

# The intangibles premium

Dion Bongaerts, Xiaowei Kang, Mathijs van Dijk\*

March 2023

## Abstract

We investigate the nature of cross-sectional asset pricing effects of intangibles. Intangible asset intensity relates strongly positively to stock returns and has more explanatory power than size, value, profitability, and investment. Adding an intangibles factor improves the Fama-French five-factor model and makes the investment factor redundant. Importantly, intangibles matter more as a characteristic than as a risk factor. Further, intangibles hardly predict future earnings and EBITDA growth (valuation-relevant performance metrics affected by accounting conservatism concerning intangibles) but strongly predict gross profit growth (unaffected by such accounting practices). Our evidence is consistent with investor underreaction to intangibles resulting from accounting conservatism.

**Key Words:** Intangible Assets, Knowledge Capital, Organization Capital, Asset Pricing, Factor Models, Information Complexity, Mispricing, Investor Underreaction.

\* Bongaerts, Kang, and van Dijk are at the Rotterdam School of Management, Erasmus University. Burgemeester Oudlaan 50, 3062 PA, Rotterdam, The Netherlands. Email: dbongaerts@rsm.nl, kang@rsm.nl, and madijk@rsm.nl. Kang is also with Abu Dhabi Investment Authority. Bongaerts is corresponding author. Declarations of interest: None. We thank Andrea Eisfeldt, Felix Goltz, Jean-Paul Kachour, Dimitris Papanikolaou, Stephen Penman, Tarek Masmoudi, Caio Natividade and team, Kai Wu, and seminar participants at the Rotterdam School of Management for helpful comments and discussions.

# The intangibles premium

March 2023

## Abstract

We investigate the nature of cross-sectional asset pricing effects of intangibles. Intangible asset intensity relates strongly positively to stock returns and has more explanatory power than size, value, profitability, and investment. Adding an intangibles factor improves the Fama-French five-factor model and makes the investment factor redundant. Importantly, intangibles matter more as a characteristic than as a risk factor. Further, intangibles hardly predict future earnings and EBITDA growth (valuation-relevant performance metrics affected by accounting conservatism concerning intangibles) but strongly predict gross profit growth (unaffected by such accounting practices). Our evidence is consistent with investor underreaction to intangibles resulting from accounting conservatism.

Key Words: Intangible Assets, Knowledge Capital, Organization Capital, Asset Pricing, Factor Models, Information Complexity, Mispricing, Investor Underreaction.

## 1. Introduction

Intangible assets have become increasingly important for the productivity growth of economies and the value of firms over the recent decades. Gu and Lev (2017) show that investments in tangible assets declined from 15% of gross added value in 1977 to 9% in 2014, while investments in intangible assets increased from 9% to 14% of added value. Ewens, Peters, and Wang (2020) estimate that intangible assets as a proportion of firms' total assets have increased from 37% in 1975 to 60% in 2016. These changes were driven by a rapid transition from a traditional economy dominated by physical assets and production processes to a knowledge economy powered by research, technology, human capital, and organization capital.

Despite the growing importance of intangible assets, the accounting and reporting rules for intangibles provide limited information to investors (Lev, 2018). Most internally created intangible assets – such as knowledge capital and organization capital – are immediately expensed and not capitalized on the balance sheet. While this approach is conservative and prudent from an accountability of management perspective, it may be problematic for valuation purposes. In particular, the failure to reflect the value of these intangible assets can lead to significant accounting mismeasurement of important firm characteristics such as book equity, EBITDA, and earnings (Srivastava, 2014; Lev and Gu, 2016). Especially the latter two are often used for firm and stock valuations.

Naturally, such mismeasurement is likely to be most severe for firms with higher levels of intangibles. High intangibles firms may therefore be associated with greater information asymmetries and/or mispricing. Consistently, analysts' earnings forecast errors are larger for intangible-intensive firms (Gu and Wang, 2005), analysts' recommendation revisions are more valuable for firms with high Research & Development (R&D) intensity (Palmon and Yezegel, 2012), and the value relevance of book equity and earnings has declined for high intangibles firms but not low intangibles firms (Dugar and Pozharny, 2021).

Accounting issues related to intangibles can also affect the factor construction in asset pricing studies. Several recent papers adjust the Fama and French (1993) value factor (HML; High Minus Low book-to-market ratio) for accounting imperfections of intangibles and show that the intangibles-adjusted HML factor yields higher returns (Park, 2019; Lev and Srivastava, 2020; Amenc, Goltz, and Luyten, 2020; Arnott, Harvey, Kalesnik, and Linnainmaa, 2021). These studies generally find that the mismeasured book equity partially contributes to the recent underperformance value strategies. Penman and Zhang (2021) discuss handling accounting data in asset pricing more generally and argue that accounting distortions can be exploited in building asset pricing models.

Motivated by these considerations, we show in this paper that intangible assets provide explanatory power about the cross-section of stock returns. Moreover, we investigate the nature of this explanatory power. On the one hand, firms' intangible intensity may be priced in the cross-section, because information frictions in accounting statements create more severe cash flow forecasting biases. Alternatively, firms with greater intangibles may be viewed as riskier by investors, for example due to key talent bargaining power, as in Eisfeldt and Papanikolaou (2013). The results of our tests are consistent with the former, but not with the latter explanation.

To test the presence and nature of asset pricing effects of intangibles, we construct an intangible intensity measure as the ratio of internally created (off-balance-sheet) intangible assets relative to total assets using all U.S. stocks in the Russell 3000 index over the sample period 1989-2020.<sup>1</sup> Following Peters and Taylor (2017), internally created intangible assets include knowledge capital and organization capital, which are estimated by accumulating past R&D and Selling, General & Administrative Expense (SG&A) expenditures, respectively, subject to depreciation over time. For our denominator, we add knowledge capital and organization capital to total assets net of goodwill as in Park (2019) and Amenc et al. (2020).

We also use our intangible intensity measure to construct an intangibles factor that is long high intangibles firms and short low intangibles firms. We find that portfolios sorted on intangible intensity exhibit large variation in average returns, for both large stocks and small stocks. The intangibles factor has an economically significant average return of 4.6% annually (the “intangibles premium”), and a Sharpe ratio of 0.51, which is close to that of the market factor. This Sharpe ratio is considerably higher than that of the size, value, profitability, investment, and momentum factors.

We also run Fama and MacBeth (1973) cross-sectional regressions of portfolio returns on the value-weighted firm characteristics of the corresponding portfolios. These portfolios are formed to produce spreads in size, book-to-market (B/M), profitability, investment, and intangible intensity, following similar procedures to Fama and French (2015). We find that intangible intensity is the strongest explanatory variable in the cross-section of returns both economically and statistically. A one standard deviation increase in intangible intensity is associated with an annualized return increase of 1.6 percentage points with a *t*-statistic of 2.83. We also find that the investment variable loses its explanatory power when intangible intensity is added to the regression. In addition, we show robustness to the use of an industry-adjusted

---

<sup>1</sup> We limit ourselves to the Russell 3000 index to exclude micro caps, which have been found to have an unduly impact on anomalies (Fama and French, 2008) and are typically not considered by institutional investors.

intangibles intensity measure as advocated by Eisfeldt, Kim, and Papanikolaou (2021). Taken together, these findings suggest that intangible intensity is priced in the cross-section of U.S. stock returns.

We then investigate whether the intangibles factor improves current factor models that explain the cross-section of stock returns and whether it contains new information compared to existing factors. The intangibles factor is associated with a Fama-French five-factor alpha of 3.9% per annum with a  $t$ -statistic of 3.1. Importantly, a substantial part of the value (HML) factor's negative average return can be attributed to its strongly negative loading on the intangibles factor. In factor spanning tests, the intangibles factor cannot be explained by the factors in the Fama-French five-factor model (market, size, value, profitability, and investment factors). Gibbons, Ross and Shanken (1989) test results show that adding the intangibles factor to the Fama-French three-factor and five-factor models improves the description of average returns. In addition, a five-factor model with the market, size, value, profitability, and intangibles factors (leaving out the investment factor) produces an improvement relative to the original Fama-French five-factor model. The investment factor is thus essentially redundant for describing average returns over our sample period after accounting for the intangibles factor.

