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Andrea L. Eisfeldt
Edward Kim
Dimitris Papanikolaou

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ABSTRACT

Intangible assets are absent from traditional measures of value, despite their very large (and growing) importance in firms' capital stocks. As a result, the fundamental anchor for value that uses book assets is mismeasured. We propose a simple improvement to the classic value factor (HML^{FF}) proposed by Fama and French (1992, 1993). Our intangible value factor, HML^{INT}, prices assets as well as or better than the traditional value factor but yields substantially higher returns. This outperformance holds over the entire sample, as well as in more recent decades in which value has underperformed. We show that this is likely due to the intangible value factor sorting more effectively on productivity, profitability, financial soundness, and on other valuation ratios such as price to earnings or price to sales.

Andrea L. Eisfeldt
UCLA Anderson School of Management
110 Westwood Plaza
Suite C4.10
Los Angeles, CA 90095
and NBER
andrea.eisfeldt@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

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

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 an 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 (see Conrad et al. (2003)). However, the value factor has underperformed for at least a decade.[1] We argue that one driver of the poor performance of value during this period is the deteriorating quality of book assets as a fundamental anchor due to the increasing importance of intangible assets.

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 (2019) 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 investment in employee, brand, and knowledge capital that is expensed. Thus, most intangible assets do not appear on corporate balance sheets, resulting 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.[2] The only difference is that we add intangible assets to the book equity of each firm, which is widely used as the traditional value anchor.[3]

In particular, following Eisfeldt and Papanikolaou (2013b), we measure firm-level stocks of intangible assets by applying the perpetual inventory method to flows of Selling, General, and Administrative (SG&A) expenses, given assumptions about

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

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

[3] 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).

depreciation and initial values. Eisfeldt and Papanikolaou (2013b) builds on two seminal contributions in measuring intangible assets. Corrado, Hulten, and Sichel (2009) uses 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 by constructing and analyzing the first 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 the selling and general administrative expense as a measure of intangible investment.[5] Measures of intangible assets using accumulated SG&A are also supported by the subsequent findings in Eisfeldt and Papanikolaou (2014), Zhang (2014), Falato, Kadyrzhanova, and Sim (2013), and Peters and Taylor (2017).

Our intangible value factor HML^{INT} has the following features: (1) It is highly correlated with HML^{FF} (81%), (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 2.4% annually, with a standard deviation of only 5.9%. Thus, HML^{INT} has an information ratio of 0.40% with respect to HML^{FF} (equivalently, the long-short portfolio's Sharpe ratio is 40%). 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 only 65%, and the alpha of intangible value in a single traditional value factor model is 3.32%.

We examine in detail the potential drivers of the ability of intangible value to price standard test assets as well as the traditional value factor, and its substantial

[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.

outperformance. We show that an intangible value factor that is first sorted within industries performs just as well against the traditional value factor, even when traditional value is sorted across all industries. This is important, since accounting practices for allocating costs to SG&A vs. Cost of Goods Sold (COGS) vary systematically across industries. Despite this, we find little difference in our results when sorting first within industry, or sorting across industries unconditionally.

We 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 going long only firms that are uniquely in the long leg of HML^{INT} (specifically, not in the long leg of HML^{FF}), and short firms that are uniquely in the short leg. These more isolated measures of intangible value continue to price standard test assets better than traditional value, and the HML^{IME} portfolio has positive and significant alphas in the three and five factor models plus momentum.

We also document important differences in firm characteristics between firms in the long (and short) legs of intangible vs. 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 and sales to price ratios (thus better valuation metrics by non-book measures), higher profits to assets, and lower debt to earnings.

The implications for our findings are: First, asset pricing researchers should consider correcting book equity for intangibles, since 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, but has higher average returns, and lower volatility. Finally, an active manager can implement a relative value strategy by going long HML^{INT} and short HML^{FF}. As noted, this strategy has a Sharpe ratio of 0.40. Importantly, this strategy has experienced good performance even in recent years, when traditional value has severely underperformed.

The most closely related paper to ours is Park (forthcoming), of which we were made aware upon circulating this paper. Because the two papers developed independently, the methodologies are fairly dissimilar. Park (forthcoming) connects more to the accounting literature, whereas our work ties in more closely to the asset pricing literature in finance. Our paper also makes substantially new contributions relative to that study, and in general the two studies are complementary. First, we show that the success of the intangible value factor does not depend on an unconditional sort. Because the accounting treatment for SG&A vs. Cost of Goods Sold (COGS) varies across industries, it is critical to verify that the asset pricing results hold using within-industry sorts. We also investigate the differences between traditional and intangible value in more detail, by studying portfolios sorted only on intangible assets to market equity values, and portfolios which consist only of the firms that are uniquely in the long or short leg of intangible value (i.e. not in the same respective leg of traditional value). We provide robustness checks including varying the fraction of SG&A that is considered investment in intangibles, and we show that our results are robust to either including or dropping particular industries such as finance or high-tech.

We examine the contribution of the long and short legs of intangible value in contributing to its outperformance, and provide examples of how the intangible value portfolio avoids "value traps" and avoids shorting low book to market firms whose book values don't 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, for example, the substantial differences in productivity. This paper also documents the difference between the intangible value factor and the organization capital factor in Eisfeldt and Papanikolaou (2013b), since the organization capital factor 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 book to market values of equity. As a result, the intangible value portfolio bears little relation 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 3.32% 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 as the alpha relative to the root mean squared pricing error is a reasonable 0.62. 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. And, this subsample is of substantial interest because it is also the prolonged period during which the performance of traditional value has been particularly poor.

In addition to these new contributions and refinements, our study is more comparable to that of the classic work of Fama and French (1992, 1993) because, unlike Park (forthcoming), we 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 construction. 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 within industries, and 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 Data

We use the Center for Research Security Prices (CRSP) - Compustat dataset from Wharton Research Data Services (WRDS) to construct HML^{INT}. We use HML^{FF} as well as other factors and test asset returns posted by Ken French.[6] First, we replicate the posted series using the procedure described in Fama and French (1992, 1993). Our replicated series has a correlation with the original series of 97.5%. This replicated series is the starting point for HML^{INT}. To construct HML^{INT}, we add intangible

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

assets to book equity, i.e.

$$B_{it}^{\text{INT}} = B_{it} + \text{Int}_{it}, \tag{1}$$

where B_{it} is book equity, and Int_{it} is intangible assets.[7] Int_{it} is computed using the perpetual inventory method as:

$$\text{Int}_{it} = (1 - \delta)\text{Int}_{it-1} + \theta SG\&A_{it} \tag{2}$$

We initialize $\text{Int}_{it} = SG\&A_1/(g + \delta)$ using the observation for selling and general administrative expenses when the firm first appears in Compustat. We set $g = 0.1$, which is the average growth rate for SG&A in our sample, and $\delta = 0.2$ as in Eisfeldt and Papanikolaou (2014). Our baseline results set $\theta = 1$, and we show in the Online Appendix that our main results are unchanged if we follow the alternative convention of separately setting $\theta = 0.3$ for SG&A minus R&D expenditures and $\theta = 1$ for R&D expenditures. As some of the expenditure line items are not readily reported in earlier years, we study the sample period beginning in January 1975 and ending in December 2018. Further details on data construction can be found in Appendix A.

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}) factor portfolios 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 81%. 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 asset pricing test results and performance.

Table 1 presents the baseline asset pricing test results. The first two columns present the results for the Fama and French (1992, 1993) model plus momentum using the traditional value factor (column one) and the intangible value factor (column two). 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 14%, and reduces the root mean squared error by 9%. Panels A

[7] Note that in order to focus on internally generated intangible capital, we subtract goodwill from the Fama and French measure of book equity. For more details, see Appendix 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 5%. The figure shows that the intangible value model doesn't improve the asset pricing results by pricing any one portfolio substantially better, but instead appears to improve the pricing of most of the test portfolios.

The last two columns of Table 1 display the results for the Fama and French (2015) five-factor model plus momentum model, which adds the conservative minus aggressive (CMA) investment factor, and the robust minus weak (RMW) profitability factor. For this model, we also include the investment (CMA) and profitability (RMW) portfolios as additional test assets. In the five factor model with momentum, the traditional value factor becomes insignificant, while the intangible value factor retains significance at over the 1% level. Root mean squared errors are also smaller using HML^{INT}. 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 a better job of pricing standard test assets when used in both the classic three factor model, and the recent five factor model.

Figure 1 shows that there is a lot of commonality between the traditional and intangible value portfolios. To further draw out the unique pricing ability of intangible value, we construct two more distinct intangible value portfolios. The first, HML^{IME}, sorts firms only based on intangible assets relative to market equity values. Table 2 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. For the three factor model plus momentum, the traditional value factor becomes insignificant when HML^{IME} is included. However, there is a slight reduction in root mean squared errors achieved by including both HML^{FF} and HML^{IME}. This is not true, however, for the five factor model plus momentum. In that model, HML^{FF} both becomes insignificant when HML^{IME} is included, and has no effect on root mean squared errors when both are included.

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 22% of firms are used to construct HML^{INT}, 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. Table 3 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. Since this portfolio is even less correlated with HML^{FF}, both factors retain their significance when they are included together. Interestingly, the pricing errors for HML^{UINT} on its own are roughly the same (slightly lower) than the model with traditional value.

The results thus far utilize unconditional sorts, across all industries, for both traditional and intangible value, as is standard in most of the literature, and consistent with the Fama and French data library construction. However, as noted in Eisfeldt and Papanikolaou (2013b), because the allocation of various costs to SG&A vs. Cost of Goods Sold (COGS) varies across industries, it is important to study the results for HML^{INT} using sorts done first within industry using the method described in Eisfeldt and Papanikolaou (2013b). Table 4 presents the results. The main takeaway from this table is that despite putting HML^{INT} on unequal footing relative to HML^{FF} by requiring the book-to-market value sorts to occur at the industry level, the models using within industry sorted HML^{INT} performs just as well as the models using traditional value. In the remainder of the main text, we use unconditional sorts for our portfolios so that traditional and intangible value are treated symmetrically, and in line with the vast majority of prior studies of cross sectional asset pricing models.

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.[8] In the Online Appendix, we present our main results without financials, utilities, and industries with SIC codes above 9000 (including the analog of Table 1). 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 than the traditional value factor. This is true despite the fact that the book-to-market test asset portfolios are formed using the traditional book-to-market measure. It is true even when the intangible value factor is sorted on total book (intangible plus recorded) to market equity first within industries prior to value weighting each leg of

[8]Several studies of the cross section of equity returns drop financials, utilities, and industries with SIC codes above 9000. However, when following the Fama and French methodology to replicate their factor portfolios, the replication is substantially better when all industries are included. Thus, we believe that the posted factors and test assets cover all industries and did not find any documentation suggesting otherwise.

the HML$^{\text{INT}}$ portfolio. And, when decomposing value into its traditional and intangible components using either HML$^{\text{IME}}$ (which sorts firms into high and low book-to-market terciles based only on intangible assets relative to market equity values) or HML$^{\text{UINT}}$ (which only includes stocks that are uniquely in either the long or short leg of HML$^{\text{INT}}$), we find that these more isolated intangible value portfolios alone produce smaller pricing errors than traditional value. We conclude that intangible value appears to capture the value effect even better than traditional value, consistent with the idea that including intangibles improves the quality of the book value anchor.

