NBER WORKING PAPER SERIES

INTANGIBLE VALUE

Andrea L. Eisfeldt
Edward Kim
Dimitris Papanikolaou

Working Paper 28056
http://www.nber.org/papers/w28056

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2020, Revised November 2021

We thank the anonymous referee as well as seminar participants at UCLA Anderson and the Bank of England for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Intangible Value
Andrea L. Eisfeldt, Edward Kim, and Dimitris Papanikolaou
NBER Working Paper No. 28056
November 2020, Revised November 2021
JEL No. E22,G12

ABSTRACT

Intangible assets are absent from traditional measures of firm value despite their growing importance in firms' capital stocks. We propose a simple improvement to the classic Fama and French (1992, 1993) value factor that incorporates intangibles and addresses differences in accounting practices across industries. Our intangible value factor prices assets as well as or better than the traditional value factor but yields substantially higher returns. This outperformance holds over the entire sample period, including in more recent decades during which value has underperformed. We show that the intangible value factor sorts more effectively within industries on productivity, profitability, financial soundness, and on other valuation ratios such as price-to-earnings.

Andrea L. Eisfeldt
Anderson School of Management
University of California at Los Angeles
110 Westwood Plaza
Suite C4.10
Los Angeles, CA 90095
and NBER
andrea.eisfeldt@anderson.ucla.edu

Edward Kim
110 Westwood Plaza
Los Angeles, CA 90095
edward.kim.phd@anderson.ucla.edu

Dimitris Papanikolaou
Kellogg School of Management
Northwestern University
2211 Campus Drive, Office 4319
Evanston, IL 60208
and NBER
d-papanikolaou@kellogg.northwestern.edu

Github data and code repository is available at https://github.com/edwardtkim/intangiblevalue

1 Introduction

Value investing requires a fundamental anchor in order to determine which stocks are priced "expensively" vs. "cheaply" relative to their fundamental value. Using the book value of a firm's assets as the value anchor was popularized by Fama and French (1992, 1993), and the value effect subsequently became one of the most storied and studied anomalies in finance. However, the value factor has underperformed for at least a decade.[1] We argue that one driver of value's poor performance during this period is the deteriorating quality of book assets as a fundamental anchor due to the omission of intangible assets. Correctly defining the fundamental anchor for the value factor is important both in the context of rational explanations of value, in which book assets capture assets in place, and for behavioral explanations, in which market to book ratios represent a measure of mispricing.

Intangible assets have become an important and fast-growing part of firms' capital stocks. Corrado, Hulten, and Sichel (2009) estimated intangibles to be about one third of the US non-residential capital stock in 2003, while, using more recent data, Eisfeldt and Papanikolaou (2013b), Falato, Kadyrzhanova, and Sim (2013), Belo, Gala, Salomao, and Vitorino (2019), and Ewens, Peters, and Wang (2020) all estimate the contribution of intangible capital to overall corporate capital stocks to be around one half. In addition, these same studies report much higher investment rates for intangible assets relative to physical assets. The majority of intangible assets are created by investments in employee, brand, and knowledge capital that is expensed, and thus do not appear on corporate balance sheets. This has resulted in a growing mis-measurement of book assets.

We propose an intangible-augmented value factor ("intangible value", HML^{INT}) and construct it using a very simple modification to the standard Fama and French value factor (HML^{FF}). Our construction of HML^{INT} precisely follows the Fama and French methodology. The key difference is that we add intangible assets to the book equity of each firm, which is widely used as the traditional value anchor.[2] We also perform our intangible value sort within industries, which is useful for two reasons.

[1] See, for example, Figure 7.6 in Ang (2014). We independently document the decline in value below.

[2] Note that this implies an inherent assumption that all intangibles are equity backed, which is consistent with, for example, Rampini and Viswanathan (2013) and Falato, Kadyrzhanova, and Sim (2013).

First, as documented by Asness et al. (2000) and confirmed in our data, both traditional and intangible value are primarily within-industry phenomena. Measuring value within industries thus increases efficiency and reduces exposure to unpriced risk. Daniel et al. (2020) document the large increase in Sharpe ratios that can be achieved by reducing exposures to unpriced risks. Second, because accounting practices vary across industries, sorting within industries alleviates some of the criticisms levied at incorporating intangibles into value measures raised by Rizova and Saito (2020). In the Internet Appendix, we show that a small (but not negligible) part of the improvement to traditional value arises from sorting firms within industries when constructing intangible value. For ease of comparison with the existing literature on traditional value, we use the standard value factor from the Fama and French Data Library as the traditional value factor in our study.[3]

We follow the method introduced in Eisfeldt and Papanikolaou (2013b) to measure firm-level stocks of intangible assets. Specifically, we apply the perpetual inventory method to flows of Selling, General, and Administrative (SG&A) expenses, given assumptions about depreciation and initial values. Eisfeldt and Papanikolaou (2013b) build on two seminal contributions in measuring intangible assets. Corrado, Hulten, and Sichel (2009) use aggregated expenditure data and the perpetual inventory method to estimate the value of three main categories of intangibles: computerized information, R&D, and economic competencies.[4] Lev and Radhakrishnan (2005) document that firms with larger SG&A expenses exhibit greater Solow (1957) residuals. Eisfeldt and Papanikolaou (2013b) extend this work and are the first to construct and analyze firm-level stocks of intangible assets measured as accumulated SG&A expenses. That paper shows that firms with higher stocks of intangible assets outperform firms with lower intangibles, and provides additional evidence supporting the use of SG&A as a measure of intangible investment.[5] Measures of intangible assets using accumulated SG&A are also supported by the subsequent findings in Eisfeldt

[3]See `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html`.

[4]See also the precursor to that paper, Corrado, Hulten, and Sichel (2005), for further details.

[5]In particular, firms with more intangible assets using their measure are more productive, smaller, have higher Tobin's Q, higher levels of executive compensation, higher managerial quality scores according to the measure of Bloom and Van Reenen (2007), spend more on information technology (IT), and are more likely to list "loss of key personnel" as a risk factor in their 10-K filings. See also Lev (2000) and Eisfeldt and Papanikolaou (2013a) for further evidence supporting SG&A as intangible investment.

and Papanikolaou (2014), Zhang (2014), Falato, Kadyrzhanova, and Sim (2013), and Peters and Taylor (2017).

Importantly, we follow Eisfeldt and Papanikolaou (2013b) and include all of SG&A as investment in intangibles, rather than using the subsequent method introduced by Peters and Taylor (2017).[6] That method generally follows Eisfeldt and Papanikolaou (2013b) but uses only 30% of (SG&A minus R&D) plus 100% of R&D as investment in intangibles. There are two important reasons why we do not use the Peters and Taylor (2017) method to construct the stock of intangible assets. The first reason is that the 30% fraction used in Peters and Taylor (2017) is a calibrated number based on a small number of firms many decades ago. Indeed, later work by one of the authors of Peters and Taylor (2017) questions this assumption and attempts to construct industry-specific investment ratios for SG&A. Ewens, Peters, and Wang (2020) state that "the only estimate of γ_S (the fraction of SG&A that is intangible investment) comes from Hulten and Hao (2008), who estimate it based on descriptions of income statement items from six pharmaceutical firms in 2006, applying the investment share of expensed items from Corrado, Hulten, and Sichel (2006)."[7]

A second key rationale for using 100% of SG&A to construct intangible capital stocks is that there is no compelling reason to break out R&D expenses but not advertising expenses or other intangible asset expenditures. We argue that including all of SG&A and sorting within industries provides more reliable intangible capital estimates. Similar to advertising expenses, R&D is reported separately by only a subset of firms. As documented by Koh and Reeb (2015), missing values for R&D should not be interpreted as zeroes.[8] Without better estimates of the fraction of SG&A spending that is investment in intangible assets, we argue that it is best to use 100% of SG&A and to sort on relative intangible capital stocks across firms that are likely to share accounting practices (i.e. within industries) to avoid introducing noise. Our method reduces reliance on imprecise estimates of free parameters. In addition, using 100% of SG&A better accounts for organization, brand and customer capital,

[6] See also Amenc et al. (2020) and Arnott et al. (2021) for studies that use the Peters and Taylor (2017) method to construct intangible capital in the context of value strategies.

[7] Note that the latter paper is published as Corrado, Hulten, and Sichel (2009) and covers a broad set of industries. However, the 30% estimate in Hulten and Hao (2008) is derived from pharmaceutical firms.

[8] See also the related older work by Bound et al. (1982) whose Table 2.2 shows substantial differences across industries in R&D spending reported in the National Science Foundation R&D survey (see `https://www.nsf.gov/statistics/industry/`) vs. in Compustat data.

the importance of which can be substantial in many industries. Note that because we sort firms within industries to construct our value factor, any heterogeneity in the fraction of SG&A spending that is investment in intangibles across industries cancels out.[9] This is important because, as we document, accounting practices for allocating costs to SG&A vs. Cost of Goods Sold (COGS) vary systematically across industries.

Our intangible value factor, HML^{INT}, has the following features: (1) It is highly correlated with the traditional value factor, HML^{FF} (76%), (2) It prices standard test assets with lower pricing errors than HML^{FF}, but, most importantly, (3) It substantially and significantly outperforms HML^{FF}. The average returns to a portfolio that is long HML^{INT} and short HML^{FF} are 2.11% annually, with a standard deviation of only 6.53%. This long-short portfolio's Sharpe ratio (or equivalently, HML^{INT}'s information ratio with respect to HML^{FF}) is 0.32 over the full sample and 0.62 in data since 2007. This outperformance holds over the entire sample, and is in fact more pronounced in the post-crisis era in which the returns to traditional value have been particularly disappointing. Thus, although HML^{INT} is highly correlated with the original value factor, it has enough independent variation to permit substantial outperformance. The R^2 in a regression of HML^{INT} on HML^{FF} is 58%. The alpha of intangible value in a single traditional value factor model is 3.86% and highly statistically significant.

We examine in detail the potential drivers of intangible value's ability to price standard test assets as well as the traditional value factor, and its substantial outperformance. We also decompose the intangible value factor into traditional value and two factors that better isolate the effects of intangible capital. The first is an isolated intangible value factor, HML^{IME}, which sorts firms based only on our measure of the book value of intangible capital relative to the market value of equity. The second decomposition, HML^{UINT}, is constructed by taking long positions in firms that are uniquely in the long leg of HML^{INT} (specifically, not in the long leg of HML^{FF}), and short positions in firms that are uniquely in the short leg. These more isolated measures of intangible value continue to price standard test assets as well as or better than traditional value. The HML^{IME} portfolio has positive and significant alphas in the three and five-factor models plus momentum, and the HML^{UINT} portfolio has a positive and significant alpha in the five-factor model plus momentum.

We also document important differences in characteristics between firms in the

[9]See the new study by Lev and Srivastava (2019) which makes progress on understanding firm-level variation in the effect of SG&A spending on intangibles.

long (and short) legs of intangible and traditional value. It appears that intangible value is long firms with better fundamentals. The long leg of intangible value contains firms with higher productivity, higher earnings to price ratios (thus better valuation metrics by non-book measures), higher profits to assets, and lower debt to earnings. By contrast, traditional value is long firms with lower gross profitability to total assets, lower sales to stockholders' equity, lower sales to book assets, and higher debt to earnings.

The implications for our findings are: First, asset pricing researchers should consider correcting book equity for intangibles as intangible assets are a large and growing part of the corporate capital stock and there is a small gain in model fit from replacing the traditional value factor with the intangible-augmented factor. Second, asset managers should consider using the intangible value factor when implementing a value tilt in a relative value strategy. HML^{INT} appears to capture the value effect in that it prices standard test portfolios just as well as traditional value, but achieves higher average returns and lower volatility. Finally, an active manager can implement a profitable long-short strategy by going long HML^{INT} and short HML^{FF}.

The paper most closely related to ours is Park (forthcoming), of which we were made aware upon circulating this paper. Because the two papers developed independently, the methodologies differ somewhat.

The theoretical benefits of the two key differences in our methodology, namely sorting within industries and using the Eisfeldt and Papanikolaou (2013b) method for constructing intangible stocks using 100% of SG&A expenses, are detailed further in the next section. Empirically, we show that our method leads to an intangible value factor that has a positive alpha of 2.42% that is significant at the 1% level with respect to the intangible value factor constructed using the Peters and Taylor (2017) method, which also does not sort firms within industries (the method used in Park (forthcoming)). Our paper also makes substantially new contributions relative to that study, and in general the two studies are complementary. In particular, we investigate the differences between traditional and intangible value in more detail by studying portfolios sorted on intangible assets only to market equity and portfolios consisting of firms that are uniquely in the long or short leg of intangible value.

Additionally, we examine the how the long and short legs of intangible value contribute to the factor's outperformance, and provide examples of how the intangible value portfolio avoids "value traps" and avoids shorting low book-to-market firms whose book values do not reflect their total capital stock. We also examine the firm-level characteristics of the long and short legs of intangible vs. traditional value, and document the substantial differences in productivity, profitability, price to earnings ratios, and leverage. This paper also documents the difference between the intangible value factor and the organization capital factor in Eisfeldt and Papanikolaou (2013b), which also utilizes the accumulated stock of SG&A expenses to measure intangible (organization) capital. The key difference is that the portfolios in Eisfeldt and Papanikolaou (2013b) are formed using sorts on book organization capital to total book assets, rather than sorts on total book assets to market values of equity. As a result, the intangible value portfolio has low loadings on, and cannot be explained by, returns to the organization capital portfolio.

Our study also more formally examines the outperformance of intangible value relative to traditional value. We construct a strategy that is long intangible value and short traditional value and document the performance statistics for that strategy. We show that intangible value has a statistically significant alpha of 3.82% with respect to a single-factor traditional value model. Despite the high correlation between the two value strategies, this is not a near-arbitrage strategy. The appraisal ratio (alpha relative to the root mean squared pricing error) is 0.91. We also examine subsamples to see when the outperformance arises. In terms of average returns, the outperformance appears to be increasing over time, and is highest in the most recent sample, post-great financial crisis. This is consistent with the importance of intangible assets continuing to grow. This subsample is also of substantial interest because it is also the prolonged period during which the performance of traditional value has been particularly poor.

Finally, we closely follow the Fama and French methodology for constructing book equity, and for constructing the long and short legs of both the traditional and intangible value portfolios. Before adding intangible capital to book equity, we confirm that we can very successfully replicate the Fama and French traditional value factor from their data library. This is crucial, because it is well-known that slight changes in methodology can lead to large differences in replication errors and a vast literature on the value effect in finance utilizes the Fama and French series.

The paper proceeds as follows. In Section 2 we describe the data sources and the construction of our intangible value factors. In Section 3 we document the high correlation between the traditional value factor and the intangible value factor, and the superior performance of the intangible value factor in pricing standard test portfolios. We conduct several important robustness exercises, including examining intangible value portfolios formed only using intangible assets or only using firms that have a different portfolio assignment than that assigned by the traditional value factor. Then, in Section 4 we examine the outperformance of the intangible value factor, particularly in more recent subsamples. Section 5 examines the drivers of the differences between intangible and traditional value, and Section 6 concludes.

2 The Intangible Value Factor (HML^{INT})

In this section, we provide details on how we construct HML^{INT} and discuss our measurement choices in more detail.

2.1 Data and Sample

As our goal is to compare the relative pricing and return performance of the published HML factor and our HML^{INT} factor, we first ensure that our factor construction matches the Fama and French (1992, 1993) data construction methodology as closely as possible. Our replicated series of the published HML factor has a correlation with the original series of 98%.

We use standard accounting data from Compustat and stock price data from the Center for Research in Security Prices (CRSP). We obtain returns data for factors and test assets, as well as 12-Industry classifications, from Ken French's website.[10] The sample period of our main study is 1975 to 2018 and we additionally conduct analyses for sub-periods from 1995 to 2018 (post-internet era) and 2007 to 2018 (post-crisis era).

2.2 Constructing the Intangible Value Factor

To construct HML^{INT}, we add intangible assets to book equity. That is, we define total book equity as

$$\text{B}_{it}^{\text{INT}} = \text{B}_{it} - \text{GDWL}_{it} + \text{INT}_{it}, \tag{1}$$

where B_{it} is book equity, GDWL_{it} is goodwill, and INT_{it} is intangible assets for firm i at time t. We subtract goodwill in order to reduce the effects of merger

[10] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

activity and to alleviate the associated double counting of intangibles. We use the perpetual inventory method following Eisfeldt and Papanikolaou (2013b), Eisfeldt and Papanikolaou (2013a), and Eisfeldt and Papanikolaou (2014) to calculate INT_{it}.

$$\text{INT}_{it} = (1-\delta)\text{INT}_{it-1} + \text{SG\&A}_{it}. \tag{2}$$

We initialize $\text{INT}_{i0} = \text{SG\&A}_{i1}/(g+\delta)$ using the observation for SG&A when the firm first appears in Compustat. We set $g = 0.1$, which is approximately the average growth rate for SG&A in our sample, and assume a depreciation rate of $\delta = 0.2$ following Eisfeldt and Papanikolaou (2014). We apply this algorithm to all firms in Compustat from 1950, and begin our main sample in 1975.

Once we have a firm-level measure of B^{INT}, we form $\text{B}^{\text{INT}}/\text{M}$ portfolios in June of each year using book equity values reported in the previous year and market equity values from the previous December. To do this, we sort firms into tercile buckets by $\text{B}^{\text{INT}}/\text{M}$ every period *within each industry*. Following the procedure of Fama and French (1992, 1993), we compute industry HML^{INT} returns using six value-weighted portfolios formed on size and book-to-market. Lastly, we value-weight the industry HML^{INT} returns by each industry's market capitalization. The resulting market-level factor is the primary intangible value factor used throughout the paper.[11]

Our industry-based sorting method is notably distinct from traditional methods popularized by Fama and French and adopted by recent papers in this literature. We argue that an industry-level sort is preferable to constructing an economy-wide sort for several reasons. First, we confirm the findings of Asness et al. (2000) that value has consistently been a within-industry phenomenon, for both traditional and intangible value. As reported in Table 1, book-to-market's ability to predict stock returns is almost entirely driven by within-industry variation. Using either the traditional or intangible measure of book-to-market, the across-industry contributions to market-wide value are not significantly different from zero. Additionally, the within-industry T-statistics (8.65 and 8.75, respectively) are actually larger than the market-wide T-statistics (5.82 and 7.56). Measuring value within industries thus reduces noise and exposure to unpriced risk, which should increase achievable Sharpe ratios (see Daniel et al. (2020)).

[11]Further details on the factor construction methodology we employ can be found in the Internet Appendix.