Next, we study the nature of the intangibles premium. As a first step, conduct tests to differentiate pricing effects resulting from mispricing versus those resulting from risk exposure. We follow Daniel and Titman (1997) and form test portfolios (independently) double-sorted by both characteristics (intangible intensity) and risk (intangibles factor beta). We then investigate across which of the two dimensions the pricing effect is stronger. Because of our double sorts, we essentially investigate the effect of one dimension controlling for the other.

We find that it is the characteristics (high or low level of intangible intensity), rather than the intangible risk, that explains average returns. This evidence is consistent with a mispricing explanation, but not with a risk-based one. In addition, we conduct a similar mispricing versus risk test for the organization capital premium, and fail to find support for the risk explanation provided by Eisfeldt and Papanikolaou (2013).

Our test on characteristics vs. risk exposure provides compelling evidence in favor of a mispricing-based interpretation of our asset pricing results. To further strengthen this interpretation and to link this mispricing-based interpretation to accounting practices, we conduct a second set of tests. The basis for these test is our conjecture that investors may underestimate future earnings for firms with high intangibles intensity due to the information complexity of intangible assets induced by accounting practices. In these tests, we assess to which extent our intangibles intensity measure predicts future growth rates of valuation-

relevant fundamental performance metrics better when such metrics are unaffected by accounting conservatism concerning intangibles. Specifically, we compare the ability of our intensity measure in predicting 3, 6, and 10 year growth rates in gross profits (unaffected by accounting practices) on the one hand and earnings (affected by accounting practices) on the other. Because earnings can also be affected by interest, taxes, and non-cash items such as depreciation, we also make a comparison between predicting growth rates of gross profits and EBITDA.

We find that intangible intensity is a strong and positive predictor of future gross profit growth in Fama-MacBeth regressions. By contrast, the effect is statistically much weaker for earnings and EBITDA growth, in several specifications not statistically significant, and even has the wrong sign for EBITDA. One should note that EBITDA and earnings are more often used as metrics to base valuations on than gross profits (especially in a multiples-based approach). Hence, the results of our second test indeed strengthen our interpretation of intangibles-related cross-sectional asset-pricing effects to be mispricing and link such mispricing with conservative accounting practices involving intangibles.

We then show that combining the intangibles factor with Fama-French factors can significantly expand the investment opportunity set of investors. Due to the intangibles factor's strong negative correlation with value and quality strategies (-0.58 with HML, -0.26 with RMW, -0.32 with CMA), the intangibles factor can provide an excellent hedge to value and/or quality strategies. Value and quality investors can capture the economically large intangibles premium while significantly reducing risks and increasing the Sharpe ratio. The ability of the intangibles factor to reduce risk exposure while offering a higher expected return is also consistent with the intangibles premium being a result of mispricing.

Our paper makes several contributions to the literature. Our study contributes to the broad literature on the anomalies associated with R&D investments, organization capital, and intangible assets. Our intangibles intensity measure and the associated risk factor are constructed based on the intensity of off-balance-sheet intangible assets consisting of both knowledge capital and organization capital. Knowledge capital and organization capital are distinct in nature. The knowledge capital intensity and organization capital intensity of firms are lowly correlated (0.16). The returns of the two long/short factors constructed based on knowledge capital intensity and organization capital intensity respectively are negatively correlated (-0.26). Thus, our intangibles factor is distinct from the R&D anomaly and organization capital anomaly in other asset pricing studies (e.g., Leung, Evans, and Mazouz,

2020 and Eisfeldt and Papanikolaou, 2013), and can serve as a more comprehensive proxy for the reporting biases and potential information asymmetries in intangible-intensive firms. We show that intangible asset intensity relates strongly positively to stock returns and has more explanatory power than size, value, profitability, and investment. The intangibles factor has a higher Sharpe ratio than these established factors. Adding the intangibles factor to the Fama-French five-factor model improves the description of average returns and makes the investment factor redundant.

Our study also adds to the mispricing versus risk explanations of intangibles related anomalies. Eberhart, Maxwell, and Siddique (2004), Lev, Sarath, and Sougiannis (2005), Gu and Wang (2005), and Palmon and Yezegel (2012) present evidence that is generally more consistent with mispricing and investor behavioral biases associated with R&D intensive or intangible-intensive firms, but do not test this explicitly. On the other hand, Eisfeldt and Papanikolaou (2013), Gu (2016), and Peters and Taylor (2017) suggest that R&D investments, organization capital, and intangible capital can be riskier than physical capital, supporting a more risk-based explanation. We explicitly test the nature of the relation between intangibles and expected returns and find that it is intangible intensity as a characteristic, as opposed to intangible risk, that explains average returns in the cross-section. Overall, our evidence points towards a mispricing explanation based on the information complexity of intangible assets and conservative accounting practices.

While our paper is motivated by the intangibles anomaly, a paper by Leung et al. (2020) investigates whether the R&D anomaly is driven by risk or mispricing. Consistent with our findings, they find that it is characteristics rather than risk exposures that drive R&D pricing anomalies. We generalize their results by showing that a characteristics-based explanation dominates a risk-exposure-based explanation not only for anomalies based on R&D but also intangible assets in general. In doing so, we provide a more comprehensive analysis that also covers firms for which R&D expenses are contained in SG&A data (separate R&D intensity data is only available for about 40% of listed firms). Crucially, we also contribute by showing the differential ability of intangibles intensity to predict valuation-relevant performance metrics that are affected by conservative accounting practices vs those that are not. Hereby, we provide a plausible explanation of intangibles anomalies as being the result of accounting rules-induced mispricing.

We also contribute to the literature on the effects of accounting conservatism on asset pricing. Park (2019), Lev and Srivastava (2020), Amenc, Goltz, and Luyten (2020), and Arnott, Harvey, Kalesnik, and Linnainmaa (2021) focus on the effects of accounting conservatism

concerning intangibles on the composition of the value factor. Our paper suggests an even more direct, mispricing-based link of intangibles to future returns through downward biases in valuation-relevant performance metrics.

## 2. Data and methods

This section describes our data and methods for measuring intangibles (Section 2.1), constructing the intangibles factor (Section 2.2), as well as constructing test assets for our asset pricing tests.

### 2.1 Measuring intangibles

Under U.S. GAAP, most internally generated intangible assets are not recognized on the balance sheet. For instance, R&D expenditures on innovation, patents, or software are expensed in the same fiscal year they are spent. Advertising spending to enhance brand value, labor expenses to build human capital, and expenditures on organizational design are expensed within Selling, General & Administrative Expense (SG&A). In contrast, similar but externally acquired intangible assets such as patents and trademarks are capitalized and reported on the balance sheet in the form of goodwill. As a result of the transition to the knowledge economy, the internally created intangible assets now represent a significant component of the firms' total capital but continue to be off-balance-sheet.

To measure intangible assets, we capitalize internally created intangible assets including knowledge capital and organization capital, following Peters and Taylor (2017). We choose not to include externally acquired intangible assets already recognized on the balance sheet, as our main objective is to examine the asset pricing implications of the reporting biases and information asymmetries associated with off-balance-sheet intangible assets. In contrast, Peters and Taylor (2017) use the sum of both externally purchased and internally created intangible assets, as their study focuses on the firm's total intangible capital and the investment-q relation.

