Intangible Value: An International Perspective

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Abstract

Existing studies, focused primarily on the U.S., show the improved value factor performance when adjusting book values for intangible assets. However, there is little evidence whether this is a U.S. specific, or wider international phenomenon. My findings expand the existing evidence to multiple international regions and suggest that the intangible-adjusted book-to-market ratio better measures the value factor globally. Especially in more recent decades, where the size of intangible assets increased dramatically, the relative outperformance of the intangible-adjusted value factor over the traditional value factor has become stronger. Economically, the adjusted value factor bears additional risk related to liquidity, financial distress and funding constraints.

Keywords. *intangible assets, value factor, book value mismeasurement, risk-premium*

JEL Classification. *G11, G15*

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1 Introduction

The value factor is one of the most documented asset pricing phenomena in the financial literature. The commonly used valuation metrics, such as book-to-market (B/M), price-to-earnings (P/E), price-to-sales (P/S) or price-to-cash flow (P/CF) establish a ratio between a market value and a fundamental anchor to assess the cheapness of a stock. Under such metrics, value stocks are shares that trade at relatively cheap valuations, whereas growth stocks trade expensively. Historically, value stocks have outperformed growth stocks significantly. However, especially over the recent decade the performance of the value factor has been rather poor globally. This development is not only puzzling for academic researchers, but also for international value investors who faced disappointing returns.

Doubts on the existence of a value premium or the mismeasurement of the traditional value factor have led to the search for alternative explanations of this extended underperformance. While the recent factor performance may be simply a result of bad luck or an increasingly cheaper factor, another explanation could lie in an ineffective accounting-based expression, which may not sufficiently capture the value premium (Arnott et al. (2021)). Greenwald et al. (2020) suggest contemporary value investors have to go beyond traditional valuation metrics listed on a company‘s balance sheet and consider intangible assets for valuation purposes.

Intangible assets can be purchased or internally generated (e.g. patents, copyrights, intellectual property, brands...). When purchased, the assets are recorded based on the purchase price. However, when internally generated, a precise measurement of intangible assets poses a challenge, as most such items, especially in the U.S., are usually expensed rather than capitalized and therefore do not appear on a company's balance sheet. Especially over the last decade, internally-generated intangible assets have become an increasingly vital part of a company's capital. Recent research in the U.S. (Corrado and Hulten (2010), Ewens et al. (2021), Belo et al. (2022)) suggests internally-generated intangible assets contribute more than one half of a firm's total capital. Thus, existing accounting rules may increasingly hinder the proper reflection of a company's book value. The failure to consider intangible assets in relevant company characteristics, such as book values, consequently leads to a misrepresentation of accounting information (Srivastava (2014)). When assessing the measurement of a company's intangible assets internationally, additional complexity arises due to differences in international accounting standards. While global accounting standards generally agree on the capitalisation of acquired intangibles, the treatment of internally-generated assets requires closer examination. While under U.S. GAAP development costs are usually expensed, under IFRS some research and development (R&D) costs can be capitalized when the underlying asset likely provides future economic benefits to a company and the costs can be reliably measured. Research expenditure is typically viewed as expense and often development expenditures are declared as costs, too.[1] In addition, costs arising from the proper estimation of internally-generated intangible assets may disincentivize firms to capitalize such assets.[2] Therefore, international firms outside of the U.S. may also misrepresent intangible assets in their balance sheet. Consequently, the fundamental anchor required by the value factor may thus be mismeasured also outside of the U.S.

Park (2019) argues that the explanatory power of the popular B/M ratio has become weaker in recent decades due to transformations in accounting rules with respect to intangible assets. Including intangible assets in a company's book value, to better reflect the fundamental anchor required by value investing, has been a promising path. Existing literature[3] shows for U.S. markets how an intangible-adjusted B/M factor significantly outperforms its traditional counterpart. Especially over the recent decade the intangible-adjusted value factor has strongly outperformed the classic value factor.

To analyse the effect of intangible-adjusted book values on the value factor in international markets, I construct an intangible-adjusted value factor, henceforth intangible value factor or simply HML^{INT}, in the U.S., Europe, Japan and Asia Pacific (ex-Japan). The construction of HML^{INT} closely follows the methodology of Fama and French's value factor (see Fama and French (1992)), but adds the described proxy for intangible assets and subtracts goodwill from the book value. When adjusting a company's book value by internally-generated intangible assets, sorting on the resulting (intangible-adjusted) book-to-market ratio delivers significantly improved performance over the traditional value factor in multiple international regions. The approach presented exploits the misspecification of accounting rules toward the capitalization of internally-generated intangible assets and therefore accounts for underestimated, but increasingly important, intangible assets to a company's book value internationally. The resulting HML^{INT} factor is highly correlated with the traditional value factor (75% , 83% , 71% and 96% in the U.S., Europe, Japan and Asia-Pacific respectively), but provides statistically significant outperformance and has been especially pronounced over the recent decade where the performance of the traditional value factor disappointed.

This paper makes several contributions to the existing literature. First, it contributes to a growing body of research that investigates the effect of including intangible assets in traditional asset pricing factors such as value, investment and profitability. While HML^{INT} is not only highly correlated to HML, it also carries significant information not subsumed by other traditional equity factors. Therefore, this research shows how equity investors can significantly expand their efficiency portfolios. Second, while most papers investigate the effect primarily in the U.S.[3], this paper expands existing empirical evidence to other international markets for which only little or mixed evidence exists (e.g.

[1] `https://www.ifrs.org/issued-standards/list-of-standards/ias-38-intangible-assets/`

[2] `https://www.fasb.org/jsp/FASB/Page/SectionPage&cid=1176173166185.`

[3] I focus primarily on the work of Eisfeldt et al. (2022), but provide further references in Section 2.

Rizova and Saito (2021) Li (2022)). The presented international evidence also mitigates any data mining concerns that could be specific to the U.S. dataset. Third, this study investigates economic explanations for the relative outperformance of HML^{INT} over HML and advocates a risk-based rationale. Thus, the paper contributes to existing literature that investigates behavioral or risk-based explanations to a factor's performance.

The remainder of this paper is organized as follows: Section 2 discusses existing literature related to intangible assets and the value factor. Section 3 presents the construction of HML^{INT} and its performance relative to HML across four international regions. Additionally, the section links the relative performance to an economic rationale. Section 3.3 reconciles the findings in the context of existing literature. Finally, Section 4 concludes with a summary of the presented findings as well as ideas for future research.

2 Literature Review

Existing U.S. studies (Park (2019), Lev and Srivastava (2019), Eisfeldt et al. (2022), Arnott et al. (2021), Gulen et al. (2021)) propose a simple improvement to the traditional U.S. value factor of Fama and French (1992) that adjusts a company's book value to include intangible assets. The resulting intangible value factor prices U.S. assets at least as well as the classical value factor and shows a superior performance over the traditional value factor for different sample periods. Eisfeldt et al. (2022) suggest the intangible value factor sorts more effectively on productivity, profitability, financial soundness, and on other valuation ratios such as P/E or P/S. Moreover, given the improved sorting on fundamentals relative to traditional value, the intangible value factor may largely avoid value traps. Their findings are related to Eisfeldt and Papanikolaou (2013), who suggest that companies with more intangible assets, referred to as organizational capital such as a firm's key employees, earn higher stock returns in the cross-section of U.S. stocks. Shareholders consider such firms as riskier since outside options of key talent govern the proportion of a company's cash flows that shareholders receive. Therefore, investors require a higher risk premium to invest in such companies.

Arnott et al. (2021) underscore that accounting-based expressions may be responsible for ineffectively capturing the value premium. In line with Eisfeldt et al. (2022), they argue that under U.S. accounting rules intangible assets are expensed rather than amortized and therefore do not appear on the balance sheet. Hence, traditional book values do not sufficiently reflect intangible assets and therefore lead to a misclassification of value and growth stocks. In addition, they suggest two likely explanations for the recent underperformance of the value factor. First, the factor may simply have become cheaper over time. Second, the performance may simply be a result of bad luck or a left-tail event. The authors emphasize the increasing importance of intangible assets and show performance improvements over the traditional U.S. value factor of Fama and French (1992) when including intangibles in a company's book value. Apart from systematic misidentification of value due to accounting deficiencies, Lev and Srivastava (2019) additionally suggest economic developments slowed down the mean-reversion of value and growth stocks, thus reducing the historical gains from value investing.

Park (2022) provides empirical evidence for the superior performance of an intangible-adjusted value factor over the traditional value factor and other value variants. The author suggests even an imperfect proxy of intangible assets to be included in the book-to-market metric leads to improved asset pricing. In line with the results of Fama and French (2015), who observe that the value factor becomes redundant when adding the factors robust-minus-weak (RMW) and conservative-minus-aggressive (CMA) to describe returns of the cross-section of stocks, the authors show in spanning regression the redundancy of traditional value but a pronounced contribution of intangible value. Gulen et al. (2021) show how a separate intangible-only value factor is no longer redundant in any of the above factor models. The relevance of accounting for intangibles is not only highlighted by the positive impact on the value factor, but also investigated in a wider spectrum. For example, Gulen et al. (2021) show the positive impact of accounting for intangibles for the value, investment and profitability factor. De Boer (2021) includes intangible assets in the total assets to enterprise value ratio and finds a significant correlation of the ratio with future expected stock performance.

Internationally, ample research discusses the traditional value factor (Chan et al. (1991), Capaul et al. (1993), Fama and French (1998), Fama and French (2012), Asness et al. (2013), Fama and French (2017)). However, little research is available on the intangible value factor. Rizova and Saito (2021) use the perpetual inventory method of Peters and Taylor (2017) to account for intangible assets in book values. They apply the approach to the cross-section of stocks in the U.S., developed ex U.S., and emerging markets. The authors do not find evidence for a significant performance improvement when adjusting book values for intangibles for the traditional value and profitability factor. The detected minor performance improvement disappears when adjusting for sector differences in each of the investigated regions. The authors indicate different sources of noise to the estimation of intangible capital which, they argue, can lead to noisy results. Li (2022) investigates the intangible value factor across the regions U.S., U.K., Continental Europe, Japan and Asia ex Japan and find improved factor performance across different subperiods. Additionally, the authors show the improved value performance comes disproportionally from the long portfolio of the factor. Furthermore, they ascertain that knowledge capital (capitalized via R&D expenditures only) plays a more important role than organizational capital (measured via SG&A). However, the difference is not significant and the authors mostly refer to the results in U.S. markets. As Rizova and Saito (2021), the authors resort to the perpetual inventory method of Peters and Taylor (2017).

While the evidence toward ineffective accounting expressions in the U.S. appears evident, do investors not account for intangibles and consequently misprice assets? Is the intangible value factor outperformance due to such a behavioral bias or does it simply contain more risk than the traditional value factor and requires a higher risk premium? In existing academic research, the rationale for the superior performance of HML^{INT} over HML is mixed. Bongaerts et al. (2021) argue that investors underreact to intangibles due to the presented accounting mismeasurement. While Eisfeldt et al. (2022) do not explicitly advocate a behavioral explanation, they hint toward a mispricing rationale. Furthermore, Cohen et al. (2013) argue that investors have difficulty in valuing intangible assets whereas other authors point out the existence of higher information asymmetries in R&D intensive firms (Lev et al. (2005), Gu and Wang (2005), Palmon and Yezegel (2012)). Contrary to the evidence on mispricing, Eisfeldt and Papanikolaou (2013) argue that firms with greater intangibles are riskier for shareholders as key talent has greater bargaining power to the firm's cash flows. Related literature suggests that intangible and tangible capital face different adjustment costs to innovations in economic regimes. Higher adjustment costs for intangibles, as suggested by Peters and Taylor (2017) and Gulen et al. (2021), makes companies with a high stock of intangibles riskier. Furthermore, Ai et al. (2020) and Giglio and Severo (2012) argue for a collateralizability premium of intangibles assets, implying stocks with high levels of intangibles should earn higher returns. If correct, the superior performance of HML^{INT} would relate to a risk-based explanation. As outlined by Park (2019), accounting issues related to intangibles can coexist with the risk-based explanation as well as the mispricing theory. In a similar vein to Gulen et al. (2021), who investigate the independent contribution of intangible assets to factor models, this paper investigates systematic differences between HML^{INT} and HML rather than HML^{INT} on a standalone basis. In particular, I analyse whether HML^{INT} is riskier or contains a higher behavioral bias than HML. My findings across all the presented regions advocate a risk-based explanation. Stocks with high intangible-adjusted B/M ratios contain considerably higher levels of operating leverage resulting in elevated levels of financial distress and are more exposed to tighter funding constraints, especially in bad economic periods. In addition, market, liquidity and intermediary risks are significantly related to the relative performance. Behavioral biases such as the extrapolation bias[4] or sentiment[5] do not indicate a significant relationship for explaining the return difference.

[4]Lakonishok et al. (1994) first presented evidence for an extrapolation bias as explanation for the traditional value factor.

[5]In relation to the sentiment index of Baker and Wurgler (2006).

3 Data and Empirical Application

In this paper, I examine the intangible value factor in the four regions: (i) United States, (ii) Europe, which includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom, (iii) Japan and (iv) Asia Pacific, including Australia, Hong Kong, New Zealand and Singapore (but not Japan). I select the Thomson Reuters Datastream (TDS) database as data provider, which offers access to international stock data via a merged database of Worldscope and Datastream data.[6] Figure 1 shows the number of available stocks that report relevant price and accounting data per region. As part of the analysis, I use risk-free rates and factor data for market, size, value, quality, investment and momentum from Ken French's website.[7]

To measure intangible assets, I follow the perpetual inventory approach of Eisfeldt and Papanikolaou (2013). The authors show how to derive a proxy for organizational capital (representing intangible capital) using accumulated selling, general and administrative (SG&A) expenses.

$$INT_{it} = (1-\delta)INT_{it-1} + SG\&A_{it}. \tag{1}$$

where δ indicates the depreciation rate of intangibles and $SG\&A_{it}$ are selling, general and administrative expenses of company i at time t. INT_{it} is initiated by calculating $INT_{i1} = SG\&A_{i1}/(g+\delta)$ with the first observation of $SG\&A_{i1}$ for company i at time 1. The variable g represents the average growth rate of $SG\&A$.

In line with Eisfeldt et al. (2022), to construct HML^{INT}, I add intangible assets (INT_{it}) to book equity (B_{it}) and subtract goodwill ($GDWL_{it}$), in order to reduce the effects of merger activity:

$$B_{it}^{INT} = B_{it} - GDWL_{it} + INT_{it} \tag{2}$$

for firm i at time t. B_{it}^{INT} is the resulting intangible-adjusted book value. I follow Eisfeldt et al. (2022) and use solely SG&A to derive a proxy for organizational capital, whereas other authors separate organizational and knowledge capital[8] and form an aggregated measure of intangibles. While both approaches may not precisely provide the stock of intangible capital, a possibly imperfect proxy is still better than assuming zero intangible capital (Peters and Taylor (2017)). In line with Eisfeldt et al. (2022), I set $g = 0.1$, which approximates the average growth rate of $SG\&A$, and $\delta = 0.2$, which approximates the depreciation rate of accumulated intangible capital following Eisfeldt and Papanikolaou (2014). While the assumptions for g and δ are based primarily on U.S. data, for

[6] Section A.1 provides detailed information on the dataset and the extensive data cleansing procedure.