Another important reason for sorting value within industries is to address the readily documented heterogeneity in accounting practices across industries. Koh and Reeb (2015) document the fact that missing R&D should not be interpreted as zeroes, arguing that doing so can underestimate intangible capital expenditures for a large subset of firms. Panel A of Table 2 documents the variation across industries in the fraction of missing R&D observations, which range from 99% to 11%. The mean and median fraction of missing R&D observations are 54% and 55% respectively. That is, the majority of R&D data are in fact missing observations. Additionally, whether R&D expenditures are broken out separately from SG&A depends on industry standard practices. Due to the discrepancy in reporting practices for R&D, we argue that sorting within industries and accumulating 100% of SG&A to measure intangible capital is the most reliable method currently available for constructing intangible capital stocks. This method, as opposed to those that accumulate organization (SG&A minus R&D) and knowledge (R&D) capital expenditures separately, avoids setting missing R&D to zero as is commonly done in the literature (Park (forthcoming); Peters and Taylor (2017)). By accumulating 100% of SG&A and sorting firms within industries, we minimize the number of assumed parameters.

Panel B of Table 2 documents the variation across industries in the contribution of SG&A to total costs as measured by (SG&A plus COGS). Such variation could lead to industry under- or over-weighting if intangible value sorts are not conducted within industries. Panel C of Table 2 confirm the possibility of distorted industry weights by reporting the variation of changes to the book to market ratio when intangibles are included. While the purpose of including intangibles is in fact to modify B/M, we argue the most reliable estimates thus far are those done on a relative basis between firms in the same industry using 100% of SG&A.

2.3 Additional Intangible Value Factors

We construct various alternative measures of intangible value in order to analyze the unique pricing ability of HML^{INT} and ensure the robustness of our main results.

In terms of alternative long-short hedged portfolios, HML^{IME} is a value factor that sorts firms into high and low buckets based on intangible assets-to-market equity, or INT/M, instead of B^{INT}/M. Moreover, HML^{UINT} sorts firms on B^{INT}/M but only takes long positions on firms that are *uniquely* in the long leg of HML^{INT} (i.e. not sorted in the long leg of HML^{FF}), and short positions on firms that are *uniquely* in the short leg of HML^{INT} (i.e. not sorted in the short leg of HML^{FF}). Lastly, INT-FF is a factor that is long HML^{INT} and short HML^{FF}, and IME-FF is long HML^{IME} and short HML^{FF}. For these two factors, there may be firms sorted into the same long-short legs but with different portfolio weights.

In the Internet Appendix, we construct alternative versions of HML^{INT} and HML^{FF} to examine the robustness of our results on pricing and outperformance. First, we compare our HML^{INT} to $\text{HML}^{\text{INDFF}}$, which is the traditional value factor that follows our within-industry sorting and weighting methodology. Similarly, we analyze the performance of HML^{INT} that drops financials (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+), which is in line with common practice in the literature.

3 Intangible vs. Traditional Value: Pricing Errors

This section examines the ability of the traditional and intangible value factors to price standard test portfolios. We begin by plotting the monthly returns to the intangible value (HML^{INT}) and traditional value (HML^{FF}) factors in Figure 1. As can be seen in the figure, the correlation between these two return series is high, with a full sample correlation coefficient estimate of 76.2%. We show that this correlation is high enough for intangible value to capture the "value effect," but low enough to allow intangible value to offer superior performance.

For our main asset pricing tests, we employ a two-step process. First, for each test asset i, we estimate betas from time-series regressions of portfolio excess returns on the risk factors

$$R_{it} = \alpha_i + \beta_{ik}\mathbf{k}_t + \epsilon_{it}, \tag{3}$$

where $\mathbf{k}_t$ is the vector of risk factors. These are MktRF, SMB, HML, and MOM for the three-factor model and the same factors plus RMW and CMA for the five-factor model.

Next, for each risk factor k, we estimate risk prices by running a cross-sectional regression of average excess returns on the estimated betas $\hat{\beta}_{ik}$

$$\mathbb{E}[R_{it}] = \eta_i + \hat{\beta}_{ik}\lambda_k + \nu_i. \tag{4}$$

The first two columns of Table 3 present the results for the Fama and French (1992, 1993) three-factor model plus momentum using the traditional value factor (column 1) and the intangible value factor (column 2). The test assets for these models are the standard size, book-to-market and momentum portfolios. As can be seen in the table, the intangible value factor reduces the alpha of this model by 5.4%, and reduces the root mean squared error by 3.7%. The χ^2 test rejects that the alphas from two models are different, and we conclude that intangible value prices standard test assets at least as well as traditional value in the three-factor model plus momentum.

Panels A and B of Figure 2 plot the results of these two models and report the mean absolute pricing errors, which HML^{INT} reduces by 2.2%. The figure shows that the fit of the two models is very similar for all test portfolios. One portfolio that has a smaller pricing error in the intangible model is S1B5, or Small Value. This portfolio displays high average returns. The higher loading on intangible value vs. traditional value brings its predicted and actual returns closer in the intangible value model. Overall, despite putting HML^{INT} on unequal footing relative to HML^{FF} by requiring the book-to-market sorts to occur at the industry level (unlike the test assets), the models using within-industry-sorted HML^{INT} perform as well as or better than the models using traditional value.

The last two columns of Table 3 display the results for the Fama and French (2015) five-factor model plus momentum, which adds the conservative minus aggressive (CMA) investment factor and the robust minus weak (RMW) profitability factor. For this model, we also include the Fama and French investment and profitability portfolios as additional test assets. In the five-factor model with momentum, the coefficient of the traditional value factor is not statistically significant, while the intangible value factor retains significance at over the 1% level. Root mean squared errors are also smaller using HML^{INT}. The χ^2 test rejects that the alphas from the two models are different. Panels C and D of Figure 2 display the results visually, and report the smaller mean absolute pricing error for the intangible value model. We conclude that the intangible value factor does at least as well in pricing standard test assets as traditional value in both the classic three-factor model and the recently popularized five-factor model.

Figure 1 shows that there is substantial commonality between the traditional and intangible value portfolios. To further draw out the unique pricing ability of intangible value, we additionally construct two distinct intangible value portfolios. The first,

HML^{IME}, sorts firms only based on intangible assets relative to market equity. Table 4 presents the results for the three- and five-factor models plus momentum when this portfolio is used both in addition to the traditional value factor, and on its own. The main message of this table is that an intangible-only value factor prices assets just as well as the traditional value factor.

The second decomposition we provide uses a portfolio, HML^{UINT}, which is long stocks that are *uniquely* in the long leg of HML^{INT} (that is, not in the long leg of HML^{FF}), and similarly goes short stocks which are in the short leg of HML^{INT} but either neutral or long in HML^{FF}. On average, about 20% of firms are used to construct HML^{UINT}, with about 60% coming from the long leg of intangible value, and 40% from the short leg. These fractions are all quite stable over time. As traditional value is not sorted within industries, we do not sort within industries first when constructing the intangible value series used to construct HML^{UINT}. Table 5 presents the results for the three- and five-factor models plus momentum when this portfolio is used both in addition to the traditional value factor and on its own. χ^2 tests show that the alpha from a three-factor model with HML^{UINT} is statistically significantly different from the model with traditional value at the 1% level. We also find that the alphas in the three- and five-factor models with HML^{UINT} are larger than in the models with traditional value.

Our main results are produced with all industries in order to be as consistent as possible with the test assets and factor portfolios posted on the Fama and French data library – the series most widely utilized by researchers.[12] In the Internet Appendix, we present our main results (including the analog of Table 3) without financials, utilities, and industries with SIC codes above 9000. We show that intangible value also generates lower pricing errors using the smaller number of industries.

This section established that the intangible value factor prices standard test assets in the three- and five-factor models plus momentum with lower errors on average, and with alphas that are not significantly different, relative to the traditional value factor. This is true despite the fact that the 25 size and book-to-market test asset portfolios are formed using the traditional book-to-market measure, and also that the intangible value factor is sorted on total book (intangible plus recorded) to market

[12] Several studies of the cross section of equity returns drop financials, utilities, and industries with SIC codes above 9000. However, the Fama and French factors include all industries as noted in the authors' online documentation. We additionally verify that our replication of HML is substantially better when all industries are included.

equity within industries prior to value weighting each leg of the HML^{INT} portfolio. When decomposing value into its traditional and intangible components using either HML^{IME} or HML^{UINT}, we find that these more isolated intangible value portfolios alone produce similar pricing errors to traditional value. Tests for differences in alphas for the models with HML^{INT} and HML^{IME} as compared to the models with traditional value are indistinguishable. We conclude that intangible value appears to capture the value effect at least as well as or better than traditional value.

4 Intangible vs. Traditional Value: Performance

Figure 1 shows that the traditional and intangible value factors are highly correlated. The previous section documented that intangible value appears to capture the value effect at least as well or better than traditional value. In this section, we show that there is enough independent variation in the two value factors to allow for substantial outperformance by the intangible value factor.

Table 6 documents the outperformance of intangible value relative to traditional value using single factor HML models. Panel A shows the results from a model of HML^{INT} regressed on the HML^{FF} factor. We present results for the full sample, and for subsamples covering the pre-internet era from 1975 to 1994, the internet era pre-crisis from 1995 to 2006, and the crisis and post-crisis era from 2007 to 2018. The alpha of HML^{INT} over HML^{FF} is 3.86% in the full sample and statistically significant at the 1% level. This outperformance is sizable given the apparent close relationship between the two factors. However, this fact is also reasonable as the appraisal ratio (α/RMSE) is 0.91. Interestingly, the alpha is fairly stable over time, and is statistically significant in all subsamples, though at a somewhat lower level in the most recent sample.

Turning to Panel B, which shows the results for the converse model in which HML^{FF} is regressed on the HML^{INT} factor, we see that the alpha is -3.03%, and statistically significant at the 1% level for the full sample. Looking at the subsamples, the third and fourth column show that the most prominent underperformance of HML^{FF} relative to HML^{INT} comes in the recent periods of 1995 to 2006 and 2007 to 2018. The recent underperformance is notable because the post-crisis era has been one of the worst periods for the traditional value strategy. We find that the intangible strategy performed significantly better in 2007 to 2018, by 3.59%.[13]

[13]The Internet Appendix contains results using a traditional value factor that is sorted within

Next, we compare the outperformance of our measure of intangible value over an intangible value factor constructed using the Peters and Taylor (2017) method employed by Park (forthcoming). To construct $\text{HML}^{\text{PTINT}}$, we sort firms unconditionally across all industries and accumulate 30% of (SG&A-R&D) plus 100% of R&D. Table 7 presents the results. Our HML^{INT} factor has a positive alpha of 2.42% over $\text{HML}^{\text{PTINT}}$ in the full sample. The alpha is positive in all subsamples, though not statistically significant in the post-crisis era. The alphas of $\text{HML}^{\text{PTINT}}$ with respect to our intangible value factor are all negative, but largely not significant. We conclude that our intangible value factor outperforms the factor used in Park (forthcoming).

Table 8 examines the outperformance of the two decompositions of intangible value, HML^{IME} and HML^{UINT}. As expected, the two portfolios that isolate the effect of intangibles display more independent variation from traditional value, as indicated by the lower R^2 compared to corresponding columns in Table 6. The full sample alpha is larger for both HML^{IME} (4.95%) and HML^{UINT} (4.71%). Moreover, the alphas for these factors are larger than alphas from the baseline intangible value regression and are also statistically significant in the post financial crisis period. Similar to the case of the baseline intangible value portfolio, the outperformance of portfolios that isolate the effect of intangibles appears to be strongest in the pre-crisis internet era from 1995 to 2006.

Eisfeldt and Papanikolaou (2013b) showed that firms with more organization capital to physical capital earned positive excess returns even when controlling for the Fama and French three factors plus momentum. They also use accumulated SG&A to measure their stock of intangible organization capital. However, that factor is substantially different from intangible value, which should not be surprising given that the organization capital factor compares two book values, while the intangible value factor compares book value (including intangibles) to market value. Table 9 clearly shows that the intangible value factor is quite different from the organization capital factor. In the full sample, the R^2 in a regression of intangible value on the organization capital factor from Eisfeldt and Papanikolaou (2013b) is negligible (0.09%). We conclude that although both factors provide evidence of the importance of intangibles for asset pricing, they capture different effects both conceptually and empirically.

Table 10 displays performance statistics for various value factors: HML^{FF}, HML^{INT},

industries and finds the same patterns, with slightly smaller magnitudes for outperformance as expected.

HML^{IME}, a portfolio which is long HML^{INT} and short HML^{FF} (INT-FF), and a portfolio that is long HML^{IME} and short HML^{FF} (IME-FF). We show results for average returns, volatility, confidence intervals, and Sharpe ratios. For the long-short portfolios, we add information and appraisal ratios using intangible value as the traditional value benchmark and vice versa for traditional value. The top panel shows that the traditional value factor had a positive and statistically significant return over the full sample. However, the significance is mainly driven by the earliest two subsamples of 1975 to 1994 and 1995 to 2006. In fact, the average returns to HML^{FF} are (not significantly) negative in the most recent subsample (2007 to 2018). In contrast, the average returns to intangible value are substantially larger in magnitude and statistically significant over the full sample, with the positive returns exhibiting higher significance through 2006. In the most recent subsample, average returns are positive but not statistically significant. We find that HML^{INT} still substantially outperforms HML^{FF}, and as shown in Table 6, this outperformance actually increases in recent years. HML^{IME} exhibits even higher returns and lower volatility across all periods, resulting in the highest Sharpe ratio.

The second to last panel displays portfolio performance statistics for the long intangible value, short traditional value strategy (INT-FF). This strategy has a positive and statistically significant average return over the full sample (2.11%), and a Sharpe ratio of 0.32. Moreover, the returns performance of this strategy has been improving over time, and most of the significantly positive outperformance actually comes from the most recent sample when traditional value underperformed. During the 2007 to 2018 sample, the Sharpe ratio of the long-short strategy is 0.62. The appraisal ratio, which compares the performance of HML^{INT} and HML^{FF}, is also positive throughout the entire sample, indicating HML^{INT}'s superior performance. The bottom panel examines the performance of a portfolio that is long HML^{IME} and short HML^{FF}. The return of this portfolio is significantly positive at 2.86% over the full sample, which is again mainly driven by the substantial outperformance of HML^{IME} over HML^{FF} in the most recent subsample. The average return of this long-short strategy is 5.05% in the most recent subsample with a Sharpe ratio of 0.70. Consistent with this, the appraisal ratio between HML^{IME} and HML^{FF} is positive throughout all periods.

Figure 3 plots the cumulative returns for several long-short strategies for the full sample and for the subsamples starting in 1995 (post internet era) and 2007 (post Great Financial Crisis). The top panel plots the cumulative returns to investing one dollar in either HML^{FF} or HML^{INT}, and clearly shows the superior returns to HML^{INT} in the full sample, and in each subsample. The middle panel plots the cumulative returns to the portfolio that is long HML^{INT} and short HML^{FF}. Again, the outperformance of HML^{INT} is apparent. In terms of the subsamples, it appears that the post-internet era is an important driver of the outperformance, as is the post-crisis era during which social media firms thrived. This is consistent with the growth in intangible capital documented in prior studies.

The bottom panel shows the cumulative returns to the intangible and traditional value strategies, along with the cumulative returns to the factors from the three- and five-factor models plus momentum for comparison. Over the full sample, the intangible value factor's performance is of a very similar magnitude to the best performing factor, momentum (UMD), while exhibiting a much lower volatility (and no extreme draw-downs as observed in the momentum crash of 2007). Intangible value's performance is clearly far superior to any other factor in the Fama and French (2015) five-factor model. In the 1995 to 2018 sample, the intangible value factor displays the highest performance of any of the long-short portfolios. In the most recent sample, intangible value outperformed all other factors with the exception of the profitability factor (RMW, or robust minus weak).

Table 4 decomposes the outperformance of intangible relative to traditional value into the contributions of the superior long leg and the superior short leg by plotting cumulative returns to the differences in each value portfolio's long and short legs, respectively. We present long and short leg returns for the full sample as well as for the post-internet subsample and the post-crisis subsample. These plots illustrate the fact that going long the short leg of traditional value and short the long leg of traditional value appears to be a fairly low volatility, positive return strategy. This implies that intangible value avoids shorting firms with book anchors that understate total book capital by not incorporating intangibles.

Table 11 displays alphas of the traditional and intangible value factors in the three- and five-factor models plus momentum. We include results for the baseline intangible value factor and for the two factors that isolate the effect of intangible capital. In the three-factor model plus momentum, the alpha for traditional value is negative but not significant. In contrast, the alpha for HML^{INT} is 2.92%, and is highly statistically significant at the 1% level. The alpha for HML^{IME}, which sorts firms using the ratio of intangible assets to market equity, is 3.87% and significant at the 1% level. The alpha for $\mathrm{HML}^{\mathrm{UINT}}$, which only contains stocks unique to the $\mathrm{HML}^{\mathrm{INT}}$ long or short leg, is positive but not significant.

In the five-factor model plus momentum, the alpha for traditional value is negative where the alphas for the intangible value factors except $\mathrm{HML}^{\mathrm{UINT}}$ are positive and strongly significant. This is notable as Fama and French (2015) find that the original value factor becomes redundant when the investment and profitability factors are added, although, as shown in Table 3, this is not true for $\mathrm{HML}^{\mathrm{INT}}$. The intangible value factor has a positive and significant loading on RMW, or the robust minus weak factor, meaning that the intangible value factor comoves with the returns to firms with stronger profitability. This is consistent with the evidence we present below that the long leg of the intangible value factor, unlike the traditional value factor, tends to contain more productive firms, and vice versa for the short leg. We conclude from Table 11 that the intangible value factors all have positive and significant alphas in the three- and five-factor models plus momentum, with the exception of $\mathrm{HML}^{\mathrm{UINT}}$, for which the positive alphas are not significant.

5 How do Intangible and Traditional Value Differ?

Intangible value generates similar pricing errors relative to traditional value but outperforms significantly, leading to a large Sharpe ratio for a strategy that is long intangible value and short traditional value. In this section, we investigate the properties of the firms that are in the long and short legs of intangible, vs. traditional, value. Table 12 presents results on firm characteristics for firms that are in the short, neutral, and long legs of intangible value and traditional value. Here, we report the time-series average of the median firm characteristic within each bucket. Not surprisingly, the first two rows show that there are larger differences in total book to market equity for intangible value, and larger differences in recorded book to market equity for traditional value, across the three possible portfolio rankings. Intangible value tends to be long slightly smaller firms, and short slightly larger firms than traditional value. This is consistent with their loadings on SMB in the three- and five-factor models, which are positive for intangible value and negative for traditional value. Importantly, intangible value has a positive and significant alpha of 2.92% controlling for the market, size, value, and momentum, as shown in Table 11. Row four of Table 12 shows that the expected pattern for intangible capital to book assets holds for the intangible value portfolio legs. On average, firms with higher intangible assets to recorded book assets appear in the long leg, and firms with a lower ratio of intangible to recorded book assets appear in the short leg. We observe the opposite pattern for the traditional value portfolio; the long leg has lower intangible to recorded book assets than the short leg. Row five shows that a similar pattern holds for intangible capital to sales, which is intuitive because intangible capital is measured as accumulated SG&A expenses.