In line with Peters and Taylor (2017), a firm's internally created knowledge capital is estimated by accumulating past R&D expenditures using the perpetual inventory method:

$$KC_{it} = (1 - \delta_{R&D})KC_{i,t-1} + R&D_{it}, \quad (1)$$

where  $KC_{it}$  is the end-of-period knowledge capital,  $\delta_{R&D}$  is the depreciation rate, and  $R&D_{it}$  is the R&D expenditures during period  $t$ . We use the industry specific R&D depreciation rates from the U.S. Bureau of Economic Analysis (BEA) (Li 2012, Li and Hall 2018), which are

widely used in the literature. Applying the perpetual inventory method requires an initial stock of intangibles. We follow the literature to calculate the initial knowledge capital stock as:

$$KC_{i0} = R&D_{i1}/(g + \delta_{R&D}), \quad (2)$$

where  $R&D_{i1}$  is the firm's first non-missing record of R&D expenditure, and  $g$  is the average R&D growth rate for the sample.<sup>2</sup>

Lev and Radhakrishnan (2005), Hulten and Hao (2008), and Eisfeldt and Papanikolaou (2014) provide arguments and support for using a portion of SG&A expenses as a proxy for investment in organization capital, through spending on advertising, human resources, business processes and systems, etc. We follow Hulten and Hao (2008), Eisfeldt and Papanikolaou (2014), Peters and Taylor (2017), Park (2019), and Amenc et al. (2020) in counting 30% of SG&A expenses (excluding R&D expenses) as an investment in organization capital. The remaining 70% of SG&A expenses not capitalized as organization capital is considered operating costs for supporting current, instead of future, operations.<sup>3</sup> Correspondingly, a firm's internally created organization capital is constructed by accumulating 30% of past SG&A expenses (excluding R&D) using the perpetual inventory method as in Equation (1) and (2) with a depreciation rate of 20%:<sup>4</sup>

$$OC_{it} = (1 - \delta_{SG&A})OC_{i,t-1} + \theta * SG&A_{it}, \quad (3)$$

where  $OC_{it}$  is the end-of-period organization capital,  $\delta_{SG&A}$  is the depreciation rate of 20%, and  $\theta$  equals 30%. The initial organization capital stock is calculated similar to Equation (2).

We then calculate each firm's intangible asset intensity as its internally created intangible assets scaled by the firm's intangible-adjusted total assets. Similar to Park (2019) and Amenc et al. (2020), we adjust total assets by adding knowledge capital and organization capital and deducting goodwill from it. We exclude goodwill because it can be polluted by market premia for non-intangibles, and its current fair value is unverifiable (Ramanna and Watts, 2012).<sup>5</sup> More specifically, we measure a firm's intangible asset intensity as:

$$IAI_{it} = (KC_{it} + OC_{it})/(TA_{it} + KC_{it} + OC_{it} - GW_{it}), \quad (4)$$

where  $TA_{it}$  is the firm's total assets and  $GW_{it}$  is the firm's goodwill at the end of period  $t$ .

<sup>2</sup> We set  $g = 10\%$  as in Eisfeldt and Papanikolaou (2013, 2014) for both knowledge capital stock and organization capital stock. A simpler assumption of  $g = 0\%$  has almost zero impact on the performance of the intangibles factor.

<sup>3</sup> Similar to the 30% fraction used by Peters and Taylor (2017), Ewens et al. (2020) estimate intangible capital with market prices and find that 27% of SG&A represents investment in organization capital (albeit with variation across industries).

<sup>4</sup> Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017) show that their results are robust to the choice of depreciation rate.

<sup>5</sup> Our results are robust to us using an alternative measure of intangibles intensity that does not correct for goodwill.

It is important to note that the two main components of the intangible assets – knowledge capital and organization capital – are very different in nature, and are capitalized differently following Peters and Taylor (2017). If we rank the firms in our stock universe by their knowledge capital intensity and organization capital intensity respectively, the correlation of the two rankings is only 0.16. In addition, the returns of long/short factors<sup>6</sup> based on knowledge capital intensity and organization capital intensity respectively are negatively correlated at -0.26. Thus, our intangible assets intensity is distinct from the R&D (knowledge capital) intensity such as in Palmon and Yezegel (2012) and Leung et al. (2020).

In contrast, Eisfeldt, Kim, and Papanikolaou (2021) follow Eisfeldt and Papanikolaou (2013) and capitalize all of SG&A expenses (including R&D) as investment in organization capital. This ignores the substantial proportion of SG&A expenses spent to support the firm's current operations. Furthermore, the organization capital in Eisfeldt and Papanikolaou (2013) is meant to capture bargaining power of key talent. By contrast, we focus on the ramifications of accounting mismeasurement on the mispricing of shares. Hence, our focus is more on intangible assets in place, i.e., what has been produced already. Given the evidence by e.g., Ewens et al. (2020), for our purposes, the suggested approach seems more appropriate. We do show that our results that support the mispricing explanation of the intangibles factor are robust to measuring intangible assets as in Eisfeldt and Papanikolaou (2013).

We recognize that each firm's intangible assets are unavoidably measured with error, as the knowledge capital and organization capital measures are simplified proxies that cannot capture the idiosyncratic firm characteristics. However, our study uses portfolios instead of individual firms as test assets, which should mitigate the noises in our intangible intensity measures.

## 2.2 Constructing the intangibles factor and test assets

We follow similar procedures as those of Fama and French (2015) to construct the intangibles factor, the factors in the Fama-French five-factor model, and the momentum factor. We use the Russell 3000 index, an established U.S. equity benchmark for institutional investors, as our stock universe to construct the factors from. Compared with the Center for Research in Security Prices (CRSP) database, the Russell 3000 stock universe contains fewer microcaps. Hou, Xue, and Zhang (2020) find that most anomalies from asset pricing studies cannot be replicated once

---

<sup>6</sup> We construct factors that long high knowledge capital or organization capital intensity firms and short low knowledge capital or organization capital intensity firms, using procedures in section 2.2.

microcaps are removed. In addition, most institutional investors do not invest in microcap stocks. Therefore, we believe that our choice of the Russell 3000 universe can enhance the robustness of our results and its relevance to both academic and practitioner audiences. Our sample excludes financial firms, following Eisfeldt and Papanikolaou (2013) and Novy-Marx (2013). All accounting data for the firms, including data for measuring intangible assets, is from the Factset Fundamentals Datafeed.

More specifically, in June of each year from 1989 to 2020, the Russell 3000 stock universe is split into two size groups, the Russell 1000 big stock universe, and the Russell 2000 small stock universe. The Russell 3000 stocks are sorted by intangible asset intensity into three groups based on the breakpoints for the top 30% (High Intangibles), middle 40% (Medium Intangibles), and bottom 30% (Low Intangibles). The intersections of the independent 2 x 3 sorts on size and intangible intensity produce six portfolios. The intangibles factor INT is the average of the two high intangibles portfolio returns minus the average of the two low intangibles portfolios returns. Consistent with the Fama and French (2015) factors we construct, the intangibles factor is not based on an industry-adjusted sorting procedure as advocated by Eisfeldt et al. (2021). This is done intentionally to be able to pick up pricing effects that result from variations in accounting imperfections across industries. Nevertheless, we also show that our results are robust when we use an industry-adjusted intangibles factor instead.

The value factor HML, profitability factor RMW, and investment factor CMA are constructed in a similar way, as averages of value, profitability, and investment factors for small and big stocks. The Size factor SMB is the average of the returns on the nine small stock portfolios of the three 2 x 3 sorts (size and value, size and profitability, size and investment), minus the average of the returns on the nine big stock portfolios. These procedures exactly follow Fama and French (2015) to enable us to examine the impact of adding the Intangibles factor to the original Fama-French five-factor model. The momentum factor MOM is constructed similarly, but with monthly rebalancing. Lastly, the market factor is constructed as the returns of Russell 3000 index minus the U.S one-month T-bill rate. Monthly returns of the portfolios and factors are all value-weighted.

We use the same methodology to construct additional value factors (EPS / Price, EBITDA / Enterprise Value (EV), Cash Flow / Price, Free Cash Flow / Price, Sales / Price, Net Payout Yield) and quality factors (Gross Profitability, Return on Equity, Return on Assets, Accruals / Total Assets). These variables are used to study the intangibles factor loadings of commonly used value and quality factors in Section 5. In addition, as proxies for factor strategies that are used in practice, we construct a value strategy and a quality strategy that are

both based on multiple variables. The value strategy is constructed by sorting stocks by a composite factor that equal-weights Book / Market, EBITDA / EV, Free CF / Price, Sales / Price, and Net Payout Yield. Similarly, the quality strategy is constructed by sorting stocks by a composite factor that equal-weights Operating Profitability, Investment, Gross Profitability, Return on Equity, Return on Assets, and Accruals/Assets.