4 Intangible vs. Traditional Value: Performance

Figure 1 shows that the traditional and intangible value factors are highly correlated, and we also reported superior pricing errors for the model with intangible value as well as its several variants. In this section, we show that there is enough independent variation to allow for substantial outperformance by the intangible value factor.

Table 5 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$^{\text{INT}}$ regressed on the HML$^{\text{FF}}$ factor. We present results for the full sample, and for subsamples covering the pre-internet era from 1975-1994, the internet era pre-crisis from 1995-2006, and the post-crisis era from 2007 to 2018. The alpha of HML$^{\text{INT}}$ over HML$^{\text{FF}}$ is highly significant and 3.32% in the full sample. This is sizable, given the apparent close relationship between the two factors. However, it is also reasonable, as the α/RMSE is 0.62%. Interestingly, the alpha is fairly stable over time, and is significant in all subsamples. In the Online Appendix, we present results for the alternative methodologies of sorting within industries, dropping financials, utilities, and firms with SIC codes greater than 9000, as well as using the $\theta = 0.3$ convention for the fraction of SG&A that is investment in intangibles. Sorting within industries when forming intangible value, we find that intangible value outperforms traditional value by about the same amount in the full sample. The pattern over time is also interesting, as the intangible value portfolio formed by sorting within industries first has stronger outperformance in recent subsamples. Dropping industries has a different effect. While again intangible value outperforms traditional value by about the same amount in the full sample, the outperformance first increases in the pre-crisis internet era, but then drops significantly in the post crisis era. While we use unconditional sorts to put intangible and traditional value on equal footing in our baseline analysis, these results underscore the importance of within industry sorts when using accounting variables such as SG&A that are treated somewhat differently across industries. Using 30% of SG&A to form the intangible capital stock, vs. 100% marginally reduces the outperformance in all subsamples.

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 negative, and significant at the 5% level for the full sample. Looking at the subsamples, however, the fourth column shows that the most significant underperformance of HML^{FF} relative to HML^{INT} comes in the recent period, from 2007-2018. The recent underperformance is notable because the post-crisis era has been one of the worst periods for the traditional value strategy, and this evidence suggests that the intangible strategy did significantly better, by 3.26%.

Table 6 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 to traditional value, as indicated by the lower R^2 as compared to Table 5. The full sample alphas are larger for both the portfolio that sorts firms only based on intangible assets relative to market equity values, and the portfolio that only includes the firms that are uniquely in either leg of intangible value. Indeed, the alpha for HML^{IME} is larger in each subsample as well, however neither portfolio has a significant alpha over traditional value in the most recent period, post financial crisis. Instead, as for the baseline intangible value portfolio, the outperformance appears to be strongest in the pre-crisis internet era from 1995 to 2006.

In prior work, 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 7 clearly shows that the intangible value factor is quite different from the organization capital factor, and, in addition, that traditional value is also quite unrelated to 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 0.5%. Likewise, for traditional value, the R^2 in the analogous regression is 3.5%. We conclude that the intangible value factor is very different from the organization capital factor both in terms of conceptual purpose and return dynamics.

Table 8 displays performance statistics for HML^{FF}, HML^{INT}, a portfolio which is long HML^{INT} and short HML^{FF}, and a portfolio that is long the firms that are uniquely in the long leg of intangible value as well as firms that are uniquely in the short leg of traditional value, and short firms that are uniquely in the short leg of intangible value as well as firms that are uniquely in the long leg of traditional value. We show results for average returns, volatility, confidence intervals, Sharpe ratios, information and appraisal ratios, using intangible value for the traditional value benchmark and vice versa. The top panel shows that the traditional long-short value factor had a statistically significantly positive return over the full sample, but the significance is mainly driven by the earliest subsample, the pre-internet era from 1975-1994. In no other subsample are the returns significantly positive at more than a 10% level, and in fact, the average returns to HML^{FF} are (insignificantly) negative in the most recent subsample, from 2007-2018. The information and appraisal ratios with respect to intangible value are negative, as expected, and fairly large in magnitude (-0.40 and -0.30 for the information and appraisal ratios, respectively, over the full sample). In contrast, the average returns to intangible value are larger in magnitude and significance over the full sample, and the positive returns remain large and significant through 2006. In the most recent sample, average returns are only insignificantly positive. However, HML^{INT} still significantly outperforms HML^{FF}, and as we saw in Table 5 this outperformance actually increases in recent years. Consistent with this, the information and appraisal ratios are large (0.40 and 0.63 respectively for the full sample).

The second to last panel displays portfolio performance statistics for the long intangible value, short traditional value strategy. This strategy has a 2.4% average return over the full sample, which is significant at the 1% level, and it has a Sharpe (1966) ratio of 0.40. Moreover, the performance of this strategy has been improving over time, and most of the significance actually comes from the most recent sample when traditional value underperformed. During the 2007-2018 sample, the Sharpe ratio of the long-short strategy is 0.70. Differences between intangible and traditional value can arise either from the intensive margin of different weighting of firms that appear in the same leg of both portfolios, or from the extensive margin of inclusion or exclusion in a particular leg. The bottom panel examines the role of the extensive margin in driving the outperformance of intangible value by forming a portfolio that focuses on the unique contributors to each leg of the two value factors. While the excess return of this portfolio is just short of significance at the 5% level in the full and most recent samples, the magnitude of the outperformance is particularly large in the recent sample.

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 more recent subsample. The middle panel plots the cumulative returns to the portfolio that is long HML^{FF}, and short HML^{INT}. Again, the outperformance of HML^{INT} is apparent. In terms of the subsamples, it appears the post-internet era was an important driver of the outperformance, but so was the post-crisis era, in 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 for comparison. Over the full sample, the intangible value factor's performance is of a very similar magnitude to the best performing factor, UMD, or momentum, and is far superior to any other factor in the Fama and French (2015) five factor model. In the sample since 1995, the intangible value factor displays the highest performance of any of the long-short portfolios. In the most recent sample, post crisis, 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. Two interesting findings emerge from these plots, which we present for the full sample as well as for the post internet subsample and the post-crisis subsample. First, we note 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. Second, and consistent with this, the outperformance of intangible value in recent years appears to be largely driven by the difference in performance of the short legs. This evidence supports the idea that intangible value avoids shorting firms with book anchors that understate total book capital by excluding intangibles.

Table 9 displays the results for the 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 both models, the alpha for traditional value is negative, and insignificant. In the three factor model plus momentum, the alpha for HML^{INT} is 2.79%, and statistically significant at the 1% level. The alpha for HML^{IME}, which is the ratio of intangible assets to market equity is 3.91%, and significant at the 1% level. The alpha for HML^{UINT}, which only contains stocks unique to the HML^{INT} long or short leg, is positive but insignificant. We note that the loading of HML^{FF} on the market factor is negative and significant, whereas HML^{INT} is market-neutral.

In the five factor model plus momentum, the HML^{IME} alpha is 2.58% and remains significant at the 1% level. All of the other alphas are insignificant. This may not be surprising as Fama and French (2015) note that the original value factor becomes redundant when the investment and profitability factors are added, although, as shown in Table 1, this is not true for HML^{INT}. Indeed, although the loadings of both traditional and intangible value on the conservative less aggressive investment factor (CMA) are both positive, the loading for traditional value on the robust minus weak profitability factor (RMW) is negative, meaning that traditional value is correlated with the returns to firms with relatively weaker profitability. In contrast, the intangible value factor, and the two factors that decompose intangible value, all load positively on the profitability factor. 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 9 that the intangible value factor has a significantly positive alpha in the three factor model plus momentum, and that the portfolio of intangible capital to market equity, which isolates the effect of intangible value, has a significantly positive alpha in the five factor model plus momentum.

5 How do Intangible and Traditional Value Differ?

Intangible value generates similar, and slightly better, 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 10 presents results on firm characteristics for firms that are in the short, neutral, or long leg of intangible value and traditional value, respectively. 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 tangible 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 2.79% controlling for size as well as value and momentum, as shown in Table 9. Row four 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. This ratio displays the opposite pattern in 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 since intangible capital is measured as accumulated Selling and General Administrative expenses.

Rows six and seven in Table 10 document that productivity is increasing in B/M^{INT}, and decreasing in B/M^{FF}. Thus, HML^{INT} is long higher productivity firms, and short lower productivity firms, while HML^{FF} is long lower productivity firms and short higher productivity firms. This is true using either sales to recorded book assets or Solow (1955, 1957) residuals to measure productivity. Similarly, row eight shows that HML^{INT} is long firms with higher sales to stockholder's equity, and short firms with lower sales to stockholder's equity, while 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 row ten shows that the intangible value portfolio has a lower average price to sales ratio in the long leg, and a much higher average price to sales ratio in the short leg, relative to traditional value. Thus, we conclude that including intangible capital better aligns the B/M measure of value with measures that use P/E or Price to Sales.

Turning to capital structure related variables, rows eleven and twelve show that, 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 is fairly flat across terciles of B/M^{INT}, but is higher for firms in the long leg of traditional value, and lower in that portfolio's short leg.

Finally, we report statistics related to the conservative minus aggressive (CMA) and the robust minus weak (RMW) sorts used to construct the two new 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 9 that intangible value, unlike traditional value, loads positively on the RMW factor.

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. Since the fundamentals (measured by productivity and 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, 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 as a way of growing future market values, 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 in the short leg of traditional value despite showing strong fundamentals and ability to adapt to trends in their respective sectors. In most periods, intangible value in fact goes long on these stocks, amplifying the difference in returns between the two value factors.

It is also interesting to examine how persistent differences in positions between HML^{INT} and HML^{FF} are. Table 11 addresses this question by reporting the empirical transition matrices and their respective stationary distributions, for 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, that is, these 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 a 61% 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 the differences between HML^{INT} and HML^{FF} are driven in part by persistently different 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, since Table 11 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 7.6% and 15% of the time in positions that differ between intangible and traditional value.