Rows six and seven in Table 12 document that productivity tends to be increasing in $\mathrm{B/M^{INT}}$, and decreasing in $\mathrm{B/M^{FF}}$. Thus, $\mathrm{HML^{INT}}$ is long higher productivity firms and short lower productivity firms, while $\mathrm{HML^{FF}}$ is long lower productivity firms and short higher productivity firms. Productivity, measured as sales to recorded assets, is monotonically increasing across the intangible value legs, and monotonically decreasing across the traditional value legs. Using Solow (1955, 1957) residuals to measure productivity yields slightly more mixed results, but still favors intangible value. The residuals are fairly flat across the intangible portfolio legs. However, the Solow residuals are monotonically decreasing across the traditional value legs, meaning that traditional value is short firms with higher Solow residuals and long firms with lower Solow residuals. Row eight shows that $\mathrm{HML^{INT}}$ is long firms with higher sales to stockholder's equity and short firms with lower sales to stockholder's equity, while $\mathrm{HML^{FF}}$ displays the opposite pattern.

In terms of alternative valuation measures, row nine shows that intangible value is long firms with slightly lower price to diluted earnings excluding extraordinary items relative to traditional value, and short firms with higher price-to-earnings (P/E) ratios. Row ten shows that the two portfolios have similar patterns for price to sales. We conclude that including intangible capital aligns the B/M measure of value with measures that use P/E.

Rows eleven and twelve focus on measures of financial soundness. While intangible and traditional value have fairly similar patterns of debt to book assets across their long and short legs, traditional value tends to be long firms with much higher debt to EBITDA, indicating that firms in the long leg of traditional value may be less financially sound. Row thirteen shows that the dividend yield increases across terciles for both intangible and traditional value, with a slightly steeper slope for $\mathrm{HML^{FF}}$.

Next, we report statistics related to the investment (conservative minus aggressive, CMA) and profitability (robust minus weak, RMW) factors in the five-factor model plus momentum. Row fourteen shows that both intangible and traditional value tend to be long firms with lower investment to physical capital (capex to PP&E), consistent with the arguments in Hou et al. (2015). Row sixteen shows that intangible value, unlike traditional value, tends to be long firms with higher gross profit to total assets, and short firms with lower gross profit to book assets. Instead, traditional value tends to be short more profitable firms and long less profitable firms by this measure. This is consistent with the evidence in Table 11 that intangible value, unlike traditional value, loads positively on the RMW factor.

Our study is aimed at documenting the pricing ability and performance statistics of an intangible value factor that is constructed efficiently and minimizes biases due to accounting differences across industries. We largely leave the underlying economic reasons why intangible value outperforms traditional value to future work. One reason behind intangible value's outperformance might be behavioral.[14] Value firms may be underpriced, and intangible assets may be more sensitive to mispricing. Another explanation is that intangible value better captures firms' exposure to technology shocks that displace the value of assets in place including intangible assets, but increase the value of growth opportunities.[15] This is consistent with the results in Goncalves and Leonard (2020) which finds that including intangible capital improves the ability of book equity to capture fundamental equity values by 30% in recent data. We also find some support for the latter explanation by comparing the exposures of HML^{INT} vs. HML^{FF} to technology shocks. We measure technology shocks following Kogan et al. (2020) using the market value of patents. The last row of Table 12 reports loadings on the these shocks, controlling for market returns. The spread in technology risk exposures between the bottom and the top 30 percent of firms increases by 42% (from 0.12 to 0.17) when intangible assets are included.[16]

In summary, the analysis of firm characteristics across B/M terciles for intangible and traditional value seems to indicate why intangible value may outperform traditional value. "Value traps" are value firms with high book to market ratios whose market values do not recover. As the fundamentals (measured by productivity and

[14]See Daniel and Titman (1997) and Golubov and Konstantinidi (2019).

[15]See, for example, Papanikolaou (2011); Kogan and Papanikolaou (2014); Kogan et al. (2020).

[16]Note that the difference in exposures between the long and short legs of value are statistically significant at the 10% (traditional value) and 1% level (intangible value). The difference in the spread in exposures, however, is not significant, perhaps due to the fact that the data for this exercise are annual and aggregate.

alternative valuation ratios) seem better for the long leg of intangible value (and worse for the short leg), relative to traditional value, it may be that intangible value avoids these value traps. For instance, Finish Line was sorted uniquely in the long leg of traditional value for 30% of the period it was traded. While the stock appeared cheap using traditional B/M, it suffered from lagging performance behind competitors (including online retail) and never recovered until its acquisition in 2018. Similarly, by including investment in intangible assets, intangible value may outperform traditional value by avoiding short positions in firms whose book values do not accurately anchor their fundamental value. Well-known companies such as Target, Nordstrom, and Estee Lauder have consistently been sorted into the short leg of traditional value despite consistently investing in systems and customer-related intangibles. In most periods, intangible value in fact takes a long position in these stocks, amplifying the difference in returns between the two value factors.

It is also interesting to examine how persistent the differences in positions between HML^{INT} and HML^{FF} are. Table 13 addresses this question by reporting the empirical transition matrices and the respective stationary distributions showing the probability that a firm is uniquely in a particular leg of either the intangible or traditional value portfolio. The first matrix shows transition probabilities for firms that are uniquely in the long leg of intangible value. Such firms are in the top 30% of firms ranked by B/M^{INT}, but in the bottom 70% of firms ranked by recorded B/M. These unique positions are fairly persistent; with 58% probability, a firm in the long leg of intangible value that is either neutral or short in traditional value remains uniquely in the long leg of intangible value in the following period. An implication of this is that differences between HML^{INT} and HML^{FF} are driven in part by persistent differences in the rankings of firms. The remaining three matrices show that the probability of remaining uniquely in the short leg of HML^{INT}, or uniquely in the long or short log of HML^{FF}, are all over 50%. Note that the actual persistence of positions that would be used to infer turnover costs are much higher as Table 13 considers only the persistence of the positions that drive the return differences between intangible and traditional value. The implied stationary distributions show that firms spend between 7% and 16% of the time in positions that differ between intangible and traditional value.

6 Conclusion

The traditional value investing strategy, which relies on using firms' book assets as the fundamental anchor of value, has lost its edge in recent years. This trend may be due to the increasing importance of intangible capital, which is not incorporated into the traditional measure of book assets. We show that a value portfolio that adds intangible capital to book assets prior to sorting provides much stronger performance in all periods. The intangible value factor also prices standard test assets with similar pricing errors as the traditional value factor.

We emphasize sorting firms within industries when constructing intangible value because industry standards for allocating costs vary across industries. Similarly, we advocate doing the within-industry sort based on an intangible capital stock that is formed using 100% of SG&A, as opposed to 30% of SG&A and 100% of R&D, due to the fact that R&D is not separately reported in a reliable manner and thus missing values should not be considered zeroes. Using 100% of SG&A also better accounts for organization, brand and customer capital, the importance of which can be substantial in many industries.

We also find that long-short strategies that better isolate the effects of intangible capital on value continue to price standard test assets and yield positive and significant alphas. Lastly, we document that, on average, intangible value is long firms with better fundamentals (productivity, earnings, and profitability) relative to traditional value.

Taken together, our findings show that asset pricing researchers should consider adjusting the value factor and accompanying test assets to incorporate intangible capital. Practitioners can also use the intangible value factor to implement a very profitable relative value strategy: long intangible value and short traditional value. This strategy has exhibited strongly positive returns and a high Sharpe ratio, especially in recent years when traditional value has underperformed.

Figures

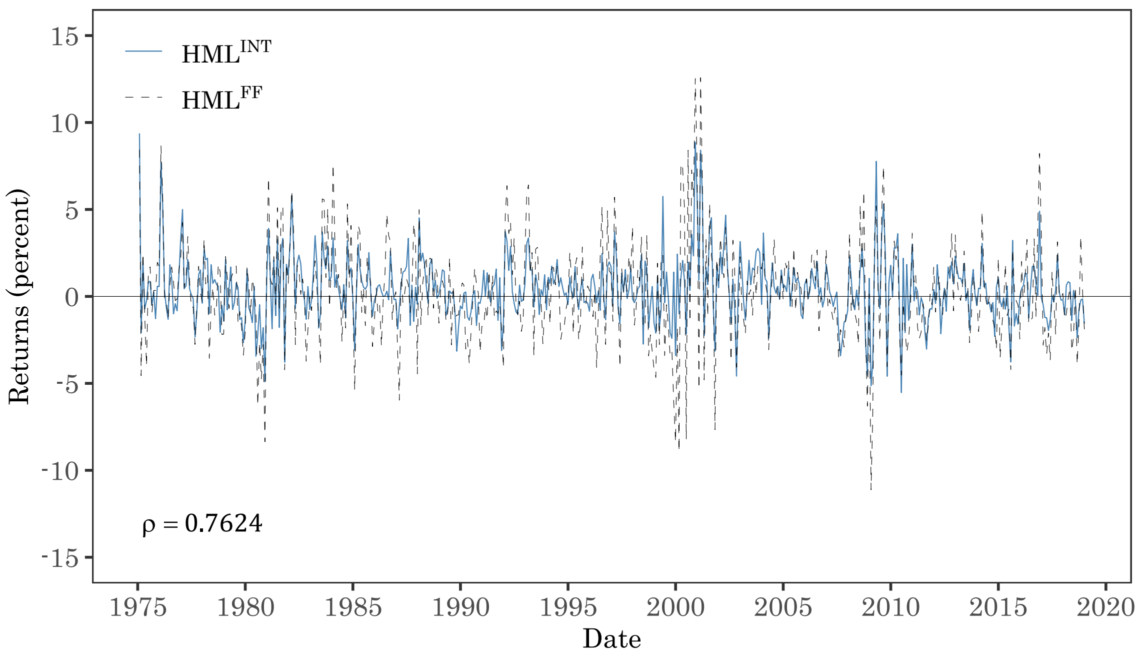

Figure 1: Relationship between Intangible and Traditional Value.

Description: This figure plots monthly returns for HML^{FF} and HML^{INT} from 1975 to 2018. The HML^{FF} portfolio mimics the risk factor in returns related to book-to-market equity, and is calculated as the difference between the returns on high-B/M portfolios and the returns on low-B/M portfolios. HML^{FF} returns are downloaded from Ken French's website. HML^{INT} adds intangible assets to the book equity term of the book-to-market equity ratio and conduct portfolio sorts within industries. Further details on factor construction can be found in Section 2 and the Internet Appendix. ρ reports the correlation between the two returns for the full sample period.

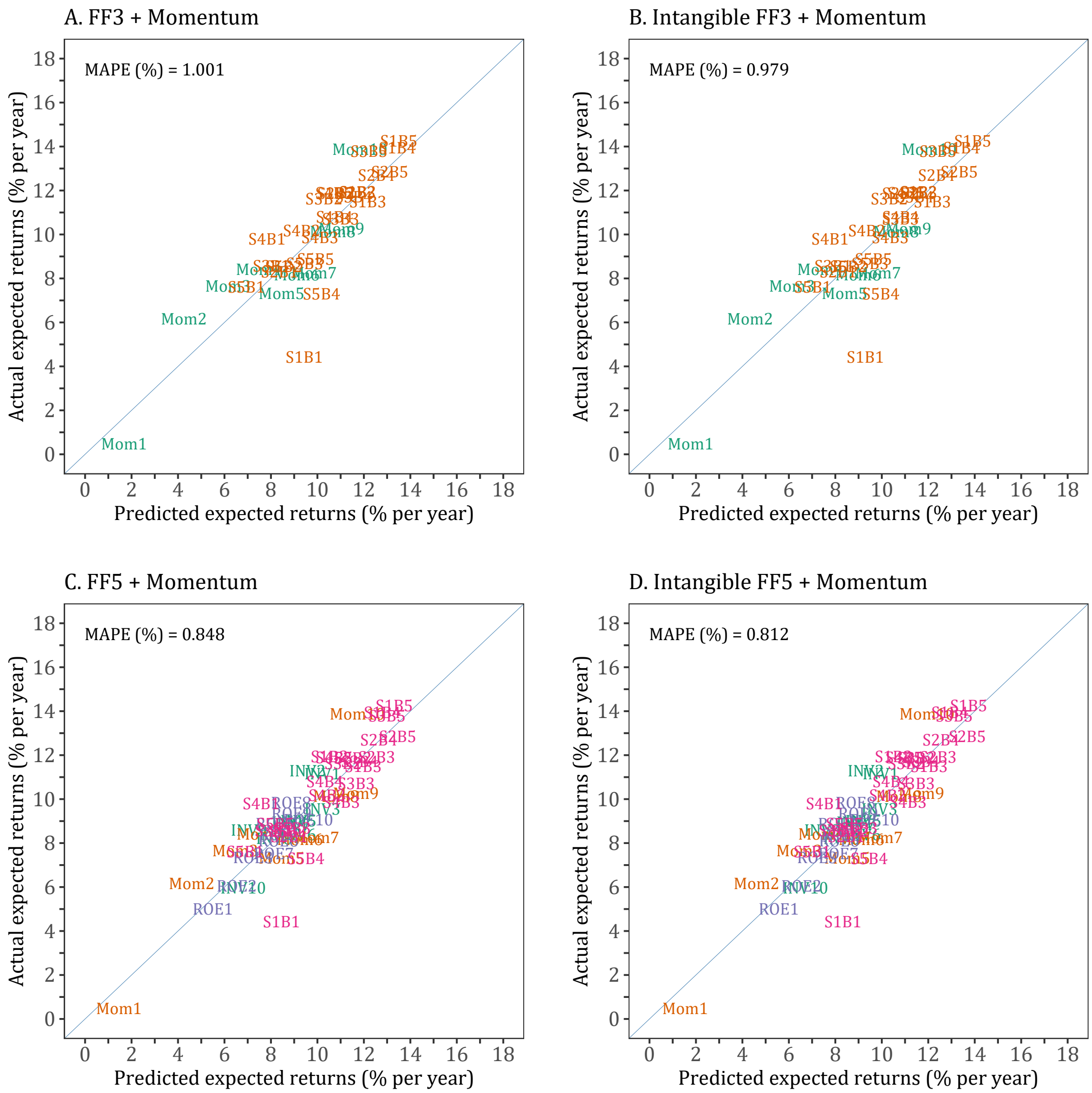

Figure 2: Cross-sectional Asset Pricing Tests – Intangible and Traditional Value.

Description: This figure shows the cross-sectional asset pricing tests from the Fama and French (1992, 1993, 2015) three-factor and five-factor models. Panel A plots realized mean excess returns of 25 size and book-to-market-sorted portfolios and 10 momentum portfolios against the mean excess returns predicted by the FF3 + momentum model. Panel C plots realized mean excess returns of 25 size and book-to-market sorted portfolios, 10 momentum portfolios, 10 portfolios sorted on operating profitability, and 10 portfolios sorted on investment, against the mean excess returns predicted by the FF5 + momentum model. Panels B and D replace HML^{FF} with HML^{INT}. The sample is monthly from 1975 to 2018. Returns are reported in percent per year.

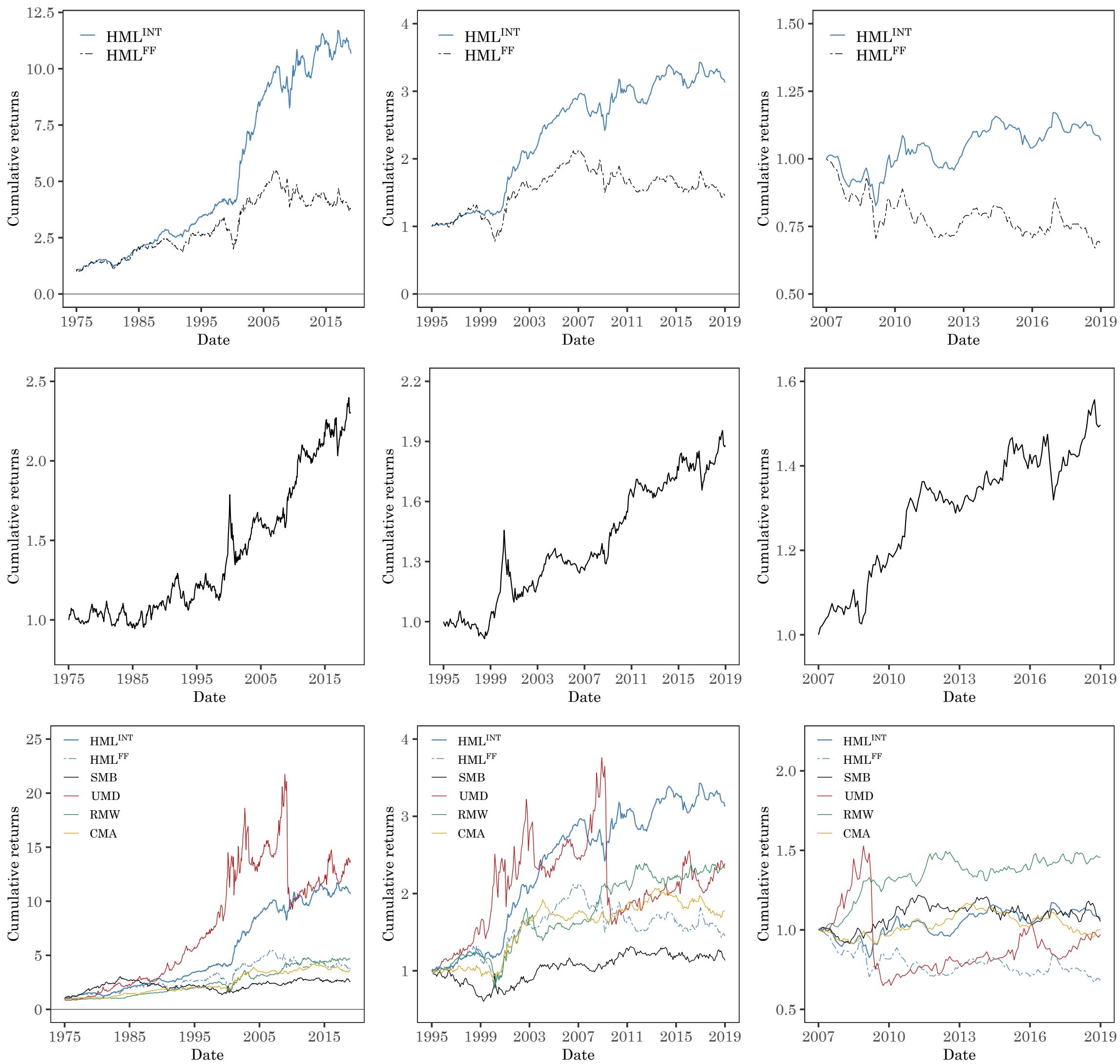

Figure 3: Performance of Intangible Value.

Description: The top panel plots the cumulative returns of one dollar invested in the HML^{FF} and HML^{INT} portfolios from the beginning of 1975, 1995, and 2007. The middle panel plots the cumulative returns of one dollar invested in the portfolio that is long the HML^{INT} portfolio and short the HML^{FF} portfolio. The bottom panel plots the cumulative returns of one dollar invested in HML^{INT}, the Fama and French five factors, and momentum.