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

[8] Knowledge capital is derived similarly to organizational capital but via R&D expenses. See for example Peters and Taylor (2017).

consistency I will use the same assumptions for growth and depreciation rates for other international regions.[9]

After the calculation of firm-specific B^{INT}, for each region I construct portfolios from 2 x 3 sorts on size (market capitalization) and intangible-adjusted book-to-market (B^{INT}/M). In June of each year t, I rank stocks in each region based on market capitalization (M) and the B^{INT}/M ratio. As in Fama and French (2017), for international markets outside the U.S., I consider big stocks as those in the top 90% of total market capitalization and others as small stocks. For the U.S., I calculate NYSE breakpoints to establish the two size groups as in Fama and French (1992). For B^{INT}/M, I use the 30th and 70th percentile to distinguish high (intangibles-adjusted) value from neutral and low (intangibles-adjusted) value stocks in each region. Stocks with negative book value are excluded from the factor construction, except for the market factor. Book values are from the fiscal year[10] $t-1$ and market capitalization is from the end of December of calender year $t-1$. The 2x3 sorts result in six portfolios, SG, SN, SV, BG, BN, and BV, where G, N, and V represent growth, neutral, and value respectively and S and B stand for small or big. I then calculate monthly value-weighted returns for each of the six portfolios from July in year t to June in year $t+1$.[11]

Table 1 reports the performance statistics of the top and bottom portfolio of the constructed factors HML and HML^{INT} for the four regions U.S., Europe, Japan and Asia-Pacific across the full sample from June 1983 to December 2021. Over the entire sample and across all regions, the returns of HML^{INT} are significantly more positive than those of HML. HML^{INT} also outperforms HML in all regions on a risk-adjusted basis. Moreoever, HML^{INT} has experienced less extreme drawdowns than HML across all presented regions. To put into perspective the performance of the top and bottom portfolios of HML^{INT} against HML, Figure 2 presents a comparison of the two factors across the four regions for the full sample.[12] The top (bottom) portfolio of HML^{INT} outperforms (underperforms) the respective portfolio of HML across all regions except Japan. To better contrast different time periods, Table 2 shows the outperformance of intangible value over the traditional value factor for the four analysed regions not only across the full sample but also over the sub-periods 1983-1994 (pre-internet era), 1995-2006 (internet era pre-crisis) and 2007-2021 (crisis and post-crisis era). As highlighted above, for the full sample only in Japan is the coefficient intercept of HML^{INT} over HML not significant (but still positive). However, in the more recent period from 2007 onwards, the outperformance of intangible value over the traditional value factor is significantly positive in all regions including Japan.

[9] The depreciation rate implies a gradual decay of the value of internally-developed intangibles, which may not be accurate for longer-lived intangibles such as a company's reputation or shorter-lived assets such as temporary legal rights.

[10] Slight deviations are possible due to TDS reporting standards as outlined in Section A.1.

[11] The correlation between my replicated value factor and the published international value factors from Fama-French is 95.55% (U.S.), 90.64% (Europe), 90.41% (Japan) and 83.85% (Asia-Pacific).

[12] The presented monthly returns are ex-post volatility scaled to 5% p.m..

Table 3 shows the loadings of the constructed intangible value factor on the five factors of Fama and French (2017) as well as Carhart (1997)'s momentum factor. With individual regional exceptions, the intangible value factor loads significantly positive (besides on HML) on the size, profitability and investment factor. Additionally, intangible value loads negatively on momentum. The spanning regressions show how particularly in Europe and Japan the intangible value factor contains additional information not captured by the remaining factors. Especially over the more recent period[13], where the stock of intangibles rose drastically, the significant intercepts in Table 4 highlight the pronounced contribution of HML^{INT} across all regions.

3.1 Economic Explanation

In this section I want to investigate whether the relative outperformance of HML^{INT} over HML can be explained from a risk-based or behavioral perspective. Generally, there are three different categories into which an explanation for an existing factor could fall. First, when a factor is exposed toward a particular type of risk, the performance of it is simply a compensation for taking on this risk. Second, a behavioral bias, such as earnings extrapolation of investors, may lead to the mispricing of assets. If investors truly extrapolate high (low) earnings growth from growth (value) stocks, then the factor performance can be explained from a behavioral standpoint. Third, a factor may simply be a statistical artefact resulting from data snooping. My findings strongly weaken the last explanation, since the intangible value factor is present not only in the U.S., but also in all of the other investigated regions. In the analysis below, I show that higher exposure to operating leverage (associated with financial distress), liquidity and intermediary risk (associated with funding constraints) can be the reason for the superior performance of HML^{INT}. Thus, the presented results advocate a risk-based rationale.

3.1.1 Risk-Based Explanation

Fama and French (1993) suggest value stocks are fundamentally riskier than growth stocks and therefore require a premium to compensate investors for taking on additional risk. Zhang (2005) supports this conclusion by showing that value stocks have higher operating leverage and therefore have less ability to flexibly adjust production levels to different economic regimes.[14] Thus, HML^{INT} may simply be more exposed to a higher degree of operating leverage than HML. If intangible-value companies cannot adjust as much, or only more expensively, to economic shocks, then a higher risk premium would be required to hold such stocks. Furthermore, existing literature relates the book-to-market effect to companies with high default risk, thus suggesting a connection between value and distress risk (Griffin and Lemmon (2002), Vassalou

[13] The period from January 2007 to December 2021.

[14] Other authors, such as Carlson et al. (2004) or García-Feijóo and Jorgensen (2010), also relate the value anomaly to operating leverage.

and Xing (2004)).[15] To empirically investigate differences in operating leverage and financial distress, I follow the approach of Mandelker and Rhee (1984) and García-Feijóo and Jorgensen (2010) and construct for each company based on overlapping rolling five-year windows the degree of operating (DOL), financial (DFL) and total (DTL) leverage, which are defined as follows:

Degree of Operating Leverage (DOL):

$$ln(EBIT_t) = ln(EBIT_0) + g_{EBIT}t + \mu_{t,EBIT}, \tag{3}$$

$$ln(SALES_t) = ln(SALES_0) + g_{SALES}t + \mu_{t,SALES} \tag{4}$$

$$\mu_{t,EBIT} = OL\mu_{t,SALES} + \epsilon_t \tag{5}$$

Degree of Financial Leverage (DFL):

$$ln(EAIT_t) = ln(EAIT_0) + g_{EAIT}t + \mu_{t,EAIT}, \tag{6}$$

$$\mu_{t,EAIT} = FL\mu_{t,EBIT} + \nu_t \tag{7}$$

where OL (operating leverage) and FL (financial leverage) are the variables of interest. $EBIT_t$, $SALES_t$ and $EAIT_t$ are earnings before interest and taxes, total revenue and earnings after interest and taxes at time t respectively. $EBIT_0$, $SALES_0$ and $EAIT_0$ are starting values of $EBIT$, $SALES$ and $EAIT$ of each respective rolling five-year window. To calculate logs of negative EBIT or EAIT, I use the transformation: $ln(1 + x)$ if $x \geq 0$ and $-ln(1 - x)$ if $x < 0$. The resulting residuals $\mu_{t,EBIT}$, $\mu_{t,SALES}$ and $\mu_{t,EAIT}$ from Equations 3, 4 and 6 are used in Equations 5 and 7 to derive operating and financial leverage. Finally, the degree of total leverage DTL for each firm is calculated as the product of operating and financial leverage. Next, I compute a t-test between the time-series of aggregated DOL, DFL and DTL of HML^{INT} and HML portfolios. Figure 3 presents the results, showing the t-statistic of differences in means of DOL, DFL and DTL between HML^{INT} and HML. Across all regions, DOL, DFL and DTL are statistically higher in HML^{INT} than HML. Thus, the results suggest intangible-value stocks are more exposed to DOL, DFL and DTL than traditional value stocks. Intangible-value stocks are more financially distressed and less flexible to adjust to different economic states. Consequently, investors should require a higher risk premium for HML^{INT}. These results are in line with the findings of Peters and Taylor (2017) and Gulen et al. (2021), who argue intangible capital cannot be adjusted as fast as physical capital to changing economic situations as such assets are more costly to reverse. Additionally, the presented finding is supported by Ai et al. (2020) and Giglio and Severo (2012), who argue for a collateralizability premium of intangible assets. Firms cannot use intangibles as collateral and therefore face tighter borrowing constraints, especially in bad times.

[15] This relation, however, stands in contrast to Dichev (1998) or Campbell et al. (2008), who argue companies with high default risk experience lower future returns.

3.1.2 Other Sources of Macroeconomic or Liquidity Risk

In addition to the explanations related to leverage, I analyse whether the difference in performance can be explained by other sources of macroeconomic and liquidity risks. In analogy to the analysis conducted by Asness et al. (2013), who investigates risk exposures for value and momentum factors, I determine whether HML^{INT} has a significantly higher risk exposure to the below-presented variables over HML. I run the following fixed-effects panel-regression:

$$HML_{i,t}^{INT} = \alpha_i + \beta_{HML} HML_{i,t} + \beta_V V_t + \epsilon_{i,t} \tag{8}$$

where i represents the region and V_t is a selected macroeconomic or liquidity variable V at time t. A significant coefficient β^V would highlight an economic risk factor that could (partially) explain the performance difference. Table 5 shows the coefficients β_V and associated t-statistics of each macroeconomic and liquidity risk variable V. For brevity, the fixed-effect intercepts α_i and coefficients β_{HML} from the regressions are not reported. The selection of the macroeconomic and liquidity risk variables follows Asness et al. (2013) and is complemented by variables potentially more closely related to intangibles. These include DEF, which represents the default spread measured by the yield difference of U.S. corporate bonds and U.S. Treasuries, TERM, which measures the term spread of U.S. government bonds (the difference between 10-year and 3-month U.S. government bond/bill yields), GDP, which is the contemporaneous GDP growth measured by changes in real gross domestic product per capita, the Chicago Fed National Activity Index (CFNAI) that proxies U.S. economic activity, the MSCI World, which is the return of world equity markets in excess of the U.S. t-bill rate, the NBER recession dummy, which represents U.S. recessions (0 = peak, 1 = trough), U.S. unemployment[16] and personal consumption expenditure (PCE), which represents long-run consumption growth and is measured by the 3-year future growth rate in per capita of nondurable goods. IAPF is the intermediate asset pricing risk factor (the AR(1) innovations to the intermediary capital ratio scaled by lagged intermediary capital ratio) by He et al. (2017). Furthermore, I include shocks, measured by the residuals of an AR(2) process of the TED spread as a funding liquidity indicator (FL Shock) and the On-the-run vs. Off-the-run 10-year government treasury note spread as a market liquidity indicator (ML Shock). To measure total liquidity (PCAL Shock), I use a principal component-weighted average index of the two liquidity shocks. Apart from the macroeconomic and liquidity variables, I include the sentiment variable from Baker and Wurgler (2006) to test for a possible behavioral explanation. PCE and GDP are measured against cumulative quarterly returns, whereas the remaining indicators are measured against monthly returns. The results from Table 5 show the difference in returns between HML^{INT} and HML is significantly positively linked to global equity returns (MSCI World), the intermediary asset pricing factor (IAPF) and liquidity (FL Shock, ML Shock,

[16] In relation to the work of Eisfeldt and Papanikolaou (2013) and their findings associated to bargaining power of employees, which might potentially be elevated in a tight labour market.

PCAL Shock). The results deliver additional evidence toward a risk-based explanation of the return difference. Market shocks, especially related to liquidity, affect companies with high levels of intangible assets more adversely, since they can use less of such assets as collateral and concurrently face tighter borrowing constraints.

3.1.3 Behavioral Explanation

Lakonishok et al. (1994) (LSV) find that the value factor's outperformance is related to investment biases and not due to taking on additional risk. LSV argue that market participants overestimate future growth rates of glamour stocks relative to value stocks. Thus, growth underperforms value. Fama and French (1995) critizise the work of LSV by arguing that earnings growth does not explain the suggested extrapolation bias but price-earnings growth does. However, the latter measure, as they argue, does not support a behavioral explanation. As outlined in the beginning of the section, I do not aim to contribute to a standalone economic rationale of any factor, I merely focus on an explanation of the outperformance of intangible to traditional value. Figure 4 shows the evolution of earnings growth of the top and bottom traditional and intangible value portfolios from five years before to five years after portfolio formation. The results in the U.S. are in line with the findings of LSV and show the generally higher (lower) earnings growth of stocks with low (high) book-to-market ratios, i.e. glamour (value) stocks before portfolio formation. In the years before portolio formation, earnings growth rises (falls) for stocks with low (high) book-to-market ratios. Subsequently to portfolio formation, earnings growth tends to mean-revert. This finding is consistent across all regions except Asia-Pacific, where the relationship appears reversed. Earnings growth of intangible-adjusted book-to-market ratios follows the same pattern. As suggested by Fama and French (1995), in Figure 5 I investigate standardized earnings-to-price growth for the top and bottom portfolios of each of the four regions in the five years before and after portfolio formation. Except for Asia-Pacific, high and low book-to-market ratios rise or remain flat in earnings-to-price after portfolio formation. From year $t + 0$ to $t + 1$ no significant differences in earnings-to-price growth exist between top or bottom traditional and intangible value portfolios. Thus, extrapolation biases do not appear to explain differences in performance between the two value measures. However, there could be other behavioral explanations for the return differences. Cohen et al. (2013) suggest investors have difficulties in valuing intangible assets. HML^{INT} has a significantly higher exposure to the size factor than HML. Smaller companies are less likely covered by financial analysts, implying higher stock valuation disagreement which may result in mispricing. In Table 5, I include the sentiment indicator from Baker and Wurgler (2006) to relate investor sentiment to the return difference. However, the results do not indicate a significant relationship.

3.2 Robustness

As addressed by Eisfeldt et al. (2022), the presented factor results may be driven by industry exposure. Table 6 shows summary statistics of firm characteristics in the top and bottom portfolios of HML and HML^{INT} and related industry weights in each portfolio. Evidently, industry exposures differ between HML and HML^{INT} and could be the driver of relative performance. For example, financial stocks frequently appear in the top portfolio of HML but less so in the top portfolio of HML^{INT}. Measuring value within industries reduces noise and exposure to unpriced risk and also addresses differences in accounting practices across separate industries. To assure that the superior performance of the presented HML^{INT} factor is not due to lucky industry overweighting, I construct an industry-neutral version of HML^{INT}. I obtain 12 industry classifications from Ken French's website[17] to construct within-industry portfolios. Subsequently, I value-weight each industry by its total market capitalization to calculate market-level portfolio returns. Table 7 shows the regression of a within-industry adjusted version of HML^{INT} on HML^{INT}. The within-industry factor has either a significant positive (U.S., Europe and Japan) or non-significant intercept (Asia-Pacific) over HML^{INT}. While the within-industry factor loads significantly on HML^{INT} in each region, the regression coefficient is remarkably below one in all regions. Overall, the presented findings do not suggest that HML^{INT} is superior to a within-industry version. In fact, the results suggest that a within-industry factor rather outperforms HML^{INT} than the other way around.[18]. This finding alleviates the concern that the outperformance of HML^{INT} over HML is simply due to historically lucky industry exposure. Thus, an industry-neutral version of HML^{INT} may be an even superior factor.

