Online Appendix

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

A Data Appendix

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

A.1 Measuring Intangible Capital: EKP Method

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.3 Intangible Value Factor

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

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

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

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

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

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

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

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

A.4 Other Measures of Intangible Value

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

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

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

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

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

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

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

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

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

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

B Further Analysis and Robustness Checks

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

B.1 Further Long and Short Leg Analysis

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

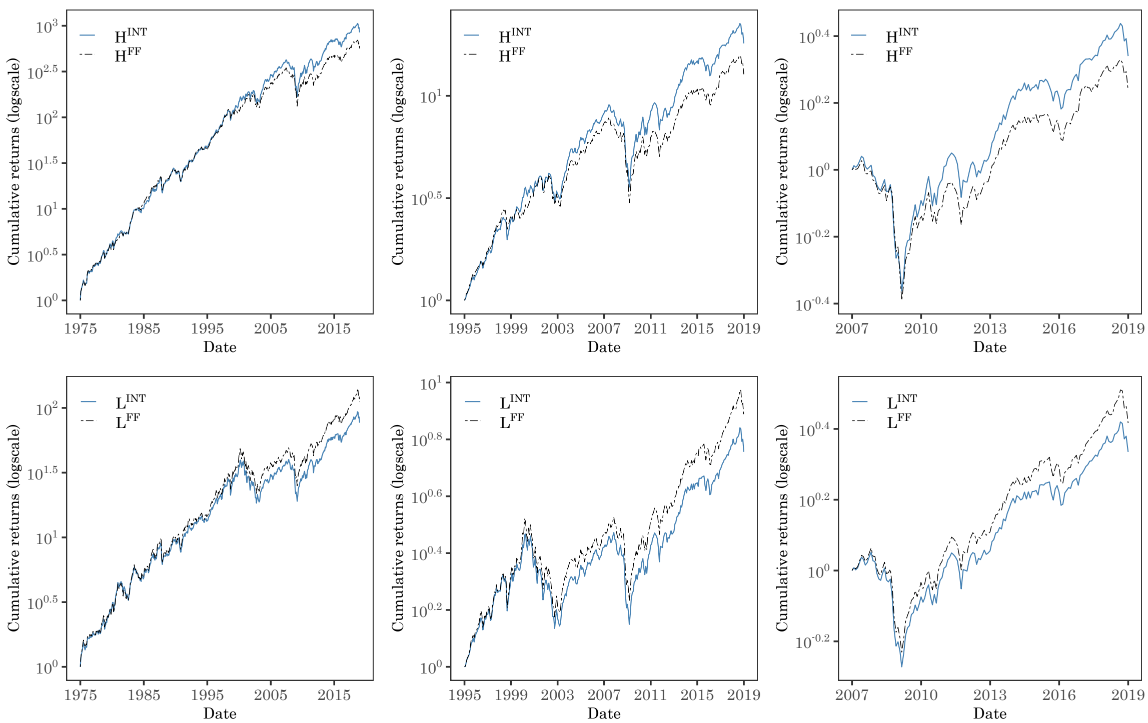

Figure B1: Performance of Long and Short Legs.

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

B.2 12 Industry Sorts for Traditional Value

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

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

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

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

Table B4 displays alphas of the traditional and intangible value factors in the three- and five-factor models plus momentum. We include results for the baseline intangible value factor, and for the two factors that isolate the effect of intangible capital. The alphas for industry-sorted traditional value (Columns (1) and (5)) are negative as in Table 11. For both models, the alpha for HML^{INT} is positive and significant. The alphas for HML^{IME} are also positive and significant under both models. The intangible value factors all have positive and significant alphas in the three- and five-factor models with momentum, with the exception of HML^{UINT}, for which the positive alpha in the three-factor model is insignificant.