6 Conclusion

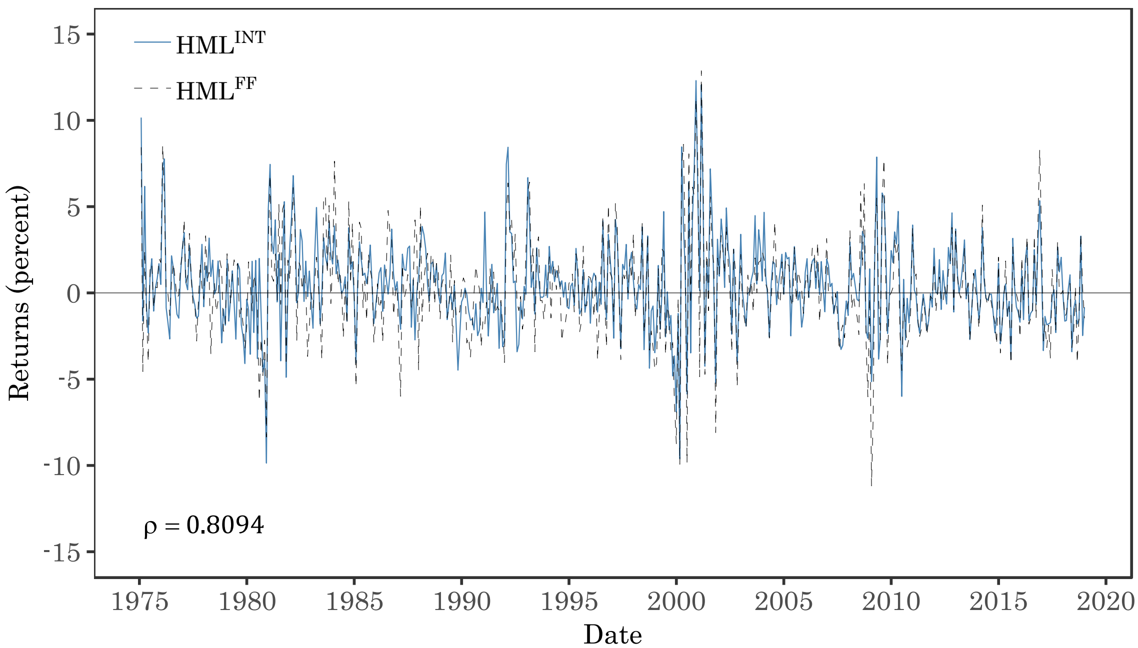
The traditional value investing strategy, which relies on using firms' book assets as the fundamental anchor of value, has lost its edge in recent years. This trend may be due to the increasing importance of intangible capital, which is not incorporated into the traditional measure of book assets. We 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.

Our results hold when sorting firms first within industries or using alternative parameter assumptions for constructing intangible capital. 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, sales to price, etc.) 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 profitable relative value strategy, especially in recent years when traditional value has underperformed.

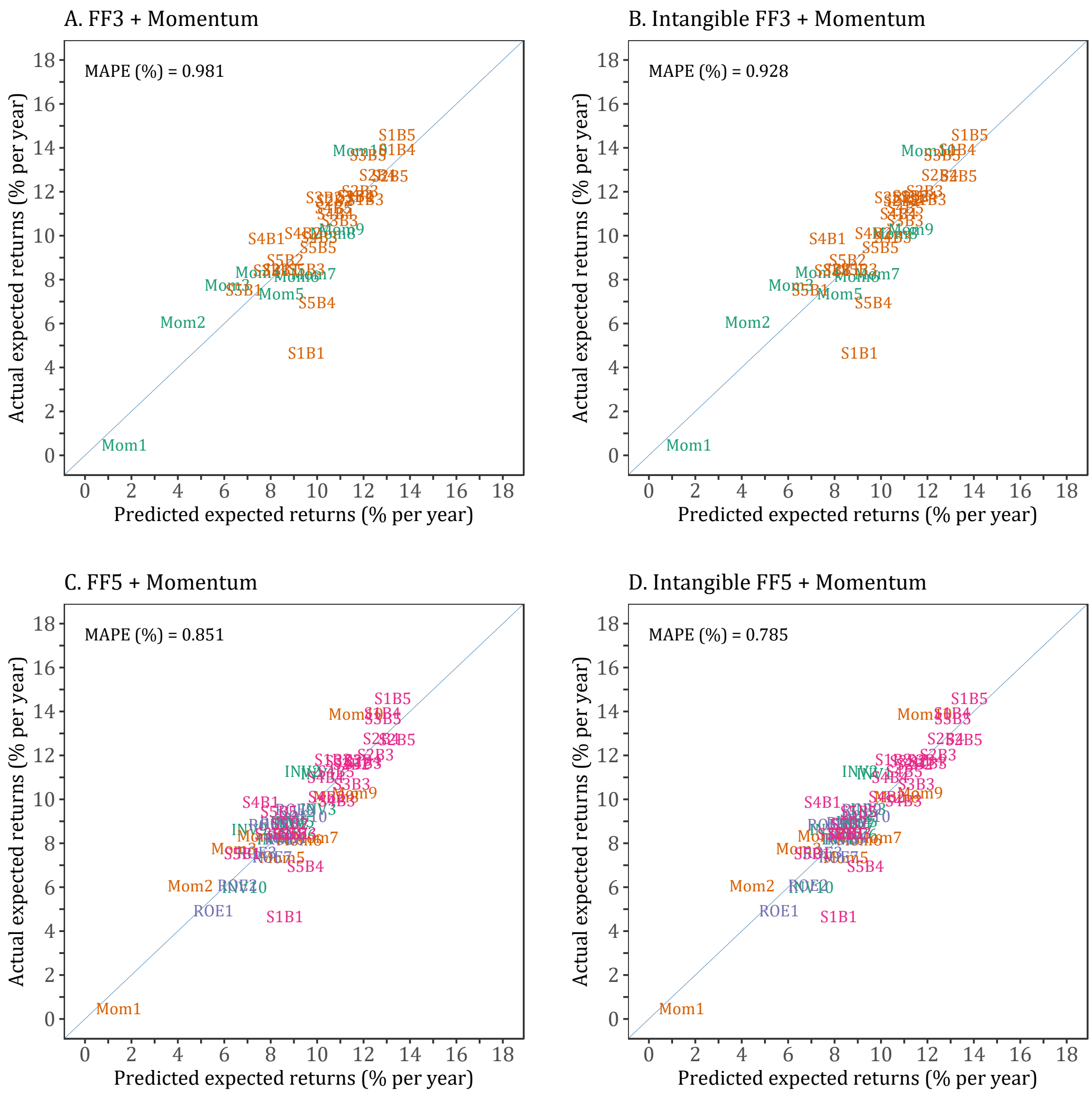
Figures

Figure 1



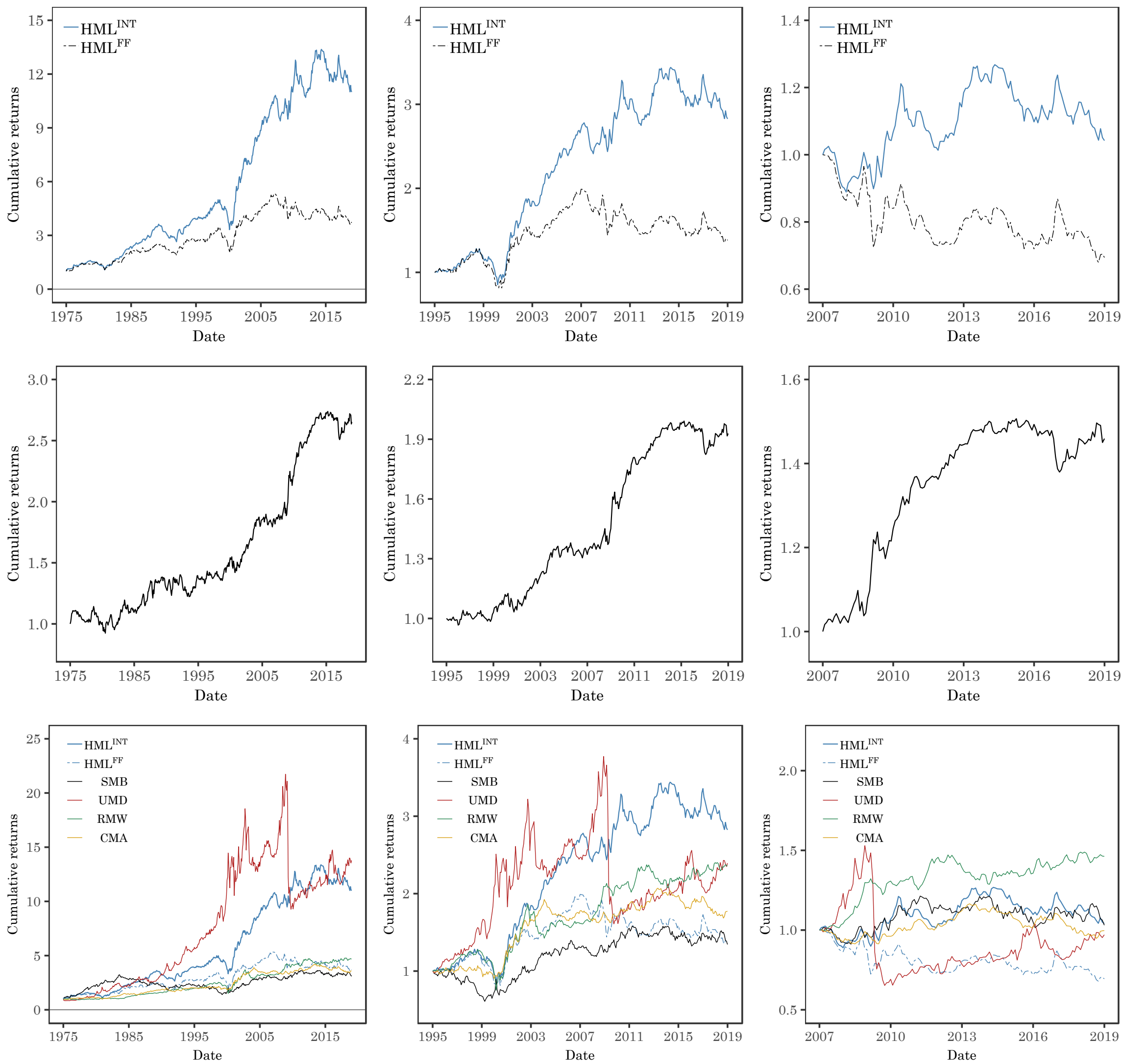
Note: This figure plots the monthly returns for HML^{FF} and HML^{INT} from 1975 to 2018. The HML^{FF} portfolio mimics the risk factor in returns related to book-to-market equity, and is calculated as the difference between the returns on high-B/M portfolios and the returns on low-B/M portfolios. HML^{INT}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

Figure 2



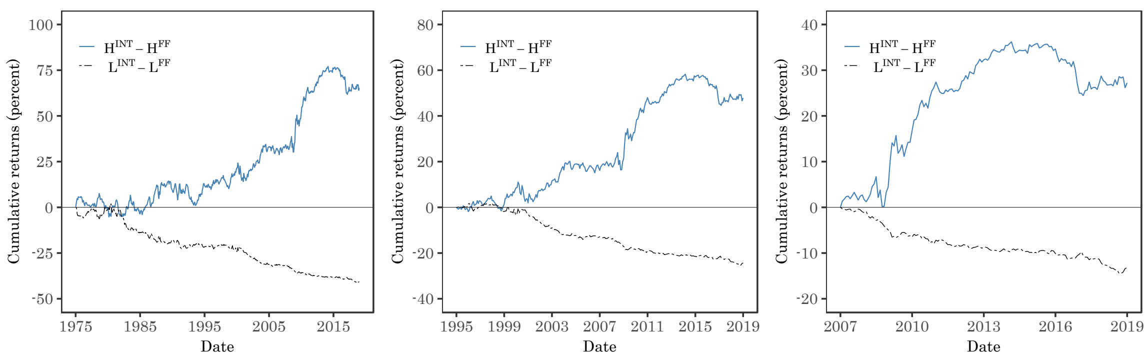
NOTE: This figure presents the cross-sectional asset pricing results from the Fama and French (1992, 1993, 2015) three factor and five factor models augmented by the momentum factor. The top row plots realized mean excess returns of 25 size and book-to-market-sorted portfolios and 10 momentum portfolios against the mean excess returns predicted by the FF3 + momentum model, where Panel B replaces HML^{FF} with HML^{INT}. 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 3



NOTE: The top panel in this figure 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, starting from the beginning of 1975, 1995, and 2007. 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} portfolios from the beginning of 1975, 1995, and 2007. HML^{INT} adds intangible assets to the book equity term of the book-to-market equity ratio prior to the HML portfolio sorts. Further details on factor construction can be found in Section 2 and Appendix A.