In regions with more than one currency, the constructed long-short factor returns are possibly not neutralized by offsetting currency positions. In this way, lucky currency timing can impact the factor performance of a whole region. In Asia-Pacific, four different currencies can substantially impact the performance of the regional HML^{INT}. To ensure factor returns are not driven by currency returns, I construct local excess returns for the full cross-section of stocks. I calculate returns in local currency and then subtract the local risk-free rate. I follow Schmidt et al. (2019) in the selection of risk-free rates from TDS. First, whenever available, I select local treasury bill rates, which are typically used in asset pricing studies (e.g. Fama and French (1992)). Second, whenever available, I use overnight index swap rates (OIS)[19] and lastly interbank rates (IBR).[20] Table 8 presents regression results of the local excess return version

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

[18] Another reason to go for industry-based sorting, instead of traditional economy-wide sorting, is because Asness et al. (2000) find value has consistently been a within-industry phenomenon. I confirm this finding in Table A4 for the four regions U.S., Europe, Japan and Asia-Pacific. Additionally, the table shows the improved cross-sectional pricing power of the intangible-adjusted B/M over the traditional B/M ratio.

[19] In Europe, I use the Euro 3 Month OIS rate only for countries after their adoption of the euro currency.

[20] Table A6 displays the selected country-wise local risk-free rates.

of HML^{INT} on the standard HML^{INT} factor.[21] The intercept is positive across all regions, suggesting the performance of a local excess return version of HML^{INT} is not inferior to HML^{INT}.

To address the differences in perpetual inventory methods, in Table 9, I show how different specifications impact the outperformance of HML^{INT} over HML. In particular, I show how varying depreciation rates for the method of Eisfeldt et al. (2022) (i.e. $\delta = 0.1$ or $\delta = 0.3$) do not materially alter the results of the strong outperformance of the intangible over the traditional value factor. In addition, the table includes different specifications of the method of Peters and Taylor (2017) and shows the lower, but mostly still significant, outperformance over traditional value. The authors distinguish between organizational and knowledge capital, which are both derived as follows:

$$\begin{aligned} O_{it} &= (1 - \delta_{SG\&A})O_{it-1} + \alpha_{SG\&A} SG\&A_{it}, \\ K_{it} &= (1 - \delta_{R\&D})K_{it-1} + \alpha_{R\&D} R\&D_{it}. \end{aligned} \tag{9}$$

where O and K stand for organizational and knowledge capital respectively of company i at time t. The fractions of SG&A and R&D used to estimate each capital are $\alpha_{SG\&A} = 30\%$ and $\alpha_{R\&D} = 100\%$. The assumed depreciation rates are $\delta_{SG\&A} = 20\%$ and $\delta_{R\&D} = 15\%$. In the base scenario, initial organizational and knowledge capital is assumed to be zero. Finally, to derive total intangible capital, both types of capital for company i are added up at time t:

$$INT_{it} = O_{it} + K_{it} \tag{10}$$

and INT_{it} is then inserted into Equation 2 to adjust the respective book value for company i at time t. Following this procedure, I separately construct organizational and knowledge capital.[22] Overall, the statistical significance of HML^{INT} over HML is higher using the approach of Eisfeldt et al. (2022) than that of Peters and Taylor (2017) (i.e. t-stat of 3.07 vs. 1.99).

To disentangle the contribution of organizational and knowledge capital within the intangible value factor, I construct the intangible value factor separately using solely organizational capital, knowledge capital or a combination. Table 10 presents the alternative intangible value factors regressed on regional Fama-French factors. The regression intercepts of these alternatives of HML^{INT} suggest no positive statistical significance except for Japan. Knowledge capital produces slightly more significant intercepts than organizational capital in the U.S. (t-stat of 0.55 vs. -1.28) and Europe (t-stat of 1.40 vs. 0.24) but not in other regions. Overall, neither knowledge nor organizational capital produces a much stronger version of HML^{INT}.

To assure DOL, DFL and DTL are not driven by financial firms (for the same reason as in Fama and French (1992)), I use only nonfinancial stocks and

[21] In the U.S. and Japan, the coefficient estimate is almost exactly 1, since from all firms I subtract the same risk-free rate.

[22] TDS includes R&D in SG&A, therefore to construct organizational capital, I subtract R&D from SG&A. Whenever R&D is higher than SG&A, I keep SG&A unchanged in line with the approach applied by Peters and Taylor (2017).

compute the t-statistic of differences in means of operating, financial and total leverage between HML^{INT} and HML across the four regions. Figure 6 shows that intangible-value stocks (excluding financials) are significantly more exposed to operating leverage. However, these stocks are not so strongly exposed to financial leverage anymore as in the case when financials are included. Overall, leverage still constitutes a significant risk factor for stocks in the HML^{INT} factor across all presented regions.

3.3 Discussion of Findings

The presented results underpin existing U.S. studies on the benefits of using intangible-adjusted book values to construct an improved version of the traditional value factor of Fama and French (1992). Besides the replication of existing U.S. results, I broaden these findings to Europe, Japan and Asia-Pacific and show that an intangible-adjusted B/M ratio reduces biases in book values globally. Furthermore, HML^{INT} is not only superior to the traditional value factor in terms of performance, but also improves existing cross-sectional asset pricing tests globally. In line with the findings of Park (2022) in the U.S., the results highlight a pronounced contribution of the intangible value factor in spanning regressions across the four presented regions. Controlling for other international factors of Fama and French (2017) and Carhart (1997), HML^{INT} contains a positive intercept in all regions. In regions outside of the U.S., the factor's alpha is at least as or even more significant.

My results stand in contrast to Rizova and Saito (2021), who suggest adding an internally-generated intangibles proxy to book values does not significantly improve the value premium in international markets. The difference in findings could be related to the following reasons. First, the authors use the measure of Peters and Taylor (2017) and therefore separate organizational and knowledge capital, using R&D and SG&A. Table A3 shows the percentage of data for SG&A and R&D that is either missing or zero. Across all regions, R&D expenses are not reported for more than half of the firms in the sample, especially financial companies lack to report these costs. Hence, the adjustment for knowledge capital concerns only a small fraction of the total market while the remaining stocks stay unadjusted. This leads to less comparable firms, when adjusting the book value of only a minor fraction of firms with knowledge capital. In comparison, the fraction of missing SG&A data are drastically smaller compared to R&D and the data shortcoming can be reduced.[23] Independent of the selected measure, noise will remain in the data. However, using solely SG&A data to proxy intangible assets is a simpler and more consistent approach to construct HML^{INT} than constructing the proxy with the method of Peters and Taylor (2017). Second, Rizova and Saito (2021) do not control for size effects and use simple univariate sorts to construct asset pricing factors. Hence, their results may be driven by large-cap companies and for instance the positive loading on the size effect, as outlined in Table 3, may be disregarded.

[23]Since TDS includes R&D in SG&A, the fraction of missing SG&A must be smaller or equal than that of R&D.

The presented findings generally agree with Li (2022), who finds that HML^{INT} outperforms HML in the regions U.S., Europe, United Kingdom, Japan and Asia-Pacific. The author shows in spanning regressions that, for the U.S. version of HML^{INT}, solely including knowledge capital leads to a larger alpha than additionally including organizational capital since the addition of organizational capital merely leads to a higher factor loading on the size effect. However, my findings suggest this is not consistent across different regions. Table 10 presents the alternative intangible value factors regressed on regional Fama-French factors. The regression intercepts of these alternatives of HML^{INT} suggest no positive statistical significance except for Japan. I find, as argued by the author, in order to improve the value valuation metric, knowledge capital is more important than organizational capital only in the U.S. (t-stat of 0.55 vs. -1.28) and Europe (t-stat of 1.40 vs. 0.24) but not in Japan (t-stat 3.06 vs. 3.77) or Asia-Pacific (0.23 vs. 0.43). Therefore, I find the statement that knowledge capital is more relevant than organizational capital in measuring intangible capital cannot be generalized across international markets. Moreover, in line with the author, in Table 9 I present evidence that the results are not particularly sensitive to the depreciation rate choice used in the perpetual inventory method in Equation 1. Furthermore, the authors do not find a significant 3-factor alphas for the more recent period from 2000 to 2019, whereas I show for the period 2007 to 2021 a significant intercept when controlling for six other asset pricing factors. Similar to Rizova and Saito (2021), the authors use the perpetual inventory method of Peters and Taylor (2017) with the above-described shortcomings, which could relate to the insignificant finding. Finally, I confirm the authors' claim that the improved value factor derives its performance from both, the long and short side of the factor. Unreflected intangibles are most severe for firms with high levels of such capital. Therefore, the long-leg of the portfolio is naturally more affected by the adjustment than the short-leg. Thus, investors with long-only constraints can benefit from the adjusted metric.

The findings related to the economic rationale behind the relative outperformance of HML^{INT} over HML advocate a risk-based explanation. Generally, firms in HML^{INT} operate with higher levels of especially operating, financial and total leverage and are more exposed to financial distress. Excluding financials, operating leverage still constitutes a major risk factor for HML^{INT} in comparison to HML. Moreover, the results from Table 5 suggest that the difference in performance can also be related to market, liquidity and intermediary financing conditions. An increase in each of the variables levels results in an improved outperformance of HML^{INT} over HML. In turn, when liquidity dries up, stock markets underperform or intermediary risk increases, the intangible value factor underperforms. This finding directly relates to the work of Ai et al. (2020) and Giglio and Severo (2012). Tight funding conditions are especially painful for companies with high levels of intangibles, since they cannot use such assets as collateral. Additionally, if such companies are highly leveraged, the risk of financial distress increases even more. While companies with mostly physical capital and high operating leverage may be able to reduce their overhead costs rather fast, firms with high levels of intangibles cannot adjust their operations commensurately since such assets are more costly to reverse (Peters and Taylor (2017), Gulen et al. (2021)).

3.4 Limitations

The presented analysis faces several limitations.

Iqbal et al. (2021) point out the merits of estimating intangible investments when using industry-specific capitalization and amortization rates in order to account for differences across industries. While this level of granularity appears justifiable within a single country, differences not only across countries but also across industries within countries would go past the holistic approach of this analysis.

The presented estimation technique of internally-generated intangible assets has several limitations. Since there is no market valuation, the true and fair value of intangible assets is highly uncertain. SG&A may not capture items such as synergies across business lines or economies of scale, as outlined by Rizova and Saito (2021). Additionally, the assumption of a constant amortization rate implies most of the long-term value of intangible assets is written off completely after several years, while the usefulness of some assets, e.g. patents or trademarks, may last much longer. Moreover, amortization rates do not capture material impairments and may thus overstate intangible capital. This can result in a distorted presentation of a company's financial soundness, especially for companies with substantially high SG&A expenses. Also, the breakdown of operating expenses into costs of goods sold (COGS) and SG&A varies across companies and introduces additional noise to the measurement. From a data perspective, the measure of Peters and Taylor (2017) suffers largely from a data availability issue. Across all regions, R&D expenses are not reported for more than half of the firms in the sample - especially financial companies often do not report these costs. Hence, the adjustment for knowledge capital concerns only a small fraction of the total market while the remaining stocks stay unadjusted. This leads to less comparable firms, when adjusting the book value of only a minor fraction of firms with knowledge capital. In comparison, the fraction of missing or unreported SG&A data is drastically smaller compared to R&D and the data shortcoming can be reduced. Hence, I choose the simpler perpetual inventory method also applied by Eisfeldt et al. (2022).

While a within-industry version of HML^{INT} appears to be at least a coequal variant to the standard intangible-value factor (see Table 7), a proper evaluation of the industry factor would require a comparison to a within-industry HML factor. Overall, the findings above could be further strengthened by conducting the presented analysis using within-industry factors only. Similar results to the ones above would additionally strenghten the argument to adjust book values for intangibles. Furthermore, while I show some results on relative industry performance between HML^{INT} and HML, I do not provide a more detailed explanation to industries that benefit the least/most from the proposed book value adjustment. In Figure A1 I show that the industries finance, consumer non-durables, and business equipment benefit the most from book value adjustments. However, a closer analysis is left to future research and beyond the scope of this paper.

In my analysis, I focus on the return differential between HML^{INT} and HML. However, I could disentangle the intangible-adjusted B/M ratio into an original B/M and intangibles-to-market ratio, as done by Gulen et al. (2021), and analyse each factor separately. My main concern about this approach is the problem with firms containing no intangibles for instance due to unreported $SG\&A$ expenses. In the intangibles-to-market ratio, the short side would be full of stocks with intangibles-to-market ratios of zero. Nevertheless, the approach could serve as a viable alternative to my presented approach.

The investigation of the economic rationale also faces several limitations. For instance, a separate approach[24] could be carried out in order to distinguish behavioral and risk-based explanations. Additionally, a much broader investigation of additional economic reasons could be completed. For instance, higher information asymmetries exist in R&D intensive firms (Lev et al. (2005), Gu and Wang (2005)) and analyst recommendations may be more valuable for such firms (Palmon and Yezegel (2012)). Since small-capitalized companies tend to be covered less by financial analysts than larger companies, greater information asymmetries could arise. Since HML^{INT} loads significantly on the size factor, the chance of a behavioral explanation related to information asymmetry may subsist. Also, according to Sadka and Scherbina (2007), liquidity is closely related to mispricing. Thus, the findings in Table 5 could also point toward a mispricing explanation.

[24] For instance studying the pricing of characteristics and factor betas in the cross-section of stock returns as done by Bongaerts et al. (2021).

4 Conclusion

While the extended value factor underperformance over the last decade could have multiple reasons, one very promising explanation is the ineffective accounting expression of book values under existing accounting rules. Intangible assets, which have become increasingly important to the economy, are not reflected in book values and therefore popular value metrics, such as the B/M ratio, are mismeasured.

In this paper I present evidence that this mismeasurement is not only present in the U.S., but also in other international regions, where different accounting regulations apply. An intangible-adjusted B/M ratio reduces biases in book values across all regions and highlights ineffective accounting rules globally. The resulting intangible value factor, or HML^{INT}, is not only superior to the traditional value factor in terms of performance, but also improves existing cross-sectional asset pricing tests. Especially over the last decade, where the stock of intangibles increased drastically, the results have been more pronounced. However, the findings are also robust in different sample periods and under alternative calculation methods of intangible assets.

The presented results support a risk-based rationale to explain the performance difference between HML^{INT} and HML. Firms in HML^{INT} are more exposed to liquidity shocks, financial distress and tighter funding constraints, as intangibles cannot be used as collateral. Moreover, firms with high levels of intangibles can less flexibly adjust their operations to changing economic conditions, as they face higher associated adjustment costs. The results are not only relevant for academics but also practitioners who are exposed to the traditional value factor. Adjusting HML by intangible assets can earn investors a higher risk premium, even under long-only constraints.

The ineffective accounting-based expressions of intangible assets may not only affect the value factor but also other factors such as quality and investment. Little research on the impact on these factors exists and is primarily restricted to the U.S.. Wider international evidence for mismeasured accounting variables in relation to these factors would further strengthen the need to account for intangibles. Moreoever, secondary analysis related to the value factor, such as the value spread, could benefit from adjusting for intangibles too.

References

H. Ai, J. E. Li, K. Li, and C. Schlag. The Collateralizability Premium. *The Review of Financial Studies*, 33(12):5821–5855, 2020.

R. D. Arnott, C. R. Harvey, V. Kalesnik, and J. T. Linnainmaa. Reports of Value's Death May Be Greatly Exaggerated. *Financial Analysts Journal*, 77 (1):44–67, 2021.