We also construct portfolios sorts to serve as test assets for our asset pricing tests, in particular the Fama-MacBeth regressions in Section 3 and GRS tests in Section 4. To study the cross-section of average returns and distinguish among the different risk exposures, we sort stocks jointly on the key characteristics Size, book-to-market (B/M), operating profitability (OP), investment (INV), and intangible intensity (INT). Sorts on four joint variables, either using  $3 \times 3 \times 3 \times 3$  sorts or  $2 \times 4 \times 4 \times 4$  sorts produces 81 or 128 poorly diversified portfolios with low power in asset pricing tests, as Fama and French (2015) point out. Therefore, we follow Fama and French (2015) to construct  $2 \times 4 \times 4$  sorts based on three variables only. More specifically, we form two Size groups (big and small) based on the Russell 1000 and Russell 2000 stocks. Stocks in each Size groups are assigned independently to four B/M groups, four OP groups, four INV groups, and four INT groups. As both the Fama-French three-factor and five-factor models include SMB and HML, we fix B/M as the second sort variable for the Size groups, and choose either OP, INV, or INT as the third sort variable. This produces 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios for our asset pricing tests.

### 3. Intangible intensity and stock returns

This section examines whether intangible intensity is priced in the cross-section of returns. First, we analyze the risk and return characteristics of the intangibles factor that is long high-intangible-intensity firms and short low-intangible-intensity firms (Section 3.1). Second, we run Fama-Macbeth regressions of portfolio returns on value-weighted firm characteristics of the portfolios (Section 3.2).

#### 3.1 The intangibles factor (sorts on intangible intensity)

Before we examine the performance of the intangibles factor, we first analyze the six portfolios double sorted on size and intangible intensity that are used to construct the intangibles factor. Table 1 shows the average monthly excess returns of these six portfolios. For both large cap sorts and small cap sorts, firms with higher intangible intensity have higher average returns. Among the large stocks, the high intangibles and low intangibles portfolios have an average

monthly return of 0.87% and 0.59% respectively. Among the small stocks, the high intangibles and low intangibles portfolios have an average return of 1.01% and 0.53% respectively. Correspondingly, the difference in average annual returns between the high and low intangibles portfolios amounts to an economically meaningful 3.4% per annum ( $t$ -stat = 2.1) for the large stocks and 5.8% per annum ( $t$ -stat = 2.8) for the small stocks. In contrast, there is no clear pattern in the standard deviations of monthly returns. For the large stocks, the high intangibles portfolio has slightly lower standard deviation than the low intangibles portfolio (4.07% versus 4.35%), while for the small stocks the high intangibles portfolio has higher standard deviation than the low intangibles portfolio (6.63% versus 5.74%).

Table 1 also reports the time-series average characteristics of the six portfolios, in terms of their value weighted intangible intensity, book-to-market, operating profitability, and investment. As expected, among the characteristics examined in Table 1, intangible intensity shows the largest variation among the low, medium, and high intangibles portfolios. For large stocks, the intangible intensity for low, medium, and high intangibles portfolios is 5%, 24% and 43% respectively, which is very similar to that of small stocks. For both large and small caps, high intangibles stocks have lower book-to-market and lower investment (total asset growth). For instance, for large stocks, the low, medium, and high intangibles portfolios have a book-to-market of 46%, 30% and 22% respectively, and an investment ratio of 21%, 18% and 10% respectively. The lower book-to-market of high intangibles stocks is partly because the internally created intangible assets are not capitalized as part of the firms' book equity. The pattern on operating profitability is not uniform in large and small stock portfolios. High intangibles stocks have marginally higher operating profitability than low intangibles stocks (37% versus 32%) in large caps, but lower operating profitability than low intangibles stocks (5% versus 18%) in small caps.

Table 2 shows the performance statistics for the intangibles factor (INT) constructed using the  $2 \times 3$  sorts on size and intangible intensity as presented in Table 1. It also reports the performance statistics for the factors in the Fama-French five-factor model (Market, SMB, HML, RMW, CMA) as well as the momentum factor (MOM), as these factors will be used in our asset pricing tests. All factors in Table 2 are constructed using the Russell 3000 stock universe for the sample period of June 1989 and November 2020, based on similar procedures to Fama and French (2015), as described in Section 2.2. Table 2 shows that the intangibles premium (average INT return) is substantial (0.38% per month,  $t$ -stat = 2.88), with a Sharpe ratio of 0.51. The only factor that has a higher Sharpe ratio is the market factor (0.56), with a market risk premium of 0.70%. The momentum factor has a substantial premium (average

MOM return) of 0.45%, but lower Sharpe ratio (0.28) and *t*-stat (1.59) due to its higher volatility. The profitability premium (average RMW return) is 0.29% (*t*-stat = 1.6), and the investment premium (average CMA return) is 0.10% (*t*-stat = 0.67). The size premium (average SMB return) and value premium (average HML return) are close to zero (0.01% and -0.02% respectively) over the sample period. The performance of the intangibles factor is thus quite striking, as it has the highest Sharpe ratio (0.51) among all non-market factors examined here, which is quite close to the Sharpe ratio of the market factor. The profitability and momentum factors have the second highest Sharpe ratio among non-market factors at only 0.28. These results show that the intangibles factor has been one of the strongest asset pricing factors in the past 30 years. In an unreported robustness check, we find that if the intangibles factor is constructed by sorting within industries, its Sharpe ratio is 0.42, lower than 0.51, which suggests that there is information in the cross-industry variation of intangible intensity.

Table 2 also shows that the intangibles factor has the lowest maximum drawdown of 38.2% among all factors, while the momentum and value factors have the highest maximum drawdown of 65.9% and 61.5% respectively. The intangibles factor also has the smallest expected shortfall at -4.6%, compared with an expected shortfall that ranges between -6.0% (SMB) and -13.4% (MOM) for other factors. Finally, the intangibles factor has a positive skewness (longer or fatter right tail) of 0.46. In comparison, the momentum factor has the most negative skewness (longer or fatter left tail) of -1.34, while the value factor has the most positive skewness of 0.83. The risk and return characteristics of the intangibles factor seem to suggest that it is not a particularly risky factor.

One question that may arise is how the performance of the intangibles factor compares with that of the value factor (HML) and the traditional growth strategy. Figure 1 plots their time-series performance over our sample period. The return of the growth strategy reflects the performance of traditional growth index relative to value index.<sup>7</sup> As expected, the value factor experienced sharp drawdowns in the late 1990s, then bounced back strongly from the burst of the technology bubble until 2007, and more recently has gone through a sustained period of significant underperformance since 2014. The cumulative return of the value factor during the whole period is -25.1%. What is more surprising is the performance of the traditional growth strategy. Although growth investing is widely believed to have dramatically outperformed the market over the recent decade, over the whole period the cumulative return of the traditional

---

<sup>7</sup> It is calculated as the average of the returns on Russell 1000 Growth and Russell 2000 Growth indices, minus the average of the returns on Russell 1000 Value and Russell 2000 Value indices.

growth strategy is only 7.6%. The cumulative return of the growth strategy collapsed during the technology bubble, and only started to rise strongly between 2017 and 2020.

In contrast, the intangibles factor delivered a large cumulative return of 270% during this period. During the burst of the technology bubble, the intangibles factor returned -19.1% peak-to-trough, before bouncing back in 2001; this drawdown was much smaller than the growth strategy, which returned -60.7% peak-to-trough by June 2002. The biggest drawdown of the intangibles factor occurred between October 2003 and June 2008, when it lost 38.2%. Since June 2008, the intangibles factor has experienced a strong performance, returning 153.6% between then and the end of 2020. The economically significant divergence between the long-term performance of the intangibles factor and that of the value and growth strategies has important implications for investors. Both the traditional value and growth investing styles have delivered disappointing long-term returns since 1989. The significant return of the intangibles factor cannot be captured by traditional growth strategies such as the Russell Growth indices. The abnormal return of the factor is not driven by the “Big Tech” companies either. Figure A1 in the Appendix shows that excluding the FAANG (Facebook, Amazon, Apple, Netflix, and Google) stocks, as well as Microsoft and Tesla from the Russell 3000 stock universe has almost no impact on the historical performance of the intangibles factor.

As a complementary note, the sustained underperformance of the value factor in the recent years can be partially attributed to intangible assets. As firms’ book equity does not include internally created intangible assets, the book-to-market ratio used in constructing the value factor is artificially low for firms with high intangibles. To test the impact of off-balance-sheet intangible assets on the performance of the value factor, we construct an intangibles-adjusted value factor by adding knowledge capital and organization capital to the firms’ book equity (similar to Park (2019), Amenc et al. (2020) and Arnott et al. (2021)). Figure A2 in the Appendix shows that such adjustment significantly improved the annualized return of the value factor over the sample period from -0.9% to 2.7%.