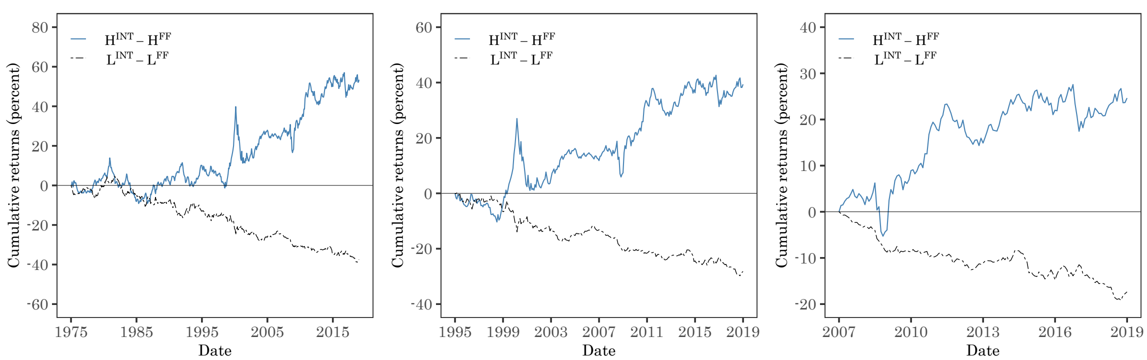

Figure 4: Decomposing the Outperformance of Intangible Value.

Description: This figure plots the cumulative returns of a portfolio that is long the long leg of HML^{INT} and short the long leg of HML^{FF} (solid blue line), as well as the returns of a portfolio that is long the short leg of HML^{INT} and short the short leg of HML^{FF} (dashed black line). Each panel plots percent returns from the beginning of 1975, 1995, and 2007.

Tables

		Market-wide ($\gamma_{B,t}$)	Across-industry ($\gamma_{1,t}$)	Within-industry ($\gamma_{2,t}$)
log(B/M)	(i)	0.38		
		(5.82)		
	(ii)		-0.32	0.44
			(-1.20)	(8.65)
log($\mathrm{B}^{\mathrm{INT}}$/M)	(i)	0.40		
		(7.56)		
	(ii)		0.04	0.43
			(0.24)	(8.75)

Table 1: Value and the Cross Section of Stock Returns.

Description: This table reports average slopes and T-statistics of monthly single variable cross-sectional regressions following Asness et al. (2000). $r_{i,t}$ refers to monthly stock returns of firm i at time t. $\mathrm{X}_{i,t}$ is log(B/M) or log($\mathrm{B}^{\mathrm{INT}}$/M) for firm i at time t, while $\mathrm{X}_{I,i,t}$ is the average log(B/M) or log($\mathrm{B}^{\mathrm{INT}}$/M) for the industry I of firm i. B/M is formed each July using prior end of December's market equity and prior year's BE. Industry definitions are adopted from the Fama-French 12 industry classifications. The sample is from January 1975 to December 2018.

Market-wide regression equation: $$r_{it} = \gamma_{A,t} + \gamma_{B,t}\mathrm{X}_{i,t} + \epsilon_{i,t} \quad \text{(i)}$$

Industry regression equation: $$r_{it} = \gamma_{0,t} + \gamma_{1,t}\mathrm{X}_{I,i,t} + \gamma_{2,t}(\mathrm{X}_{i,t} - \mathrm{X}_{I,i,t}) \quad \text{(ii)}$$

	Panel A					Panel B				
	xrd/sale					***xsga/(cogs+xsga)***				
						Full Sample			1995-2006	2007-2018
Industry	% NA	% 0	Mean	s.d.	p50	Mean	s.d.	p50	Mean	Mean
Consumer Nondurables	68.29	3.42	3.15	21.61	0.78	27.31	15.31	25.50	30.77	31.65
Consumer Durables	34.07	1.27	9.12	206.87	1.79	23.36	14.82	20.29	24.55	25.82
Manufacturing	34.86	1.34	10.70	299.35	1.60	21.92	13.33	19.42	23.18	22.24
Energy	80.77	6.93	43.88	1114.35	0.28	28.99	24.21	21.61	26.12	24.24
Chemicals	22.32	0.56	9.09	112.04	2.18	29.92	18.79	25.49	30.43	26.59
Business Equipment	11.74	0.98	71.20	3704.26	9.62	44.10	21.72	41.06	48.49	47.80
Telecommunications	79.26	2.93	95.33	1522.05	2.22	40.11	19.15	39.49	40.43	40.76
Utilities	99.34	0.34	0.08	0.18	0.00	20.02	17.42	16.65	19.21	33.49
Wholesale and Retail	39.29	53.61	1.05	43.56	0.00	24.42	14.95	22.47	24.62	23.65
Healthcare	12.38	5.87	1511.40	29821.61	11.73	53.67	25.64	51.64	53.35	62.65
Finance	95.36	1.91	17.32	109.16	0.38	40.50	20.76	36.34	38.15	52.96
Other	77.09	8.56	77.36	1203.57	0.48	27.09	21.58	20.55	27.13	28.07

Table 2: Descriptive Statistics.

Panel C

Industry	N	% Mkt Cap	B/M Mean	B/M s.d.	B/M p10	B/M p50	B/M p90	B^{INT}/M Mean	B^{INT}/M s.d.	B^{INT}/M p10	B^{INT}/M p50	B^{INT}/M p90
Consumer Nondurables	11843	7.24	1.10	1.19	0.24	0.79	2.23	4.62	8.32	0.52	2.21	10.63
Consumer Durables	5181	2.67	0.99	0.97	0.25	0.73	2.02	3.66	6.01	0.5	1.85	8.52
Manufacturing	23387	10.27	1.04	1.05	0.27	0.78	2.00	3.32	4.75	0.49	1.84	7.50
Energy	7874	9.04	0.88	0.89	0.22	0.68	1.65	1.48	1.91	0.34	0.97	2.97
Chemicals	4489	4.39	0.78	0.77	0.20	0.56	1.57	2.98	4.80	0.40	1.44	6.73
Business Equipment	29404	14.66	0.67	0.66	0.14	0.49	1.35	2.29	3.67	0.30	1.21	5.05
Telecommunications	3418	6.35	0.84	1.12	0.14	0.57	1.66	1.63	2.82	0.23	0.86	3.23
Utilities	6468	5.43	1.12	0.54	0.61	1.03	1.73	1.18	1.05	0.61	1.04	1.80
Wholesale and Retail	19981	8.40	1.04	1.14	0.23	0.72	2.12	6.32	13.22	0.53	2.32	14.97
Healthcare	16034	8.90	0.50	0.62	0.09	0.33	1.03	1.35	2.46	0.17	0.62	3.09
Finance	30239	14.97	1.02	1.13	0.36	0.81	1.75	1.86	4.78	0.43	1.08	3.39
Other	22139	7.68	0.98	1.50	0.20	0.68	1.89	2.54	5.28	0.30	1.19	5.43

Table 2: *Continued*

Description: This table summarizes key variables related to the calculation of intangible capital. *xrd*, *sale*, *cogs*, and *xsga* are Compustat variables for R&D expenditures, sales, SG&A expenditures, and cost of goods sold. % NA and % 0 refer to the fraction of firms reporting missing numbers or zero, respectively. In Panel C, N is the total number of firm-year observations for each industry, and % Mkt Cap is the fraction of each industry's market capitalization for the full period. B/M is the traditional book-to-market ratio and B^{INT}/M denotes the intangible-adjusted book-to-market ratio used to construct HML^{INT}. We report statistics using annual data at time of portfolio formation (June of each year) from 1975 to 2018. All fractions except B/M and B^{INT}/M are denoted in percent.

	(1)	(2)	(3)	(4)
α (%)	13.28	12.56	8.59	9.12
	(4.15)	(3.94)	(2.89)	(3.06)
β_{MktRF}	-0.38	-0.33	-0.04	-0.08
	(-1.18)	(-1.02)	(-0.12)	(-0.26)
β_{SMB}	0.18	0.19	0.24	0.23
	(1.36)	(1.38)	(1.78)	(1.75)
$\beta_{HML^{\text{FF}}}$	0.30		0.24	
	(2.35)		(1.92)	
$\beta_{HML^{\text{INT}}}$		0.29		0.30
		(2.87)		(2.88)
β_{UMD}	0.54	0.55	0.53	0.54
	(2.79)	(2.80)	(2.74)	(2.77)
β_{RMW}			0.32	0.32
			(2.87)	(2.90)
β_{CMA}			0.18	0.16
			(1.95)	(1.69)
Adj. R^2	73.14	75.12	78.74	79.84
RMSE	0.43	0.42	0.34	0.33
Prob $> \chi^2$		0.19		0.24

Table 3: Pricing Errors – Intangible Value vs. Traditional Value.

Description: This table represents pricing results for the Fama and French (1992, 1993, 2015) three- and five-factor models plus momentum. In terms of test assets, columns (1) and (2) use 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Columns (3) and (4) additionally include 10 investment and 10 profitability portfolios. Fama and MacBeth (1973) T-statistics are reported in parentheses. Prob $> \chi^2$ is the p-value of the test that the alpha from the model using HML^{INT} is significantly different from the alpha from the model using HML^{FF}. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

	(1)	(2)	(3)	(4)	(5)	(6)
α (%)	13.28	13.30	12.80	8.59	8.55	8.40
	(4.15)	(4.02)	(3.90)	(2.89)	(2.89)	(2.81)
β_{MktRF}	-0.38	-0.38	-0.34	-0.04	-0.03	-0.02
	(-1.18)	(-1.17)	(-1.04)	(-0.12)	(-0.11)	(-0.07)
β_{SMB}	0.18	0.18	0.18	0.24	0.23	0.23
	(1.36)	(1.36)	(1.35)	(1.78)	(1.77)	(1.77)
$\beta_{HML^{\text{FF}}}$	0.30	0.30		0.24	0.25	
	(2.35)	(2.35)		(1.92)	(1.92)	
$\beta_{HML^{\text{IME}}}$		0.16	0.31		0.22	0.27
		(1.01)	(2.73)		(1.46)	(2.34)
β_{UMD}	0.54	0.54	0.54	0.53	0.53	0.53
	(2.79)	(2.79)	(2.78)	(2.74)	(2.74)	(2.73)
β_{RMW}				0.32	0.32	0.33
				(2.87)	(2.93)	(2.95)
β_{CMA}				0.18	0.18	0.19
				(1.95)	(1.95)	(2.02)
Adj. R^2	73.14	72.22	72.56	78.74	78.32	78.67
RMSE	0.43	0.44	0.44	0.34	0.34	0.34
Prob > χ^2		0.98	0.43		0.83	0.51

Table 4: Pricing Errors – Intangible Assets to Market Equity.

Description: This table represents pricing results for the Fama and French (1992, 1993, 2015) three- and five-factor models plus momentum. In terms of test assets, columns (1) through (3) use 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Columns (4) through (6) additionally include 10 investment and 10 profitability portfolios. HML^{IME} is the HML factor that replaces book-to-market with intangibles-to-market as the sorting variable. Fama and MacBeth (1973) T-statistics are reported in parentheses. Prob > χ^2 is the p-value of the test that the alpha from the model using HML^{IME} is significantly different from the alpha from the model using HML^{FF}. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

	(1)	(2)	(3)	(4)	(5)	(6)
α (%)	13.28	12.81	20.34	8.59	9.40	8.77
	(4.15)	(4.00)	(5.19)	(2.89)	(3.15)	(2.92)
β_{MktRF}	-0.38	-0.32	-0.89	-0.04	-0.09	-0.03
	(-1.18)	(-0.99)	(-2.47)	(-0.12)	(-0.28)	(-0.11)
β_{SMB}	0.18	0.17	0.16	0.24	0.22	0.23
	(1.36)	(1.29)	(1.20)	(1.78)	(1.68)	(1.74)
$\beta_{HML^{\mathrm{FF}}}$	0.30	0.27		0.24	0.25	
	(2.35)	(2.13)		(1.92)	(2.00)	
$\beta_{HML^{\mathrm{UINT}}}$		1.20	1.53		1.09	1.07
		(4.34)	(4.88)		(4.26)	(4.23)
β_{UMD}	0.54	0.52	0.44	0.53	0.51	0.49
	(2.79)	(2.64)	(2.25)	(2.74)	(2.59)	(2.51)
β_{RMW}				0.32	0.34	0.34
				(2.87)	(3.05)	(3.04)
β_{CMA}				0.18	0.20	0.27
				(1.95)	(2.14)	(2.72)
Adj. R^2	73.14	79.71	71.56	78.74	83.60	82.64
RMSE	0.43	0.37	0.44	0.34	0.30	0.31
Prob > χ^2		0.78	0.00		0.48	0.89

Table 5: Pricing Errors – Intangible Value with Unique Sort.

Description: This table represents pricing results for the Fama and French (1992, 1993, 2015) three- and five-factor models plus momentum. In terms of test assets, columns (1) through (3) use 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Columns (4) through (6) additionally include 10 investment and 10 profitability portfolios. $\mathrm{HML}^{\mathrm{UINT}}$ is a factor that goes long firms that are in the long leg of $\mathrm{HML}^{\mathrm{INT}}$ but not in the long leg of $\mathrm{HML}^{\mathrm{FF}}$, and vice versa for the short leg ("unique" intangible factor). Fama and MacBeth (1973) T-statistics are reported in parentheses. Prob > χ^2 is the p-value of the test that the alpha from the model using $\mathrm{HML}^{\mathrm{UINT}}$ is significantly different from the alpha from the model using $\mathrm{HML}^{\mathrm{FF}}$. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

	Full sample	1975-1994	1995-2006	2007-2018
	(1)	(2)	(3)	(4)
A. $\mathbf{HML_t^{INT} = \alpha + \beta_{HML^{FF}} \cdot HML_t^{FF} + \epsilon_t}$				
α (%)	3.86	3.68	6.18	2.32
	(6.10)	(4.18)	(4.82)	(1.92)
$\beta_{HML^{\mathrm{FF}}}$	0.50	0.52	0.43	0.56
	(19.46)	(13.24)	(9.46)	(11.93)
Adj. R^2	58.04	57.12	56.67	60.79
RMSE	4.23	4.07	4.47	4.12
α/RMSE	0.91	0.91	1.38	0.56
B. $\mathbf{HML_t^{FF} = \alpha + \beta_{HML^{INT}} \cdot HML_t^{INT} + \epsilon_t}$				
α (%)	-3.03	-1.88	-5.10	-3.59
	(-3.00)	(-1.30)	(-2.14)	(-2.18)
$\beta_{HML^{\mathrm{INT}}}$	1.16	1.11	1.31	1.08
	(23.33)	(16.96)	(13.49)	(11.21)
Adj. R^2	58.04	57.12	56.67	60.79
RMSE	6.45	5.95	7.77	5.71
α/RMSE	-0.47	-0.32	-0.66	-0.63

Table 6: Single Factor Models – Intangible Value vs. Traditional Value.

Description: In this table, we study the relative performance of the HML^{FF} and HML^{INT} factors. We report alphas and betas of a regression of each return on the other, for the full sample as well as for sub-periods around the Internet Bubble and the Great Recession. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

	Full sample	1975-1994	1995-2006	2007-2018
	(1)	(2)	(3)	(4)
A. $\mathbf{HML}_t^{\mathbf{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{PTINT}}} \cdot \mathbf{HML}_t^{\mathbf{PTINT}} + \boldsymbol{\epsilon}_t$				
α (%)	2.42	1.78	4.60	1.72
	(4.41)	(2.75)	(4.18)	(1.42)
$\beta_{HML^{\text{PTINT}}}$	0.60	0.64	0.52	0.69
	(25.80)	(20.96)	(13.11)	(11.99)
Adj. R^2	70.12	77.65	70.69	59.36
RMSE	3.57	2.93	3.67	4.19
α/RMSE	0.68	0.61	1.25	0.41
B. $\mathbf{HML}_t^{\mathbf{PTINT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{INT}}} \cdot \mathbf{HML}_t^{\mathbf{INT}} + \boldsymbol{\epsilon}_t$				
α (%)	-1.24	-0.57	-3.67	-2.06
	(-1.66)	(-0.59)	(-2.18)	(-1.53)
$\beta_{HML^{\text{INT}}}$	1.16	1.21	1.36	0.87
	(26.17)	(23.79)	(18.16)	(11.98)
Adj. R^2	70.12	77.65	70.69	59.36
RMSE	4.94	4.04	5.91	4.70
α/RMSE	-0.25	-0.14	-0.62	-0.44

Table 7: Single Factor Models – Alternative Intangible Asset Calculation Methods.

Description: In this table, we study the relative performance of our baseline HML^{INT} and $\text{HML}^{\text{PTINT}}$, the factor that accumulates 30% of (SG&A-R&D) plus 100% of R&D to construct intangible assets and sort firms across all industries (see Internet Appendix for details). We report alphas and betas of a regression of each return on the other, for the full sample as well as for sub-periods around the Internet Bubble and the Great Recession. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

	Full sample	1975-1994	1995-2006	2007-2018
	(1)	(2)	(3)	(4)
A. $\mathbf{HML_t^{IME}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{HML^{FF}}} \cdot \mathbf{HML_t^{FF}} + \boldsymbol{\epsilon_t}$				
α (%)	4.95	4.65	6.99	3.41
	(7.03)	(4.71)	(5.21)	(2.42)
$\beta_{HML^{\text{FF}}}$	0.40	0.46	0.33	0.41
	(14.23)	(11.43)	(6.59)	(7.19)
Adj. R^2	41.59	45.17	40.60	36.35
RMSE	4.73	4.60	4.70	4.86
α/RMSE	1.05	1.01	1.49	0.70
B. $\mathbf{HML_t^{UINT}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{HML^{FF}}} \cdot \mathbf{HML_t^{FF}} + \boldsymbol{\epsilon_t}$				
α (%)	4.71	3.46	7.69	6.19
	(2.85)	(1.35)	(2.36)	(2.25)
$\beta_{HML^{\text{FF}}}$	-0.07	-0.07	-0.28	0.27
	(-1.09)	(-0.59)	(-2.56)	(2.96)
Adj. R^2	0.25	-0.10	7.63	5.77
RMSE	10.91	11.36	10.97	9.41
α/RMSE	0.43	0.30	0.70	0.66

Table 8: Single Factor Models – Decompositions of Intangible Value.