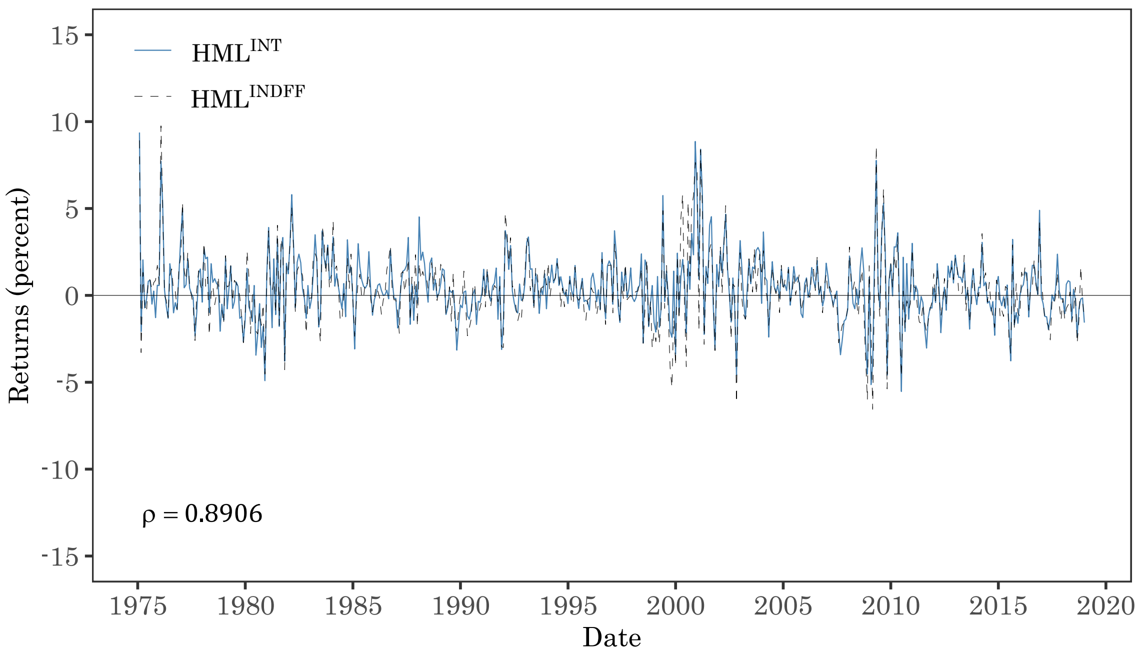

Figure B2: Traditional Value Sorted Within Industries.

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

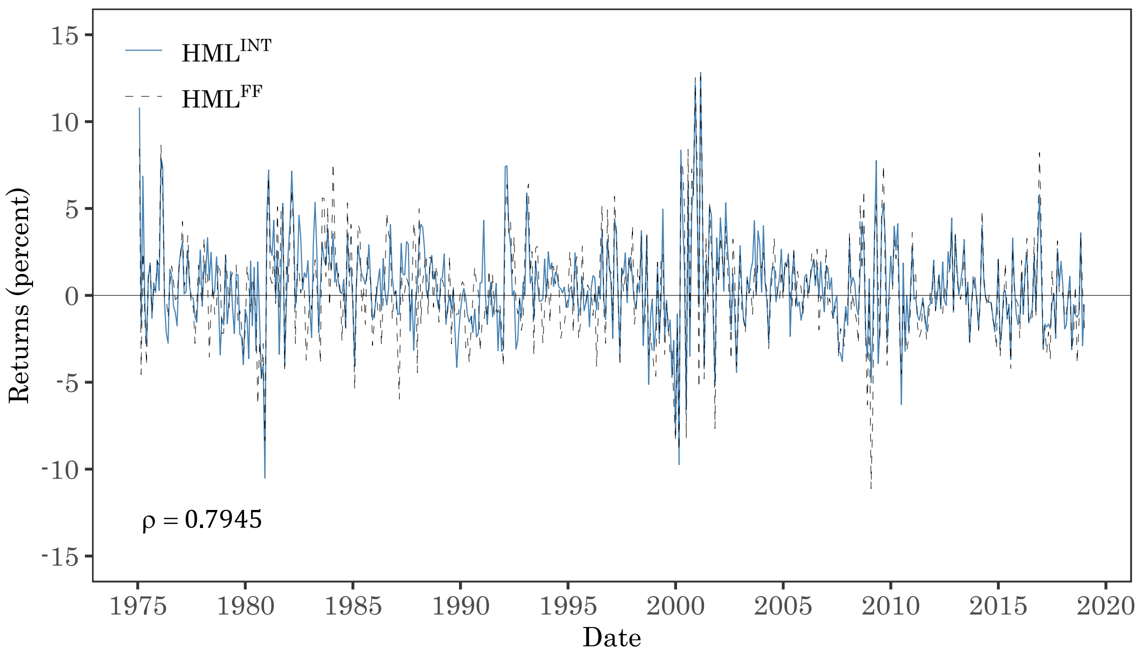

Figure B3: Intangible Value Sorted Across Industries.