C. Asness and A. Frazzini. The Devil in HML's Details. *The Journal of Portfolio Management*, 39(4):49–68, 2013.

C. S. Asness, R. B. Porter, and R. L. Stevens. Predicting Stock Returns Using Industry-Relative Firm Characteristics. *Available at SSRN 213872*, 2000.

C. S. Asness, T. J. Moskowitz, and L. H. Pedersen. Value and Momentum Everywhere. *The Journal of Finance*, 68(3):929–985, 2013.

M. Baker and J. Wurgler. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, 61(4):1645–1680, 2006.

V. Batista, T. Palmiero, and J. G. Lobo. The Euromoney Guide to World Equity Markets 2002, 2002.

F. Belo, V. D. Gala, J. Salomao, and M. A. Vitorino. Decomposing Firm Value. *Journal of Financial Economics*, 143(2):619–639, 2022.

D. Bongaerts, X. Kang, and M. A. Van Dijk. Intangible Assets and the Cross-Section of Stock Returns. *Available at SSRN 3927990*, 2021.

C. J. Campbell, A. R. Cowan, and V. Salotti. Multi-Country Event-Study Methods. *Journal of Banking & Finance*, 34(12):3078–3090, 2010.

J. Y. Campbell, J. Hilscher, and J. Szilagyi. In Search of Distress Risk. *The Journal of Finance*, 63(6):2899–2939, 2008.

C. Capaul, I. Rowley, and W. F. Sharpe. International Value and Growth Stock Returns. *Financial Analysts Journal*, 49(1):27–36, 1993.

M. M. Carhart. On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1):57–82, 1997.

M. Carlson, A. Fisher, and R. Giammarino. Corporate Investment and Asset Price Dynamics: Implications for the Cross-Section of Returns. *The Journal of Finance*, 59(6):2577–2603, 2004.

I. Chaieb, H. Langlois, and O. Scaillet. Factors and Risk Premia in Individual International Stock Returns. *Journal of Financial Economics*, 141(2):669–692, 2021.

L. K. Chan, Y. Hamao, and J. Lakonishok. Fundamentals and Stock Returns in Japan. *The Journal of Finance*, 46(5):1739–1764, 1991.

A. C. Chui, S. Titman, and K. J. Wei. Individualism and Momentum Around the World. *The Journal of Finance*, 65(1):361–392, 2010.

L. Cohen, K. Diether, and C. Malloy. Misvaluing Innovation. *The Review of Financial Studies*, 26(3):635–666, 2013.

C. A. Corrado and C. R. Hulten. How Do You Measure a "Technological Revolution"? *American Economic Review*, 100(2):99–104, 2010.

S. De Boer. Intangible Ironies: Investor Mispricing of Company Assets On and Off its Balance Sheet. *The Journal of Investing*, 2021.

I. D. Dichev. Is the Risk of Bankruptcy a Systematic Risk? *the Journal of Finance*, 53(3):1131–1147, 1998.

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

A. L. Eisfeldt and D. Papanikolaou. The Value and Ownership of Intangible Capital. *American Economic Review*, 104(5):189–94, 2014.

A. L. Eisfeldt, E. T. Kim, and D. Papanikolaou. Intangible Value. *Critical Finance Review*, 11(2):299–332, 2022. ISSN 2164-5744. doi: 10.1561/104.00000113. URL http://dx.doi.org/10.1561/104.00000113.

M. Ewens, R. H. Peters, and S. Wang. Measuring Intangible Capital with Market Prices. Technical report, 2021. URL https://ssrn.com/abstract=3287437.

E. F. Fama and K. R. French. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 47(2):427–465, 1992.

E. F. Fama and K. R. French. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

E. F. Fama and K. R. French. Size and Book-to-Market Factors in Earnings and Returns. *The journal of finance*, 50(1):131–155, 1995.

E. F. Fama and K. R. French. Value Versus Growth: The International Evidence. *The Journal of Finance*, 53(6):1975–1999, 1998.

E. F. Fama and K. R. French. Size, Value, and Momentum in International Stock Returns. *Journal of Financial Economics*, 105(3):457–472, 2012.

E. F. Fama and K. R. French. A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 116(1):1–22, 2015.

E. F. Fama and K. R. French. International Tests of a Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 123(3):441–463, 2017.

L. García-Feijóo and R. D. Jorgensen. Can Operating Leverage be the Cause of the Value Premium? *Financial Management*, 39(3):1127–1154, 2010.

S. Giglio and T. Severo. Intangible Capital, Relative Asset Shortages and Bubbles. *Journal of Monetary Economics*, 59(3):303–317, 2012.

B. C. Greenwald, J. Kahn, E. Bellissimo, M. A. Cooper, and T. Santos. *Value Investing: From Graham to Buffett and Beyond*. John Wiley & Sons, 2020.

J. M. Griffin and M. L. Lemmon. Book-to-Market Equity, Distress Risk, and Stock Returns. *The Journal of Finance*, 57(5):2317–2336, 2002.

J. M. Griffin, P. J. Kelly, and F. Nardari. Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets. *The Review of Financial Studies*, 23(8):3225–3277, 2010.

F. Gu and W. Wang. Intangible Assets, Information Complexity, and Analysts' Earnings Forecasts. *Journal of Business Finance & Accounting*, 32(9-10): 1673–1702, 2005.

H. Gulen, D. Li, R. H. Peters, and M. Zekhnini. Intangible Capital in Factor Models. *Available at SSRN 3725002*, 2021.

M. X. Hanauer. *Risk Factors and Capital Market Anomalies*. PhD thesis, Technische Universität München, 2014.

Z. He, B. Kelly, and A. Manela. Intermediary Asset Pricing: New Evidence from Many Asset Classes. *Journal of Financial Economics*, 126(1):1–35, 2017.

O. S. Ince and R. B. Porter. Individual Equity Return Data from Thomson Datastream: Handle with Care! *Journal of Financial Research*, 29(4):463–479, 2006.

A. Iqbal, S. Rajgopal, A. Srivastava, and R. Zhao. Value of Internally Generated Intangible Capital. *Available at SSRN 3917998*, 2021.

G. A. Karolyi and Y. Wu. The Role of Investability Restrictions on Size, Value, and Momentum in International Stock Returns. *Johnson School Research Paper Series*, (12-2012), 2012.

J. Lakonishok, A. Shleifer, and R. W. Vishny. Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance*, 49(5):1541–1578, 1994.

C. Landis and S. Skouras. Guidelines for Asset Pricing Research Using International Equity Data from Thomson Reuters Datastream. *Journal of Banking & Finance*, 130:106128, 2021.

K.-H. Lee. The World Price of Liquidity Risk. *Journal of Financial Economics*, 99(1):136–161, 2011.

B. Lev and A. Srivastava. Explaining the Recent Failure of Value Investing. *NYU Stern School of Business*, 2019.

B. Lev, B. Sarath, and T. Sougiannis. R&D Reporting Biases and Their Consequences. *Contemporary Accounting Research*, 22(4):977–1026, 2005.

F. Li. Intangibles: The Missing Ingredient in Book Value. *The Journal of Portfolio Management*, 48(3):164–184, 2022.

G. N. Mandelker and S. G. Rhee. The Impact of the Degrees of Operating and Financial Leverage on Systematic Risk of Common Stock. *Journal of Financial and Quantitative Analysis*, 19(1):45–57, 1984.

D. Palmon and A. Yezegel. R&D Intensity and the Value of Analysts' Recommendations. *Contemporary Accounting Research*, 29(2):621–654, 2012.

H. Park. Intangible Assets and the Book-to-Market Effect. *European Financial Management*, 25(1):207–236, 2019.

H. Park. An Intangible-Adjusted Book-to-Market Ratio Still Predicts Stock Returns. *Critical Finance Review*, 11(2):265–297, 2022. ISSN 2164-5744. doi: 10.1561/104.00000100. URL `http://dx.doi.org/10.1561/104.00000100`.

R. H. Peters and L. A. Taylor. Intangible Capital and the Investment-q Relation. *Journal of Financial Economics*, 123(2):251–272, 2017.

S. Rizova and N. Saito. Internally Developed Intangibles and Expected Stock Returns. *Available at SSRN 3697452*, 2021.

R. Sadka and A. Scherbina. Analyst Disagreement, Mispricing, and Liquidity. *The Journal of Finance*, 62(5):2367–2403, 2007.

P. S. Schmidt, U. Von Arx, A. Schrimpf, A. F. Wagner, and A. Ziegler. On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications. *CCRS Working Paper Series*, (01/11), 2015.

P. S. Schmidt, U. von Arx, A. Schrimpf, A. F. Wagner, and A. Ziegler. Common Risk Factors in International Stock Markets. *Financial Markets and Portfolio Management*, 33(3):213–241, 2019.

A. Srivastava. Why Have Measures of Earnings Quality Changed Over Time? *Journal of Accounting and Economics*, 57(2-3):196–217, 2014.

M. Vassalou and Y. Xing. Default Risk in Equity Returns. *The Journal of Finance*, 59(2):831–868, 2004.

L. Zhang. The Value Premium. *The Journal of Finance*, 60(1):67–103, 2005.

Region	Stats	High	Low	HML	$High^{INT}$	Low^{INT}	HML^{INT}
U.S.	Mean	11.26	9.81	1.46	12.53	8.41	4.12
	t-stat	4.01	3.38	0.85	4.50	3.17	3.15
	SD	17.42	18.01	10.58	17.29	16.43	8.12
	Sharpe	0.65	0.54	0.14	0.72	0.51	0.51
	MDD	61.60	55.36	51.27	54.69	53.92	29.11
Europe	Mean	10.65	7.19	3.46	11.57	6.49	5.08
	t-stat	3.45	2.65	2.54	3.79	2.37	4.25
	SD	19.21	16.84	8.47	18.98	17.05	7.43
	Sharpe	0.55	0.43	0.41	0.61	0.38	0.68
	MDD	63.52	67.07	52.69	61.78	66.80	27.85
Japan	Mean	9.83	3.60	6.23	8.63	3.83	4.80
	t-stat	2.93	1.06	3.54	2.69	1.13	3.63
	SD	20.81	21.20	10.91	19.93	21.13	8.22
	Sharpe	0.47	0.17	0.57	0.43	0.18	0.58
	MDD	72.98	87.73	47.85	72.42	87.56	28.25
Asia-Pacific	Mean	14.95	6.52	8.43	16.08	6.01	10.07
	t-stat	3.62	1.90	4.02	3.92	1.76	4.95
	SD	25.62	21.27	13.04	25.48	21.25	12.65
	Sharpe	0.58	0.31	0.65	0.63	0.28	0.80
	MDD	71.17	67.32	38.41	69.77	67.83	35.53

Table 1: Summary Statistics of HML and HML^{INT} Factor Excess Returns. This table presents summary statistics from the long ($High$ or $High^{INT}$), short (Low or Low^{INT}) and long-short (HML or HML^{INT}) portfolios of the traditional and intangible value factors across the four regions U.S., Europe, Japan and Asia-Pacific. I report the annualized mean (Mean), standard deviation (SD), maximum drawdown (MDD) in percentage as well as t-statistics (t-stat) and Sharpe Ratio (Sharpe) for each portfolio. The sample period is from June 1983 to December 2021.

	Full Sample (1983-2021)			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
HML	0.5790***	0.7303***	0.5362***	0.9329***
	$t = 12.6319$	$t = 23.1310$	$t = 11.5603$	$t = 53.6289$
Constant	0.0029***	0.0021***	0.0010	0.0018***
	$t = 4.0174$	$t = 3.5290$	$t = 1.2972$	$t = 3.4392$
	Pre-Internet Era (1983-1994)			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
HML	0.3978***	0.8138***	0.5698***	0.9954***
	$t = 4.6469$	$t = 12.6080$	$t = 5.4965$	$t = 62.5947$
Constant	0.0030*	0.0008	−0.0016	0.0003
	$t = 1.9313$	$t = 0.7987$	$t = -1.1553$	$t = 0.5853$
	Internet Era Pre-Crisis (1995-2006)			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
HML	0.6138***	0.7001***	0.6016***	0.9284***
	$t = 8.2768$	$t = 9.9523$	$t = 12.2001$	$t = 40.1881$
Constant	0.0043***	0.0019	0.0015	0.0012
	$t = 3.6453$	$t = 1.6531$	$t = 1.4356$	$t = 1.6179$
	Crisis Post-Crisis (2007-2021)			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
HML	0.6437***	0.7288***	0.4489***	0.8545***
	$t = 15.1437$	$t = 19.1037$	$t = 6.8088$	$t = 21.1444$
Constant	0.0021**	0.0030***	0.0024**	0.0031***
	$t = 2.1527$	$t = 4.1330$	$t = 2.3671$	$t = 3.6259$
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2: Regression of Intangible Value Factor Returns on Traditional Value Factor Returns. This table shows the regression results from the right-hand side (RHS) traditional value factor returns on the left-hand side (LHS) intangible value factor returns between June 1983 to December 2021 and three different sub-periods. A statistically significant positive intercept indicates superior performance of the intangible value factor over the traditional value factor. Reported t-statistics are Newey-West corrected.

	HML^{INT}			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
Mkt	0.0915***	0.0496**	0.0059	0.0341
	$t = 3.2055$	$t = 2.2369$	$t = 0.2861$	$t = 1.5915$
SMB	0.2406***	−0.0338	0.0645**	0.1684***
	$t = 7.4144$	$t = -1.0525$	$t = 2.3498$	$t = 5.6927$
HML	0.3733***	0.6591***	0.6051***	0.8938***
	$t = 9.8180$	$t = 14.7770$	$t = 18.1577$	$t = 16.4208$
RMW	0.2654***	0.1172**	0.3112***	−0.0506
	$t = 4.8714$	$t = 2.5490$	$t = 5.5547$	$t = -0.6759$
CMA	0.3434***	0.1632***	0.1018*	−0.1402**
	$t = 5.9863$	$t = 2.8054$	$t = 1.7654$	$t = -2.1570$
UMD	−0.0057	−0.0140	−0.0263	−0.0315
	$t = -0.2501$	$t = -0.7135$	$t = -0.9875$	$t = -1.0234$
Constant	0.0003	0.0016**	0.0019***	0.0018
	$t = 0.4309$	$t = 2.5585$	$t = 3.4117$	$t = 1.4558$

Note: *p<0.1; **p<0.05; ***p<0.01
Full sample (1983 - 2021).

Table 3: Regression of Regional Intangible Value Factor Returns on Fama-French Five Factors and Momentum. This table shows the regression results from the right-hand side (RHS) Fama-French five factor returns on the left-hand side (LHS) intangible value factor returns between June 1983 to December 2021. Statistically significant coefficients indicate a significant loading on the respective factor. Reported t-statistics are Newey-West corrected.