Description: In this table, we report alphas and betas of a regression of HML^{IME} and HML^{UINT} on HML^{FF}, for the full sample as well as for sub-periods around the Internet Bubble and the Great Recession. HML^{IME} is constructed using the intangible capital-to-market value ratio as the sorting variable. HML^{UINT} is a portfolio that is long firms that are sorted in the long leg when using B^{INT}/M but not when using B/M, and similarly, short firms that are uniquely in the short leg of HML^{INT}. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

	Full sample	1975-1994	1995-2006	2007-2018
	(1)	(2)	(3)	(4)
$\mathbf{HML_t^{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{OMK}} \cdot \mathbf{OMK_t} + \boldsymbol{\epsilon_t}$				
α (%)	5.51	6.47	8.29	0.99
	(5.65)	(4.60)	(4.86)	(0.55)
β_{OMK}	0.04	-0.05	0.25	-0.27
	(0.79)	(-0.74)	(4.30)	(-2.93)
Adj. R^2	0.09	0.04	18.72	10.21
RMSE	6.52	6.21	6.12	6.23
α/RMSE	0.85	1.04	1.36	0.16

Table 9: Single Factor Models – Intangible Value and Organization Capital Factor.

Description: In this table, we report alphas and betas of a regression of HML^{INT} on the OMK factor (Eisfeldt and Papanikolaou (2013b)), for the full sample as well as for sub-periods around the Internet Bubble and the Great Recession. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

		Full sample	1975-1994	1995-2006	2007-2018
		(1)	(2)	(3)	(4)
HML$^{\mathbf{FF}}$	$\mathbb{E}[R]$	3.49	5.14	6.99	-2.77
		(2.33)	(2.53)	(2.05)	(-1.05)
	σ	9.95	9.08	11.80	9.11
	[0.05, 0.95]	[-48.36, 63.24]	[-45.72, 63.12]	[-55.92, 78.24]	[-44.04, 48.84]
	Sharpe	0.35	0.57	0.59	-0.30
HML$^{\mathbf{INT}}$	$\mathbb{E}[R]$	5.60	6.34	9.21	0.76
		(5.70)	(4.57)	(4.70)	(0.40)
	σ	6.52	6.21	6.78	6.57
	[0.05, 0.95]	[-27.54, 40.43]	[-23.63, 40.17]	[-25.95, 48.42]	[-36.38, 35.93]
	Sharpe	0.86	1.02	1.36	0.12
HML$^{\mathbf{IME}}$	$\mathbb{E}[R]$	6.35	7.02	9.30	2.28
		(6.81)	(5.06)	(5.28)	(1.30)
	σ	6.18	6.21	6.10	6.09
	[0.05, 0.95]	[-26.48, 40.80]	[-25.11, 40.98]	[-20.31, 45.42]	[-35.03, 36.87]
	Sharpe	1.03	1.13	1.53	0.37
HML$^{\mathbf{INT}}$ - HML$^{\mathbf{FF}}$	$\mathbb{E}[R]$	2.11	1.20	2.22	3.53
		(2.15)	(0.90)	(0.96)	(2.14)
	σ	6.53	5.97	8.03	5.71
	[0.05, 0.95]	[-36.59, 36.54]	[-32.60, 34.39]	[-44.07, 45.00]	[-26.31, 30.74]
	Information	0.32	0.20	0.28	0.62
	Appraisal	0.91	0.91	1.38	0.56
HML$^{\mathbf{IME}}$ - HML$^{\mathbf{FF}}$	$\mathbb{E}[R]$	2.86	1.88	2.31	5.05
		(2.50)	(1.25)	(0.87)	(2.41)
	σ	7.60	6.71	9.18	7.27
	[0.05, 0.95]	[-40.67, 43.14]	[-39.18, 39.02]	[-50.84, 53.19]	[-37.68, 41.31]
	Information	0.38	0.28	0.25	0.70
	Appraisal	1.05	1.01	1.49	0.70

Table 10: Performance Statistics – Intangible Value vs. Traditional Value.

Description: This table summarizes the risk and return associated with intangible and traditional value. HML$^{\text{INT}}-$HML$^{\text{FF}}$ refers to the portfolio that is long HML$^{\text{INT}}$ and short HML$^{\text{FF}}$, and HML$^{\text{IME}}-$HML$^{\text{FF}}$ refers to the portfolio that is long HML$^{\text{IME}}$ and short HML$^{\text{FF}}$. The numbers in parentheses are T-statistics for the test that the average return, $\mathbb{E}[R]$, is different from zero. The information ratio is $\mathbb{E}[R_p - R_b]/\sigma(R_p - R_b)$, or the Sharpe Ratio of the long-short portfolio. The appraisal ratio is α/RMSE of a regression of intangible value returns (HML$^{\text{INT}}$ or HML$^{\text{IME}}$) on traditional value returns. The underlying data are monthly and the full sample period is 1975 to 2018. All factors are annualized in percent per year.

	HML$^{\text{FF}}$	HML$^{\text{INT}}$	HML$^{\text{IME}}$	HML$^{\text{UINT}}$	HML$^{\text{FF}}$	HML$^{\text{INT}}$	HML$^{\text{IME}}$	HML$^{\text{UINT}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α (%)	-1.43	2.92	3.87	2.81	-1.67	2.15	3.15	1.27
	(-1.51)	(4.93)	(5.67)	(1.82)	(-1.84)	(3.64)	(4.69)	(0.82)
β_{MktRF}	-0.09	0.04	0.04	0.06	-0.05	0.06	0.07	0.10
	(-5.26)	(2.96)	(3.17)	(1.55)	(-2.36)	(4.92)	(5.00)	(2.69)
β_{SMB}	-0.27	0.19	0.19	0.51	-0.23	0.21	0.20	0.58
	(-9.62)	(10.98)	(9.68)	(11.72)	(-7.70)	(10.81)	(9.47)	(11.77)
$\beta_{HML^{\text{INT}}}$	1.20				0.97			
	(26.12)				(15.63)			
$\beta_{HML^{\text{FF}}}$		0.55	0.46	0.05		0.46	0.35	-0.09
		(26.42)	(17.71)	(0.95)		(17.56)	(11.13)	(-1.35)
β_{UMD}	-0.05	-0.01	0.00	-0.05	-0.06	-0.02	-0.01	-0.07
	(-1.87)	(-0.33)	(0.12)	(-1.21)	(-2.83)	(-1.26)	(-0.88)	(-2.02)
β_{RMW}					0.00	0.09	0.06	0.23
					(0.04)	(3.45)	(1.82)	(3.33)
β_{CMA}					0.36	0.20	0.24	0.25
					(6.20)	(5.39)	(5.13)	(2.65)
Adj. R^2	70.57	68.46	53.98	25.47	73.50	70.90	57.17	28.12
RMSE	5.40	3.66	4.19	9.43	5.12	3.52	4.05	9.27

Table 11: Alphas – Intangible Value vs. Traditional Value.

Description: In this table, we report portfolio alphas and betas of a regression of different variants of HML portfolio returns on traditional factor models. Columns (1) through (4) use the Fama and French (1992, 1993) three factor model, and columns (5) through (8) use the Fama and French (2015) five factor model. Both specifications are augmented with the momentum factor. Columns (1) and (5) are benchmarks that set HML$^{\text{IME}}$ as the dependent variable and replace the intangibles-adjusted HML factor in the aforementioned models. We include T-statistics that adjust for heteroskedasticity in parentheses. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

	B^{INT}/M			B/M		
	Low 30 (1)	Mid 40 (2)	High 30 (3)	Low 30 (4)	Mid 40 (5)	High 30 (6)
B/M Int	0.58	1.56	3.93	0.75	1.66	3.42
B/M FF	0.34	0.70	1.15	0.31	0.74	1.38
Market capitalization (log, real)	5.45	4.88	3.34	5.03	4.76	3.58
Intangible capital to book assets (%)	37.44	56.78	97.92	74.97	53.27	48.29
Intangible capital to sales (%)	43.15	60.13	87.10	72.64	59.49	62.18
Productivity - sales to book assets (%)	81.62	90.32	103.31	96.13	92.29	80.95
Productivity - Solow residual (%)	1.30	1.77	0.07	6.10	1.33	-5.51
Sales to Stockholder's equity (%)	175.72	188.92	227.94	205.61	194.92	186.85
Price to Earnings (Diluted, excluding extraordinary items) (%)	14.00	11.96	7.33	13.40	11.95	8.34
Price to sales (%)	1.91	1.11	0.62	1.86	0.97	0.59
Debt to book assets (%)	15.44	12.60	15.25	10.43	14.15	16.92
Debt to EBITDA (%)	77.00	141.84	172.95	45.98	159.27	231.85
Dividend yield	2.14	2.86	3.01	1.92	2.94	3.30
Investment to physical capital (%)	14.69	11.19	8.72	14.85	10.66	8.19
Gross profit to total assets (%)	26.69	27.77	30.53	37.88	27.51	19.19
Exposure to Technology Shocks	-0.015	-0.096	-0.182	-0.027	-0.093	-0.146

Table 12: Summary Statistics of Firm Characteristics.

Description: This table summarizes the characteristics of firms sorted into the long ("High 30") and short ("Low 30") legs of the HML^{FF} and HML^{INT} factors. B/M is the traditional book-to-market ratio, and B^{INT}/M denotes the intangible-adjusted book-to-market ratio used to construct HML^{INT}. We report the time-series average of the median firm characteristic within each percentile bucket. The sample period is January 1975 to December 2018.

j	High^{INT}	Low^{INT}	High^{FF}	Low^{FF}
$\mathbf{P}$	$\begin{bmatrix} 57.87 & 42.13 \\ 8.00 & 92.00 \end{bmatrix}$	$\begin{bmatrix} 54.23 & 45.77 \\ 3.57 & 96.43 \end{bmatrix}$	$\begin{bmatrix} 51.49 & 48.51 \\ 4.19 & 95.81 \end{bmatrix}$	$\begin{bmatrix} 57.51 & 42.49 \\ 6.90 & 93.10 \end{bmatrix}$
$\mathbf{w}$	$(15.97, 84.03)$	$(7.23, 92.77)$	$(7.95, 92.05)$	$(13.97, 87.03)$

Table 13: Persistence of Positions.

Description: This table represents transition matrices $\mathbf{P}$ for being sorted uniquely into a particular leg of the HML^{INT} and HML^{FF} portfolios. For instance, the state $j = \text{High}^{\text{INT}}$ refers to a given firm being sorted in the top 30th percentile in terms of $\text{B}^{\text{INT}}/\text{M}$ and in the bottom 70th percentile in terms of B/M. In this case, the alternative state can be either i) being sorted in the top 30th percentiles of both $\text{B}^{\text{INT}}/\text{M}$ and B/M, or ii) being sorted in the bottom 70th percentile of $\text{B}^{\text{INT}}/\text{M}$, regardless of the B/M sort. Below each panel, we report the stationary distribution, $\mathbf{w} = (\pi_j, 1 - \pi_j)$, of each Markov Chain, where π_j denotes the long run proportion of time that each chain spends in state j. All numbers are expressed in percentages.

References

Noël Amenc, Felix Goltz, and Ben Luyten. Intangible capital and the value factor: Has your value definition just expired? The Journal of Portfolio Management, 46 (7):83–99, 2020.

Andrew Ang. Asset management: A systematic approach to factor investing. Oxford University Press, 2014.

Robert D Arnott, Campbell R Harvey, Vitali Kalesnik, and Juhani T Linnainmaa. Reports of values death may be greatly exaggerated. Financial Analysts Journal, 77(1):44–67, 2021.

Clifford S Asness, R Burt Porter, and Ross L Stevens. Predicting stock returns using industry-relative firm characteristics. Available at SSRN 213872, 2000.

Frederico Belo, Vito Gala, Juliana Salomao, and Maria Ana Vitorino. Decomposing firm value. Technical report, National Bureau of Economic Research, 2019.

Nicholas Bloom and John Van Reenen. Measuring and explaining management practices across firms and countries. The quarterly journal of Economics, 122(4):1351–1408, 2007.

John Bound, Clint Cummins, Zvi Griliches, Bronwyn H Hall, and Adam B Jaffe. Who does r&d and who patents? Technical report, National Bureau of Economic Research, 1982.

Carol Corrado, Charles Hulten, and Daniel Sichel. Measuring capital and technology: an expanded framework. In Measuring capital in the new economy, pages 11–46. University of Chicago Press, 2005.

Carol Corrado, Charles Hulten, and Daniel Sichel. Intangible capital and us economic growth. Review of income and wealth, 55(3):661–685, 2009.

Kent Daniel and Sheridan Titman. Evidence on the characteristics of cross sectional variation in stock returns. The Journal of Finance, 52(1):1–33, 1997.

Kent Daniel, Lira Mota, Simon Rottke, and Tano Santos. The cross-section of risk and returns. The Review of Financial Studies, 33(5):1927–1979, 2020.

Andrea L. Eisfeldt and Dimitris Papanikolaou. Internet appendix to organization capital and the cross-section of expected returns. Technical report, 2013a.

Andrea L. Eisfeldt and Dimitris Papanikolaou. Organization capital and the cross-section of expected returns. The Journal of Finance, 68(4):1365 – 1406, Feburary 2013b. doi: 10.1111/jofi.12034.

Andrea L. Eisfeldt and Dimitris Papanikolaou. The value and ownership of intangible capital. American Economic Review, 104(5):189–94, May 2014. URL http://ideas.repec.org/a/aea/aecrev/v104y2014i5p189-94.html.

Michael Ewens, Ryan H Peters, and Sean Wang. Measuring intangible capital with market prices. Technical report, 2020. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3287437.

Antonio Falato, Dalida Kadyrzhanova, and Jae Sim. Rising intangible capital, shrinking debt capacity, and the us corporate savings glut. Technical report, FEDS Working Paper No. 2013-67, September 2013. URL http://ssrn.com/abstract=2350863.

Eugene F. Fama and Kenneth R. French. The cross-section of expected stock returns. Journal of Finance, 1992.

Eugene F. Fama and Kenneth R. French. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 1993.

Eugene F Fama and Kenneth R French. A five-factor asset pricing model. Journal of financial economics, 116(1):1–22, 2015.

Eugene F. Fama and James D. MacBeth. Risk, return, and equilibrium: Empirical tests. The Journal of Political Economy, 81(3):607–636, 1973.

Andrey Golubov and Theodosia Konstantinidi. Where is the risk in value? evidence from a market-to-book decomposition. The Journal of Finance, 74(6):3135–3186, 2019.

Andrei Goncalves and Gregory Leonard. The fundamental-to-market ratio and the value premium decline. Kenan Institute of Private Enterprise Research Paper, 2020.

Kewei Hou, Chen Xue, and Lu Zhang. Digesting anomalies: An investment approach. The Review of Financial Studies, 28(3):650–705, 2015.

Charles R Hulten and Xiaohui Hao. What is a company really worth. Intangible capital and the market to book value puzzles, NBER Working Paper Series, 14548, 2008.

Leonid Kogan and Dimitris Papanikolaou. Growth opportunities, technology shocks, and asset prices. The Journal of Finance, 69(2):675–718, 2014. doi: https://doi.org/10.1111/jofi.12136. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12136.

Leonid Kogan, Dimitris Papanikolaou, and Noah Stoffman. Left behind: Creative destruction, inequality, and the stock market. Journal of Political Economy, 128 (3):855–906, 2020. doi: 10.1086/704619. URL https://doi.org/10.1086/704619.

Ping-Sheng Koh and David M Reeb. Missing r&d. Journal of Accounting and Economics, 60(1):73–94, 2015.

Baruch Lev. Intangibles: Management, measurement, and reporting. Brookings institution press, 2000.

Baruch Lev and Suresh Radhakrishnan. The valuation of organization capital. In Measuring Capital in the New Economy, NBER Chapters, pages 73–110. National Bureau of Economic Research, Inc.,, July 2005. URL http://ideas.repec.org/h/nbr/nberch/10619.html.

Baruch Lev and Anup Srivastava. Explaining the recent failure of value investing. NYU Stern School of Business, 2019.

Wendy C. Y. Li and Bronwyn H. Hall. Depreciation of business r&d capital. Review of Income and Wealth, 2020.

Dimitris Papanikolaou. Investment shocks and asset prices. Journal of Political Economy, 119(4):639–685, 2011. doi: 10.1086/662221. URL https://doi.org/10.1086/662221.

Hyuna Park. An intangible-adjusted book-to-market ratio still predicts stock returns. Critical Finance Review, forthcoming.

Ryan H Peters and Lucian A Taylor. Intangible capital and the investment-q relation. Journal of Financial Economics, 123(2):251–272, 2017.

Adriano A Rampini and S Viswanathan. Collateral and capital structure. Journal of Financial Economics, 109(2):466–492, 2013.

Savina Rizova and Namiko Saito. Intangibles and expected stock returns. Available at SSRN 3697452, 2020.

Robert M. Solow. The production function and the theory of capital. The Review of Economic Studies, pages 103–107, 1955.

Robert M. Solow. Technical change and the aggregate prodution function. The Review of Economics and Statistics, 39(3):312–320, 1957. URL http://www.jstor.org/stable/1926047.

Mindy Xiaolan Zhang. Who bears firm-level risk? Implications for cash flow volatility. Un, 2014.

Internet Appendix: Not For Print Publication

This Internet Appendix contains two sections. The first section provides details on data construction. The second section provides additional analysis and robustness checks. Please cite this Appendix as "Internet Appendix to "Intangible Value" by Eisfeldt, Kim, and Papanikolaou".

A Data Appendix

Constructing $\mathrm{HML}^{\mathrm{INT}}$ involves a three-step process: First, we calculate the firm-level stock of intangibles using the perpetual inventory method. Next, we add intangibles to book value of equity and subtract goodwill. Lastly, we sort firms within industries based on their intangibles-augmented book-to-market ratio and form hedged long-short portfolios. In this section, we describe this process in further detail. The relevant programs and data are also posted on the authors' websites.

A.1 Measuring Intangible Capital: EKP Method

We compute a measure of book equity including intangibles using the following formula:

$$\mathrm{B}_{it}^{\mathrm{INT}} = \mathrm{B}_{it} - \mathrm{GDWL}_{it} + \mathrm{INT}_{it}, \tag{5}$$

where B_{it} is book equity, GDWL_{it} is goodwill (Compustat item *gdwl*), and INT_{it} is intangible assets for firm i at time t.[17]

To compute $\mathrm{B}_{it}^{\mathrm{INT}}$, we first calculate the stock of intangible assets at the firm-level using methodology based on Eisfeldt and Papanikolaou (2013b), and Eisfeldt and Papanikolaou (2013a), Eisfeldt and Papanikolaou (2014). Intangible assets created internally are expensed and typically do not appear explicitly on the balance sheet. This means that the replacement cost of internally generated intangible assets must be calculated based on past investments in intangibles. As this investment is also not measured and reported under standard accounting practices, we must find a proxy and accumulate this identity over time. Our preferred method follows the original method in Eisfeldt and Papanikolaou (2013b), which we denote in the context of intangible value by "EKP method". Using this method, we construct $\mathrm{B}_{it}^{\mathrm{INT}}$ using past

[17] Following Fama and French (1992, 1993), we calculate book equity using Compustat data: $be = (seq \text{ or } ceq + pstk \text{ or } at - lt) + (txditc \text{ or } txdb + itcb) + (pstkrv \text{ or } pstkl \text{ or } pstk)$

investments in selling, general, and administrative (SG&A) expenses (item *xsga*). Specifically, the perpetual inventory method allows for the stock of intangibles to grow with the law of motion:

$$\text{INT}_{it} = (1-\delta)\text{INT}_{it-1} + \text{SG\&A}_{it}. \tag{6}$$

where $\delta_{SG\&A}$ is the depreciation rate for SG&A expenses and $\text{SG\&A}_{it}$ is real SG&A expenditure, calculated by deflating *xsga* by the consumer price index. Moreover, we set $\text{INT}_{i0} = \text{SG\&A}_{i1}/(g+\delta)$ and use $g = 0.1$ to compute the initial stock of organization capital prior to the first observation in Compustat. Prior works including Eisfeldt and Papanikolaou (2013a) provide detailed justification for this procedure. For our analysis, we set $\delta = 0.2$, and in unreported results, we verify that using different values of reasonable depreciation rates do not meaningfully change our conclusions. Lastly, we apply this algorithm to all firms in Compustat from 1950 and begin our sample in 1975.