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

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

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

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

Interpretation: Sorting firms within industry improves the asset pricing performance of the traditional value factor.

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

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

Description: In this table, we study the relative performance of the $\text{HML}^{\text{INDFF}}$ 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. Firms are sorted within industry first to form the $\text{HML}^{\text{INDFF}}$ factor. The data are monthly and the sample period is 1975 to 2018. We include T-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

Interpretation: Traditional value factor's returns are marginally improved when employing the within-industry sorting and weighting methodology.

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

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

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

Interpretation: Traditional value factor's returns are marginally improved when employing the within-industry sorting and weighting methodology.

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

Table B4: Alphas – Industry-sorted Traditional Value.

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

Interpretation: The alphas for industry-sorted traditional value are negative as in Table 11, but are now significant for the five-factor model.

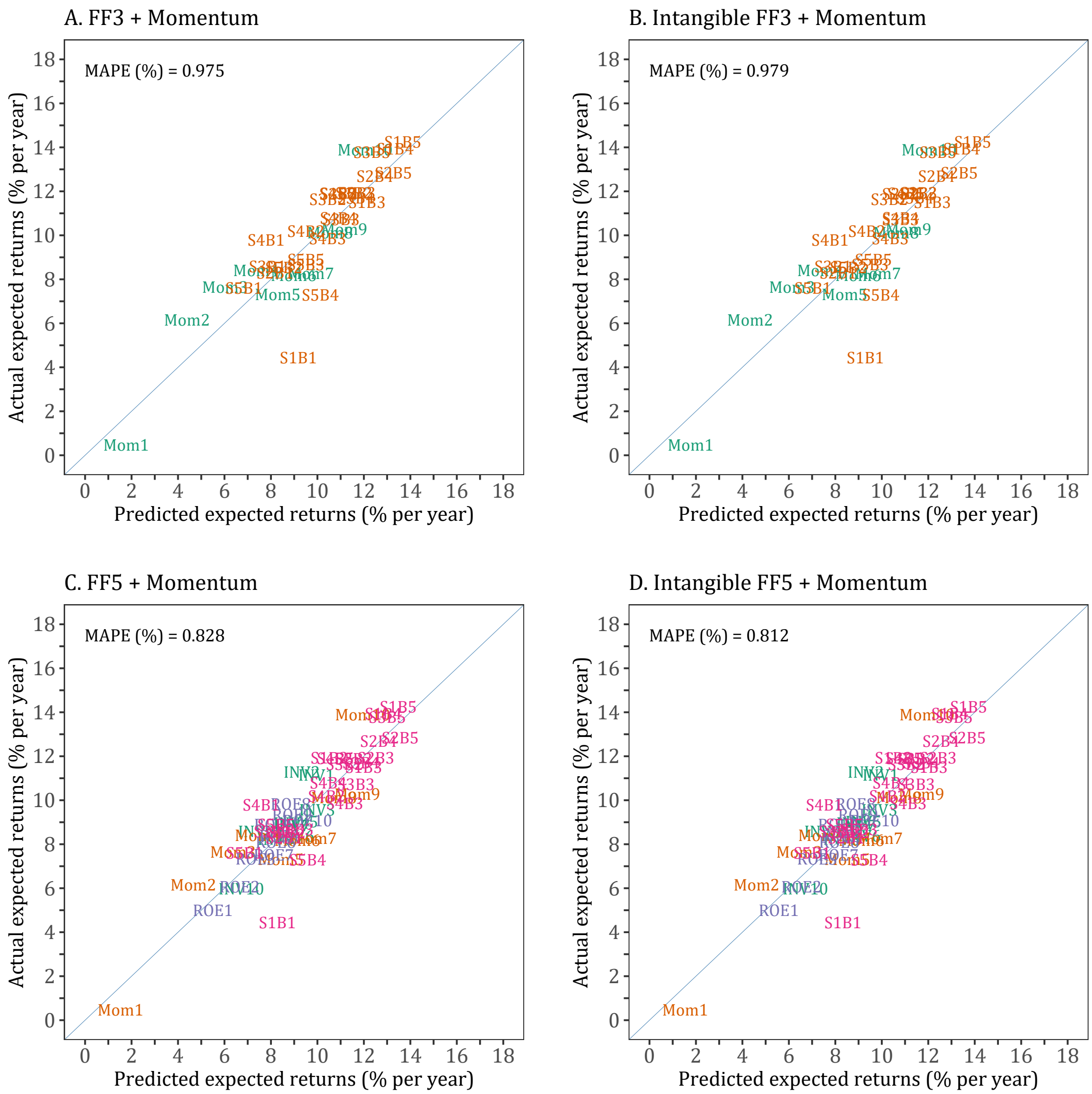

Figure B4: Cross-sectional Asset Pricing Tests – Industry-sorted Traditional Value.