Figure 4



Note: 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. HML^{INT} adds intangible assets to the book equity term of the book-to-market equity ratio prior to the HML portfolio sorts. Further details on factor construction can be found in Section 2 and Appendix A.

Tables

Table 1

Pricing Errors: Intangible Value vs. Traditional Value

This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. 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. 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)
α (%)	12.97	11.19	8.73	9.85
	(4.04)	(3.47)	(2.92)	(3.30)
β_{MktRF}	-0.36	-0.23	-0.05	-0.14
	(-1.11)	(-0.70)	(-0.17)	(-0.46)
β_{SMB}	0.22	0.24	0.29	0.29
	(1.68)	(1.79)	(2.28)	(2.23)
$\beta_{HML^{\text{FF}}}$	0.30		0.25	
	(2.33)		(1.98)	
$\beta_{HML^{\text{INT}}}$		0.37		0.43
		(2.74)		(3.13)
β_{MOM}	0.54	0.55	0.53	0.54
	(2.78)	(2.81)	(2.74)	(2.78)
β_{RMW}			0.31	0.31
			(2.76)	(2.81)
β_{CMA}			0.16	0.11
			(1.75)	(1.20)
Adj. R^2	73.66	77.56	78.21	80.38
RMSE	0.43	0.39	0.34	0.33

Table 2

Pricing Errors: Intangible Assets to Market Equity

This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. 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. $\mathrm{HML}^{\mathrm{IME}}$ 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. 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 (%)	12.97	8.71	9.66	8.73	8.32	8.87
	(4.04)	(2.66)	(2.94)	(2.92)	(2.76)	(2.95)
β_{MktRF}	-0.36	-0.02	-0.10	-0.05	-0.02	-0.06
	(-1.11)	(-0.08)	(-0.31)	(-0.17)	(-0.05)	(-0.20)
β_{SMB}	0.22	0.23	0.23	0.29	0.28	0.28
	(1.68)	(1.75)	(1.75)	(2.28)	(2.14)	(2.18)
$\beta_{HML^{\mathrm{FF}}}$	0.30	0.23		0.25	0.23	
	(2.33)	(1.78)		(1.98)	(1.77)	
$\beta_{HML^{\mathrm{IME}}}$		1.00	0.54		0.86	0.63
		(4.41)	(3.21)		(4.30)	(3.47)
β_{MOM}	0.54	0.47	0.53	0.53	0.48	0.51
	(2.78)	(2.40)	(2.70)	(2.74)	(2.45)	(2.61)
β_{RMW}				0.31	0.29	0.30
				(2.76)	(2.66)	(2.68)
β_{CMA}				0.16	0.15	0.11
				(1.75)	(1.67)	(1.14)
Adj. R^2	73.66	83.11	79.76	78.21	82.65	81.87
RMSE	0.43	0.34	0.37	0.34	0.31	0.31

Table 3

Pricing Errors: Intangible Value with Unique Sort

This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. 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^{UINT} is a factor that goes long firms that are in the long leg of HML^{INT} but not in the long leg of HML^{FF}, and vice versa for the short leg ("unique" intangible factor). Fama and MacBeth (1973) t-statistics are reported 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).

	(1)	(2)	(3)	(4)	(5)	(6)
α (%)	12.97	13.54	19.24	8.73	9.52	8.96
	(4.04)	(4.22)	(5.17)	(2.92)	(3.17)	(2.94)
β_{MktRF}	-0.36	-0.38	-0.82	-0.05	-0.10	-0.05
	(-1.11)	(-1.18)	(-2.34)	(-0.17)	(-0.32)	(-0.17)
β_{SMB}	0.22	0.21	0.18	0.29	0.28	0.28
	(1.68)	(1.56)	(1.36)	(2.28)	(2.19)	(2.20)
$\beta_{HML^{\text{FF}}}$	0.30	0.29		0.25	0.26	
	(2.33)	(2.27)		(1.98)	(2.07)	
$\beta_{HML^{\text{UINT}}}$		1.17	1.58		1.16	1.18
		(3.84)	(4.28)		(4.27)	(4.30)
β_{MOM}	0.54	0.53	0.48	0.53	0.52	0.50
	(2.78)	(2.71)	(2.42)	(2.74)	(2.66)	(2.58)
β_{RMW}				0.31	0.35	0.34
				(2.76)	(3.03)	(3.05)
β_{CMA}				0.16	0.19	0.26
				(1.75)	(2.08)	(2.56)
Adj. R^2	73.66	78.27	74.10	78.21	82.84	82.24
RMSE	0.43	0.39	0.42	0.34	0.31	0.31

Table 4

Pricing Errors: Within Industry Sorts for HML$^{\text{INT}}$

This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. 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. Book-to-market value sorts for $\beta_{HML^{\text{INT}}}$ are done at the industry level using 12 industry portfolio definitions from Ken French's website. Fama and MacBeth (1973) t-statistics are reported 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).

	(1)	(2)	(3)	(4)
α (%)	12.97	13.45	8.73	8.43
	(4.04)	(4.14)	(2.92)	(2.79)
β_{MktRF}	-0.36	-0.40	-0.05	-0.03
	(-1.11)	(-1.22)	(-0.17)	(-0.09)
β_{SMB}	0.22	0.22	0.29	0.29
	(1.68)	(1.65)	(2.28)	(2.28)
$\beta_{HML^{\text{FF}}}$	0.30		0.25	
	(2.33)		(1.98)	
$\beta_{HML^{\text{INT}}}$		0.27		0.21
		(2.55)		(2.00)
β_{MOM}	0.54	0.54	0.53	0.53
	(2.78)	(2.77)	(2.74)	(2.72)
β_{RMW}			0.31	0.31
			(2.76)	(2.80)
β_{CMA}			0.16	0.18
			(1.75)	(1.96)
Adj. R^2	73.66	72.09	78.21	77.82
RMSE	0.43	0.44	0.34	0.35

Table 5

Single Factor Models for Intangible and Traditional Value

In this table, we study the relative performance between the HML^{FF} and HML^{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. 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. $\mathbf{HML_t^{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{HML^{FF}}} \cdot \mathbf{HML_t^{FF}} + \boldsymbol{\epsilon_t}$				
α (%)	3.32	3.68	3.69	2.55
	(4.13)	(2.54)	(2.83)	(2.23)
$\beta_{HML^{\text{FF}}}$	0.73	0.66	0.81	0.73
	(23.46)	(10.66)	(19.48)	(13.46)
Adj. R^2	65.46	46.93	81.47	74.70
RMSE	5.31	6.31	4.54	3.93
α/RMSE	0.62	0.58	0.81	0.65
B. $\mathbf{HML_t^{FF}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{HML^{INT}}} \cdot \mathbf{HML_t^{INT}} + \boldsymbol{\epsilon_t}$				
α (%)	-1.76	0.17	-2.54	-3.26
	(-1.93)	(0.12)	(-1.63)	(-2.42)
$\beta_{HML^{\text{INT}}}$	0.89	0.72	1.01	1.02
	(27.77)	(14.66)	(23.08)	(13.83)
Adj. R^2	65.46	46.93	81.47	74.70
RMSE	5.86	6.61	5.08	4.64
α/RMSE	-0.30	0.03	-0.50	-0.70

Table 6

Single Factor Models for Decompositions of Intangible Value

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 $\text{B}^{\text{INT}}/\text{M}$ 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)
A. $\mathbf{HML}_t^{\mathbf{IME}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{FF}}} \cdot \mathbf{HML}_t^{\mathbf{FF}} + \boldsymbol{\epsilon}_t$				
α (%)	4.54	4.87	4.57	2.75
	(4.46)	(3.09)	(2.40)	(1.51)
$\beta_{HML^{\text{FF}}}$	0.50	0.59	0.50	0.35
	(12.00)	(8.62)	(7.53)	(4.79)
Adj. R^2	35.16	37.13	42.68	20.22
RMSE	6.80	6.98	6.86	6.28
α/RMSE	0.67	0.70	0.67	0.44
B. $\mathbf{HML}_t^{\mathbf{UINT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{FF}}} \cdot \mathbf{HML}_t^{\mathbf{FF}} + \boldsymbol{\epsilon}_t$				
α (%)	3.64	3.53	7.51	3.41
	(2.04)	(1.39)	(2.13)	(1.03)
$\beta_{HML^{\text{FF}}}$	0.05	-0.04	-0.16	0.54
	(0.72)	(-0.30)	(-1.27)	(4.37)
Adj. R^2	0.03	-0.34	2.08	15.57
RMSE	11.60	11.25	11.33	11.38
α/RMSE	0.31	0.31	0.66	0.30

Table 7

Single Factor Models for Intangible and Traditional Value: Organization Capital

In this table, we report alphas and betas of a regression of HML^{FF} and HML^{INT} factors 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)
A. $\boldsymbol{\text{HML}_t^{\text{INT}} = \alpha + \beta_{OMK} \cdot \text{OMK}_t + \epsilon_t}$				
α (%)	5.68	8.10	8.29	0.60
	(4.16)	(4.18)	(2.92)	(0.27)
β_{OMK}	0.08	-0.22	0.35	-0.06
	(1.29)	(-2.24)	(3.74)	(-0.51)
Adj. R^2	0.51	3.47	14.76	-0.38
RMSE	9.02	8.51	9.74	7.83
α/RMSE	0.63	0.95	0.85	0.08
B. $\boldsymbol{\text{HML}_t^{\text{FF}} = \alpha + \beta_{OMK} \cdot \text{OMK}_t + \epsilon_t}$				
α (%)	3.04	5.25	5.64	-2.63
	(2.05)	(2.57)	(1.80)	(-0.98)
β_{OMK}	0.21	0.02	0.41	-0.02
	(3.07)	(0.22)	(3.94)	(-0.11)
Adj. R^2	3.48	-0.39	17.45	-0.69
RMSE	9.79	9.09	10.72	9.26
α/RMSE	0.31	0.58	0.53	-0.28

Table 8

Performance Statistics: Intangible Value vs. Traditional Value

This table summarizes the risk and return associated with HML^{FF} and HML^{INT}. The numbers in parentheses are t-statistics for the test that the average return, $\mathbb{E}[R]$, is different from zero. All factors are annualized in percent per year. The underlying data are monthly and the full sample period is 1975 to 2018. HML^{LS} refers to the portfolio that is long HML^{INT} and short HML^{FF}. HML^{ULS} refers to the portfolio that is long the firms that are uniquely in the long leg of HML^{INT} as well as firms that are uniquely in the short leg of HML^{FF}, and short firms that are uniquely in the short leg of HML^{INT} as well as firms that are uniquely in the long leg of HML^{FF}. The information ratio is given by $\mathbb{E}[R_p - R_b]/\sigma(R_p - R_b)$, where R_p is the portfolio return and R_b is the benchmark return. The appraisal ratio is α/RMSE of a regression of portfolio returns on benchmark returns. The benchmark portfolios for HML^{FF} and HML^{INT} are HML^{INT} and HML^{FF}, respectively.