Overall, the empirical results in Section 3.1 suggest that high-intangible-intensity firms significantly outperformed low-intangible-intensity firms over our sample period. The intangibles factor delivers a much higher Sharpe ratio than any of the non-market factors in the Fama-French five-factor model and is very distinct from traditional growth strategies.

### *3.2 Fama-Macbeth regressions*

As a complementary test of whether intangibility is priced in the cross-section of stock returns, in this subsection, we turn to Fama-MacBeth regressions to compare the explanatory power of

intangible intensity for average returns with that of the other characteristics. More specifically, we run Fama-MacBeth cross-sectional regressions of portfolio returns on value-weighted firm characteristics of the portfolios. The portfolios used in the cross-sectional regressions are the 96 portfolios we construct from three sorts following similar procedures to Fama and French (2015), which include 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios as described in Section 2.2.

As a prerequisite to the Fama-MacBeth regressions, Table 3 reports the average excess returns for the portfolios that serve as test assets in these regressions. The table shows that, for both big and small stocks, the value effect in average returns is weak over the sample period. Either controlling for OP, INV or INT, the average portfolio returns show no clear pattern with regard to B/M. Similarly, the investment effect in average returns is also weak. In contrast, there is a stronger profitability effect: controlling for B/M the average return generally increases with OP. The intangibles effect is even stronger: controlling for B/M, the average return increases significantly with INT for both big and small stocks.

Using these 96 portfolios, we run monthly cross-sectional regressions of portfolio returns in month  $t+1$ , on different specifications of lagged characteristics in month  $t$ , which include beta, natural logarithm of market capitalization, book-to-market, operating profitability, investment, 12-1 month momentum, and intangible intensity. For each portfolio, the independent variables of individual firms in the portfolio are winsorized at the 1% and 99% level, and value weighted to calculate portfolio level characteristics. The portfolio characteristics of the 96 portfolios are standardized into  $z$ -scores for each of the monthly regressions.

Table 4 shows the results of Fama-MacBeth regressions for five different specifications. The first specification includes beta,  $\ln(\text{mcap})$ , book-to-market, profitability, and investment in the regression, corresponding to the five characteristics used in the Fama-French five-factor model. The regression shows that investment is the only characteristic that has statistically significant power in predicting the cross-section of returns (coefficient -0.98,  $t$ -statistic = -2.56, lower investment predicting higher returns). Book-to-market has a coefficient of -0.35 with a  $t$ -statistic of -0.50, and profitability has a coefficient of 0.66 with a  $t$ -statistic of 1.52. The second regression adds intangible intensity and shows that intangible intensity is the strongest predictive variable for the cross-section of returns. One standard deviation move in intangible intensity is associated with 1.57% annualized return impact, with a  $t$ -statistic of 2.83. At the same time, investment loses statistical significance (coefficient -0.49,  $t$ -stat = -1.22) and profitability gains statistical significance in predictive power (coefficient 0.89,  $t$ -stat = 2.29).

In addition, the first and second regressions also show that the coefficient of book-to-market changes from -0.35 to 0.29 once intangible intensity is added.

The third regression adds momentum to the second specification and shows that this does not have significant impact on the predictive power of the other variables. Intangible intensity remains the strongest predictor, with a coefficient of 1.36 and *t*-statistic of 2.68. Momentum has a statistically insignificant coefficient of 0.63. The  $R^2$  is 85.1%, 86.3% and 87.2% for the first, second and third regression respectively. The fourth specification includes only beta, ln(mcap), and book-to-market, corresponding to the three characteristics used in the Fama-French three-factor model, while the fifth specification adds intangible intensity to the fourth specification. Similarly, we observe that the negative coefficient of book-to-market of -0.70 changes to 0.01 once intangible intensity is added to the fifth regression, and intangible intensity is the strongest predictor of the cross-section of returns.

We also conduct a robustness test, where the sorts on intangible intensity is done within industries when we construct the test assets. Table A1 in the Appendix shows that, for the Fama-Macbeth regression with beta, ln(mcap), book-to-market, profitability, investment, and intangible intensity, intangible intensity remains the strongest explanatory variable for the cross-section of returns, followed by profitability. A one standard deviation move in intangible intensity is associated with 1.22% annualized return impact, with a *t*-statistic of 2.55.

In summary, in Section 3 we use two alternative approaches – portfolios sorted by intangible intensity and Fama-Macbeth cross-sectional regressions on intangible intensity while controlling for other firm characteristics – to examine the relation between intangible intensity and stock returns. The empirical results of both approaches are consistent and support the hypothesis that intangible intensity is priced in the cross-section of stock returns and this evidence is robust to industry-adjustments. In the next section, we examine whether the intangibles factor has the potential to enhance the performance of existing factor models.

#### **4. The intangibles factor and asset pricing models**

In this section, we first test whether the intangibles factor contains incremental information for describing average stock returns beyond the established asset pricing factors (Section 4.1). We then add the intangibles factor to well-known factor models and test whether it improves the description of average stock returns (Section 4.2). Subsequently, we explore potential explanations for the intangibles premium (Section 4.3).

#### *4.1 Factor spanning tests*

While Table 2 and Figure 1 show that the average return of the intangibles factor is both statistically and economically significant, they are not conclusive about whether the intangibles factor contains new information about average returns beyond what is already captured by the established asset pricing factors. In fact, Table 1 shows that portfolios sorted on intangibles exhibit variation in other characteristics, such as book-to-market, operating profitability, and investment. Therefore, the intangibles factor may have systematic loadings to other factors such as HML, RMW, and CMA.

As a starting point, Table 5 shows the correlations between the intangibles factor, the five Fama-French factors (Market, SMB, HML, RMW, and CMA) and the momentum factor (MOM). The intangibles factor is negatively correlated with HML (-0.58), CMA (-0.32), and RMW (-0.26). This is broadly consistent with Table 1, which shows that high intangibles portfolios tend to have lower book-to-market, lower investment, and lower operating profitability (more mixed evidence). Therefore, the intangibles factor can provide a hedge to value strategies and quality strategies such as profitability and investment. In addition, the intangibles factor has low correlations with the Market (0.02), SMB (0.19), and MOM (0.19) factors. In contrast, all other non-market factors have a relatively strong correlation with the Market factor, ranging from -0.47 (RMW) to 0.30 (SMB). Another notable observation in the correlation matrix is that HML is highly correlated with CMA (0.75) and RMW (0.47).

These non-negligible correlations raise the possibility that commonly used factors span the intangibles factor such that it does not add to the explanatory power of factor models. To investigate this possibility, in Panel A of Table 6, we report the results of factor spanning tests for the intangibles factor (INT), the five Fama-French factors, and momentum. Each spanning regression uses six factors to explain the average returns of the seventh factor. In contrast, Panel B reports the results from factor spanning tests that exclude the intangibles factor, where each regression uses five factors to explain the average returns of the sixth factor.

Panel A of Table 6 shows that the intercept in the INT regression is strongly positive (0.32% per month,  $t$ -stat = 3.0), which indicates that the intangibles factor is not spanned by the other six factors and thus contains important new information for describing average returns. The intangibles factor does have statistically significant loadings on HML (coefficient -0.66,  $t$ -stat = -12.83), CMA (coefficient 0.29,  $t$ -stat = 5.27), and SMB (coefficient 0.22,  $t$ -stat = 5.59). Among the other six regressions in Panel A, the profitability (RMW) factor is the only other non-market factor that has a statistically significant intercept (0.39%,  $t$ -stat = 2.93). These observations are broadly consistent with our results from the Fama-MacBeth regressions

(Table 4) that intangible intensity and profitability have statistically significant power in explaining the cross-section of returns, despite the different nature of the tests (cross-section versus time-series).