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

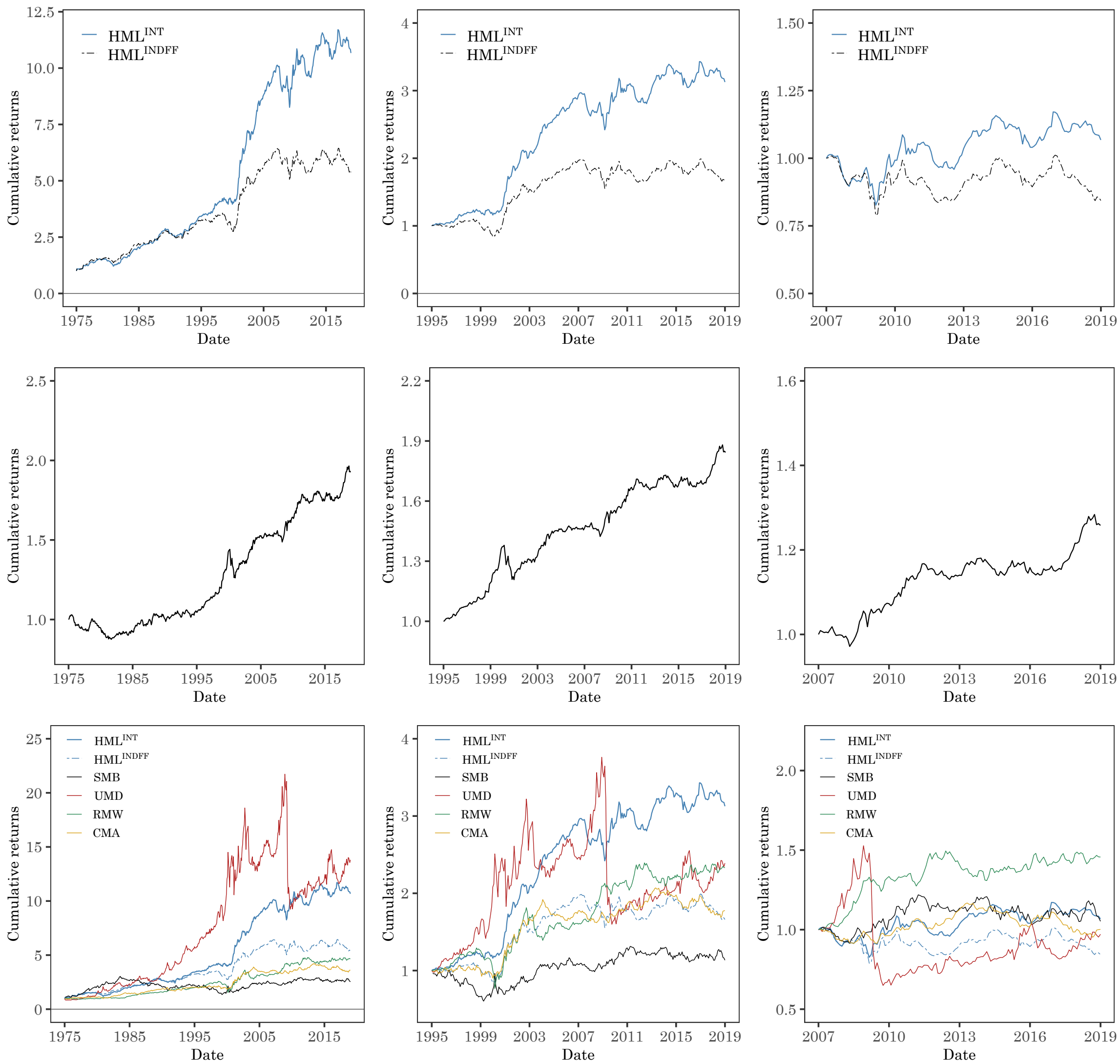

Figure B5: Performance of Industry-sorted Traditional Value.

Description: The top panel plots the cumulative returns of one dollar invested in the HML$^{\text{INDFF}}$ and HML$^{\text{INT}}$ 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$^{\text{INT}}$ portfolio and short the HML$^{\text{INDFF}}$ portfolio. The bottom panel plots the cumulative returns of one dollar invested in HML$^{\text{INT}}$, the Fama and French five factors, and momentum.
Interpretation: Intangible value outperforms traditional value in both the full sample period and recent sub-samples. A long-short portfolio of intangible and traditional value also has positive returns. Lastly, intangible value exhibits similar performance as the top-performing momentum factor without suffering from the drawdown in the post-crisis era.

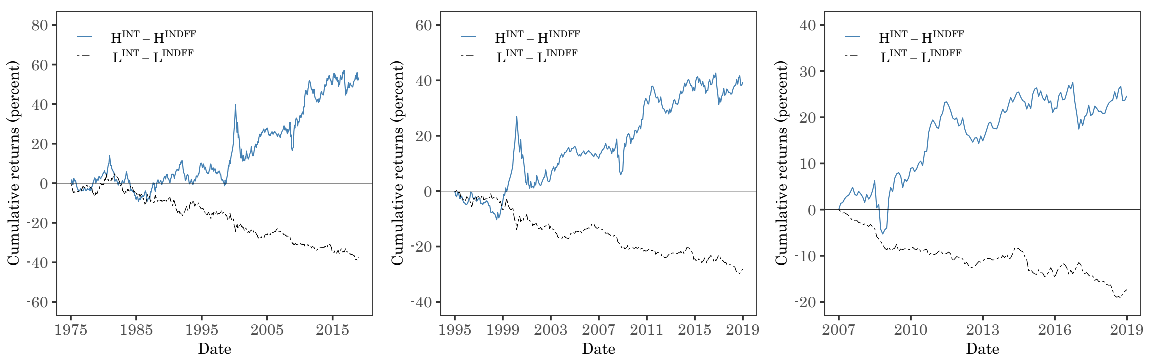

Figure B6: Decomposing Outperformance with Industry-sorted Traditional Value.

Description: This figure plots the cumulative returns of a portfolio that is long the long leg of HML^{INT} and short the long leg of $\text{HML}^{\text{INDFF}}$ (solid blue line), as well as the returns of a portfolio that is long the short leg of HML^{INT} and short the short leg of $\text{HML}^{\text{INDFF}}$ (dashed black line). Each panel plots percent returns from the beginning of 1975, 1995, and 2007.
Interpretation: Each leg of intangible value outperforms traditional value that is industry-sorted.

B.3 Industry Filters

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

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

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

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

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

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

Interpretation: Cross-sectional asset pricing performance of intangible value is invariant to dropping nontraditional industries.

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

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

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

Interpretation: An intangible value factor that excludes nontraditional industries exhibits even higher outperformance over the traditional value factor.

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

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

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

Interpretation: Intangible value with industry filters outperforms traditional value.

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

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

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

Interpretation: The alphas for HML^{INT} and HML^{IME} with industry filters are positive and significant.