		Full sample	1975-1994	1995-2006	2007-2018
		(1)	(2)	(3)	(4)
HML^{FF}	$\mathbb{E}[R]$	3.47	5.34	6.44	-2.62
		(2.31)	(2.63)	(1.89)	(-0.98)
	σ	9.97	9.07	11.80	9.23
	[0.05, 0.95]	[-48.24, 63.84]	[-44.52, 63.12]	[-56.64, 73.56]	[-45.36, 49.92]
	Sharpe	0.35	0.59	0.55	-0.28
	Information	-0.40	-0.26	-0.48	-0.70
	Appraisal	-0.30	0.03	-0.50	-0.70
HML^{INT}	$\mathbb{E}[R]$	5.86	7.18	8.89	0.64
		(4.30)	(3.71)	(2.92)	(0.28)
	σ	9.04	8.66	10.55	7.81
	[0.05, 0.95]	[-40.94, 56.53]	[-38.02, 57.00]	[-48.00, 62.80]	[-36.46, 45.52]
	Sharpe	0.65	0.83	0.84	0.08
	Information	0.40	0.26	0.48	0.70
	Appraisal	0.62	0.58	0.81	0.65
HML^{LS}	$\mathbb{E}[R]$	2.39	1.84	2.45	3.26
		(2.67)	(1.17)	(1.68)	(2.44)
	σ	5.93	7.03	5.06	4.63
	[0.05, 0.95]	[-32.49, 33.79]	[-38.12, 37.07]	[-26.56, 29.39]	[-19.32, 25.35]
	Sharpe	0.40	0.26	0.48	0.70
HML^{ULS}	$\mathbb{E}[R]$	5.15	2.69	5.16	9.23
		(1.94)	(0.71)	(0.90)	(1.95)
	σ	17.57	16.90	19.74	16.40
	[0.05, 0.95]	[-92.89, 101.92]	[-94.43, 103.75]	[-98.52, 104.72]	[-88.34, 97.95]
	Sharpe	0.29	0.16	0.26	0.56

Table 9

Intangible Value vs. Traditional Value: Alphas

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^{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).

	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 (%)	-0.36	2.79	3.91	1.90	-0.62	1.19	2.58	0.62
	(-0.36)	(3.27)	(3.79)	(1.13)	(-0.66)	(1.44)	(2.49)	(0.37)
β_{MktRF}	-0.09	0.03	0.00	0.05	-0.04	0.07	0.05	0.10
	(-3.76)	(1.41)	(0.18)	(1.35)	(-1.88)	(3.69)	(2.06)	(2.47)
β_{SMB}	-0.12	0.14	0.22	0.55	-0.14	0.21	0.25	0.58
	(-4.66)	(4.21)	(6.71)	(10.59)	(-5.23)	(8.35)	(7.75)	(11.01)
$\beta_{HML^{INT}}$	0.88				0.73			
	(24.86)				(16.87)			
$\beta_{HML^{FF}}$		0.75	0.52	0.09		0.62	0.35	-0.08
		(22.91)	(12.55)	(1.87)		(17.79)	(7.97)	(-1.09)
β_{MOM}	-0.03	-0.03	-0.02	-0.07	-0.04	-0.06	-0.04	-0.10
	(-1.44)	(-1.31)	(-0.71)	(-1.52)	(-2.11)	(-2.97)	(-1.83)	(-2.07)
β_{RMW}					-0.09	0.27	0.16	0.14
					(-2.32)	(7.30)	(3.56)	(1.73)
β_{CMA}					0.39	0.22	0.34	0.35
					(6.65)	(4.45)	(5.31)	(3.42)
Adj. R^2	69.58	68.59	41.98	25.97	74.05	73.34	46.24	28.02
RMSE	5.50	5.07	6.44	9.98	5.08	4.67	6.20	9.84

Table 10

Summary Statistics of Firm Characteristics

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.

	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	0.55	1.46	3.93	0.72	1.60	3.26
B/M FF	0.30	0.67	1.12	0.27	0.68	1.33
Market capitalization (log, real)	5.29	4.79	3.25	5.00	4.67	3.48
Intangible capital to book assets (%)	7.62	13.55	31.47	21.88	15.61	12.42
Intangible capital to sales (%)	11.21	17.08	25.89	21.27	17.68	17.73
Productivity - sales to book assets (%)	70.95	82.91	115.62	97.40	93.47	76.25
Productivity - Solow residual (%)	-0.17	1.80	3.06	5.30	3.10	-3.76
Sales to Stockholder's equity (%)	156.13	172.32	248.03	203.91	187.41	174.16
Price to Earnings (Diluted, excluding extraordinary items) (%)	13.41	12.09	7.30	13.80	11.80	8.54
Price to sales (%)	2.23	1.18	0.54	1.8367	1.08	0.68
Debt to book assets (%)	12.42	11.13	16.52	12.38	8.94	13.79
Debt to EBITDA (%)	66.12	150.97	165.05	52.62	134.99	219.17
Dividend yield	2.21	2.95	2.89	1.91	2.92	3.39
Investment to physical capital (%)	15.34	11.11	9.00	15.17	11.13	8.18
Gross profit to total assets (%)	24.23	24.24	33.36	37.99	27.86	17.4

Table 11

Persistence of Positions

This table represents transition matrices $\mathbf{P}$ for being sorted uniquely into a particular leg of the HML$^{\text{INT}}$ and HML$^{\text{FF}}$ portfolios. For instance, the state j = High$^{\text{INT}}$ refers to a given firm being sorted in the top 30th percentile in terms of B$^{\text{INT}}$/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 B$^{\text{INT}}$/M and B/M, or ii) being sorted in the bottom 70th percentile of B$^{\text{INT}}$/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.

j	High$^{\text{INT}}$	Low$^{\text{INT}}$	High$^{\text{FF}}$	Low$^{\text{FF}}$
P	$\begin{bmatrix} 60.72 & 39.28 \\ 6.95 & 93.05 \end{bmatrix}$	$\begin{bmatrix} 53.35 & 46.65 \\ 3.84 & 96.16 \end{bmatrix}$	$\begin{bmatrix} 56.61 & 43.39 \\ 4.22 & 95.78 \end{bmatrix}$	$\begin{bmatrix} 59.84 & 40.16 \\ 5.69 & 94.31 \end{bmatrix}$
w	$(15.03, 84.97)$	$(7.61, 92.39)$	$(8.86, 91.14)$	$(12.42, 87.58)$

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A Appendix: Data Documentation

A.1 Measuring Intangible Capital

In order to calculate the intangible value factor, we first calculate the stock of intangible assets at the firm-level using methodology introduced by prior works (Eisfeldt and Papanikolaou, 2013b,a, 2014; Zhang, 2014; Peters and Taylor, 2017).

In the U.S., accounting rules for intangible capital are different depending on whether an intangible asset is created internally or acquired through a purchase. 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 capital must be calculated based on past investments. We calculate intangible capital by accumulating past spending on SG&A using the perpetual inventory method using assumptions described in section 2.

On the other hand, intangible assets acquired through a purchase — for instance, by acquiring another firm — are capitalized on the balance sheet as "Goodwill". However, goodwill suffers from known issues of impairment and also incorporates acquisition costs for non-intangible capital, which could contaminate our measure. Thus, for all our specifications, we subtract goodwill from the Fama and French measure of book equity.

In a robustness exercise, we further break down a firm's intangible capital (Int) as the sum of two components — *knowledge capital* or Int^{know} (e.g. R&D spending) and *organization capital* or Int^{org} (e.g. human capital, brand capital, and customer relationships). Following previous works, we use the R&D and SG&A line items as proxies for Int^{know} and Int^{org}, respectively. Specifically, we estimate the following for Int^{know}:

$$\text{Int}_{i,t}^{know} = (1 - \delta_{R\&D})\text{Int}_{i,t-1}^{know} + R\&D_{i,t}, \tag{3}$$

where $\text{Int}_{i,t}^{know}$ is the stock of knowledge capital, $\delta_{R\&D}$ is an industry-specific depreciation rate, and $R\&D_{i,t}$ is the real expenditures on R&D, which is measured by Compustat variable *xrd*. Data on industry-specific depreciation rates are obtained from the Bureau of Economic Analysis (BEA), and range from 10% to 40%.[9]

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

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

$$\text{Int}_{i,t}^{org} = (1 - \delta_{SG\&A})\text{Int}_{i,t-1}^{org} + \theta SG\&A_{i,t}, \tag{4}$$

where $\delta_{SG\&A}$ is now the depreciation rate for SG&A expenses and $SG\&A_{i,t}$ is real SG&A expenditure, calculated by subtracting xrd from $xsga$ and deflating the resulting stock by the consumer price index. Eisfeldt and Papanikolaou (2013b), Eisfeldt and Papanikolaou (2013a), and Eisfeldt and Papanikolaou (2014) provide detailed justification for this procedure. For our analysis, we follow the convention of $\delta = 0.2$ and $\theta = 0.3$. We verify that using different values of reasonable depreciation and investment rates do not meaningfully change our results. Finally, our robustness measure of total intangible capital is calculated as:

$$\text{Int}_{i,t} = \text{Int}_{i,t}^{know} + \text{Int}_{i,t}^{org}. \tag{5}$$

A.2 Intangible Value Factor

The key empirical goal of estimating intangible capital is to construct a modified book-to-market equity ratio (B/M), 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. To improve the measurement of value, we add intangible capital (Int) computed in Section A.1 to the book value of each firm (B_{it}). For this, we closely follow the data description and factor construction methods outlined in Fama and French (1993).