	HML^{INT}			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
Mkt	0.0213	0.0166	0.0023	0.0184
	$t = 0.7597$	$t = 0.6243$	$t = 0.0924$	$t = 0.6722$
SMB	0.1038**	−0.0447	0.0998**	0.2271***
	$t = 2.3992$	$t = -0.7830$	$t = 2.0922$	$t = 5.6850$
HML	0.4886***	0.7762***	0.5922***	0.8198***
	$t = 10.5309$	$t = 10.2879$	$t = 13.0062$	$t = 11.2880$
RMW	0.0941*	0.1110	0.4639***	0.0473
	$t = 1.6694$	$t = 1.1174$	$t = 4.9633$	$t = 0.6669$
CMA	0.3690***	0.0906	0.1544**	−0.0676
	$t = 4.7259$	$t = 1.2397$	$t = 1.9905$	$t = -0.8583$
UMD	0.0043	0.0150	−0.0627	0.0309
	$t = 0.1621$	$t = 0.4412$	$t = -1.6087$	$t = 0.9773$
Constant	0.0018*	0.0024***	0.0021***	0.0033***
	$t = 1.9124$	$t = 3.2426$	$t = 2.8267$	$t = 2.6105$

Note: *p<0.1; **p<0.05; ***p<0.01
Crisis and Post-Crisis (2007-2021).

Table 4: Regression of Regional Intangible Value Factor Returns on Fama-French Five Factors and Momentum. This table shows the regression results from the right-hand side (RHS) Fama-French five factor returns on the left-hand side (LHS) intangible value factor returns between January 2007 to December 2021. Statistically significant coefficients indicate a significant loading on the respective factor. Reported t-statistics are Newey-West corrected.

Variable	β_V	t-statistic
DEF	0.0008	1.72
TERM	0.0003	0.9
GDP	0.1165	1.29
CFNAI	0.0002	0.49
MSCI World	**0.0232**	**2.91**
Recession Dummy	-0.0005	-0.47
US Unemployment	0.0585	0.98
PCE	-0.0172	-1.6
IAPF	**0.0148**	**2.73**
FL Shock	**0.0038**	**2.44**
ML Shock	**0.0027**	**2.05**
PCAL Shock	**0.001**	**2.78**
SENT	-0.0006	-1.28

Table 5: Macroeconomic and Liquidity Risk Exposure Differences between HML^{INT} and HML. Displayed are coefficients (β_V) and associated t-statistics from a fixed-effects panel regression of the form $HML_{i,t}^{INT} = \alpha_i + \beta_{HML} HML_{i,t} + \beta_V V_t + \epsilon_{i,t}$ for country i at time t on a selected macroeconomic or liquidity shock variable V. Fixed effects are the regions U.S., Europe, Japan and Asia-Pacific. DEF represents the default spread measured by the yield difference of U.S. corporate bonds and U.S. Treasuries, TERM is the term spread on U.S. government bonds, GDP is the contemporaneous GDP growth measured by annual changes in real gross domestic product per capita, CFNAI is the Chicago Fed National Activity Index, MSCI World is the return of world equity markets in excess of the U.S. T-Bill rate, the Recession Dummy represents U.S. recessions (0 = peak, 1 = trough), U.S. Unemployment is the seasonally-adjusted national unemployment rate year by year, PCE represents long-run consumption growth, which is the 3-year future growth rate in per capita nondurable goods, IAPF is the intermediary asset pricing factor of He et al. (2017) and SENT is the sentiment indicator from Baker and Wurgler (2006). Additionally, I include shocks, measured by the residuals of an AR(2) process of the TED spread as a funding liquidity indicator (FL Shock) and the On-the-run vs. Off-the-run 10-year government treasury note spread as a market liquidity indicator (ML Shock). To measure total liquidity, I use a principal component-weighted average index of the two liquidity shocks (PCAL Shock). For brevity, the intercepts from the regressions are not reported. PCE and GDP are measured against cumulative quarterly returns, whereas the remaining indicators are measured against monthly returns.

Region	Item	HML High	HML Low	HML^{INT} $High^{INT}$	HML^{INT} Low^{INT}
U.S.	**Mkt-Cap (log)**	9.83	10.76	9.72	10.72
	B/M	1.24	0.24	0.98	0.34
	B^{INT}/M	2.39	0.79	3.27	0.47
	BusinessEquipment	2.09	3.72	3.31	2.40
	Chemicals	0.21	0.44	0.42	0.23
	ConsumerDurables	0.31	0.35	0.49	0.20
	ConsumerNondurables	0.74	0.83	1.10	0.43
	Energy	0.51	0.40	0.28	0.63
	Finance	6.14	1.31	1.97	3.43
	Healthcare	0.79	2.78	1.46	1.75
	Manufacturing	1.68	1.28	2.01	0.97
	Other	2.13	2.27	2.49	1.99
	Shops	1.48	1.49	2.46	0.78
	Telecommunication	0.29	0.38	0.27	0.40
	Utilities	0.67	0.14	0.26	0.78
Europe	**Mkt-Cap (log)**	9.62	9.89	9.43	9.71
	B/M	3.84	0.25	3.57	0.32
	B^{INT}/M	9.25	0.64	10.26	0.36
	BusinessEquipment	1.01	2.87	1.57	2.62
	Chemicals	0.30	0.44	0.42	0.39
	ConsumerDurables	0.41	0.36	0.58	0.29
	ConsumerNondurables	1.40	1.26	1.51	1.29
	Energy	0.36	0.27	0.28	0.34
	Finance	4.14	1.85	2.50	2.19
	Healthcare	0.35	1.04	0.53	0.89
	Manufacturing	2.20	1.63	2.33	1.72
	Other	2.83	3.12	2.89	3.20
	Shops	1.40	1.47	1.90	1.26
	Telecommunication	0.15	0.44	0.15	0.44
	Utilities	0.31	0.30	0.21	0.43
Japan	**Mkt-Cap (log)**	8.62	9.58	8.69	9.65
	B/M	1.47	0.37	1.03	0.49
	B^{INT}/M	2.91	1.13	4.11	0.65
	BusinessEquipment	1.32	3.13	1.53	2.73
	Chemicals	0.72	0.64	0.80	0.50
	ConsumerDurables	0.94	0.43	0.85	0.47
	ConsumerNondurables	1.25	0.92	1.64	0.92
	Energy	0.05	0.06	0.04	0.08
	Finance	1.23	1.09	0.49	1.96
	Healthcare	0.21	0.63	0.29	0.55
	Manufacturing	3.26	1.85	2.34	2.38
	Other	3.09	3.18	2.27	3.34
	Shops	2.69	2.77	4.54	1.71
	Telecommunication	0.07	0.16	0.08	0.13
	Utilities	0.12	0.13	0.08	0.26
Asia-Pacific	**Mkt-Cap (log)**	8.22	9.96	7.70	10.02
	B/M	1.98	0.32	1.99	0.36
	B^{INT}/M	2.30	0.43	2.70	0.39
	BusinessEquipment	1.09	1.84	1.35	1.63
	Chemicals	0.25	0.22	0.29	0.22
	ConsumerDurables	0.32	0.26	0.41	0.20
	ConsumerNondurables	1.18	0.96	1.36	0.81
	Energy	0.62	0.80	0.50	0.95
	Finance	2.37	1.42	2.00	1.56
	Healthcare	0.30	0.90	0.41	0.81
	Manufacturing	1.41	0.71	1.44	0.67
	Other	5.24	5.42	4.48	5.96
	Shops	1.76	1.82	2.25	1.47
	Telecommunication	0.14	0.37	0.15	0.40
	Utilities	0.22	0.32	0.18	0.40

Table 6: Summary Statistics of Firm Characteristics. This table shows the characteristics of firms from the long ("High") and short ("Low") portfolios of the HML and HML^{INT} factors across the four regions U.S., Europe, Japan and Asia-Pacific. Mkt-Cap (log) is the logarithmic market capitalization, B/M is the traditional book-to-market ratio and B^{INT}/M is the intangible-adjusted book-to-market ratio. The presented statistics are market-capitalization weighted characteristics within each portfolio. Additionally, the table presents average industry weights of each portfolio. In Asia-Pacific, B/M and B^{INT}/M are windsorized by the 99% quantile. All numbers are expressed as percentages except for Mkt-Cap (log), B/M and B^{INT}/M. The sample period is from June 1983 to December 2021.

	Within-Industry HML^{INT}			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
HML^{INT}	0.7960***	0.6368***	0.6505***	0.2675***
	(0.0349)	(0.0585)	(0.0800)	(0.0603)
Constant	0.0014**	0.0015*	0.0020**	−0.0002
	(0.0006)	(0.0009)	(0.0010)	(0.0016)
Note:				*p<0.1; **p<0.05; ***p<0.01
				Full sample.

Table 7: Regression of Within vs. Economy-Wide Intangible Value Returns. This table shows the regression results from the right-hand side (RHS) economy-wide intangible value factor returns on the left-hand side (LHS) within-industry intangible value factor returns between June 1983 to December 2021. A statistically significant positive intercept indicates superior performance of the within-industry intangible value factor over the economy-wide counterpart. The economy-wide factor ranks across all stocks based on the intangible-value adjusted book-to-market ratio, whereas the within-industry factor ranks stocks within the same industry only. Reported standard errors are Newey-West corrected.

	Local HML^{INT}			
	U.S.	Europe	Japan	Asia-Pacific
	(1)	(2)	(3)	(4)
HML^{INT}	1.0000***	0.8657***	0.9995***	0.7924***
	(0.0001)	(0.0248)	(0.0027)	(0.0670)
Constant	0.00002***	0.0004	0.0001***	0.0003
	(0.000004)	(0.0005)	(0.00003)	(0.0010)
Note:				*p<0.1; **p<0.05; ***p<0.01
				Full sample.

Table 8: Regression of Local Excess vs. USD Intangible Value Returns. This table shows the regression results from the right-hand side (RHS) standard intangible value factor (with returns in USD) and the local excess return version of HML^{INT} on the left-hand side (LHS). A statistically significant positive intercept indicates superior performance of the local excess return version of HML^{INT} over the presented standard factor HML^{INT}. To construct the local excess return factor version of HML^{INT}, I first calculate for each stock the returns in excess of the local risk free rate at time t. Then, I rank across all stocks based on the intangible-adjusted book-to-market ratio and calculate portfolio returns based on local excess returns. Returns are between June 1983 to December 2021. Reported standard errors are Newey-West corrected.

Specification	$\delta_{R\&D}$	$\delta_{SG\&A}$	$\alpha_{R\&D}$	$\alpha_{SG\&A}$	US	EU	JP	AP	$\bar{t}$
EKP	-	20%	-	100%	4.02	3.53	1.30	3.44	3.07
EKP Depr 10%	-	10%	-	100%	4.10	3.19	1.03	3.68	3.00
EKP Depr 30%	-	30%	-	100%	3.51	3.25	1.79	2.87	2.85
EKP Init Cap = 0	-	20%	-	100%	3.98	3.87	1.51	3.15	3.13
PT	15%	20%	100%	30%	2.45	3.01	0.78	1.72	1.99
PT Org Cap	-	20%	-	30%	1.71	1.79	1.33	2.19	1.75
PT Know Cap	15%	-	100%	-	1.90	2.10	1.66	1.84	1.88
PT incl. Init Cap	-	20%	100%	30%	1.91	2.78	0.84	1.79	1.83
PT Org Cap incl. Init	-	20%	-	30%	2.53	1.74	0.69	2.91	1.97
PT Know Cap incl. Init	15%	-	100%	-	1.71	1.87	1.59	2.32	1.87

Table 9: Significance of Outperformance of Different Intangible Value Measures over Traditional Value. This table presents t-statistics of γ from a regression of the form $HML^{INT} = \gamma + \beta HML + \epsilon$ for different intangible value specifications for the four different regions U.S., Europe, Japan and Asia-Pacific (excluding Japan). EKP is the abbreviation for the perpetual inventory method used by Eisfeldt et al. (2022), whereas PT stands for the method of Peters and Taylor (2017). All authors apply a perpetual inventory method of the form $C_{i,t} = (1-\delta)C_{i,t-1} + \alpha X_{i,t}$ where $C_{i,t}$ is the accumulated capital for company i at time t, δ is the depreciation rate and α is the fraction of item $X_{i,t}$ (either $SG\&A$ or $R\&D$) that represents an investment in capital in the firm. While EKP consider only $SG\&A$ to construct the intangible value factor, PT use a fraction of $SG\&A$ ($\alpha_{SG\&A}$) to calculate organizational capital and combine it with knowledge capital derived via $R\&D$. For the PT measure, I subtract R&D from SG&A because TDS includes the former in the latter item. Whenever R&D is larger than SG&A, I do not change SG&A (see Peters and Taylor (2017)). The initial capital is derived via $C_{i,0} = X_{i,0}/(g+\delta)$, where $g = 0.1$ is the assumed average growth rate of SG&A (or R&D) as in Eisfeldt et al. (2022). PT do not use initial capital for the approximation of intangible assets, however the above specification 'incl. Init' includes an initial estimate. The other specifications concern different levels of Depreciation ('Depr'), Initial Capital ('Init Cap') or estimate intangible capital solely from Organizational Capital ('Org Cap') or Knowledge Capital ('Know Cap'). The last column indicates the average t-statistic for the four regions.

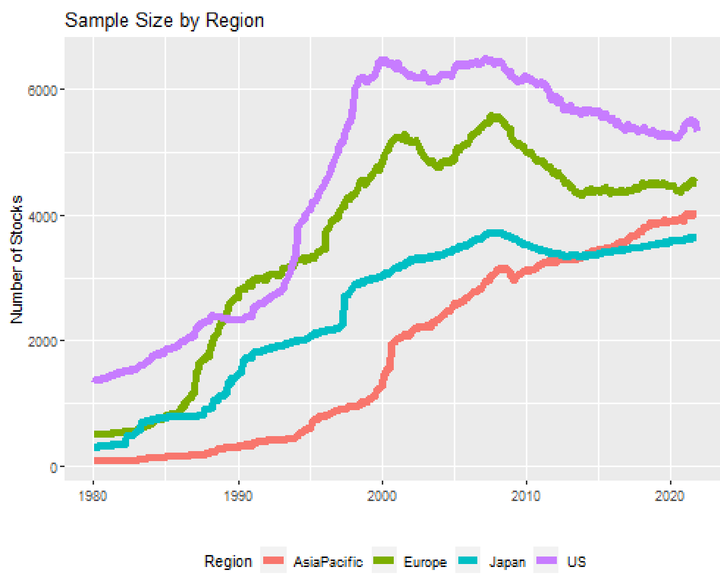

Figure 1: Sample Size by Region.This figure shows the number of available stocks for each of the four regions: U.S., Europe, Japan and Asia-Pacific between June 1983 and December 2021. To be included in the sample, a stock must show a valid price, book and market value in June of year t.

Figure 2: Intangible vs. Traditional Value Performance by High and Low Portfolio.This figure shows the long, short and long-short leg performance of the intangible value factor in comparison to the traditional value factor. The performance is shown for each of the four regions: U.S., Europe, Japan and Asia-Pacific between June 1983 and December 2021. The monthly returns are ex-post volatility scaled to 5% p.m..