Intangible assets acquired through a purchase — for instance, by acquiring another firm — are capitalized on the balance sheet as either "Goodwill (item *gdwl*)" or "Other Intangible Assets (item *intano*)," the sum of which is readily available as item *intan*. *intan* is already incorporated into book assets (item *at*), so we do not add this variable to our measure of total assets accounting for intangibles. The goodwill component of *intan* arises when merger values exceed book values by more than the value of identifiable intangible assets, and reflects market values in excess of book values including identifiable intangibles at the time of the merger. We thus subtract goodwill from book equity.

A.2 Comparison to Alternative Intangible Capital Method: PT Method

In a robustness exercise ("PT method"), we follow Peters and Taylor (2017) that break down a firm's intangible capital (INT_{it}) into the sum of two components — *knowledge capital* (e.g. R&D spending) and *organization capital* (e.g. human capital, brand capital, and customer relationships). Here, we use the R&D (item *xrd*) and SG&A (item *xsga*) variables from Compustat to calculate INT^{know} and INT^{org}, respectively. Specifically, we estimate the following for INT^{know}

$$\text{INT}^{know}_{it} = (1-\delta_{R\&D})\text{INT}^{know}_{it-1} + \text{R\&D}_{it}, \tag{7}$$

where INT_{it}^{know} is the stock of knowledge capital, $\delta_{R\&D}$ is an industry-specific depreciation rate for knowledge capital, and $\mathrm{R\&D}_{it}$ is the real expenditures on R&D, which is measured by deflating Compustat item *xrd*. Data on industry-specific depreciation rates are obtained from Li and Hall (2020) and range from 10% to 40%.[18] We initialize $\mathrm{INT}_{i0}^{know} = \mathrm{R\&D}_{i1}/(g + \delta_{R\&D})$ where $g = 0.1$.

The book stock of organization capital, INT^{org}, can be similarly estimated by applying the law of motion

$$\mathrm{INT}_{it}^{org} = (1 - \delta_{SG\&A})\mathrm{INT}_{it-1}^{org} + \theta \mathrm{SG\&A}_{it}, \tag{8}$$

where $\mathrm{SG\&A}_{it}$ is real SG&A expenditure calculated by subtracting xrd from $xsga$ and deflating the resulting stock by the consumer price index. We subtract xrd from $xsga$ because xrd is included in $xsga$ under standard accounting practices. $\delta_{SG\&A}$ is the depreciation rate specific to SG&A expenses, which we assume is 0.2. θ is the investment rate for organization capital, which we set $\theta = 0.3$ following Peters and Taylor (2017). We initialize $\mathrm{INT}_{i0}^{org} = \theta \mathrm{SG\&A}_{i1}/(g + \delta_{SG\&A})$ where $g = 0.1$. We verify that using different values of reasonable depreciation and investment rates do not meaningfully change our results. Finally, the PT measure of total intangible capital is calculated as

$$\mathrm{PTINT}_{it} = \mathrm{INT}_{it}^{know} + \mathrm{INT}_{it}^{org}. \tag{9}$$

A.3 Intangible Value Factor

The key empirical goal of estimating intangible capital is to construct a modified book-to-market equity ratio, which is in turn used to form the Fama and French (1992, 1993) value factor. Book assets serve as a balance sheet benchmark for each firm's intrinsic value, and the ratio between this anchor and the market equity value measures the extent of over- or under-valuation. For our intangibles-adjusted measure of value, we divide $\mathrm{B}_{it}^{\mathrm{INT}}$ computed in Section A.1 by the market value of equity, which is computed as $shrout \times prc$ using data from Center for Research in Security Prices (CRSP).

The intangible value factor is constructed using six annually rebalanced and value-

[18]We apply $\delta = 0.15$ for the majority of SIC codes that are not assigned a specific depreciation rate.

weighted portfolios formed on size and $\mathrm{B^{INT}/M}$. The six portfolios span the combination of two size (Small and Big with cutoff at median market capitalization) and three book-to-market (Value, Neutral, and Growth with book-to-market ratios in the top 30th percentile, between the 30th and 70th percentiles, and the bottom 30th percentile, respectively) portfolios. The *value factor*, commonly abbreviated as HML (High Minus Low), is the average return on the two value portfolios minus the average return on the two growth portfolios. Notably, unlike other works in the literature, we first compute a within-industry measure of HML

$$\mathrm{HML}_{It} = \frac{1}{2}\left(\text{Small Value}_{It} + \text{Big Value}_{It}\right) - \frac{1}{2}\left(\text{Small Growth}_{It} + \text{Big Growth}_{It}\right), \tag{10}$$

where stock returns are measured monthly and I refers to each of the 12 industries classified by Fama and French. Then we compute $\mathrm{HML^{INT}}$ as

$$\mathrm{HML}_t^{\mathrm{INT}} = \sum_{I=1}^{12} w_{It} \times \mathrm{HML}_{It}, \tag{11}$$

where w_{It} is the weight of each industry's total market capitalization. While common in the literature, we do not drop industries such as financials or regulated utilities for our intangible value factor in order to ensure that our method replicates the original Fama and French method as closely as possible. The PT method follows this procedure, the only distinction being the use of $\mathrm{B^{PTINT}}$ in the numerator of the B/M ratio.

A.4 Other Measures of Intangible Value

For our main analyses, we additionally study various alternative measures of intangible value in order to analyze the unique pricing ability of $\mathrm{HML^{INT}}$.

First, $\mathrm{HML^{IME}}$ is a value factor that sorts firms into high and low buckets based on INT/ME instead of $\mathrm{B^{INT}/M}$. This factor isolates the portion of value that is purely attributable to intangible assets. Specifically, we define Value as high-INT/ME and Growth as low-INT/ME and construct six annually rebalanced portfolios for each industry I following the EKP method

$$\text{HML}_{It}^{\text{IME}} = \frac{1}{2}\left(\text{Small Value}_{It} + \text{Big Value}_{It}\right) - \frac{1}{2}\left(\text{Small Growth}_{It} + \text{Big Growth}_{It}\right). \tag{12}$$

The IME factor construction process is also consistent with the EKP method

$$\text{HML}_{t}^{\text{IME}} = \sum_{I=1}^{12} w_{It} \times \text{HML}_{It}^{\text{IME}}, \tag{13}$$

We also introduce HML^{UINT}, which sorts firms on $\text{B}^{\text{INT}}/\text{M}$ but only goes long firms that are *uniquely* in the long leg of HML^{INT} (i.e. not sorted in the long leg of HML^{FF}), and goes short firms that are *uniquely* in the short leg of HML^{INT} (i.e. not sorted in the short leg of HML^{FF}). To construct HML^{UINT}, we identify "unique long" firms as those above the 70th percentile in $\text{B}^{\text{INT}}/\text{M}$ but below the 70th percentile in the distribution of B/M across all industries. An analagous approach is used to identify the "unique short" firms. After identifying this subset of firms, we value-weight the returns of each stock in each leg and construct the long-short portfolio:

$$\text{HML}_{t}^{\text{UINT}} = \sum_{i=1}^{n} w_{it} \times \text{Unique Long}_{it} - \sum_{j=1}^{m} w_{jt} \times \text{Unique Short}_{jt}. \tag{14}$$

Note that HML^{UINT} is not sorted within industries and industry-weighted in the second step because of the lower number of firms included in each leg. For this process, we adhere to the simple sorting and portfolio formation methodology that mimics Fama and French (1992, 1993).

INT-FF is a factor that is simply HML^{INT} minus HML^{FF}. Similarly, IME-FF is HML^{IME} minus HML^{FF}. For these two factors, note that there may be firms sorted into the same long-short legs but with different portfolio weights. We assume an investor can passively buy HML^{INT} (or HML^{IME}) and sell HML^{FF} in exactly offsetting amounts. Moreover, we construct $\text{HML}^{\text{INDFF}}$, which is the Fama and French HML factor that follows our within-industry sorting and weighting methodology.

Lastly, we also create a version of HML^{INT} that drops financials (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+).

B Further Analysis and Robustness Checks

In this section, we study the relative performance of the long and short legs of HML^{INT} and HML^{FF}, and report our main results using various robustness measures of value.

B.1 Further Long and Short Leg Analysis

In this section, we study the relative performance of the long and short legs of HML^{INT} and HML^{FF}. For H^{INT} and L^{INT}, we compute the returns of the long and short leg for each industry, and weight those industry leg returns by industry market cap. H^{FF} and L^{FF} are obtained from Ken French's website. The top panel of Figure B1 shows that on net, the cumulative returns of the long leg of intangible value is higher than the returns of traditional value's long leg. Similarly, the short leg of HML^{INT} consistently underperforms the short leg of HML^{FF}, meaning that the short side of the intangible value strategy is also more profitable (Figure B1, bottom panel). These results together show that the outperformance of intangible value is coming from both the long and short legs, and are not driven by a single leg. However, the long leg's outperformance is more pronounced starting in the 2010s while the short leg's outperformance begins earlier in the 1990s.

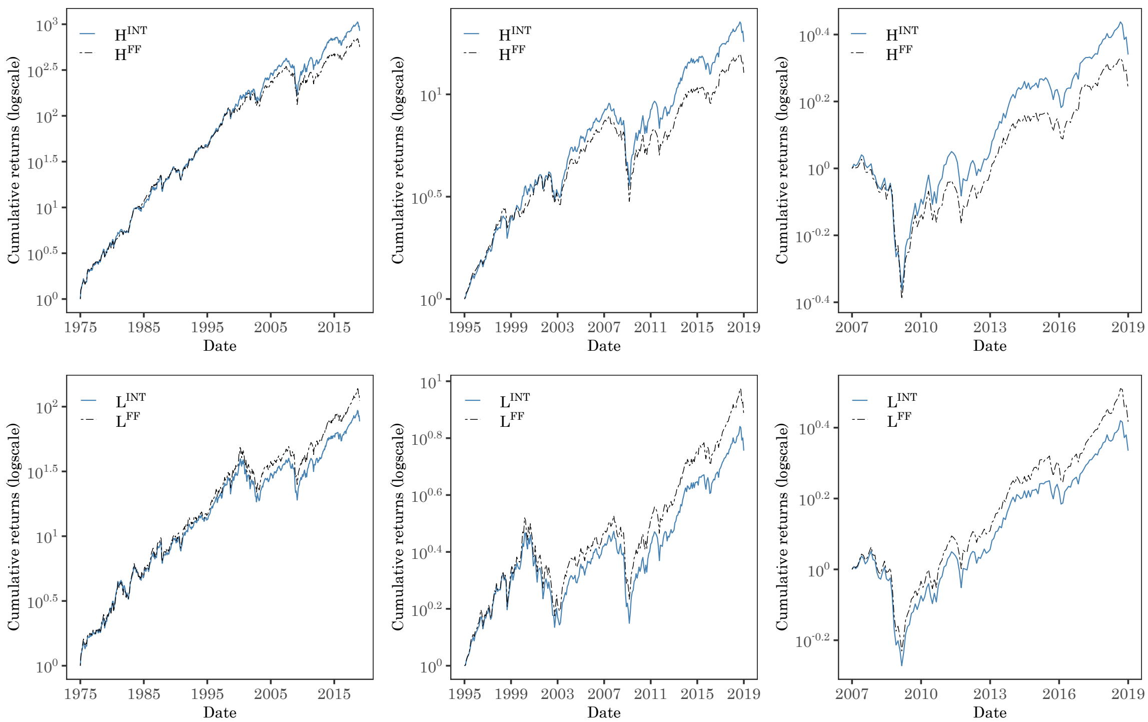

Figure B1: Performance of Long and Short Legs.

Description: The top panel plots cumulative returns of the long leg of HML^{INT} (solid blue line) and the long leg of HML^{FF} (dashed black line). In the bottom panel, we plot the cumulative returns of the short leg of HML^{INT} (solid blue line) and the short leg of HML^{FF} (dashed black line). Each panel plots on a dollar invested in each leg from the beginning of 1975, 1995, and 2007.

B.2 12 Industry Sorts for Traditional Value

In this section, we test whether our main asset pricing and performance results are driven by the within-industry sorting method. As noted in Section 2, we employ two crucial innovations to calculate our value factor – incorporating intangible capital to book value and sorting firms within industries. In this exercise, we replicate the original Fama and French HML factor (full-sample correlation of 98.0%) and create a within-industry sorted version, $\text{HML}^{\text{INDFF}}$. We compare $\text{HML}^{\text{INDFF}}$ to HML^{INT} and reproduce the main results below.

First, we examine the relationship between HML^{INT} and $\text{HML}^{\text{INDFF}}$. Figure B2 shows that the full-period correlation between returns of the two series is 0.89, which is markedly higher than the 0.76 correlation we reported in Figure 1 using HML^{FF}. In Figure B3, we see that the correlation between an unconditionally sorted HML^{INT} and unconditionally sorted HML^{FF} is 0.79. Taken together, both incorporating intangibles *and* sorting firms within industries help provide the variation in our baseline HML^{INT} series.

We reproduce our main regression results and compare the industry-sorted HML^{INT} to industry-sorted HML^{FF}. First, Table B1 shows that industry-adjustment improves the asset pricing performance of $\text{HML}^{\text{INDFF}}$ as seen in the reduction of root mean squared errors in Columns (1) and (3). Moreover, the mean absolute pricing error of the three-factor model plus momentum in Figure B4 is noticeably reduced when using $\text{HML}^{\text{INDFF}}$. This is to be expected given the higher correlation between the $\text{HML}^{\text{INDFF}}$ and HML^{INT}. Despite this, the results are consistent with our observation that HML^{INT} prices assets as well as or better than HML^{FF} or $\text{HML}^{\text{INDFF}}$.

Table B2 shows single factor models that test the outperformance of HML^{INT} over $\text{HML}^{\text{INDFF}}$. While the magnitude is slightly lower, the alpha of HML^{INT} over $\text{HML}^{\text{INDFF}}$ is positive and highly significant (2.16% vs. 3.86% for the baseline using HML^{FF}), consistent with findings in Table 6. Summary statistics on factor returns (Table B3) also confirm that returns of $\text{HML}^{\text{INDFF}}$ are marginally improved when employing the within-industry sorting and weighting methodology (4.06% vs 3.49% for the full sample).

Table B4 displays alphas of the traditional and intangible value factors in the three- and five-factor models plus momentum. We include results for the baseline intangible value factor, and for the two factors that isolate the effect of intangible capital. The alphas for industry-sorted traditional value (Columns (1) and (5)) are negative as in Table 11. For both models, the alpha for $\mathrm{HML}^{\mathrm{INT}}$ is positive and significant. The alphas for $\mathrm{HML}^{\mathrm{IME}}$ are also positive and significant under both models. The intangible value factors all have positive and significant alphas in the three- and five-factor models with momentum, with the exception of $\mathrm{HML}^{\mathrm{UINT}}$, for which the positive alpha in the three-factor model is not significant.

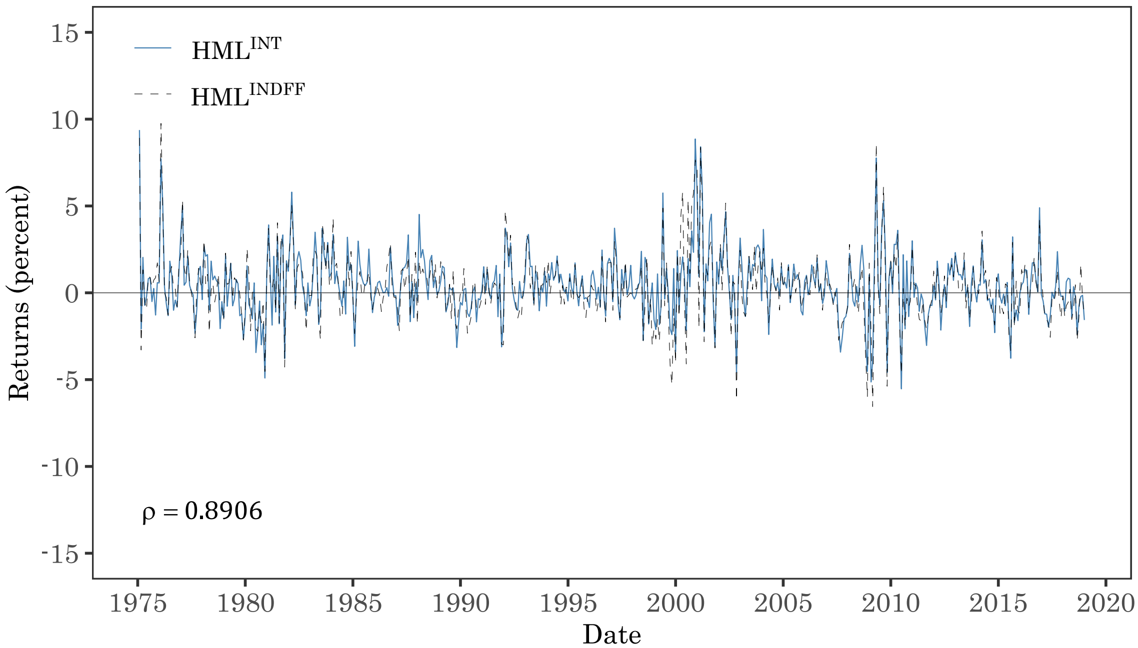

Figure B2: Traditional Value Sorted Within Industries.

Description: This figure plots the monthly returns for $\text{HML}^{\text{INDFF}}$ and HML^{INT} from 1975 to 2018. Firms are sorted within industries for both factors. The HML^{FF} portfolio mimics the risk factor in returns related to book-to-market equity, and is calculated as the difference between the returns on high-B/M portfolios and the returns on low-B/M portfolios.