The Fama-French factors are constructed using six annually rebalanced and value-weighted portfolios formed on size and book-to-market.[10] 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

$$\text{HML} = \frac{1}{2}\,(\text{Small Value} + \text{Big Value}) - \frac{1}{2}\,(\text{Small Growth} + \text{Big Growth}), \tag{6}$$

[10]The six portfolios span the combination of two size (Small and Big with cutoff at median) 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.

where stock returns are measured monthly and obtained from the Center for Research in Security Prices (CRSP). Following this methodology, we construct HML^{INT} using book-to-market values that are augmented with intangible capital.

A.3 Other Measures of Intangible Value

Our main measure of HML^{INT} follows the Fama and French convention of sorting by the book-to-market ratio across all firms in a given period. We additionally 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 distinct portfolios, HML^{IME} is a value factor that sorts firms into high and low buckets based on Int/ME instead of $(B + \text{Int})/\text{ME}$. Additionally, HML^{UINT} sorts firms on $(B + \text{Int})/\text{ME}$ 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}). HML^{ULS} refers to the portfolio that is long the firms that are uniquely in the long leg of HML^{INT} as well as firms that are uniquely in the short leg of HML^{FF}, and short firms that are uniquely in the short leg of HML^{INT} as well as firms that are uniquely in the long leg of HML^{FF}. For the aforementioned factors, "long" and "short" leg returns are value-weighted separately prior to taking their difference, resulting in a zero-cost portfolio. Lastly, HML^{LS} is simply a factor that goes long HML^{INT} and short HML^{FF}. Note that for HML^{LS}, there may be firms in both the long and short legs but with different portfolio weights as those were calculated when forming the individual factors. Put simply, we assume an investor can passively buy HML^{INT} and sell HML^{FF} in exactly offsetting amounts.

We also incorporate several alternative methodologies for constructing HML^{INT} in order to ensure the robustness of our main results on pricing and outperformance. First, we sort firms into long and short buckets within each industry group using the 12 industry portfolio definitions from Ken French's website. This helps address concerns that the sorts may be heavily tilted towards a particular industry. Similarly, we have 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+), which is in line with common practice in the literature. We also include a version that only looks at high-tech firms, following the augmented 5 industry designations adopted from Zhang (2014). Note that when conducting analysis on the industry filters, we reproduce the Fama and French test assets using the filtered sample (25 sorted on size and book to market, 10 sorted on momentum, 10 sorted on profitability, and 10 sorted on investment).

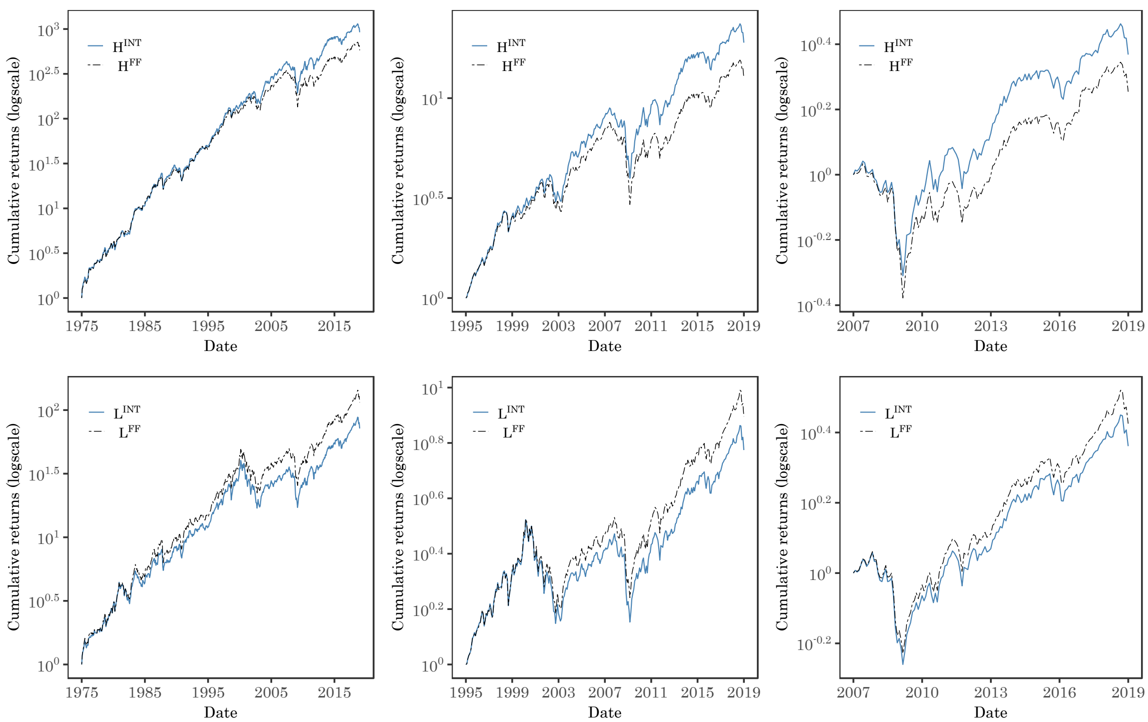
B Internet Appendix: Not for print publication

In this Internet Appendix, we report pricing and outperformance results using various robustness measures of $\mathrm{HML}^{\mathrm{INT}}$. Details on data construction can be found in Appendix A.

B.1 Further Long and Short Leg Analysis

In this section, we study the relative performance of the long and short legs of $\mathrm{HML}^{\mathrm{INT}}$ and $\mathrm{HML}^{\mathrm{FF}}$. The top panel of Figure B1 shows that on net, the returns to going long the long leg of intangible value, and short the long leg of traditional value has had positive returns over the full sample, and each subsample. Similarly, the short leg of $\mathrm{HML}^{\mathrm{INT}}$ consistently underperforms the short leg of $\mathrm{HML}^{\mathrm{FF}}$, 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 mid 1990s while the short leg's outperformance is consistent throughout the full sample period. The outperformance in recent years following the dip in 2017 is mostly driven by the short leg, as discussed in the main text.

Figure B1



NOTE: The top panel plots the cumulative returns of the long leg of HML$^{\text{INT}}$ (solid blue line) and the long leg of HML$^{\text{FF}}$ (dashed black line). In the bottom panel, we plot the cumulative returns of the short leg of HML$^{\text{INT}}$ (solid blue line) and the short leg of HML$^{\text{FF}}$ (dashed black line). Each panel plots on a dollar invested in each leg from the beginning of 1975, 1995, and 2007. HML$^{\text{INT}}$ adds intangible assets to the book equity term of the book-to-market equity ratio prior to the HML portfolio sorts. Further details on factor construction can be found in Section 2 and Appendix A.

B.2 Separately Accumulating Knowledge and Organization Capital

Our main measure for intangible capital uses the perpetual inventory method on SG&A expenses because R&D expenditures, the key driver of knowledge capital, is incorporated into SG&A. Previous works such as Peters and Taylor (2017), however, separate out knowledge capital-related investment by first subtracting R&D from SG&A, and then applying industry-specific depreciation rates for R&D. Below we test whether constructing intangible capital this way alters our main results.

Table B1 reproduces the baseline asset pricing test results in Table 1. We find that replacing HML^{INT} with the version that treats intangible capital components separately yields consistent pricing performance. In particular, for the three-factor model with momentum, the intangible value factor reduces the alpha of the model by 8%, and reduces the root mean square error by 5%. For the five-factor model with momentum, HML^{INT} retains significance at over the 1% level and the root mean square error falls by 3%. We conclude that our asset pricing tests are robust to treating intangible capital components separately.

Table B2 shows single factor models that test the outperformance of intangible value relative to traditional value. Consistent with the main results in Table 5, the alpha of HML^{INT} over HML^{FF} is highly significant at 2.96% for the full sample, and the outperformance persists in each sub-period. Patterns regarding the evolution of outperformance over time are also consistent with results shown in Table 5.

Table B3 displays alphas of the traditional and intangible value factors in the three and five factor models, plus momentum. Consistent with results from 9, only the alpha for the three factor model with intangible value is positive and significant.

Table B1

Pricing Errors: Intangible Value vs. Traditional Value

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 calculating B^{INT}, we accumulate 30% of non-R&D SG&A expenses and add knowledge capital separately to book equity values (See Appendix A for details). 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. 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)
α (%)	12.97	11.92	8.73	9.52
	(4.04)	(3.70)	(2.92)	(3.19)
β_{MktRF}	-0.36	-0.28	-0.05	-0.12
	(-1.11)	(-0.86)	(-0.17)	(-0.37)
β_{SMB}	0.22	0.23	0.29	0.29
	(1.68)	(1.71)	(2.28)	(2.23)
$\beta_{HML^{\text{FF}}}$	0.30		0.25	
	(2.33)		(1.98)	
$\beta_{HML^{\text{INT}}}$		0.36		0.37
		(2.88)		(2.87)
β_{MOM}	0.54	0.55	0.53	0.54
	(2.78)	(2.82)	(2.74)	(2.78)
β_{RMW}			0.31	0.31
			(2.76)	(2.77)
β_{CMA}			0.16	0.12
			(1.75)	(1.33)
Adj. R^2	73.66	77.97	78.21	79.59
RMSE	0.43	0.41	0.34	0.33

Table B2

Single Factor Models for Intangible and Traditional Value

In this table, we study the relative performance between the HML^{FF} and HML^{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. When calculating B^{INT}, we accumulate 30% of non-R&D SG&A expenses and add knowledge capital separately to book equity values (See Appendix A for details). 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. $\mathbf{HML}_t^{\mathbf{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML^{FF}}} \cdot \mathbf{HML}_t^{\mathbf{FF}} + \boldsymbol{\epsilon}_t$				
α (%)	2.96	2.02	4.26	2.75
	(5.50)	(2.68)	(3.65)	(2.62)
$\beta_{HML^{FF}}$	0.62	0.65	0.63	0.56
	(30.02)	(23.59)	(19.45)	(10.84)
Adj. R^2	75.05	76.46	77.44	67.91
RMSE	3.56	3.25	4.00	3.53
α/RMSE	0.83	0.62	1.07	0.78
B. $\mathbf{HML}_t^{\mathbf{FF}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML^{INT}}} \cdot \mathbf{HML}_t^{\mathbf{INT}} + \boldsymbol{\epsilon}_t$				
α (%)	-2.73	-1.14	-3.82	-4.20
	(-3.53)	(-1.08)	(-2.41)	(-2.76)
$\beta_{HML^{INT}}$	1.21	1.18	1.24	1.22
	(32.87)	(24.11)	(19.94)	(13.57)
Adj. R^2	75.07	76.46	77.44	67.91
RMSE	4.98	4.40	5.60	5.23
α/RMSE	-0.55	-0.26	-0.68	-0.80

Table B3

Intangible Value vs. Traditional Value: Alphas

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) and (2) use the Fama and French (1992, 1993) three factor model, and columns (3) and (4) use the Fama and French (2015) five factor model. Both specifications are augmented with the momentum factor. When calculating B^{INT}, we accumulate 30% of non-R&D SG&A expenses and add knowledge capital separately to book equity values (See Appendix A for details). 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).

