109 (-1.16)	-0.054 (-0.73)	-0.049 (-0.57)	-0.037 (-0.49)
2	0.030 (0.43)	-0.052 (-0.74)	0.029 (0.40)	-0.022 (-0.31)	-0.034 (-0.50)	0.050 (0.79)
3	-0.010 (-0.14)	0.054 (0.78)	-0.009 (-0.13)	0.028 (0.40)	0.036 (0.48)	-0.040 (-0.55)
4	-0.141 (-1.79)	0.104 (1.31)	0.101 (1.42)	-0.025 (-0.31)	0.072 (0.98)	-0.042 (-0.52)
5	-0.004 (-0.05)	-0.014 (-0.19)	0.057 (0.63)	0.002 (0.03)	0.039 (0.42)	0.025 (0.30)
6	0.080 (0.89)	-0.015 (-0.18)	-0.051 (-0.53)	-0.023 (-0.27)	0.024 (0.26)	0.096 (1.21)
7	-0.056 (-0.61)	0.044 (0.53)	0.013 (0.12)	0.084 (0.93)	0.083 (0.91)	-0.092 (-1.03)
8	-0.187 (-1.98)	0.108 (1.09)	0.086 (0.85)	0.121 (1.21)	-0.015 (-0.16)	-0.052 (-0.54)
9	0.024 (0.20)	0.089 (0.77)	0.004 (0.03)	-0.086 (-0.74)	0.059 (0.55)	-0.138 (-1.19)
High	0.019 (0.14)	0.290 (2.16)	0.030 (0.22)	0.224 (1.69)	0.305 (2.32)	0.278 (2.04)
High – Low	-0.028 (-0.17)	0.362 (2.28)	0.140 (0.80)	0.278 (1.76)	0.354 (2.17)	0.315 (1.94)

Figure 1. Tangibles, Recorded Other Intangibles, and Unrecorded Intangibles

This figure presents how the proportions of tangible and intangible assets in total capital have changed over time using the total amounts in the sample each year from 1975 to 2016. Roint is recorded other intangibles. Kcap is unrecorded knowledge capital. Ocap is unrecorded organization capital. As tangibles, Roint, Kcap, and Ocap are the components of total capital, they are presented as a percent of total capital in the primary axis. Gdwl means goodwill and Gdwl normalized by total capital is presented in the secondary axis.

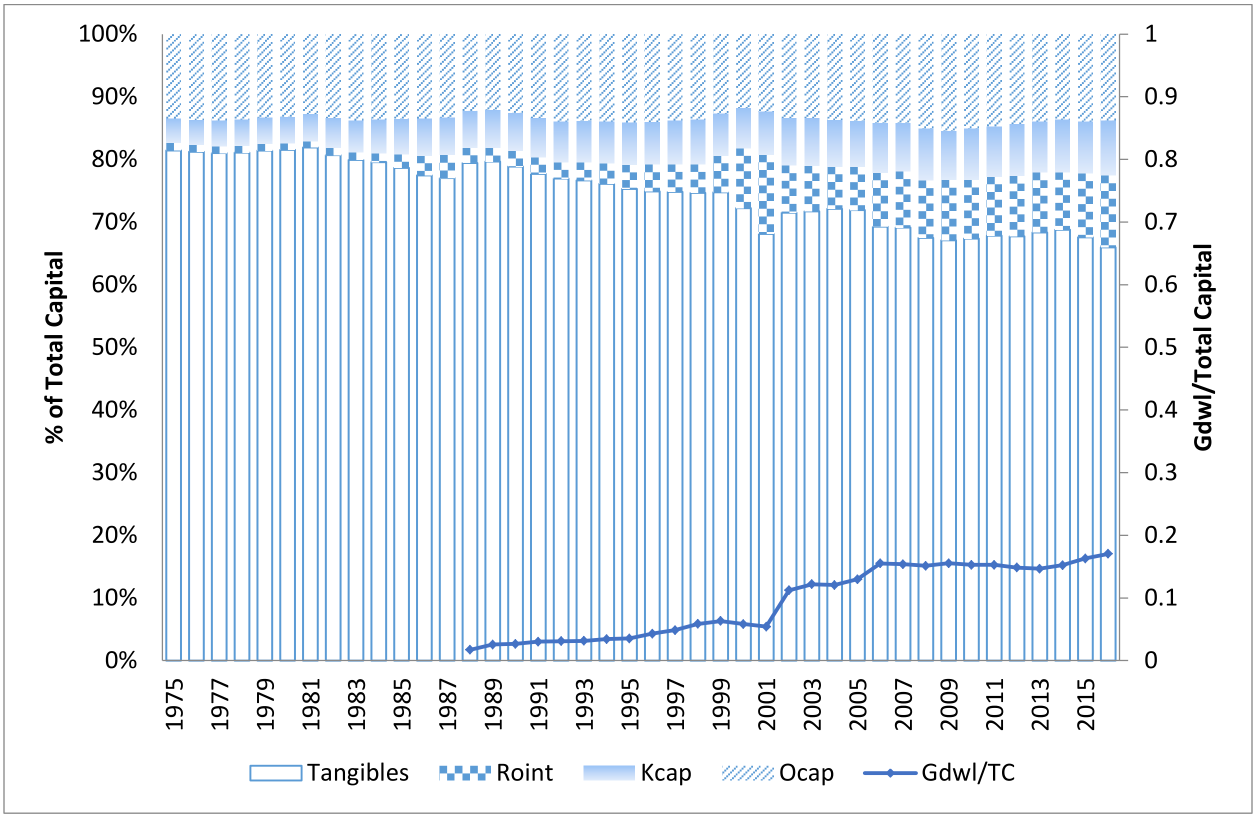

Figure 2. Cumulative returns on HML vs. iHML

This figure shows the growth of B/M (iB/M) high minus low HML (iHML) portfolios during June 30, 1976 – 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.