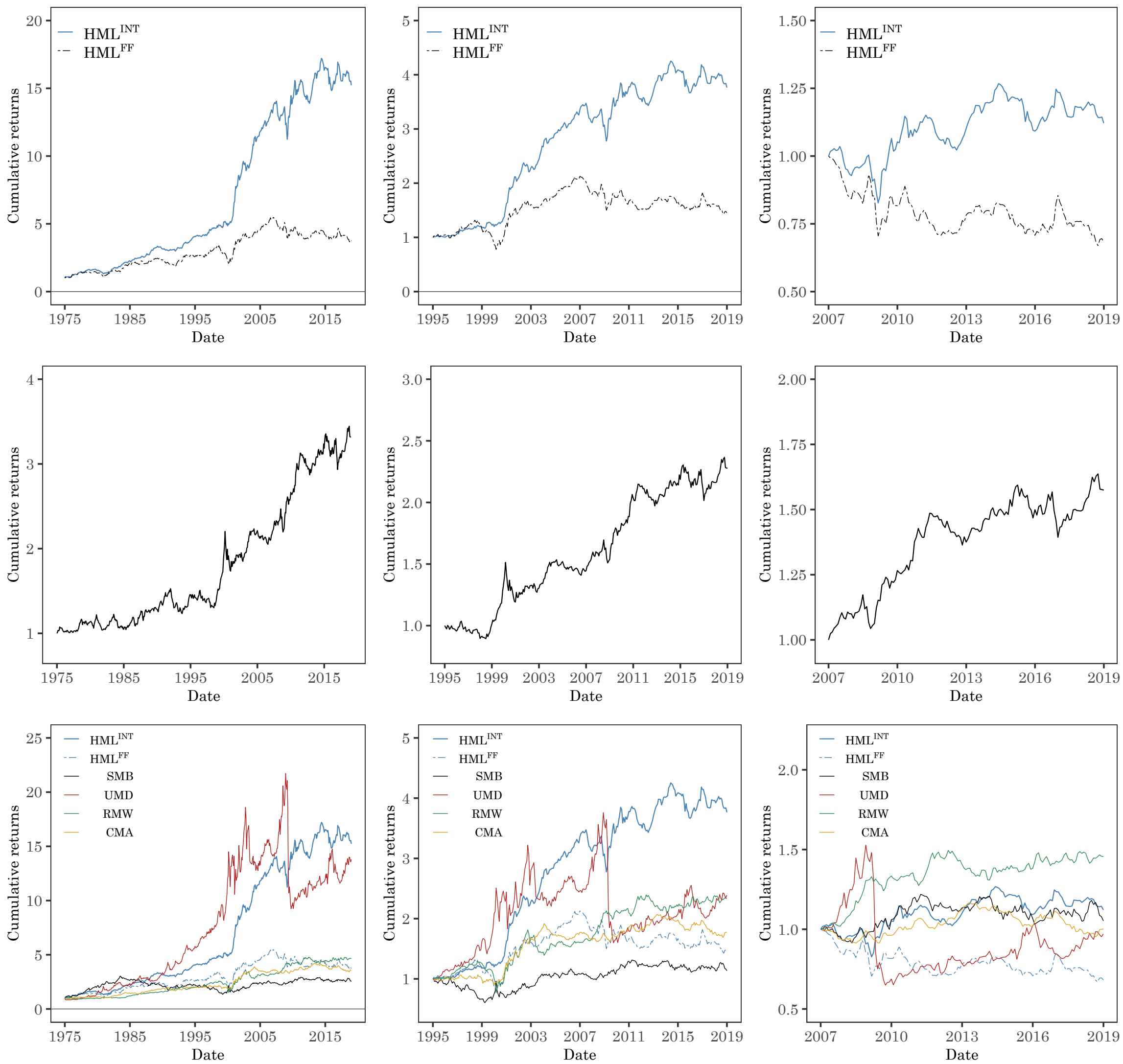

Figure B7: Performance of Intangible Value with Industry Filters.

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

Interpretation: Intangible value's outperformance is more pronounced when financials, utilities, and public service firms are dropped during portfolio formation.