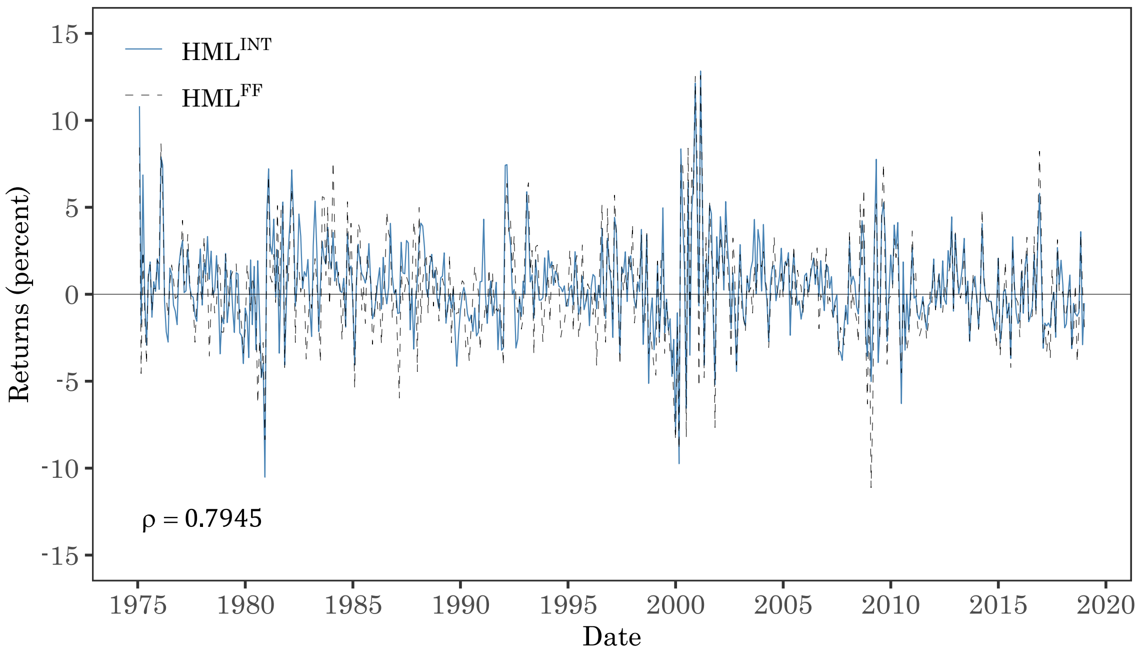

Figure B3: Intangible Value Sorted Across Industries.

Description: This figure plots the monthly returns for HML^{FF} and HML^{INT} from 1975 to 2018. Firms are sorted unconditionally across industries for both factors. The HML^{FF} portfolio mimics the risk factor in returns related to book-to-market equity, and is calculated as the difference between the returns on high-B/M portfolios and the returns on low-B/M portfolios.

	(1)	(2)	(3)	(4)
α (%)	12.93	12.56	9.45	9.12
	(4.14)	(3.94)	(3.18)	(3.06)
β_{MktRF}	-0.36	-0.33	-0.11	-0.08
	(-1.14)	(-1.02)	(-0.35)	(-0.26)
β_{SMB}	0.19	0.19	0.23	0.23
	(1.41)	(1.38)	(1.76)	(1.75)
$\beta_{HML^{\text{INDFF}}}$	0.27		0.26	
	(2.71)		(2.60)	
$\beta_{HML^{\text{INT}}}$		0.29		0.30
		(2.87)		(2.88)
β_{UMD}	0.54	0.55	0.54	0.54
	(2.79)	(2.80)	(2.76)	(2.77)
β_{RMW}			0.32	0.32
			(2.83)	(2.90)
β_{CMA}			0.16	0.16
			(1.74)	(1.69)
Adj. R^2	75.38	75.12	79.49	79.84
RMSE	0.41	0.41	0.33	0.33
Prob $> \chi^2$		0.21		0.41

Table B1: Pricing Errors – Industry-Sorted Traditional Value.

Description: This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models plus momentum. In terms of test assets, columns (1) and (2) use 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Columns (3) and (4) additionally include 10 investment and 10 profitability portfolios. Fama and MacBeth (1973) T-statistics are reported in parentheses. Prob $> \chi^2$ tests the hypothesis that alphas of the models using either intangible or traditional value factors are significantly different. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

	Full sample	1975-1994	1995-2006	2007-2018
	(1)	(2)	(3)	(4)
A. $\mathbf{HML}_t^{\mathbf{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{INDFF}}} \cdot \mathbf{HML}_t^{\mathbf{INDFF}} + \boldsymbol{\epsilon}_t$				
α (%)	2.16	0.94	4.66	1.83
	(4.89)	(1.43)	(5.35)	(2.32)
$\beta_{HML^{\mathrm{INDFF}}}$	0.85	0.89	0.76	0.90
	(33.08)	(27.96)	(13.70)	(23.89)
Adj. R^2	79.27	79.22	77.26	82.30
RMSE	2.97	2.83	3.24	2.77
α/RMSE	0.73	0.33	1.44	0.66
B. $\mathbf{HML}_t^{\mathbf{INDFF}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{INT}}} \cdot \mathbf{HML}_t^{\mathbf{INT}} + \boldsymbol{\epsilon}_t$				
α (%)	-1.19	0.42	-3.38	-1.89
	(-2.43)	(0.64)	(-3.18)	(-2.32)
$\beta_{HML^{\mathrm{INT}}}$	0.94	0.89	1.01	0.92
	(36.45)	(22.76)	(23.21)	(17.20)
Adj. R^2	79.27	79.22	77.26	82.30
RMSE	3.12	2.84	3.73	2.81
α/RMSE	-0.38	0.15	-0.91	-0.68

Table B2: Single Factor Models – Industry-sorted Traditional Value.

Description: In this table, we study the relative performance of the $\mathrm{HML}^{\mathrm{INDFF}}$ and $\mathrm{HML}^{\mathrm{INT}}$ factors. Specifically, we report alphas and betas of a regression of each return on the other, for the full sample as well as for sub-periods around the Internet Bubble and the Great Recession. Firms are sorted within industry first to form the $\mathrm{HML}^{\mathrm{INDFF}}$ factor. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

		Full sample	1975-1994	1995-2006	2007-2018
		(1)	(2)	(3)	(4)
HML$^{\text{INDFF}}$	$\mathbb{E}[R]$	4.06	6.08	5.96	-1.20
		(3.93)	(4.37)	(2.64)	(-0.62)
	σ	6.86	6.23	7.82	6.67
	[0.05, 0.95]	[-31.12, 41.26]	[-26.51, 39.72]	[-33.84, 60.48]	[-32.78, 33.41]
	Sharpe	0.59	0.98	0.76	-0.18
HML$^{\text{INT}}$	$\mathbb{E}[R]$	5.60	6.34	9.21	0.76
		(5.70)	(4.57)	(4.70)	(0.40)
	σ	6.52	6.21	6.78	6.57
	[0.05, 0.95]	[-27.54, 40.43]	[-23.63, 40.17]	[-25.95, 48.42]	[-36.38, 35.93]
	Sharpe	0.86	1.02	1.36	0.12
HML$^{\text{IME}}$	$\mathbb{E}[R]$	6.35	7.02	9.30	2.28
		(6.81)	(5.06)	(5.28)	(1.30)
	σ	6.18	6.21	6.10	6.09
	[0.05, 0.95]	[-26.48, 40.80]	[-25.11, 40.98]	[-20.31, 45.42]	[-35.03, 36.87]
	Sharpe	1.03	1.13	1.53	0.37
HML$^{\text{INT}}$ - HML$^{\text{INDFF}}$	$\mathbb{E}[R]$	1.54	0.26	3.25	1.95
		(3.24)	(0.40)	(3.03)	(2.38)
	σ	3.15	2.91	3.72	2.84
	[0.05, 0.95]	[-14.94, 18.00]	[-15.32, 16.37]	[-14.36, 24.97]	[-10.90, 16.72]
	Information	0.49	0.09	0.88	0.69
	Appraisal	0.73	0.33	1.44	0.66
HML$^{\text{IME}}$ - HML$^{\text{INDFF}}$	$\mathbb{E}[R]$	2.29	0.94	3.34	3.48
		(3.37)	(1.10)	(2.10)	(2.73)
	σ	4.50	3.83	5.51	4.41
	[0.05, 0.95]	[-23.18, 26.83]	[-23.26, 22.40]	[-22.67, 37.23]	[-21.28, 26.83]
	Information	0.51	0.25	0.61	0.79
	Appraisal	0.89	0.58	1.40	0.79

Table B3: Performance Statistics – Industry-sorted Traditional Value.

Description: This table summarizes the risk and return associated with intangible and traditional value. Firms are sorted within industry first to form the HML$^{\text{INDFF}}$ factor. HML$^{\text{INT}}-$HML$^{\text{INDFF}}$ refers to the portfolio that is long HML$^{\text{INT}}$ and short HML$^{\text{INDFF}}$, and HML$^{\text{IME}}-$HML$^{\text{FF}}$ refers to the portfolio that is long HML$^{\text{IME}}$ and short HML$^{\text{INDFF}}$. The numbers in parentheses are T-statistics for the test that the average return, $\mathbb{E}[R]$, is different from zero. The information ratio is $\mathbb{E}[R_p - R_b]/\sigma(R_p - R_b)$, or the Sharpe Ratio of the long-short portfolio. The appraisal ratio is α/RMSE of a regression of intangible value returns (HML$^{\text{INT}}$ or HML$^{\text{IME}}$) on traditional value returns. The underlying data are monthly and the full sample period is 1975 to 2018. All factors are annualized in percent per year.

	HML^{INDFF}	HML^{INT}	HML^{IME}	HML^{UINT}	HML^{INDFF}	HML^{INT}	HML^{IME}	HML^{UINT}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α (%)	-0.77	2.00	3.17	0.63	-0.97	1.65	2.78	2.06
	(-1.44)	(4.11)	(5.19)	(0.48)	(-1.90)	(3.37)	(4.57)	(1.65)
β_{MktRF}	-0.01	0.00	0.01	0.10	0.01	0.02	0.04	0.07
	(-1.03)	(0.00)	(1.14)	(3.71)	(0.73)	(1.69)	(3.01)	(2.53)
β_{SMB}	-0.04	0.06	0.08	0.35	-0.01	0.08	0.10	0.24
	(-1.89)	(3.38)	(4.18)	(5.83)	(-0.68)	(4.81)	(5.18)	(5.46)
$\beta_{HML^{\mathrm{INT}}}$	0.93				0.83			
	(32.57)				(20.86)			
$\beta_{HML^{\mathrm{INDFF}}}$		0.84	0.69	-0.10		0.76	0.57	-0.03
		(32.16)	(20.74)	(-1.37)		(27.03)	(16.13)	(-0.42)
β_{UMD}	-0.03	0.00	0.01	0.01	-0.03	-0.01	-0.00	0.04
	(-2.02)	(0.31)	(0.57)	(0.41)	(-2.80)	(-0.43)	(-0.19)	(1.21)
β_{RMW}					0.03	0.04	0.02	-0.33
					(0.91)	(1.58)	(0.71)	(-4.78)
β_{CMA}					0.15	0.12	0.19	-0.03
					(4.13)	(4.19)	(4.64)	(-0.39)
Adj. R^2	80.00	79,92	60.81	22.88	81.04	80.82	62.71	28.58
RMSE	3.07	2.92	3.87	8.00	2.99	2.86	3.78	7.70

Table B4: Alphas – Industry-sorted Traditional Value.

Description: In this table, we report portfolio alphas and betas of a regression of different variants of HML portfolio returns on traditional factor models. Firms are sorted within industry first to form the HML^{INDFF} factor. Columns (1) through (4) use the Fama and French (1992, 1993) three factor model, and columns (5) through (8) use the Fama and French (2015) five factor model. Both specifications are augmented with the momentum factor. Columns (1) and (5) are benchmarks that set HML^{IME} as the dependent variable and replace the intangibles-adjusted HML factor in the aforementioned models. We include T-statistics that adjust for heteroskedasticity in parentheses. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

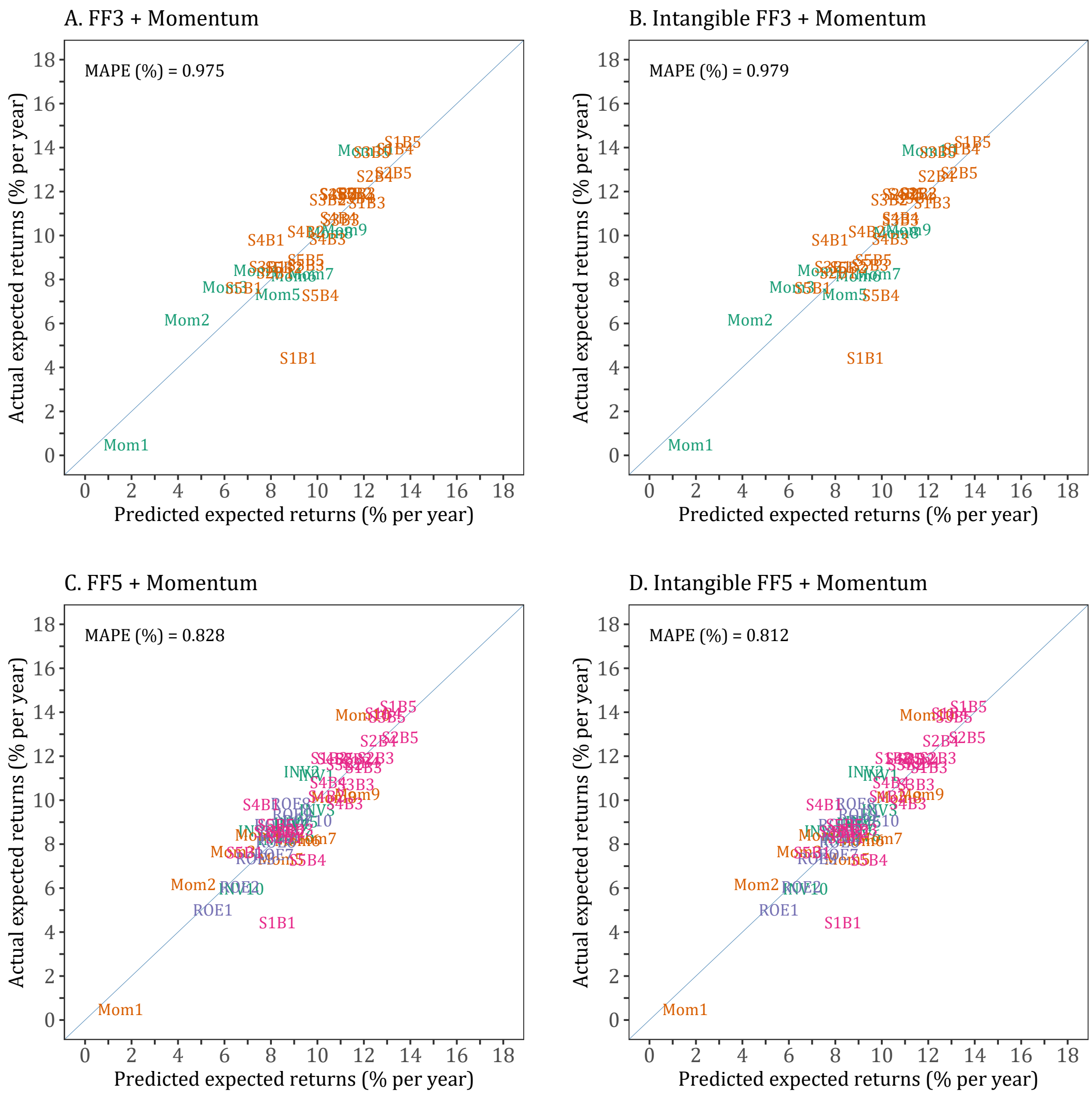

Figure B4: Cross-sectional Asset Pricing Tests – Industry-sorted Traditional Value.

Description: This figure shows the cross-sectional asset pricing tests from the Fama and French (1992, 1993, 2015) three-factor and five-factor models augmented by the momentum factor. The top row plots realized mean excess returns of 25 size and book-to-market-sorted portfolios and 10 momentum portfolios against the mean excess returns predicted by the FF3 + momentum model, where Panel B replaces HML^{INDFF} with HML^{INT}. Firms are sorted within industries for both factors. The bottom row plots realized mean excess returns of 25 size and book-to-market-sorted portfolios, 10 momentum portfolios, 10 portfolios sorted on operating profitability, and 10 portfolios sorted on investment, against the mean excess returns predicted by the FF5 + momentum model. The sample is monthly from 1975 to 2018. Returns are reported in percent per year.

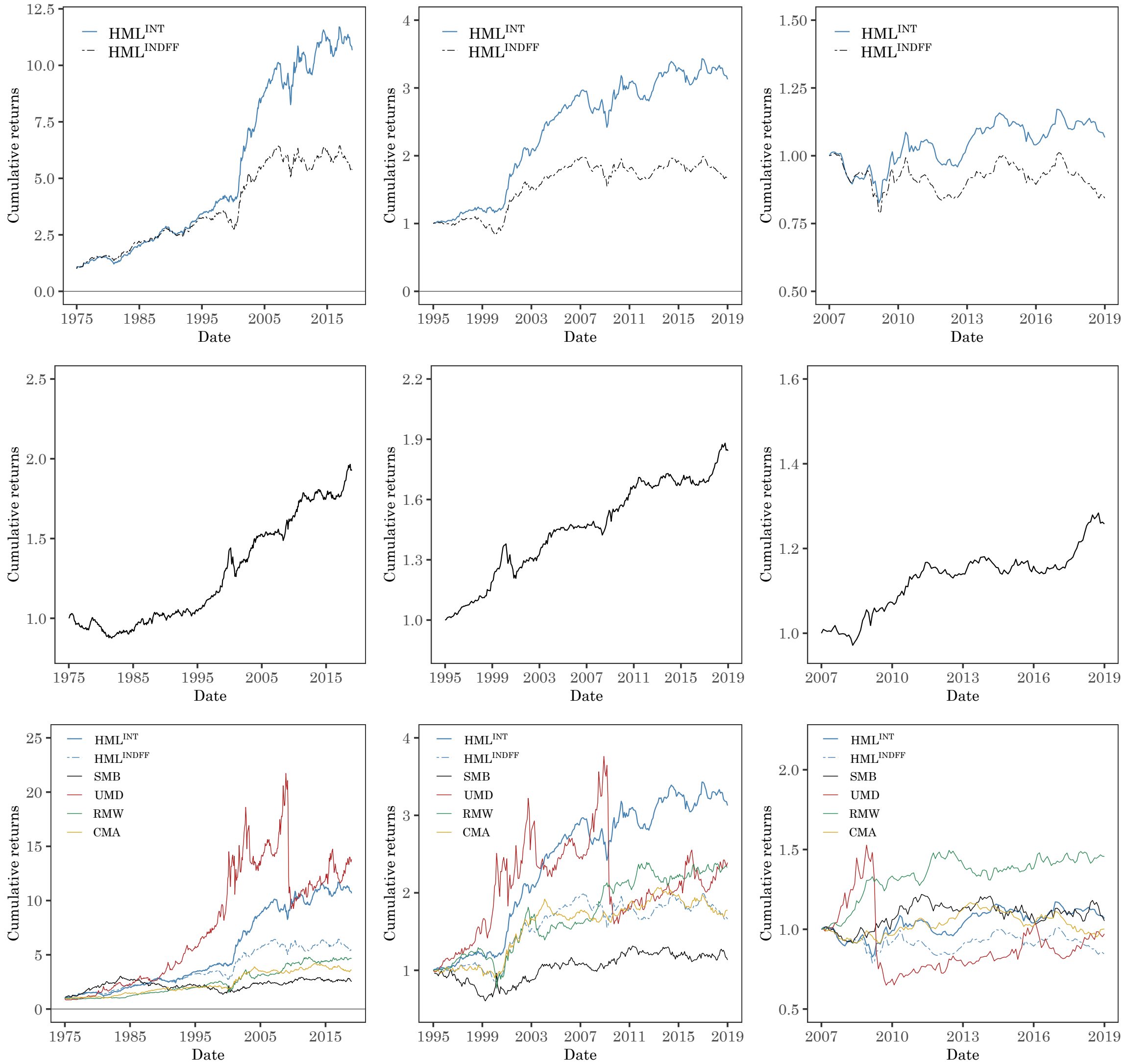

Figure B5: Performance of Industry-sorted Traditional Value.