	HML^{FF}	HML^{INT}	HML^{FF}	HML^{INT}
	(1)	(2)	(3)	(4)
α (%)	-0.40	1.79	-0.52	0.79
	(-0.49)	(2.47)	(-0.64)	(1.19)
β_{MktRF}	-0.04	-0.00	-0.02	0.03
	(-1.73)	(-0.15)	(-0.95)	(1.81)
β_{SMB}	-0.11	0.12	-0.11	0.14
	(-5.76)	(6.67)	(-5.01)	(7.10)
$\beta_{HML^{\text{INT}}}$	0.96		0.88	
	(36.44)		(24.38)	
$\beta_{HML^{\text{FF}}}$		0.82		0.69
		(25.93)		(17.78)
β_{MOM}	-0.06	0.02	-0.06	0.00
	(-3.89)	(1.62)	(-4.15)	(0.22)
β_{RMW}			-0.02	0.12
			(-0.70)	(3.90)
β_{CMA}			0.17	0.25
			(3.39)	(5.63)
Adj. R^2	80.85	80.09	81.46	82.21
RMSE	4.36	4.04	4.29	3.82

B.3 Fama and French 12 Industry Sorts

In this section, we test whether the main outperformance results are robust to sorting firms within industries. Note that the results on pricing tests are reported in Table 4.

Table B4 shows single factor models that test the outperformance of intangible value relative to traditional value. Again, the alpha of HML^{INT} over HML^{FF} is positive and highly significant for all periods, consistent with findings in Table 5.

Table B5 displays alphas of the traditional and intangible value factors in the three and five factor models, plus momentum. Here, the alphas for both the three and five factor models with intangible value are positive and significant, while the alphas for models with traditional value are negative and significant at the 1% level in the case of the five factor model.

Figure B2 plots the cumulative returns for intangible value strategies that sort firms within industries. We see that compared to the baseline results from Figure 3, the outperformance of intangible value is more consistent in the most recent decade, especially after 2017.

Table B4

Single Factor Models for Intangible and Traditional Value

In this table, we study the relative performance between the HML^{FF} and HML^{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. Book-to-market value sorts for $\beta_{HML^{\text{INT}}}$ are done at the industry level using 12 industry portfolio definitions from Ken French's website. 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. $\mathbf{HML_t^{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{HML^{FF}}} \cdot \mathbf{HML_t^{FF}} + \boldsymbol{\epsilon_t}$				
α (%)	2.96	2.02	4.26	2.76
	(5.50)	(2.68)	(3.65)	(2.62)
$\beta_{HML^{\text{FF}}}$	0.62	0.65	0.63	0.56
	(30.02)	(23.59)	(19.45)	(10.84)
Adj. R^2	75.05	76.46	77.44	67.91
RMSE	3.56	3.25	4.00	3.53
α/RMSE	0.83	0.62	1.07	0.78
B. $\mathbf{HML_t^{FF}} = \boldsymbol{\alpha} + \boldsymbol{\beta_{HML^{INT}}} \cdot \mathbf{HML_t^{INT}} + \boldsymbol{\epsilon_t}$				
α (%)	-2.73	-1.14	-3.82	-4.20
	(-3.53)	(-1.08)	(-2.41)	(-2.76)
$\beta_{HML^{\text{INT}}}$	1.21	1.18	1.24	1.22
	(32.87)	(24.11)	(19.94)	(13.57)
Adj. R^2	75.05	76.46	77.44	67.91
RMSE	4.98	4.40	5.60	5.23
α/RMSE	-0.55	-0.26	-0.68	-0.80

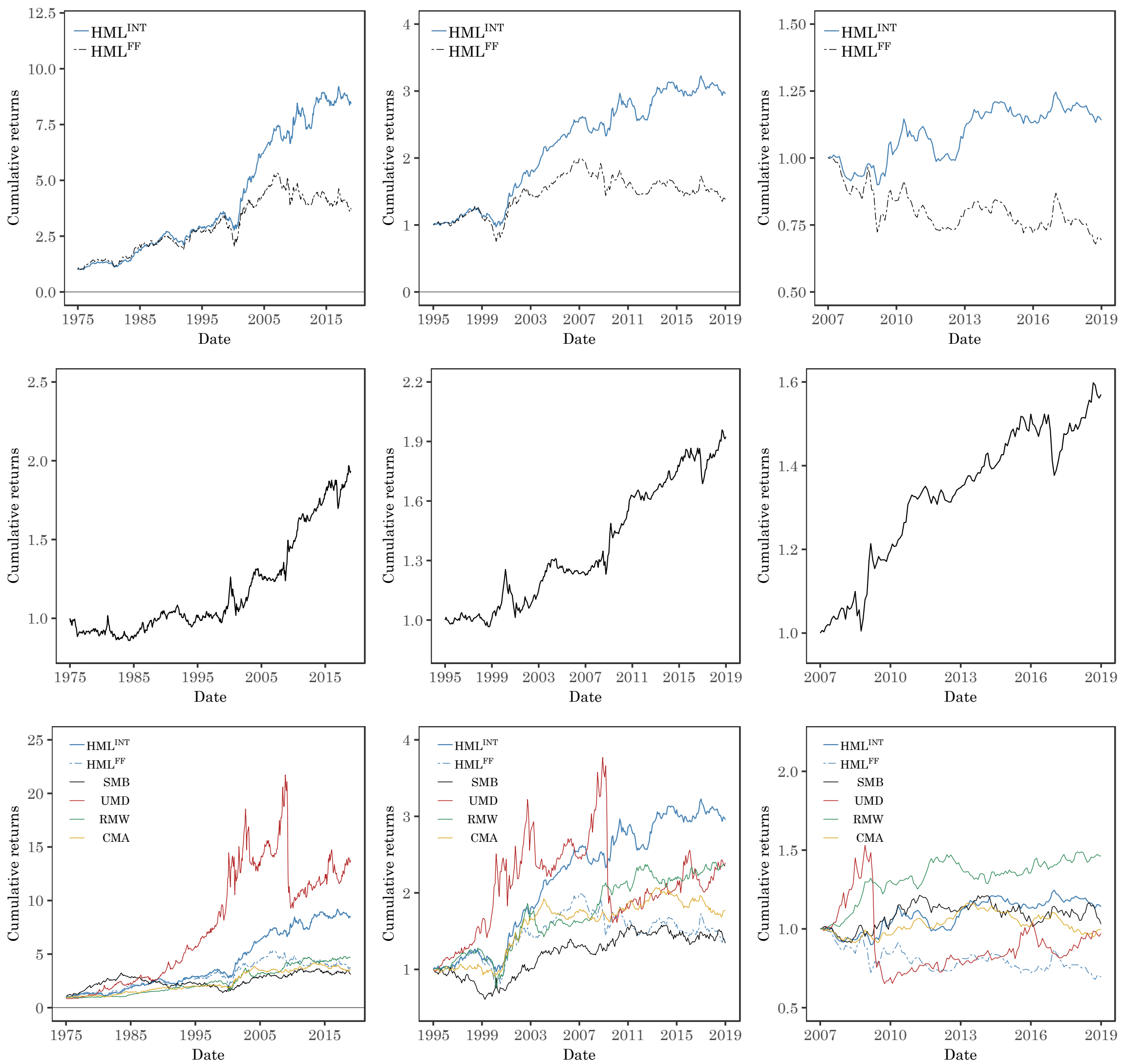
Table B5

Intangible Value vs. Traditional Value: Alphas

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) and (2) use the Fama and French (1992, 1993) three factor model, and columns (3) and (4) use the Fama and French (2015) five factor model. Both specifications are augmented with the momentum factor. Book-to-market value sorts for $\beta_{HML^{\text{INT}}}$ are done at the industry level using 12 industry portfolio definitions from Ken French's website. 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).

	HML^{FF}	HML^{INT}	HML^{FF}	HML^{INT}
	(1)	(2)	(3)	(4)
α (%)	-1.73	2.85	-2.26	2.51
	(-1.92)	(4.61)	(-2.58)	(3.83)
β_{MktRF}	-0.03	-0.01	0.01	-0.00
	(-1.52)	(-1.05)	(0.32)	(-0.01)
β_{SMB}	-0.06	0.05	-0.04	0.05
	(-2.25)	(2.77)	(-1.56)	(2.85)
$\beta_{HML^{\text{INT}}}$	1.18		0.98	
	(30.08)		(18.57)	
$\beta_{HML^{\text{FF}}}$		0.62		0.56
		(25.69)		(20.12)
β_{MOM}	-0.05	0.01	-0.07	0.00
	(-1.91)	(0.41)	(-3.14)	(0.01)
β_{RMW}			0.07	0.02
			(2.13)	(0.77)
β_{CMA}			0.32	0.13
			(4.95)	(3.04)
Adj. R^2	76.21	75.47	78.60	76.14
RMSE	4.86	3.53	4.61	3.48

Figure B2



NOTE: The top panel in this figure 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, starting from the beginning of 1975, 1995, and 2007. 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} portfolios from the beginning of 1975, 1995, and 2007. HML^{INT} adds intangible assets to the book equity term of the book-to-market equity ratio prior to the HML portfolio sorts. Further details on factor construction can be found in Section 2 and Appendix A.

B.4 Industry Filters

In this section, we report main results after implementing two distinct industry filters. First, 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+), as is common in the literature. Additionally, we report a version of results that only keep high-tech firms, as defined in Eisfeldt and Papanikolaou (2014).

Table B6 reproduces the baseline asset pricing test results dropping financials, utilities, and public service firms from the sample. While in general the alphas are higher and adjusted R^2 is lower than reported in Table 1, we find that dropping these industries do not materially change the pricing results. In particular, for the three-factor model with momentum, the intangible value factor reduces both the alpha and root mean square error. For the five-factor model with momentum, HML^{INT} is significant and the root mean squared error falls. When only analyzing high-tech firms (Table B7), the R^2 falls quite significantly. While the patterns regarding alphas and betas are consistent with those in Table 1, the root mean squared error increases slightly for both models when including HML^{INT}. However, the difference is minor and we can conclude that dropping highly regulated industries or focusing on a specific high-tech industry yields similar or better asset pricing performance compared to models with HML^{FF}.

Tables B8 and B9 shows single factor models that test the outperformance of intangible value relative to traditional value. Consistent with the main results in Table 5, the alpha of HML^{INT} over HML^{FF} is highly significant at for the full sample for both industry filter versions. However, the outperformance is no longer significant in the most recent period (2007-2018). However, patterns regarding the evolution of outperformance over time are consistent with results shown in Table 5.