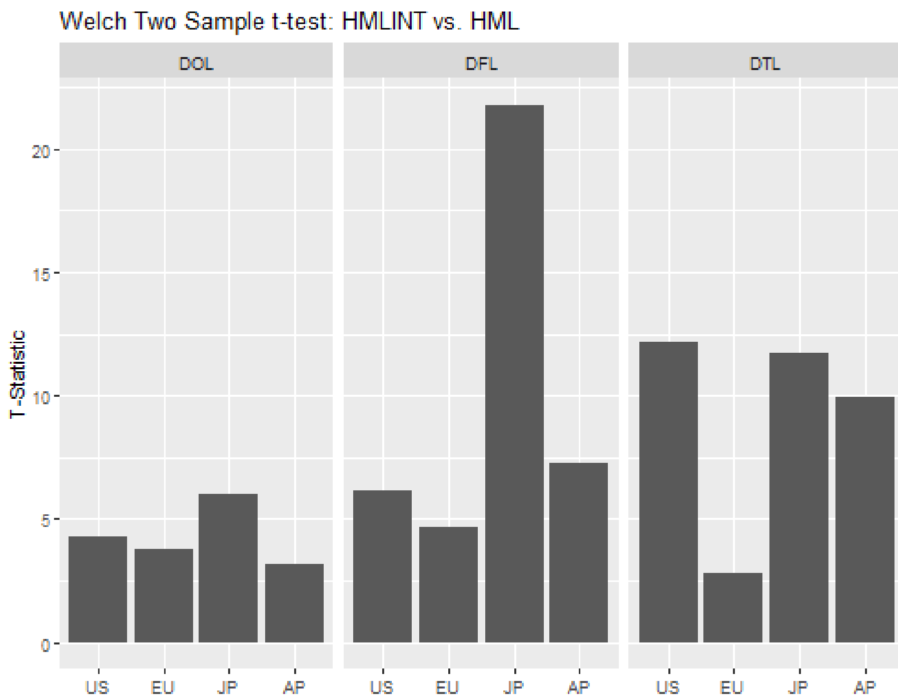

Figure 3: T-Statistic of Differences in Mean of DOL, DFL and DTL.This figure shows the t-statistics of the differences in means (using the Welch Two Sample t-test) of degree of operating leverage (DOL), degree of financial leverage (DFL) and degree of total leverage (DTL) between HML^{INT} and HML across the regions U.S. (US), Europe (EU), Japan (JP) and Asia-Pacific (AP). The data sample is from June 1983 to December 2021.

DOL and DFL are calculated for each stock based on rolling five-year windows:

$$\begin{aligned} \text{DOL} : ln(EBIT_t) &= ln(EBIT_0) + g_{EBIT}t + \mu_{t,EBIT}, \\ ln(SALES_t) &= ln(SALES_0) + g_{SALES}t + \mu_{t,SALES} \\ \mu_{t,EBIT} &= OL\mu_{t,SALES} + \epsilon_t \\ \text{DFL} : ln(EAIT_t) &= ln(EAIT_0) + g_{EAIT}t + \mu_{t,EAIT}, \\ \mu_{t,EAIT} &= FL\mu_{t,EBIT} + \nu_t \end{aligned} \tag{i}$$

where OL (operating leverage) and FL (financial leverage) are the variables of interest. Total leverage TL is calculated as the product of operating and financial leverage.

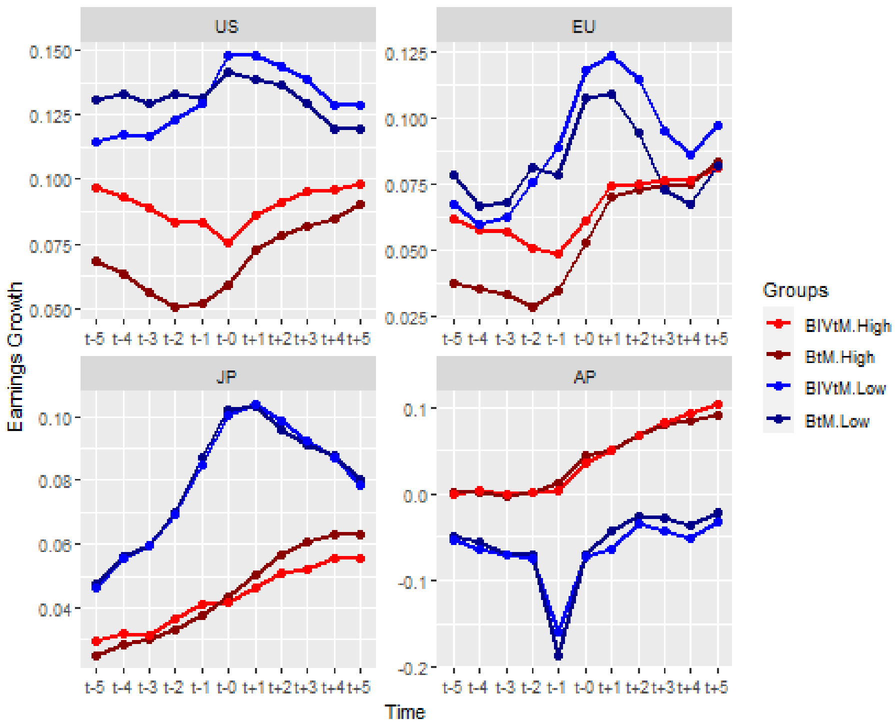

Figure 4: Evolution of Regional Earnings Growth of Top and Bottom HML and HML^{INT} portfolios. This figure presents the earnings growth from five years before $(t-5)$ to five years after $(t+5)$ portfolio formation of the top and bottom traditional and intangible value portfolios across the regions U.S. (US), Europe (EU), Japan (JP), Asia-Pacific (AP). The data sample is from June 1983 to December 2021. Earnings growth in year t is measured as the ratio of income before extraordinary expenses in year t over common equity in year $t-1$.

Figure 5: Evolution of Standardized Regional Earnings to Price Growth of Top and Bottom HML and HML^{INT} portfolios. This figure presents the standardized average earnings to price ratio growth from five years before $(t-5)$ to five years after $(t+5)$ portfolio formation of the top and bottom traditional and intangible value portfolios across the regions U.S. (US), Europe (EU), Japan (JP), Asia-Pacific (AP). The data sample is from June 1983 to December 2021. Earnings to price growth in year t is measured as the ratio of income before extraordinary expenses in year t over the market capitalization in year $t-1$ divided by the market earnings-to-price growth $(EAIT_p(t+i)/MV_p(t+i-1)/EAIT_m(t+i)/MV_m(t+i-1))$. The resulting growth rates are then standardized to equal 1 at time $t=0$.

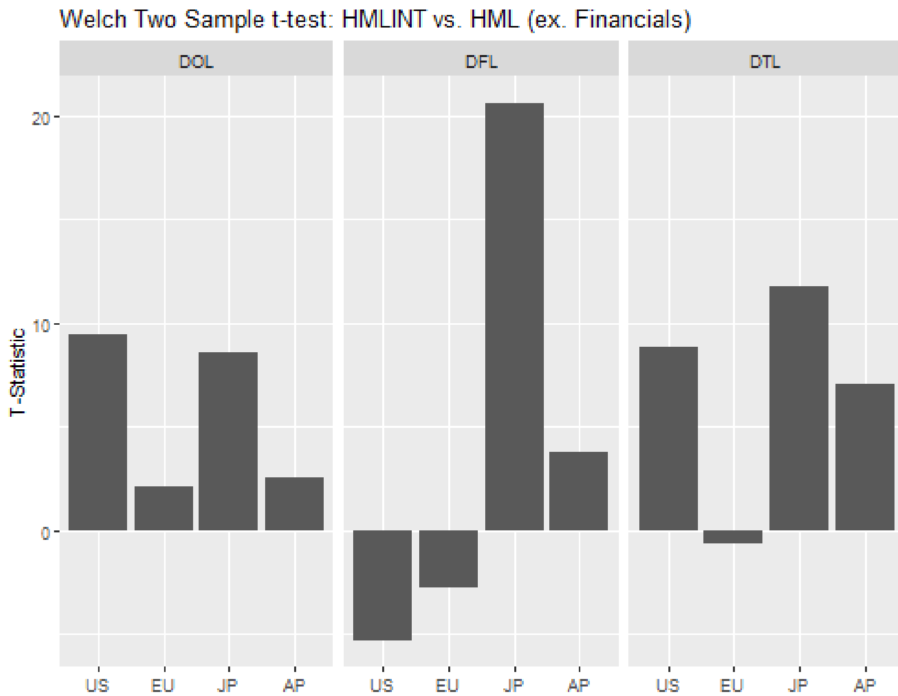

Figure 6: T-Statistic of Differences in Mean of DOL, DFL and DTL (excl. Financials).This figure shows the t-statistics of the differences in means (using the Welch Two Sample t-test) of degree of operating leverage (DOL), degree of financial leverage (DFL) and degree of total leverage (DTL) between HML^{INT} and HML (excluding financials) across the regions U.S. (US), Europe (EU), Japan (JP) and Asia-Pacific (AP). The data sample is from June 1983 to December 2021.

DOL and DFL are calculated for each stock based on rolling five-year windows:

$$\begin{aligned} \text{DOL} : ln(EBIT_t) &= ln(EBIT_0) + g_{EBIT}t + \mu_{t,EBIT}, \\ ln(SALES_t) &= ln(SALES_0) + g_{SALES}t + \mu_{t,SALES} \\ \mu_{t,EBIT} &= OL\mu_{t,SALES} + \epsilon_t \\ \text{DFL} : ln(EAIT_t) &= ln(EAIT_0) + g_{EAIT}t + \mu_{t,EAIT}, \\ \mu_{t,EAIT} &= FL\mu_{t,EBIT} + \nu_t \end{aligned} \tag{i}$$

where OL (operating leverage) and FL (financial leverage) are the variables of interest. Total leverage TL is calculated as the product of operating and financial leverage.

	US		
	PT-O	PT-K	PT
	(1)	(2)	(3)
Mkt	0.0619***	0.0351**	0.0395**
	$t = 2.6781$	$t = 2.0070$	$t = 1.9689$
SMB	0.1178***	0.0973***	0.1008***
	$t = 4.3980$	$t = 4.1774$	$t = 3.6158$
HML	0.7413***	0.7828***	0.6786***
	$t = 18.2120$	$t = 31.5648$	$t = 24.9194$
RMW	0.2122***	−0.0323	−0.0641
	$t = 5.5464$	$t = -0.8072$	$t = -1.4685$
CMA	0.1500***	0.0750*	0.1469***
	$t = 2.7754$	$t = 1.7919$	$t = 3.0335$
UMD	−0.0574***	−0.0485***	−0.0651***
	$t = -2.9535$	$t = -2.7879$	$t = -3.1251$
Constant	−0.0008	0.0003	0.0009
	$t = -1.2834$	$t = 0.5462$	$t = 1.4859$

	Japan		
	PT-O	PT-K	PT
	(1)	(2)	(3)
Mkt	0.0036	0.0744***	0.0458**
	$t = 0.1964$	$t = 3.2756$	$t = 2.2194$
SMB	0.1153***	−0.0245	−0.0592**
	$t = 3.8250$	$t = -0.8784$	$t = -2.4203$
HML	0.7644***	0.8895***	0.7547***
	$t = 22.3914$	$t = 19.1071$	$t = 18.4605$
RMW	0.2000***	0.1446*	0.1601***
	$t = 3.4984$	$t = 1.9322$	$t = 2.6764$
CMA	0.1361**	−0.1236	−0.0794
	$t = 2.2451$	$t = -1.4686$	$t = -1.1011$
UMD	−0.0229	−0.0214	−0.0606**
	$t = -0.9615$	$t = -0.6502$	$t = -2.1435$
Constant	0.0019***	0.0021***	0.0014**
	$t = 3.7710$	$t = 3.0564$	$t = 2.0134$

	Europe		
	PT-O	PT-K	PT
	(1)	(2)	(3)
Mkt	0.0424*	0.0378**	0.0453**
	$t = 1.8285$	$t = 2.1896$	$t = 2.5370$
SMB	−0.0445	−0.0580*	−0.0560*
	$t = -1.3050$	$t = -1.8360$	$t = -1.8467$
HML	0.9251***	0.8422***	0.7773***
	$t = 19.8599$	$t = 22.0283$	$t = 20.7204$
RMW	0.1225*	−0.0215	0.0248
	$t = 1.8615$	$t = -0.4020$	$t = 0.4606$
CMA	0.0938*	−0.0523	0.0302
	$t = 1.8233$	$t = -0.8422$	$t = 0.4565$
UMD	−0.0296	0.0064	0.0102
	$t = -1.4587$	$t = 0.2673$	$t = 0.4377$
Constant	0.0002	0.0007	0.0009*
	$t = 0.2391$	$t = 1.4036$	$t = 1.7027$
Note:			*p<0.1; **p<0.05; ***p<0.01 Full sample.

	Asia-Pacific		
	PT-O	PT-K	PT
	(1)	(2)	(3)
Mkt	0.0128	0.0292	0.0248
	$t = 0.5781$	$t = 1.4244$	$t = 1.3374$
SMB	0.1151***	0.0988***	0.0968***
	$t = 3.5339$	$t = 3.1165$	$t = 3.1797$
HML	0.9529***	0.9462***	0.9433***
	$t = 18.4361$	$t = 18.3013$	$t = 17.9771$
RMW	−0.1089	−0.1173	−0.1221
	$t = -1.4072$	$t = -1.5283$	$t = -1.5729$
CMA	−0.1525**	−0.1517**	−0.1648**
	$t = -2.2098$	$t = -2.1683$	$t = -2.4760$
UMD	−0.0129	−0.0131	−0.0208
	$t = -0.3639$	$t = -0.3411$	$t = -0.5877$
Constant	0.0005	0.0003	0.0005
	$t = 0.4316$	$t = 0.2288$	$t = 0.4131$
Note:			*p<0.1; **p<0.05; ***p<0.01 Full sample.

Table 10: Regression of Alternative Intangible Value Factor Returns on Fama-French Five Factors and Carhart's Momentum Factor. This table displays the regression results from the traditional Fama-French five factor returns on varying specifications of HML^{INT}. PT-O (organization capital only), PT-K (knowledge capital only) and PT (organization & knowledge capital combined) are HML^{INT} with solely organizational, knowledge capital or a combination of both respectively, as outlined in Peters and Taylor (2017). The data period is from June 1983 to December 2021 and for each of the four regions (U.S., Europe, Japan and Asia-Pacific) I use regional Fama-French factors. Reported t-statistics are Newey-West corrected.

A Appendix

A.1 Data Handling

Empirical research on international equity markets beyond the U.S. (for research on U.S. markets, the databases CRSP and Compustat are usually used) lacks consensus as to which data source to use. Fama and French (Fama and French (2012), Fama and French (2017)) primarily use Bloomberg data supplemented by data from Worldscope and Datastream to construct asset pricing factors for four regions in 23 countries including Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, UK, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Sweden, Singapore, United States. Asness and Frazzini (2013) and other AQR affiliates use the XpressFeed Global database, whereas others use FactSet and the Pacific-Basin Research Center. TDS offers the advantage that Ince and Porter (2006), Schmidt et al. (2015), Schmidt et al. (2019), Karolyi and Wu (2012) and Landis and Skouras (2021) provide detailed advice on preprocessing data. As Ince and Porter (2006) point out, unprocessed data can lead to erroneous results and consequently incorrect economic inference. Landis and Skouras (2021) present in their Internet Appendix a list of papers in top finance journals using TDS data, indicating the quality acceptance across the academic community.

A.1.1 Data Screening

To identify the set of international stocks, I work with constituent lists that are supposed to cover the entire range of single stocks, containing active, delisted and dead stocks and therefore the analysis controls for survivorship bias. All constituent lists used are outlined in Table A.1.1. A different way of collecting the set of global stocks is to follow the procedure in the Internet Appendix of Landis and Skouras (2021), who argue their approach leads to a much larger cross-section of equities than has been used in other earlier studies. The data is extracted with full data accuracy and in local currency, while dealing with changes in the currencies in which stocks are traded over time (e.g. pre/post euro adoption) to cope with significant rounding problems identified in default TDS data. The currencies of all stocks are converted to U.S. dollars.