Description: The top panel plots the cumulative returns of one dollar invested in the $\text{HML}^{\text{INDFF}}$ and HML^{INT} portfolios from the beginning of 1975, 1995, and 2007. The middle panel plots the cumulative returns of one dollar invested in the portfolio that is long the HML^{INT} portfolio and short the $\text{HML}^{\text{INDFF}}$ portfolio. The bottom panel plots the cumulative returns of one dollar invested in HML^{INT}, the Fama and French five factors, and momentum.

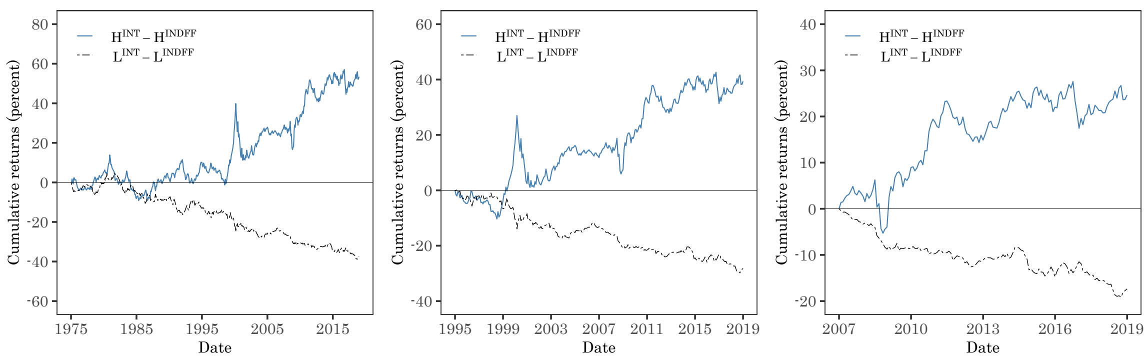

Figure B6: Decomposing Outperformance with Industry-sorted Traditional Value.

Description: This figure plots the cumulative returns of a portfolio that is long the long leg of HML^{INT} and short the long leg of HML^{INDFF} (solid blue line), as well as the returns of a portfolio that is long the short leg of HML^{INT} and short the short leg of HML^{INDFF} (dashed black line). Each panel plots percent returns from the beginning of 1975, 1995, and 2007.

B.3 Industry Filters

In this section, we report our main results after dropping financial firms (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+), as is common in the literature. As our factor construction methodology accounts for industry differences, these filters likely only affect the relative weighting of the remaining industries' HML factors.

Table B5 reproduces the baseline asset pricing test results dropping financials, utilities, and public service firms from the sample. While in general the alphas in models using intangible value are similar to or marginally higher than reported in Table 3, we find that dropping these industries do not materially change the pricing results. In particular, for the three-factor model with momentum, replacing the traditional value factor with the intangible value factor reduces both the alpha and root mean squared error. For the five-factor model with momentum, the alpha and root mean squared error under the two versions of value are largely analogous to results in Table 3.

Table B6 shows single factor models that test the outperformance of intangible value relative to traditional value. Consistent with the main results in Table 6, the alpha of HML^{INT} over HML^{FF} is highly significant for the full sample and earlier sub-periods even after applying the industry filter. In fact, the magnitude of the alphas are notably higher when dropping these industries (e.g. 4.66% vs 3.86% for the full sample). These results are further corroborated by the improved performance statistics of HML^{INT}, HML^{IME}, HML^{INT}-HML^{FF}, and HML^{IME}-HML^{FF} in Table B7. Figure B7 visually shows the marked outperformance of HML^{INT} (solid blue line in top and bottom panels) when applying the industry filters. While the R^2 drop slightly, the portfolio alphas and betas reported in Table B8 are also mostly unchanged.

	(1)	(2)	(3)	(4)
α (%)	13.28	12.55	8.59	9.25
	(4.15)	(3.95)	(2.89)	(3.09)
β_{MktRF}	-0.38	-0.33	-0.04	-0.09
	(-1.18)	(-1.03)	(-0.12)	(-0.30)
β_{SMB}	0.18	0.19	0.24	0.23
	(1.36)	(1.40)	(1.78)	(1.75)
$\beta_{HML^{\text{FF}}}$	0.30		0.24	
	(2.35)		(1.92)	
$\beta_{HML^{\text{INT}}}$		0.33		0.33
		(2.82)		(2.73)
β_{UMD}	0.54	0.55	0.53	0.54
	(2.79)	(2.79)	(2.74)	(2.76)
β_{RMW}			0.32	0.32
			(2.87)	(2.88)
β_{CMA}			0.18	0.16
			(1.95)	(1.79)
Adj. R^2	73.14	74.93	78.74	79.46
RMSE	0.43	0.42	0.34	0.33
Prob $> \chi^2$		0.20		0.17

Table B5: Pricing Errors – Excluding Utilities, Financials, and Public Service Firms.

Description: This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. When forming the HML$^{\text{INT}}$ portfolio, we drop financial firms (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+). In terms of test assets, columns (1) and (2) use 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Columns (3) and (4) additionally include 10 investment and 10 profitability portfolios. Fama and MacBeth (1973) T-statistics are reported in parentheses. Prob $> \chi^2$ is the p-value of the test that the alpha from the model using HML$^{\text{INT}}$ is significantly different from the alpha from the model using HML$^{\text{FF}}$. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

	Full sample	1975-1994	1995-2006	2007-2018
	(1)	(2)	(3)	(4)
A. $\mathbf{HML}_t^{\mathbf{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{FF}}} \cdot \mathbf{HML}_t^{\mathbf{FF}} + \boldsymbol{\epsilon}_t$				
α (%)	4.66	4.56	7.21	2.85
	(6.29)	(4.58)	(4.87)	(1.82)
$\beta_{HML^{\mathrm{FF}}}$	0.51	0.52	0.46	0.58
	(17.06)	(11.70)	(8.65)	(9.24)
Adj. R^2	51.32	51.01	51.72	50.31
RMSE	4.98	4.60	5.19	5.27
α/RMSE	0.94	0.99	1.39	0.54
B. $\mathbf{HML}_t^{\mathbf{FF}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{INT}}} \cdot \mathbf{HML}_t^{\mathbf{INT}} + \boldsymbol{\epsilon}_t$				
α (%)	-2.96	-2.00	-4.86	-3.84
	(-2.74)	(-1.30)	(-1.92)	(-2.07)
$\beta_{HML^{\mathrm{INT}}}$	1.99	0.99	1.14	0.87
	(19.50)	(15.47)	(12.03)	(8.69)
Adj. R^2	51.32	51.01	51.72	50.31
RMSE	6.94	6.36	8.20	6.42
α/RMSE	-0.43	-0.31	-0.59	-0.60

Table B6: Single Factor Models – Excluding Utilities, Financials, and Public Service Firms.

Description: In this table, we study the relative performance of the $\mathrm{HML}^{\mathrm{FF}}$ and $\mathrm{HML}^{\mathrm{INT}}$ factors. When forming the $\mathrm{HML}^{\mathrm{INT}}$ portfolio, we drop financial firms (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+). We report alphas and betas of a regression of each return on the other, for the full sample as well as for sub-periods around the Internet Bubble and the Great Recession. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

		Full sample	1975-1994	1995-2006	2007-2018
		(1)	(2)	(3)	(4)
	$\mathbb{E}[R]$	3.49	5.14	6.99	-2.77
		(2.33)	(2.53)	(2.05)	(-1.05)
HML$^{\mathbf{FF}}$	σ	9.95	9.08	11.80	9.11
	[0.05, 0.95]	[-48.36, 63.24]	[-45.72, 63.12]	[-55.92, 78.24]	[-44.04, 48.84]
	Sharpe	0.35	0.57	0.59	-0.30
	$\mathbb{E}[R]$	6.46	7.22	10.40	1.23
		(6.00)	(4.91)	(4.82)	(0.57)
HML$^{\mathbf{INT}}$	σ	7.14	6.58	7.48	7.48
	[0.05, 0.95]	[-29.78, 41.67]	[-23.24, 41.06]	[-22.13, 53.5]	[-44.31, 39.12]
	Sharpe	0.90	1.10	1.39	0.16
	$\mathbb{E}[R]$	6.68	7.28	9.73	2.64
		(6.88)	(5.19)	(4.90)	(1.49)
HML$^{\mathbf{IME}}$	σ	6.44	6.27	6.87	6.13
	[0.05, 0.95]	[-25.67, 43.40]	[-23.80, 42.22]	[-20.34, 46.91]	[-31.91, 33.58]
	Sharpe	1.04	1.16	1.42	0.43
	$\mathbb{E}[R]$	2.97	2.08	3.41	4.00
		(2.84)	(1.47)	(1.43)	(2.14)
HML$^{\mathbf{INT}}$	σ	6.94	6.35	8.24	6.48
- HML$^{\mathbf{FF}}$	[0.05, 0.95]	[-35.49, 40.01]	[-33.31, 39.27]	[-39.66, 49.29]	[-31.82, 34.57]
	Information	0.43	0.33	0.41	0.62
	Appraisal	0.94	0.99	1.39	0.54
	$\mathbb{E}[R]$	3.19	2.13	2.73	5.40
		(2.78)	(1.39)	(1.05)	(2.58)
HML$^{\mathbf{IME}}$	σ	7.60	6.87	8.98	7.27
- HML$^{\mathbf{FF}}$	[0.05, 0.95]	[-40.89, 44.53]	[-39.84, 38.67]	[-51.31, 53.18]	[-37.27, 40.43]
	Information	0.42	0.31	0.30	0.74
	Appraisal	1.06	1.04	1.35	0.77

Table B7: Performance Statistics – Excluding Utilities, Financials, and Public Service Firms.

Description: This table summarizes the risk and return associated with intangible and traditional value. When forming the HML$^{\text{INT}}$ portfolio, we drop financial firms (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+). HML$^{\text{INT}}-$HML$^{\text{FF}}$ refers to the portfolio that is long HML$^{\text{INT}}$ and short HML$^{\text{INT}}$, and HML$^{\text{IME}}-$HML$^{\text{FF}}$ refers to the portfolio that is long HML$^{\text{IME}}$ and short HML$^{\text{INT}}$. The numbers in parentheses are T-statistics for the test that the average return, $\mathbb{E}[R]$, is different from zero. The information ratio is $\mathbb{E}[R_p - R_b]/\sigma(R_p - R_b)$, or the Sharpe Ratio of the long-short portfolio. The appraisal ratio is α/RMSE of a regression of intangible value returns (HML$^{\text{INT}}$ or HML$^{\text{IME}}$) on traditional value returns. The underlying data are monthly and the full sample period is 1975 to 2018. All factors are annualized in percent per year.

	HML^{FF}	HML^{INT}	HML^{IME}	HML^{UINT}	HML^{FF}	HML^{INT}	HML^{IME}	HML^{UINT}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α (%)	-1.20	3.50	4.24	2.03	-1.56	2.59	3.35	0.80
	(-1.19)	(4.92)	(5.85)	(1.15)	(-1.64)	(3.73)	(4.75)	(0.43)
β_{MktRF}	-0.11	0.05	0.03	0.06	-0.05	0.08	0.07	0.09
	(-5.94)	(3.62)	(2.29)	(1.63)	(-2.48)	(5.57)	(4.33)	(2.30)
β_{SMB}	-0.27	0.21	0.18	0.42	-0.22	0.23	0.20	0.48
	(-8.81)	(10.07)	(8.23)	(7.63)	(-6.67)	(9.48)	(8.40)	(8.28)
$\beta_{HML^{\mathrm{INT}}}$	1.04				0.79			
	(22.25)				(12.78)			
$\beta_{HML^{\mathrm{FF}}}$		0.58	0.47	0.22		0.46	0.34	0.13
		(22.83)	(16.28)	(3.52)		(14.77)	(10.11)	(1.79)
β_{UMD}	-0.06	-0.01	0.00	-0.05	-0.07	-0.02	-0.02	-0.07
	(-1.95)	(-0.21)	(0.19)	(-0.97)	(-3.06)	(-0.98)	(-0.89)	(-1.43)
β_{RMW}					0.02	0.10	0.08	0.20
					(0.56)	(2.99)	(2.22)	(2.26)
β_{CMA}					0.44	0.25	0.27	0.16
					(7.03)	(5.65)	(5.27)	(1.34)
Adj. R^2	65.34	62.71	51.42	15.23	69.67	65.75	55.44	16.46
RMSE	5.86	4.36	4.49	11.09	5.48	4.18	4.30	11.01

Table B8: Alphas – Excluding Utilities, Financials, and Public Service.

Description: In this table, we report portfolio alphas and betas of a regression of different variants of HML portfolio returns on traditional factor models. When forming the HML^{INT} portfolio, we drop financial firms (SIC codes 6000-6999), regulated utilities (4900-4999), and firms categorized as public service, international affairs, or non-operating establishments (9000+). Columns (1) through (4) use the Fama and French (1992, 1993) three factor model, and columns (5) through (8) use the Fama and French (2015) five factor model. Both specifications are augmented with the momentum factor. Columns (1) and (5) are benchmarks that set HML^{IME} as the dependent variable and replace the intangibles-adjusted HML factor in the aforementioned models. We include T-statistics that adjust for heteroskedasticity in parentheses. The sample is monthly from January 1975 to December 2018. All coefficients are reported in percentage per year (monthly percentages multiplied by twelve).

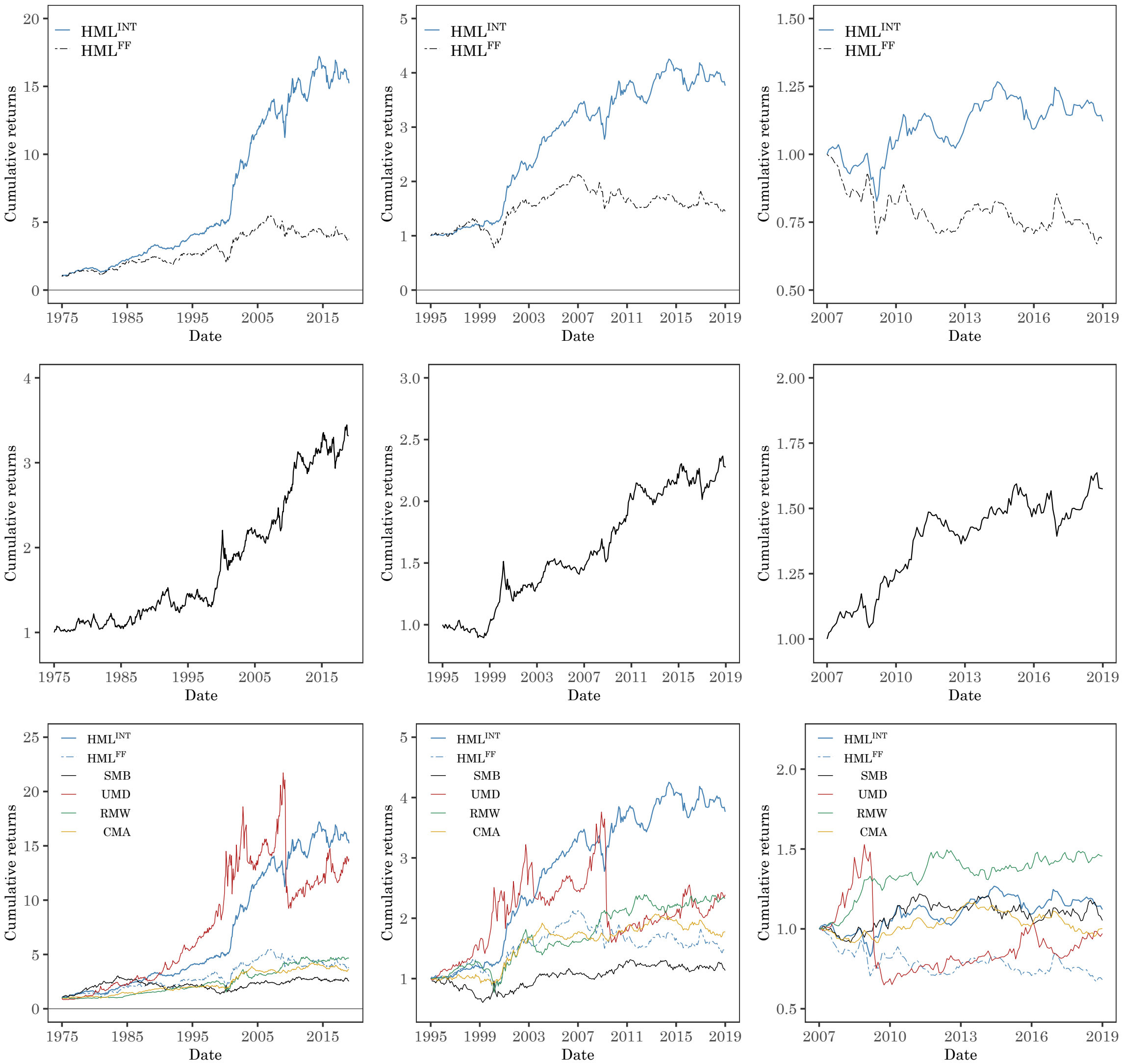

Figure B7: Performance of Intangible Value with Industry Filters.

Description: This figure plots the performance of HML^{INT} that is formed after dropping financials, utilities, and public service firms from the sample. The top panel plots the cumulative returns of one dollar invested in the HML^{FF} and HML^{INT} portfolios from the beginning of 1975, 1995, and 2007. The middle panel plots the cumulative returns of one dollar invested in the portfolio that is long the HML^{INT} portfolio and short the HML^{FF} portfolio. The bottom panel plots the cumulative returns of one dollar invested in the factors from the three- and five-factor models plus momentum, along with the the HML^{FF} and HML^{INT}.