Tables B10 and B11 displays performance statistics for HML^{FF}, HML^{INT}, and a portfolio that is long HML^{INT} and short HML^{FF}. Consistent with Table 8, we see that intangible value outperforms traditional value in all periods in expectation, and significantly so in the full sample as well as in earlier years.

Table B6

Pricing Errors Excluding Utilities, Financials, and Public Service Firms

This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. 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. When forming portfolios and test assets, 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+). Fama and MacBeth (1973) t-statistics are reported 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).

	(1)	(2)	(3)	(4)
α (%)	13.68	12.26	11.14	12.53
	(4.06)	(3.56)	(3.33)	(3.85)
β_{MktRF}	-0.40	-0.29	-0.20	-0.32
	(-1.18)	(-0.84)	(-0.58)	(-0.95)
β_{SMB}	0.00	0.00	0.00	0.00
	(1.21)	(1.28)	(1.42)	(1.41)
$\beta_{HML^{\text{FF}}}$	0.00		0.00	
	(2.32)		(2.10)	
$\beta_{HML^{\text{INT}}}$		0.39		0.41
		(2.74)		(2.82)
β_{MOM}	0.47	0.47	0.48	0.48
	(2.34)	(2.38)	(2.42)	(2.42)
β_{RMW}			0.33	0.31
			(2.58)	(2.45)
β_{CMA}			0.07	0.05
			(0.75)	(0.52)
Adj. R^2	65.72	70.23	71.19	74.66
RMSE	0.46	0.43	0.37	0.35

Table B7

Pricing Errors for High Tech Firms

This table represents pricing results for the Fama and French (1992, 1993, 2015) three factor and five factor models augmented with the momentum factor. 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. When forming portfolios and test assets, we limit the sample of firms to those in "high tech" industries using the BEA *Industry Economic Accounts* (Zhang, 2014). Fama and MacBeth (1973) t-statistics are reported 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).

	(1)	(2)	(3)	(4)
α (%)	15.57	14.48	9.41	8.93
	(2.75)	(2.50)	(1.79)	(1.69)
β_{MktRF}	-0.32	-0.23	0.16	0.20
	(-0.74)	(-0.53)	(0.41)	(0.50)
β_{SMB}	0.21	0.22	0.22	0.22
	(1.44)	(1.47)	(1.49)	(1.51)
$\beta_{HML^{\text{FF}}}$	0.28		0.23	
	(1.78)		(1.47)	
$\beta_{HML^{\text{INT}}}$		0.33		0.29
		(1.98)		(1.74)
β_{MOM}	0.58	0.59	0.60	0.61
	(1.57)	(2.63)	(2.70)	(2.75)
β_{RMW}			0.18	0.17
			(1.01)	(0.95)
β_{CMA}			0.07	0.08
			(0.47)	(0.59)
Adj. R^2	37.93	38.01	33.07	32.56
RMSE	0.83	0.83	0.74	0.74

Table B8

Single Factor Models Excluding Utilities, Financials, and Public Service Firms

In this table, we study the relative performance between the HML^{FF} and HML^{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. When forming the HML^{FF} and HML^{INT} portfolios, 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+). 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. $\mathbf{HML}_t^{\mathbf{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{FF}}} \cdot \mathbf{HML}_t^{\mathbf{FF}} + \boldsymbol{\epsilon}_t$				
α (%)	3.14	2.74	5.45	1.79
	(3.85)	(2.19)	(3.53)	(1.16)
$\beta_{HML^{FF}}$	0.77	0.77	0.75	0.81
	(28.09)	(15.81)	(18.70)	(13.49)
Adj. R^2	68.57	61.85	75.41	67.50
RMSE	5.40	5.41	5.47	5.32
α/RMSE	0.58	0.51	0.99	0.34
B. $\mathbf{HML}_t^{\mathbf{FF}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{INT}}} \cdot \mathbf{HML}_t^{\mathbf{INT}} + \boldsymbol{\epsilon}_t$				
α (%)	-1.63	0.06	-3.98	-2.38
	(-1.81)	(0.05)	(-2.05)	(-1.54)
$\beta_{HML^{INT}}$	0.89	0.80	1.01	0.83
	(27.97)	(19.71)	(17.81)	(17.87)
Adj. R^2	68.57	61.85	75.41	67.50
RMSE	5.78	5.50	6.38	5.38
α/RMSE	-0.28	0.01	-0.62	-0.44

Table B9

Single Factor Models for High Tech Firms

In this table, we study the relative performance between the HML^{FF} and HML^{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. When forming the HML^{FF} and HML^{INT} portfolios, we limit the sample of firms to those in "high tech" industries using the BEA *Industry Economic Accounts* (Zhang, 2014). 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. $\mathbf{HML}_t^{\mathbf{INT}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{FF}}} \cdot \mathbf{HML}_t^{\mathbf{FF}} + \boldsymbol{\epsilon}_t$				
α (%)	3.63	2.49	7.47	1.19
	(3.63)	(1.78)	(3.29)	(0.66)
$\beta_{HML^{\text{FF}}}$	0.80	0.81	0.81	0.68
	(26.39)	(18.69)	(15.58)	(11.78)
Adj. R^2	70.31	75.15	72.17	49.38
RMSE	6.62	5.93	7.90	6.14
α/RMSE	0.55	0.42	0.95	0.19
B. $\mathbf{HML}_t^{\mathbf{FF}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{HML}^{\mathbf{INT}}} \cdot \mathbf{HML}_t^{\mathbf{INT}} + \boldsymbol{\epsilon}_t$				
α (%)	-1.81	-0.62	-4.49	-1.85
	(-1.71)	(-0.42)	(-1.86)	(-1.00)
$\beta_{HML^{\text{INT}}}$	0.88	0.93	0.89	0.73
	(29.77)	(21.63)	(17.78)	(12.57)
Adj. R^2	70.31	75.15	72.17	49.38
RMSE	6.98	6.38	8.26	6.39
α/RMSE	-0.26	-0.10	-0.54	-0.29

Table B10

Performance Statistics Excluding Utilities, Financials, and Public Service Firms

This table summarizes the risk and return associated with HML^{FF} and HML^{INT}. The numbers in parentheses are t-statistics for the test that the average return, $\mathbb{E}[R]$, is different from zero. All factors are annualized in percent per year. When forming the HML^{INT} and HML^{FF} portfolios, 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+). The underlying data are monthly and the full sample period is 1975 to 2018. HML^{LS} refers to the portfolio that is long HML^{INT} and short HML^{FF}. The information ratio is given by $\mathbb{E}[R_p - R_b]/\sigma(R_p - R_b)$, where R_p is the portfolio return and R_b is the benchmark return. The appraisal ratio is α/RMSE of a regression of portfolio returns on benchmark returns. The benchmark portfolios for HML^{FF} and HML^{INT} are HML^{INT} and HML^{FF}, respectively.

		Full sample	1975-1994	1995-2006	2007-2018
		(1)	(2)	(3)	(4)
	$\mathbb{E}[R]$	3.66	5.94	6.31	-2.76
		(2.36)	(2.98)	(1.70)	(-1.01)
	σ	10.31	8.91	12.86	9.44
HML^{FF}	[0.05, 0.95]	[-49.77, 61.23]	[-40.11, 64.71]	[-51.91, 80.25]	[-56.44, 46.94]
	Sharpe	0.36	0.67	0.49	-0.29
	Information	-0.32	-0.26	-0.38	-0.35
	Appraisal	-0.20	-0.01	-0.34	-0.40
	$\mathbb{E}[R]$	5.98	7.33	10.15	-0.46
		(4.11)	(3.74)	(3.19)	(-0.17)
	σ	9.64	8.75	11.04	9.34
HML^{INT}	[0.05, 0.95]	[-42.12, 57.30]	[-37.64, 56.68]	[-41.49, 68.93]	[-48.54, 53.60]
	Sharpe	0.62	0.84	0.92	-0.05
	Information	0.27	0.23	0.39	0.23
	Appraisal	0.49	0.53	0.76	0.15
	$\mathbb{E}[R]$	2.31	1.39	3.85	2.31
		(2.61)	(1.08)	(2.10)	(1.43)
HML^{LS}	σ	5.88	5.76	6.36	5.59
	[0.05, 0.95]	[-30.32, 35.10]	[-31.60, 33.96]	[-31.45, 36.39]	[-28.71, 32.08]
	Sharpe	0.39	0.24	0.61	0.41

Table B11

Performance Statistics for High Tech Firms

This table summarizes the risk and return associated with HML^{FF} and HML^{INT}. The numbers in parentheses are t-statistics for the test that the average return, $\mathbb{E}[R]$, is different from zero. All factors are annualized in percent per year. When forming the HML^{FF} and HML^{INT} portfolios, we limit the sample of firms to those in "high tech" industries using the BEA *Industry Economic Accounts* (Zhang, 2014). The underlying data are monthly and the full sample period is 1975 to 2018. HML^{LS} refers to the portfolio that is long HML^{INT} and short HML^{FF}. The information ratio is given by $\mathbb{E}[R_p - R_b]/\sigma(R_p - R_b)$, where R_p is the portfolio return and R_b is the benchmark return. The appraisal ratio is α/RMSE of a regression of portfolio returns on benchmark returns. The benchmark portfolios for HML^{FF} and HML^{INT} are HML^{INT} and HML^{FF}, respectively.

		Full sample	1975-1994	1995-2006	2007-2018
		(1)	(2)	(3)	(4)
	$\mathbb{E}[R]$	4.72	6.88	7.77	-1.93
		(2.44)	(2.41)	(1.72)	(-0.75)
	σ	12.81	12.79	15.66	8.99
HML^{FF}	[0.05, 0.95]	[-62.45, 70.69]	[-59.48, 75.43]	[-83.40, 93.24]	[-55.33, 51.82]
	Sharpe	0.37	0.54	0.50	-0.22
	Information	-0.38	-0.18	-0.72	-0.27
	Appraisal	-0.26	-0.10	-0.54	-0.29
	$\mathbb{E}[R]$	7.39	8.05	13.79	-0.12
		(4.03)	(3.03)	(3.19)	(-0.05)
	σ	12.14	11.90	14.98	8.62
HML^{INT}	[0.05, 0.95]	[-57.13, 79.49]	[-64.39, 77.47]	[-69.21, 108.96]	[-43.31, 47.01]
	Sharpe	0.61	0.68	0.92	-0.01
	Information	0.30	0.19	0.42	0.32
	Appraisal	0.49	0.41	0.67	0.20
	$\mathbb{E}[R]$	2.67	1.17	6.02	1.81
		(2.49)	(0.81)	(2.48)	(0.93)
HML^{LS}	σ	7.11	6.41	8.40	6.77
	[0.05, 0.95]	[-37.93, 39.95]	[-37.12, 32.04]	[-33.88, 53.66]	[-42.87, 38.22]
	Sharpe	0.38	0.18	0.72	0.27