The TDS stock database has numerous data quality issues that need to be taken care of. Ince and Porter (2006) compare TDS with CRSP data and point out numerous data inconsistencies when working with TDS that can largely impact economic inferences:

1. Time-series classification variables often reflect only most current value (e.g. security begins trading on NASDAQ NMS and later delists and trades on non-NASDAQ OTC and is classified as non-NASDAQ OTC by TDS throughout sample period). When choosing to analyse only

Table A1: Worldscope Constituent Lists. This table displays for each country the relevant constituent lists used for the analysis. These lists are used in combination with a datatype to source fundamental or market data for the majority of single stocks within the respective country. The displayed lists are an aggregation of lists used by TDS (`https://blogs.cul.columbia.edu/business/files/2014/02/Worldscopelist_TRbranding.pdf`), Campbell et al. (2010), Chui et al. (2010), Lee (2011), Hanauer (2014), Schmidt et al. (2015) and Schmidt et al. (2019). The lists not only cover active, but also delisted and dead stocks and therefore control for survivorship bias.

Country	Constituent Lists		
Australia	WSCOPEAU	FAUS	DEADAU
Austria	WSCOPEOE	LATXWBIX	DEADOE
Belgium	WSCOPEBG	FBEALL	DEADBE
Cyprus	WSCOPECP	FCYP	DEADCY
Denmark	WSCOPEDK	FDEN	DEADDK
Finland	WSCOPEFN	FFIN	DEADFN
France	WSCOPEFR	FFRA	ALLFF
	DEADFR		
Germany	WSCOPEBD	FGER1	FGER2
	DEADBD1	DEADBD2	
Greece	WSCOPEGR	FGREE	FGRPM
	FGRMM	FNEXA	DEADGR
Hong Kong	WSCOPEHK	HGKG	DEADHK
Ireland	WSCOPEIR	FIRL	DEADIR
Italy	WSCOPEIT	FITA	DEADIT
Japan	WSCOPEJP	JAPALL1	JAPALL2
	JAPALL3	JAPALL4	DEADJP
Luxembourg	WSCOPELX	FLUX	DEADLX
Netherlands	WSCOPENL	FHOL	ALLFL
	DEADNL		
New Zealand	WSCOPENZ	FNWZ	DEADNZ
Norway	WSCOPENW	FNOR	DEADNW
Portugal	WSCOPEPT	FPOR	DEADPT
Singapore	WSCOPESG	FSINQ	DEADSG
Spain	WSCOPEES	FSPN	DEADES
Sweden	WSCOPESD	FSWD	DEADSW
Switzerland	WSCOPESW	FSWS	DEADSW
United Kingdom	WSCOPEUK	FBRIT	DEADUK
United States	FUSAA	FUSAB	FUSAC
	FUSAD	FUSAE	FUSAF
	FUSAG	DEADUS1	DEADUS2
	DEADUS3	DEADUS4	DEADUS5
	DEADUS6	WSUS1	WSUS2
	WSUS3	WSUS4	WSUS5
	WSUS6	WSUS7	WSUS8
	WSUS9	WSUS10	WSUS11
	WSUS12	WSUS13	WSUS14
	WSUS15	WSUS16	WSUS17
	WSUS18	WSUS19	WSUS20
	WSUS21	WSUS22	WSUS23
	WSUS24	WSUS25	WSUS26

NYSE/AMEX/NASDAQ stocks, survivorship bias will be induced given that multiple firms with poor historical returns are often delisted. Another approach of Landis and Skouras (2021) is to condition analyses directly on size rather than by excluding exchanges. The classification issue makes it difficult to e.g. correctly identify NYSE stocks from which breakpoints are calculated (e.g. as in Fama and French (1992)), especially early in the sample. Many of these stocks may have belonged to one major exchange previously but were e.g. delisted and traded OTC subsequently.

2. Delisted firms: TDS repeats the last valid data point for delisted firms. To eliminate these dummy records, one needs to delete all observations from TDS from the end of the sample period to the first nonzero return.

3. Instances of data errors: Prices can rarely fluctuate at unreasonable levels with jumps from e.g. \$2.38 to \$13.60 (Magellan Petroleum Corp in 1995) within a few days.

4. Smaller stocks seem to have a large impact on the validity of results. Value-weighted market portfolios show high similarity to local indices, whereas momentum or equal-weighted portfolios (likely dominated or greatly impacted by small-cap stocks) show large and economic performance differences.

5. Currency setting issues: The return index of a stock in certain countries can have small values because of poor performance or because it has been extracted in a currency with units in a different scale (e.g. ITL in USD which has a factor above 1000, see Landis and Skouras (2021)).

6. Total return calculation: TDS rounds prices to the nearest penny which can cause differences in calculated returns when prices are small.

The list above highlight a number of, among other, issues that have to be considered when working with TDS. I will outline in Section A.2.1 and Section A.2.2 the exact procedure how to account for and resolve the presented inconsistencies.

Another crucial part is the timely availability of data. Table A2 shows a representative example where book value data (WC03501) is misrepresented in 11 out of 12 months when downloading monthly data as the data is backfilled and would not have been available at the respective timepoint. Constructing a factor using TDS book value data from December at year t-1 may therefore be incorrect.[25] One approach to account for this backfill bias is to use the TDS field 'Date Of Fiscal Year End'. However, for numerous stocks this item is not available. I choose to select book value or accounting data from June t-1, which assures that data is available in June t. Therefore, my methodology slightly deviates from Fama and French (1992) as I am including backfilled book values from e.g. May in year t to be included in June of year t, whereas Fama

[25] Unless the company fiscal year end is exactly in December.

Year	Book Value CORRECT	Book Value TDS
Jul2006	**1,738**	**1,738**
Aug2006	1,738	2,035
⋮	⋮	⋮
Jun2007	1,738	2,035
Jul2007	**2,035**	**2,035**
Aug2007	2,035	2,073
⋮	⋮	⋮

Table A2: TDS Book Value Misrepresentation for Intuit Inc (DSCD 328184) with fiscal year end in July. This table shows how TDS backfills book value data. When constructing common risk factors, this induces a foreward looking bias, as the data from December of t-1 is not available at June in year t.

and French (1992) use book values from no earlier than year t-1. The backfill-issue outlined with the book value data example above applies also for other fundamental data. Hence, I control this backfill-issue with other accounting data (e.g. SG&A or R&D expenses) too in order to stay consistent throughout the analysis.

A.2 Data and Filtering

For this project, I download the static datatypes (with TDS acronym in brackets): unique datastream identifiers (DSCD), major stock listings (MAJOR), geographical country code (GEOG), equity type (TYPE), local exchange mnemonic (EXMNEM), availability of adjusted price data (ADP), primary isin identification (ISINID), extended name (ENAME), local pricing currency (PCUR), local ISIN code (GGISN) security type classification (TRAC) and SIC industry classification code (WC07021). Dynamic datatypes include: unadjusted price (UP), price (P), adjustment factor (AF), return index (RI), market value (MV), book value (WC03501), Selling, General & Administrative Expenses (WC01101), Research & Development Expenses (WC01201) and Goodwill (WC18280).

A.2.1 Static Filtering

Based on Ince and Porter (2006), Griffin et al. (2010), Hanauer (2014) Schmidt et al. (2019), and Landis and Skouras (2021), I construct static and dynamic filters to properly clean the available dataset. In addition, I use Batista et al. (2002) to identify security types in specific markets. Static filter criteria that are applied in the preprocessing of TRD data include:

1. DSCD (unique identifier): Datastream Code to check for duplicates
2. MAJOR="Y": Select stock when major listing

3. GEOGN="United States" or respective country: Stock must be located in domestic market
4. TYPE="EQ": Select only firm that are of equity type
5. EXMNEM: Include stocks listed only on all domestic exchanges (exception in Canada: exclude stocks listed on TSX Venture exchange, U.S.: include NYSE, AMEX, NASDAQ and NMS stocks only)
6. ADP="1": Select only firms with adjusted price data
7. ISINID="P": When multiple ISIN-codes, only use security where with primary ISIN
8. ENAME (1): Search for suspicious word parts like "Preference", "REIT", "Unit Trust" and others
9. ENAME (2): Remove stock if it contains country specific keywords
10. PCUR="US" or respective currency: quoted currency must be national to country with an exception for euro area former currencies and ISIN "BM" & "KY" in Hong Kong
11. GGISN="US" or other quoted ISIN country code of respective country
12. Exclude 6 obscure U.S.-stocks (Appendix footnote 18 of Schmidt et al. (2015))
13. TRAC (TDS security type classification): Exclude all stocks with security type code taking any value other then "ORD", "ORDSUBR", "FULLPAID", "UKNOWN", "UNKNOW" or "KNOW"

After the static filtering steps, I source daily data including price (UP), price (P), adjustment factor (AF), return index (RI), market value (MV), book value (WC03501), Selling, General & Administrative Expenses (WC01101), Research & Development Expenses (WC01201) and Goodwill (WC18280) for all stocks that remain in the sample.

A.2.2 Dynamic Filtering

Dynamic filters on daily data will be applied independently of each other (meaning, the order of applying the filters does not matter). The dynamic filtering steps are:

1. Remove zero returns at end of sample (TDS keeps price stale after dead/delist/..). Ince and Porter (2006) and Schmidt et al. (2019) implement this by removing the second an subsequent padded value in monthly data, whereas we remove the tenth and subsequent padded daily observations (Landis and Skouras (2021)).

2. RI (Holidays): Exclude likely holidays or days on which markets are closed by removing days on which non-missing or non-zero returns account for less than 0.5% of the total number of stocks available for that country across all days (after removing zero returns at end of sample (Filter 1)) Landis and Skouras (2021).

3. RI (Staleness): If 30 consecutive prices are identical, all subsequent price observations are eliminated until the next price change Landis and Skouras (2021).

4. UP (Nonsense-values): Use only days for which unadjusted price (UP) is positive Chaieb et al. (2021), Landis and Skouras (2021).

5. UP/AF/P (Adjustment inconsistencies): Filter out cases when UP is more than 5% different to P * AF Ince and Porter (2006), Landis and Skouras (2021).

6. RI (Return Reversal or Outliers): Remove (both) daily observations when R_t or R_{t-1} is greater than 100%, and $(1 + R_t)(1 + R_{t-1}) - 1$ is smaller than -50%.

7. RI (Implausibility): Remove stocks of which more than 98% of their non-zero daily returns are either non-negative or non-positive (see e.g. DSCD 912391 incorrect payout of dividend every day betwwen 1985-1989) Landis and Skouras (2021).

8. RI (few non-zero return observations): If return is zero in more than 95% of sample, stock is removed after accounting for zero returns at end of sample (Filter 1) Landis and Skouras (2021).

9. RI (high/low volatility): Stocks with a daily standard deviation of more than 40% and less than 0.01 bps are eliminated from the sample Landis and Skouras (2021).

10. RI (RI unavailable): Remove stocks when RI is unavailable (even when accounting data exists) Landis and Skouras (2021).

11. RI (Few observations): Exclude stocks that have less than 120 valid daily return observations unless the observations are within the last 120 days of the sample Landis and Skouras (2021).

12. Recommended sample start dates: Remove observations before start dates for TDS after which delisting rates are non-zero in TDS and Worldscope book value data and ex dividend data is also available (see Table 1 in Landis and Skouras (2021) or Landis and Skouras (2021) IA Table B4).

13. RI (Nonsense-values): Use only days for which return index (RI) is positive

14. UP (Penny stocks): Remove "penny stocks" when unadjusted price (UP) is below 5% percentile

		SG&A		R&D		Mkt-Cap Weighted	
Region	Industry	% NA	% 0	% NA	% 0	B/M	B^{INT}/M
U.S.	BusinessEquipment	1.36	0.00	13.88	5.44	0.23	0.51
	Chemicals	0.77	0.00	20.03	5.91	0.28	0.72
	ConsumerDurables	1.19	0.05	23.61	11.00	0.36	0.95
	ConsumerNondurables	2.01	0.00	45.27	26.44	0.26	0.73
	Energy	2.37	0.00	67.57	21.14	0.51	0.67
	Finance	65.97	0.04	95.33	2.79	0.64	0.85
	Healthcare	1.61	0.00	20.52	6.52	0.22	0.55
	Manufacturing	1.78	0.00	28.28	12.50	0.35	0.72
	Other	5.25	0.01	52.05	24.68	0.34	0.75
	Shops	2.78	0.00	49.65	41.83	0.25	1.04
	Telecommunication	8.74	0.00	57.72	21.36	0.42	0.62
	Utilities	47.99	0.00	75.22	18.77	0.57	0.83
Europe	BusinessEquipment	36.89	0.01	54.83	2.20	0.30	0.63
	Chemicals	35.65	0.00	47.43	1.30	0.39	1.13
	ConsumerDurables	35.21	0.00	53.56	1.37	0.81	2.13
	ConsumerNondurables	43.10	0.00	78.18	2.79	0.35	0.75
	Energy	25.36	0.00	78.88	1.65	0.76	1.12
	Finance	48.07	0.35	97.60	0.69	0.86	1.17
	Healthcare	25.01	0.00	39.87	1.52	0.34	0.88
	Manufacturing	42.55	0.00	59.66	1.52	0.53	1.05
	Other	38.52	0.01	84.80	2.58	0.58	0.93
	Shops	36.86	0.01	89.91	3.52	0.43	1.13
	Telecommunication	37.74	0.00	73.32	2.95	0.49	0.70
	Utilities	50.95	0.00	76.54	1.42	0.62	0.84
Japan	BusinessEquipment	3.91	0.00	27.59	1.09	0.54	1.54
	Chemicals	3.24	0.00	18.12	0.23	0.62	1.70
	ConsumerDurables	4.64	0.00	30.52	0.29	0.70	1.82
	ConsumerNondurables	3.78	0.00	41.10	0.87	0.62	1.60
	Energy	2.69	0.00	41.03	0.45	0.88	1.71
	Finance	52.54	0.04	95.71	0.99	0.69	0.90
	Healthcare	3.37	0.00	17.71	0.46	0.53	1.26
	Manufacturing	5.02	0.00	27.62	0.29	0.67	1.54
	Other	8.39	0.00	63.41	1.83	0.63	1.27
	Shops	6.23	0.00	81.37	4.16	0.67	2.58
	Telecommunication	15.56	0.00	56.72	0.85	0.54	1.01
	Utilities	43.99	0.00	31.75	1.76	0.65	0.70
Asia-Pacific	BusinessEquipment	27.64	0.00	56.59	5.87	0.26	0.41
	Chemicals	24.06	0.00	56.51	3.94	0.61	0.80
	ConsumerDurables	21.19	0.00	53.15	4.68	0.56	1.07
	ConsumerNondurables	28.83	0.00	73.94	6.40	0.69	1.25
	Energy	38.61	0.00	84.28	9.10	0.58	0.64
	Finance	41.62	0.16	92.94	3.67	0.68	0.73
	Healthcare	30.98	0.00	50.54	4.34	0.29	0.45
	Manufacturing	23.88	0.00	68.87	3.64	0.72	1.04
	Other	36.68	0.00	83.87	7.60	0.83	1.00
	Shops	28.42	0.02	83.89	6.67	0.60	0.95
	Telecommunication	38.24	0.00	85.22	6.11	0.46	0.53
	Utilities	40.22	0.00	78.41	6.39	0.61	0.66

Table A3: Descriptive Industry Statistics. This tables describes the relevant information, per region and industry, for the key variable $SG\&A$, necessary for assessing the level of intangible capital. Additionally, information for the variable $R\&D$ (necessary for the perpetual inventory method of Peters and Taylor (2017)) is outlined. $\%NA$ and $\%0$ indicate the fraction of firms with missing or zero numbers, respectively, and are denoted in percent. B/M and B^{INT}/M are the market-capitalization weighted valuation ratios. In Asia-Pacific, B/M and B^{INT}/M are windsorized by the 99% quantile. The presented statistics use annual data in June each year, i.e. when portfolios are formed, between June 1983 and December 2021.