Panel A of Table 6 further shows that the value factor is spanned by the other five factors during the sample period of 1989 to 2020, as the intercept (alpha) of the HML regression is 0.00% ( $t$ -stat = 0.02). Importantly, the value factor has a strongly negative exposure to the intangibles factor (-0.46,  $t$ -stat = -12.83). When the intangibles factor is excluded from the factor spanning regression, Panel B shows that the value factor has an economically significant negative intercept of -0.22% per month with a  $t$ -statistic of -2.06, and is thus not spanned by the other four Fama-French factors and the momentum factor. This finding suggests that the vast majority of the value factor's negative return can be attributed to its strongly negative loadings to the intangibles factor. Controlling for the intangibles factor loadings, the average return of the value factor is zero during this period.

Furthermore, Panel A of Table 6 shows that CMA has statistically significant loadings on the intangibles factor (coefficient 0.24,  $t$ -stat = 5.27). After the intangibles factor is added to the CMA regression, the intercept reduces from a statistically significant 0.22% per month ( $t$ -stat = 2.22, Panel B) to an insignificant 0.13% ( $t$ -stat = 1.31, Panel A). This accords well with our findings from Table 4 that investment loses statistical significance in predictive power when intangible intensity is added to the Fama-Macbeth regression of portfolio returns on portfolio characteristics.

In sum, the analyses in this subsection indicate that the intangibles factor is not spanned by the established asset pricing factors and thus contains important new information for describing average returns. Furthermore, when the intangibles factor is added to the factor spanning test, HML (and to a lesser degree CMA) become spanned by the other factors. These results suggest that adding the intangibles factor to the existing asset pricing models may potentially improve the model performance, which we investigate in Section 4.2.

#### *4.2 Asset pricing models with the intangibles factor*

To examine whether the intangibles factor may improve the performance of established factor models, we test asset pricing models that add the intangibles factor to the Fama-French (1993, 2015) three-factor and five-factor models. Our tests of the asset pricing models center on the time series regressions of the returns of the test portfolios on the market risk premium and the returns of the size, value, profitability, investment, and intangibles factors (constructed as described in section 2.2).

Table 7 summarizes the impact of adding the intangibles factor to the Fama-French three-factor and five-factor models on the explanation of U.S average returns. In particular, it reports the statistics on the performance of different asset pricing models, and the ability of the models to explain monthly excess returns on the 96 portfolios analyzed in Table 3: 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios. Panel A reports the model performance statistics for the combined 96 regressions for the three sets of portfolios. We consider this a fairer playing field than each set of the 32 regressions in Panel B, C, and D, where the performance statistics may be biased towards models that include factors related to the sort variables of the 32 portfolios. For instance, for the 32 Size-B/M-INT portfolios, asset pricing models that include INT would tend to perform better by design. Therefore, combining the 96 regressions can remove potential biases towards models that include either RMW, CMA, or INT.

Overall, we test eight asset pricing models: the original Fama-French three-factor model of Market, SMB and HML; three four-factor models that combine the original three factors with INT, RMW, or CMA; the original Fama-French five-factor model, and two other five-factor models that combine the original three factors with RMW and INT, and CMA and INT respectively; and a six-factor model that adds INT to the Fama-French five-factor model. For the 96 regressions in Panel A and each set of the 32 regressions in Panel B, C and D, Table 7 shows the factors used in the regressions as well as the GRS statistic of Gibbons, Ross and Shanken (1989), which tests the null hypothesis that the intercepts (alphas) of all 96 (or 32) time-series regressions are jointly equal zero. The *p*-value of the GRS statistic is the probability of getting a GRS statistic greater than the one reported (in absolute values) if the true intercepts from all regressions are all zero. In addition, Table 7 reports the average absolute value of the intercepts  $A|a_i|$ , and the average  $R^2$  of the regressions. The more complete an asset pricing model captures expected returns, the lower the average absolute intercept, and the higher the average  $R^2$  should be.

Panel A of Table 7 shows that, for each of the eight asset pricing models, the hypothesis that the model provides a complete description of average returns is rejected at the 1% significance level, consistent with the results in Fama and French (2015, 2017). But, in the spirit of Fama and French (2015, 2017) and other recent papers, we are primarily interested in the relative performance of competing models, i.e., which models capture average returns relatively better. We first compare the performance of the original Fama-French three-factor (FF3) model with the three four-factor models. Relative to the FF3 model, the four-factor model with INT produces the biggest performance improvement. It lowers the GRS statistic

from 1.80 to 1.61, reduces the average absolute intercept from 0.172% to 0.148% per month, and increases the average  $R^2$  from 0.824 to 0.833. The four-factor model with RMW also produces decent improvement over the FF3 model, lowering the GRS statistic from 1.80 to 1.65, and reducing the average absolute intercept from 0.172% to 0.150%. In contrast, the four-factor model with CMA produces a relatively small improvement over the FF3 model, with a GRS statistic of 1.75 and average absolute intercept of 0.164%. These observations suggest that the INT factor and RMW factor contain significant new information for describing expected returns relative to the FF3 model, while the CMA factor contains relatively little new information.

Next, we examine the performance of the three five-factor models in Panel A of Table 7. The five-factor model with RMW and INT improves performance relative to the original Fama-French five-factor (FF5) model (average absolute intercept of 0.145%), yielding a GRS statistic of 1.49 and average absolute intercept of 0.137%. The five-factor model with CMA and INT (average absolute intercept of 0.149%) produces no improvement relative to the four-factor model of FF3 + INT. Finally, the six-factor model with INT also improves performance relative to the FF5 model, with very similar GRS statistic and average absolute intercept to that of the five-factor model with RMW and INT. These findings can have significant implications. CMA seems essentially redundant for describing average returns in the sample period, and the five-factor model with RMW and INT produces an improvement relative to the original FF5 model. These findings are also generally consistent with our observations from the Fama-MacBeth regressions on characteristics (Table 4) that intangible intensity and profitability are the strongest explanatory variables of cross-sectional returns, while investment loses its explanatory power when intangible intensity is added to the regression.

Panels B, C, and D of Table 7 provide similar model performance statistics for each set of the regressions for the 32 Size-B/M-INT portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-OP portfolios respectively. For brevity, we focus on the performance of the four-factor model with INT, and the five-factor model with RMW and INT. For the 32 Size-B/M-INT portfolios, Panel B shows that the four-factor model with INT noticeably improves performance relative to the FF3 model, lowering the GRS statistic from 1.86 to 1.35, and reducing the average absolute intercept from 0.179% to 0.105%. Similarly, five-factor model with RMW and INT produces large improvement relative to the FF5 model, lowering the GRS statistic from 1.76 to 1.41, and reducing the average absolute intercept from 0.160% to 0.120%. Importantly, the  $p$ -value of the GRS statistic is 0.105 for the four-factor model with INT and 0.076 for the five-factor model with RMW and INT, which means that we cannot reject the

hypothesis that these two models are complete descriptions of average returns at conventional confidence levels.<sup>8</sup>

For the 32 Size-B/M-INV portfolios, Panel C shows that the four-factor model with INT marginally improves performance relative to the FF3 model, lowering the GRS statistic from 2.13 to 1.88, and reducing the average absolute intercept from 0.139% to 0.133%. The five-factor model with RMW and INT produces similar performance to the FF5 model. For the 32 Size-B/M-OP portfolios, Panel D shows that the four-factor model with INT produces no improvement relative to the FF3 model, as the portfolios are sorted on profitability not on intangibles. Similarly, the five-factor model with RMW and INT produces lower performance relative to the FF5 model. However, the *p*-values for both the FF5 model and the five-factor model with RMW and INT are large (0.461 and 0.165 respectively), which suggests that we cannot reject the hypothesis that these two models completely capture the cross-section of returns.

Taken together, our GRS test results show that adding the intangibles factor to the Fama-French models leads to a non-negligible improvement in the descriptions of average returns. In addition, a five-factor model with the market, size, value, profitability, and intangibles factors produces improvement relative to the original Fama-French five-factor model. The investment factor is essentially redundant for describing average returns in the sample period.

#### *4.3 Potential explanations for the intangibles premium*

In this subsection, we first review potential mispricing versus risk explanations for the anomalies associated with (R&D) investments, organization capital, and intangible assets. Thereafter, we conduct empirical tests to shed some light on whether the intangibles premium may reflect mispricing or compensation for additional risks.