	U.S.			
	log(B/M)		log(B^{INT}/M)	
	(1)	(2)	(3)	(4)
Market-Wide	0.0024***		0.0046***	
	$t = 3.4769$		$t = 8.1394$	
Across-industry		−0.0048		0.0067***
		$t = -1.5488$		$t = 3.3987$
Within-industry		0.0030***		0.0044***
		$t = 5.6922$		$t = 8.1900$
	Europe			
	log(B/M)		log(B^{INT}/M)	
	(1)	(2)	(3)	(4)
Market-Wide	0.0025***		0.0024***	
	$t = 6.3503$		$t = 7.2099$	
Across-industry		−0.0006		−0.0001
		$t = -0.3386$		$t = -0.0531$
Within-industry		0.0027***		0.0025***
		$t = 8.5391$		$t = 8.6701$
	Japan			
	log(B/M)		log(B^{INT}/M)	
	(1)	(2)	(3)	(4)
Market-Wide	0.0034***		0.0026***	
	$t = 4.5054$		$t = 5.5461$	
Across-industry		−0.0005		0.0010
		$t = -0.1653$		$t = 0.5828$
Within-industry		0.0036***		0.0029***
		$t = 5.5666$		$t = 6.7878$
	Asia-Pacific			
	log(B/M)		log(B^{INT}/M)	
	(1)	(2)	(3)	(4)
Market-Wide	0.0058***		0.0063***	
	$t = 6.6955$		$t = 7.4439$	
Across-industry		0.0005		0.0015
		$t = 0.2269$		$t = 0.6749$
Within-industry		0.0061***		0.0065***
		$t = 6.9001$		$t = 7.6554$
Note:				*p<0.1; **p<0.05; ***p<0.01 Full sample.

Table A4: Cross-Sectional Regressions. This table shows the coefficients and t-statistics of monthly cross-sectional regressions of single variables on stock returns as in Asness et al. (2000). $r_{i,t}$ are returns of stock i at time t. $X_{i,t}$ is either $log(B/M)$ or $log(B^{INT}/M)$ for stock i at time t, $X_{I,i,t}$ is the equally weighted average average $log(B/M)$ or $log(B^{INT}/M)$ for firm i in industry I. The 12 industry classifications are adopted from Fama-French. Data is from June 1983 to December 2021.

$$\begin{aligned}\text{Market-Wide Regression} : r_{it} &= \gamma_{A,t} + \gamma_{B,t} X_{i,t} + \epsilon_{i,t}.\\ \text{Industry Regression} : r_{it} &= \gamma_{0,t} + \gamma_{1,t} X_{I,i,t} + \gamma_{2,t}(X_{i,t} - X_{I,i,t}) + \mu_{i,t}.\end{aligned} \tag{i}$$

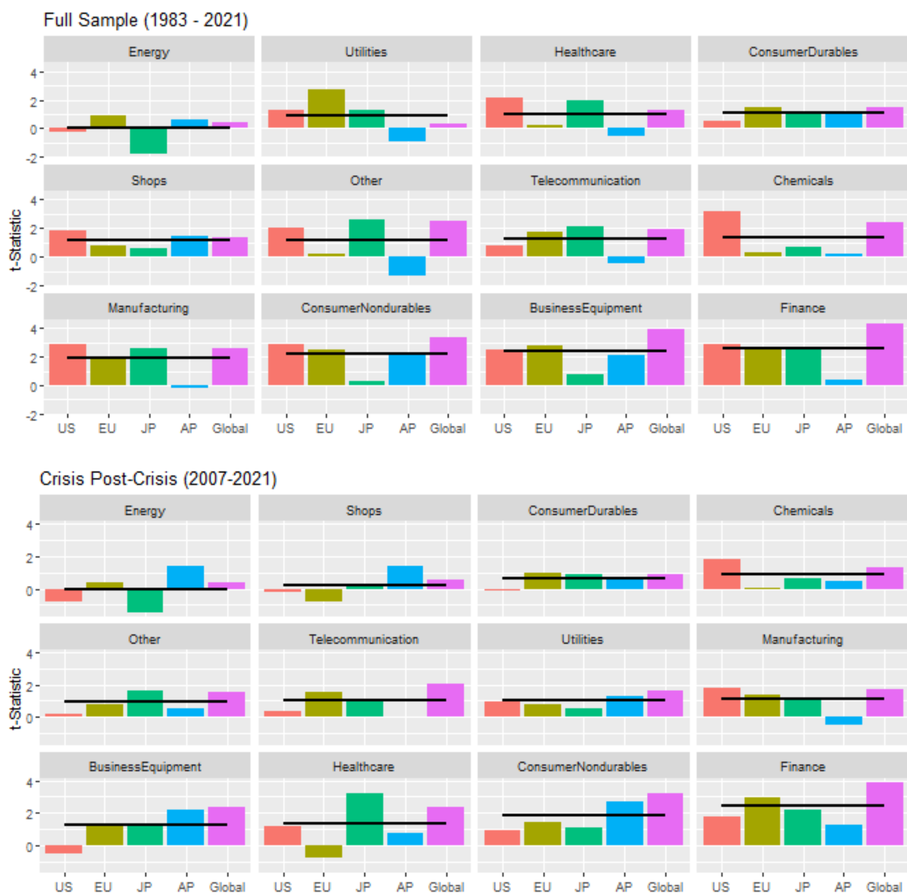

Figure A1: Significance of Oupterformance of HML^{INT} vs. HML by Industry and Region.This figure shows the t-statistics of the intercept from a time-series regression of HML^{INT} on HML across the regions U.S. (US), Europe (EU), Japan (JP), Asia-Pacific (AP) and within each industry (Business Equipment, Chemicals, Consumer Durables, Consumer Non-Durables, Energy, Finance, Healthcare, Manufacturing, Other, Shops, Telecommunication, Utilities) between June 1983 and December 2021 (full sample - top panel) and January 2007 and December 2021 (Crisis Post-Crisis - bottom panel). The reported t-statistics are Newey-West corrected.

Risk Measure	HML	HMLINT	HML	HMLINT	HML	HMLINT	HML	HMLINT
	US		EU		JP		AP	
DEF	-0.0025	5e-04	-0.0026	-9e-04	-2e-04	-6e-04	-0.0018	-0.001
	(-1.04)	(0.34)	(-1.41)	(-0.63)	(-0.09)	(-0.46)	(-0.8)	(-0.46)
TERM	0.0017	0.0016	9e-04	0.0011	0.002	8e-04	0.002	0.0023
	(0.88)	(0.98)	(0.62)	(0.83)	(1.27)	(0.63)	(1.11)	(1.37)
GDP_pch	0.7359	0.8267	0.7539	0.4337	-0.3585	-0.0367	0.0966	0.1425
	(2.47)	(3.89)	(2.9)	(1.74)	(-0.98)	(-0.12)	(0.28)	(0.43)
CFNAI	0.002	0.0016	0.0024	0.0015	7e-04	0.0013	8e-04	4e-04
	(2.22)	(3.43)	(3.05)	(2.49)	(0.68)	(1.71)	(0.91)	(0.4)
MSCI_World_ER	-0.0614	-0.0047	0.0938	0.0871	-0.1322	-0.0812	0.0354	0.0455
	(-0.96)	(-0.09)	(2.26)	(2.65)	(-3.35)	(-2.69)	(0.78)	(1.04)
Recession_Dummy	-0.0048	-6e-04	-0.0054	-0.0032	0.0012	-0.0036	-0.0084	-0.0073
	(-0.98)	(-0.18)	(-1.09)	(-0.84)	(0.19)	(-0.78)	(-1.71)	(-1.5)
US_Unemployment	0.2225	0.3356	-0.0664	0.0658	-0.2114	-0.3493	0.0971	0.2318
	(0.81)	(1.34)	(-0.26)	(0.3)	(-0.64)	(-1.45)	(0.24)	(0.67)
PCE	0.0567	0.0543	0.078	0.0389	0.0506	-0.0428	0.1515	0.1519
	(2.29)	(2.47)	(2.2)	(1.2)	(1.34)	(-1.72)	(2.44)	(2.48)
IAPF	0.0355	0.0453	0.0907	0.0794	-0.0307	-0.0131	0.0639	0.0607
	(1.07)	(2.15)	(4.67)	(5.46)	(-1.14)	(-0.83)	(1.27)	(1.24)
FLiqu_Shock	-2e-04	0.0102	0.0016	2e-04	-0.0056	-0.0018	-0.0028	0.0016
	(-0.02)	(1.44)	(0.28)	(0.03)	(-1.27)	(-0.37)	(-0.4)	(0.25)
MLiqu_Shock	0.008	0.0097	0.0124	0.0094	0.0057	0.0086	0.0084	0.0077
	(1.05)	(1.64)	(2.2)	(1.86)	(0.86)	(1.94)	(1.3)	(1.25)
PCALiqu_Shock	0.0015	0.0032	0.0034	0.002	0	9e-04	0.0018	0.0025
	(0.6)	(1.73)	(2.23)	(1.52)	(0)	(0.77)	(1.11)	(1.88)

Table A5: Macroeconomic and Liquidity Risk Exposures. Displayed are coefficient estimates and t-statistics (in parentheses) from time-series regressions of the traditional and intangible value factors across all regions on a selection of macroeconomic and liquidity shock variables. DEF represents the default spread measured by the yield difference of U.S. corporate bonds and U.S. Treasuries, TERM is the term spread on U.S. government bonds, GDP_pch is the contemporaneous GDP growth measured by changes in real gross domestic product per capita, MSCI World ER is the return of world equity markets in excess of the U.S. T-bill rate, the Recession Dummy represents U.S. recessions (0 = peak, 1 = trough), PCE represents long-run consumption growth, which is the 3-year future growth rate in per capita nondurable goods. Additionally, I include shocks, measured by the residuals of an AR(2) process of the TED spread as a funding liquidity indicator (FLiqu_Shock) and the On-the-run vs. Off-the-run 10-year government treasury note spread as a market liquidity indicator (MLiqu_Shock). To measure total liquidity (PCALiqu_Shock), I use a principal component-weighted average index of the two liquidity shocks. For brevity, the intercepts from the regressions are not reported. PCE and GDP_pch are measured against cumulative quarterly returns, whereas the remaining indicators are measured against monthly returns.

Country	Risk-free rate proxy	Tenor	Start	TDS Series	Description
Australia	TBill	3 month	1976	ADBR090	Australia Dealer Bill 90 D - Middle Rate
Austria	IBR + OIS	3 month	1991	OEINTER3, OIEUR3M	OE Interbank Offered Rate: Three Month, Euro 3 Month OIS - Middle Rate
Belgium	TBill	3 month	1991	BGTBL3M, OIEUR3M	Belgium Treasury Bill 3 Month - Middle Rate , Euro 3 Month OIS - Middle Rate
Cyprus	IBR + OIS	3 month	1999	CPINTER3, OIEUR3M	CYP Interbank Offered Rate: Three Month, Euro 3 Month OIS - Middle Rate
Denmark	IBR + OIS	3 month	1988	CIBOR3M, OIDKK3M	Denmark Interbank 3 Month - Offered Rate, Danish Krone 3 Month OIS - Middle Rate
Finland	IBR + OIS	3 month	1987	FNINTER3, OIEUR3M	Finalnd Interbank Fixing 3 Month - Offered Rate, Euro 3 Month OIS - Middle Rate
France	TBill	3 month	1989	FRTBL3M	France Treasury Bill 3 Months - Bid Rate
Germany	IBR + OIS	3 month	1986	FIBOR3M, OIEUR3M	Germany Interbank 3 Month - Offered Rate, Euro 3 Month OIS - Middle Rate
Greece	TBill	3 month	1960	GDTBL3M	Greece Treasury Bill 3 Month - Middle Rate
Hong Kong	TBill	3 month	1991	HKGBILL3	HK Treasury Bill Rate - 3 Month
Ireland	IBR + OIS	3 month	1984	IRINTER3, OIEUR3M	Ireland Interbank 3 Month - Offered Rate, Euro 3 Month OIS - Middle Rate
Italy	TBill	3 month	1988	ITBT03G	Italy T-Bill Auct. Gross 3 Month - Middle Rate
Japan	IBR	3 month	1986	JPINTER3, OIJPY3M	Japan Interbank 3 Month - Middle Rate, Japanese Yen 3 Month OIS - Middle Rate
Luxembourg	OIS	3 month	1999	OIEUR3M	Euro 3 Month OIS - Middle Rate
Netherlands	IBR + OIS	3 month	1979	HOLIB3M, OIEUR3M	Netherland Interbank 3 Month - Middle Rate, Euro 3 Month OIS - Middle Rate
New Zealand	IBR + OIS	3 month	1986	NZINTER3, OINZD3M	New Zealand Interbank 3 Month - Middle Rate, New Zealand Dollar 3 Month OIS - Middle Rate
Norway	TBill + IBR	3 month	1986	NWIBK3M, NWTBL3M	Norway Interbank 3 Month - Offered Rate, Norway T Bill 3 Month - Red. Yield
Portugal	IBR + OIS	3 month	1993	PTINTER3, OIEUR3M	Portugal Interbank 3 Month - Middle Rate, Euro 3 Month OIS - Middle Rate
Singapore	TBill + OIS	3 month	1988	SNGTB3M, OISGD3M	Singapore T-Bill 3 Month - Middle Rate, Singapore Dollar 3 Month OIS - Middle Rate
Spain	TBill + OIS	1-3 month	1988	ESTBL3M, OIEUR3M	Spain Treasury Bill 1-3 Month - Red. Yield, Euro 3 Month OIS - Middle Rate
Sweden	TBill	3 month	1989	SDTB90D	Sweden Treasury Bill 90 Day - Middle Rate
Switzerland	IBR + OIS	3 month	1974	SWIBK3M, OICHF3M	Swiss Interbank 3M (ZRC:SNB) - Bid Rate, Swiss Franc 3 Month OIS - Middle Rate
United Kingdom	TBill	3 month	1985	UKTBTND	UK Treasury Bill Tender 3M - Middle Rate
United States	TBill	1 month	1963		U.S. Treasury Bill 1 Month (from Ibbotson Associates)

Table A6: Country Risk-Free Rates. This table displays for each country the relevant risk-free rate used for the analysis. The selection procedure follows Schmidt et al. (2019). Whenever available, I use local treasury-bill rates (TBill). If not available, I choose overnight index swap rates (OIS) and lastly interbank rates (IBR).