The literature on R&D investments and intangible assets often refers to potential mispricing explanations for documented asset pricing effects. For example, Eberhart, Maxwell, and Siddique (2004) suggest that investors underreact to the benefits of increases in R&D investments, and Lev et al. (2005) present evidence of misvaluations due to the reporting biases in R&D expenditures. Palmon and Yezegel (2012) find that analysts' recommendations are

---

<sup>8</sup> Note that RMW and INT are two distinct and strong predictors, and the Size-B/M-INT portfolios are sorted on intangibles not on profitability. This likely explains why the four-factor model with RMW produces no improvement relative to the FF3 model, and the five-factor model with RMW and INT produces lower performance relative to the four-factor model with INT (e.g., average absolute intercept of 0.12% vs 0.105%).

more valuable for R&D intensive firms, due to greater information asymmetries. On intangible intensity, Gu and Wang (2005) find that analysts' earnings forecast errors are greater for more intangible-intensive firms, which suggests mispricing arising from the information complexity of intangible assets. Dugar and Pozharny (2021) show that the value relevance of book equity and earnings has declined in high intangibles firms in the U.S. and internationally.

However, another potential explanation for intangible assets to impact stock prices is that intangible intensive firms may be exposed to additional risks that need to be compensated. Gu (2016) suggests that R&D intensive firms are riskier in competitive industries, where the positive R&D-return relation is more pronounced. Eisfeldt and Papanikolaou (2013) suggest that shareholders in high organization capital firms demand higher risk premia because investing in key talents and organization capital is risky, as unlike with physical capital, shareholders and key talents share the claims to the firm's cash flows. Peters and Taylor (2017) suggest that intangible capital adjusts more slowly than physical capital to changes in investment opportunities and is therefore riskier. Gulen et al. (2021) also argue that intangible assets are likely to be more difficult to reduce than physical assets, as features such as technology and organizational capital are more costly to reverse. Hence, intangible intensive firms may be associated with a risk premium in the stock market.

To test the alternative explanations of mispricing versus risk for the intangibles premium, we follow Daniel and Titman (1997) and Daniel, Titman, and Wei (2001), who study the pricing of characteristics and factor betas in the cross-section of stock returns. While Fama and French (1993) suggest that the return premium associated with size and book-to-market are compensation for risk and are determined by the covariance structure of returns, Daniel and Titman (1997) propose an alternative hypothesis where the expected returns are directly related to characteristics for reasons such as behavioral biases. By sorting on both firm characteristics and factor betas, Daniel and Titman (1997) and Daniel et al. (2001) find that expected returns are not positively related to factor betas once controlled for characteristics, but are closely associated with characteristics instead. In the same spirit, we form test portfolios that are controlled for both the intangible intensity and intangibles factor beta of stocks. To strike a balance between increasing the number of test portfolios and avoiding poorly diversified portfolios, we form  $2 \times 2 \times 2 \times 2$  sorts (16 portfolios) on size, intangible intensity, intangibles

factor beta,<sup>9</sup> and either book-to-market, operating profitability, or investment as the fourth sort variable. In total this produces 48 ( $16 \times 3$ ) portfolios for our test.

We then split the 48 portfolios into four groups of 12 portfolios, based on intangible intensity (high or low) and intangibles factor beta (high or low), corresponding to characteristics and risk respectively. Table 8 reports the average returns, intangible intensity, and intangibles factor beta for the four groups of portfolios. This follows a similar analysis by Bongaerts, de Jong, and Driessen (2017), who compare the effects of liquidity level and liquidity risk on expected corporate bond returns. In addition, for the two pairs of high versus low intangible characteristics groups and two pairs of high versus low intangible risk groups, we also report for each pair the difference in the average returns, intangible intensity, and intangibles factor beta. Table 8 shows that the difference in the average intangible intensity is quite significant (0.25 and 0.26) for the two pairs of high versus low intangible characteristics groups, but negligible (0.01 and 0.02) for the two pairs of high versus low intangible risk groups. Similarly, the difference in average intangibles factor beta for the two pairs of high versus low intangible risk groups (2.02 and 1.99) are almost 10 times of that of the high versus low intangible characteristics groups (0.24 and 0.21). These observations suggest that the intangible intensity and intangibles factor beta are largely independent of each other among the 48 portfolios (we calculate the correlation to be a relatively weak 0.18). The *t*-statistic for the differences in average intangible intensity and intangibles factor beta are all large, as these two measures are relatively consistent across the 48 portfolios, leading to small standard errors.

More importantly, Table 8 shows that the sorts on intangible intensity and intangibles factor beta produces large and statistically significant variation in average returns between high and low intangible characteristics portfolios. Controlling for intangibles factor beta, the high intangible intensity portfolios outperformed the low intangible intensity portfolios by 0.34% (*t*-stat = 6.2) and 0.23% (*t*-stat = 5.9) per month respectively. In contrast, controlling for intangible intensity, the return variations between the high and low intangible risk portfolios are small and inconsistent in sign (0.05% and -0.06% respectively). These results suggest that it is the intangible intensity rather than the intangibles factor loading that explains average returns. In short, the intangibles premium is associated with the characteristic rather than with risk. This is consistent with the mispricing explanation, in which high intangible intensity firms

---

<sup>9</sup> The intangibles factor betas are the exposure of stock returns to the intangibles factor, obtained from linear regressions of stock returns on the returns of the intangibles factor and the factors in the Fama-French five-factor model, using 36-month data prior to the formation of the test portfolios.

are more exposed to the reporting biases and information asymmetries that may create mispricing.

As a complementary analysis, we repeat the same test for the mispricing versus risk explanations for the organization capital (OC) premium in Eisfeldt and Papanikolaou (2013). We follow the same procedure as our test for intangibles premium, except that the intangible intensity characteristic is replaced by OC intensity, and the intangibles factor beta is replaced by OC factor beta. Table A2 in the Appendix shows that OC intensity explains average returns more than OC factor loading. Controlling for OC factor beta, the high OC intensity portfolios outperformed the low intangible intensity portfolios by 0.14% per month ( $t\text{-stat} = 3.5$ ) and 0.1% per month ( $t\text{-stat} = 1.9$ ), respectively. In contrast, controlling for OC intensity, the return variations between the high and low OC risk portfolios are very small (0.07% and 0.03% respectively). These results do not directly support the risk explanation provided in Eisfeldt and Papanikolaou (2013), while these are consistent with (an even broader) mispricing interpretation.

To further examine the mispricing explanation of the intangibles premium, we first turn to the information complexity and asymmetries associated with intangible assets, e.g., as documented by Lev et al. (2005), Gu and Wang (2005), and Palmon and Yezegel (2012). In particular, as intangible-intensive firms invest heavily in off-balance-sheet knowledge capital and organization capital to drive future growth, their current earnings and profitability may be biased downwards, at the same time their future growth may be more difficult to forecast. Therefore, we hypothesize that the intangibles premium may be attributed to investors underestimating the future growth and profitability of intangible-intensive firms. To test the hypothesis, we examine whether intangible intensity has power in predicting future growth in earnings and gross profitability, which are key determinants of future stock returns. To that end, we follow Novy-Marx (2013) and run quarterly Fama-MaBeth cross-sectional regressions of three-year gross profit growth (scaled by total assets) and earnings growth (scaled by book equity) on fundamental firm characteristics including book-to-market, operating profitability, investment, and intangible intensity. Similar to the Fama-MacBeth regression of portfolio returns on portfolio characteristics in section 3.2, we use the 96 test portfolios including 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios.

Table 9 reports the results of the Fama-MacBeth regressions. It shows that intangible intensity has statistically significant power in positively predicting the three-year gross profit growth in the cross-section (coefficient = 2.04,  $t\text{-stat} = 8.08$ ). Book-to-market and low investment (corrected for the sign) are associated with negative gross profit growth. In contrast,

intangible intensity has no predictive power for three-year earnings growth, while low investment (corrected for the sign) is the only characteristics in Table 9 that positively predicts three-year earnings growth. The difference in the predictive power of intangible intensity for gross profit growth and earnings growth is not surprising. As Novy-Marx (2013) points out, gross profit is the cleanest accounting measure of profitability, while measures such as earnings are polluted. For instance, the firm's spending in R&D and organizational capital increases future productivity but reduces current earnings. Therefore, the more intangible-intensive a firm is, the more biased its earnings measure may be. This may explain why intangible intensity predicts gross profit growth, but not earnings growth. Furthermore, one potential explanation of the mispricing of intangible assets may be that investors underestimate the future profitability of intangible-intensive firms due to information complexity, leading to higher returns for these firms as the mispricing is corrected in later years. Such a potential behavioral bias would be similar to what is documented by Gu and Wang (2005), who identified greater analysts' forecast errors associated with intangible-intensive firms. However, the caveat is that our test does not measure investors' forecast errors, and thus cannot directly establish a causal effect between the mispricing of intangible assets and potential investor underestimation to future profitability.

In sum, consistent with the mispricing explanation, our test on intangible intensity versus intangibles factor loading suggests that it is the characteristics of high or low intangible intensity, rather than the intangible risk, that determines average returns. Our Fama-MacBeth regression finds that intangible intensity is a strong predictor of future gross profit growth. Under a potential hypothesis that conservative accounting practices regarding intangibles may lead investors to underestimate the future profitability of intangible-intensive firms, our findings suggest a plausible mispricing explanation driven by investor underreaction to intangible assets due to accounting mismeasurement issues.

#### *4.4 Combining the intangibles factor with Fama-French factors*

We briefly examine whether the intangibles factor can expand the investment opportunity set of investors. If an anomaly is based on mispricing, exposure to its associated factor has more potential to increase the Sharpe ratio without taking on significant exposure to systematic risk or established risk factors (e.g., Fama-French factors). Section 2 shows that the intangibles factor is a distinct factor that is not spanned by the existing asset pricing factor. It yields sizable

premium historically, and importantly, has low or even negative correlations with other factors (in particular, correlation of -0.58, -0.26 and -0.32 with HML, RMW and CMA respectively).

Table 10 illustrates the performance impact of combining the intangibles factor (INT) with other factors or factor strategies, using equal weights across factors. Combing HML with INT dramatically reduces the annual volatility from 11.5% to 4.8%, increases the average annual return from -0.3% to 2.1%, and increases the Sharpe ratio from -0.02 to 0.45. Similarly, combining RMW with INT significantly increases the Sharpe ratio from 0.28 to 0.61, decreasing the annual volatility from 12.3% to 6.6% while boosting the average return from 3.5% to 4.0%. Novy-Marx (2013) finds that profitability factor provides a hedge for value strategies, and a value investor can capture the profitability premium without additional risk. Table 10 confirms this and shows that combining HML and RMW achieves slightly lower volatility (10.2%) than that of HML or RMW. However, the diversification benefit of combining HML and RMW with INT is considerably larger due to INT's strong negative correlation with HML and RMW: it reduces the volatility from 10.2% to 6.0%, and significantly increases Sharpe ratio from 0.16 to 0.43. The implications of these observations are significant. The intangibles factor provides an excellent hedge for both the value factor and the profitability factor, to a much greater degree than the hedge profitability factor provides to the value factor. Therefore, the intangibles factor has a much greater potential to improve investors' opportunity set. Hence, value and quality investors can capture an additional intangibles premium while considerably reducing the overall risk. While not conclusive on its own, this finding is also more consistent with an intangibles premium due to mispricing rather than being a risk premium.

## 6. Conclusions

The growing significance of intangible assets for U.S. firms can lead to declining value relevance of important firm characteristics such as book equity and earnings, and affect the construction of asset pricing factors. In this paper, we find that intangible assets themselves are priced in the cross-section of U.S. stock returns. We construct an intangibles factor that is long high intangibles firms and short low intangibles firms, and find that it generates an economically significant average return of 4.6% per annum, with a Sharpe ratio close to the market factor. Furthermore, in Fama-MacBeth regressions, intangible intensity has more power than size, value, profitability and investment in explaining the cross-section of stock returns over the sample period.

The intangibles factor cannot be explained by established asset pricing factors and thus contains important new information for describing average stock returns. We add the intangibles factor to the Fama-French five-factor model, and show that it improves the description of average returns, and makes the investment factor redundant. Importantly, the intangibles factor is strongly negatively correlated with value and quality factors, thus allows investors to dramatically reduce the overall risk while harvesting the significant factor premium. The intangibles factor is also distinct from traditional growth strategies. These characteristics suggest that the intangibles factor has significant investment applications in practice, and can expand investors' opportunity set.

We further examine the alternative explanations of mispricing versus risk for the intangibles premium. We show that it is the characteristics of high or low intangible intensity, as opposed to intangible risk, that determines average returns in the cross-section. In addition, we find that intangible intensity is a strong predictor of future gross profit growth, and conjecture that investors may underestimate the future growth and profitability of intangible-intensive firms, leading to mispricing. Overall, our findings suggest a plausible mispricing explanation based on investors underreacting to intangible assets given their inherent accounting mismeasurement issues. Finally, we believe that the measurement of intangible assets in the existing literature is imperfect and should continue to evolve. Future developments in this field would further facilitate the study on the relation between intangible assets and stock returns.

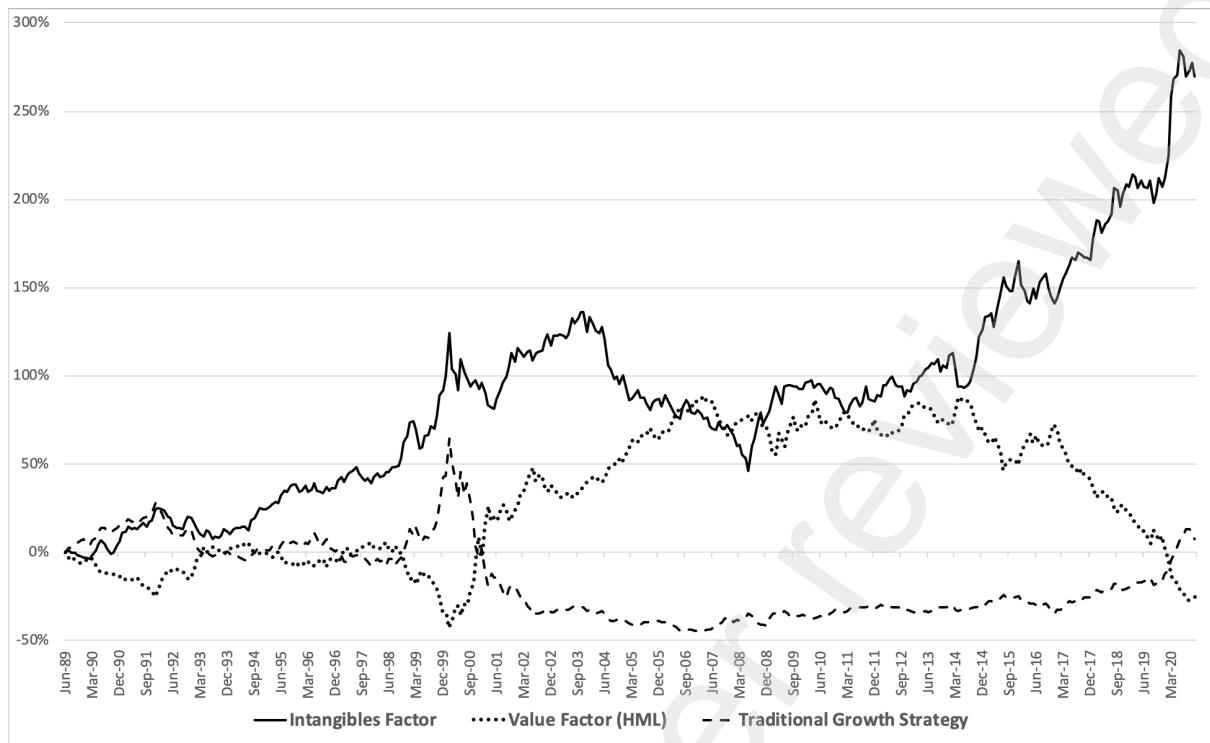
## References

- Amenc, N., F. Goltz, and B. Luyten, 2020, Intangible capital and the value factor: Has your value definition just expired?, *Journal of Portfolio Management* 46(7): 83-99
- Arnott, R.D., C.R. Harvey, V. Kalesnik, and J.T. Linnainmaa, 2021, Reports of value's death may be greatly exaggerated, *Financial Analyst Journal* 77(1): 44-67
- Baker, M., and J. Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61:1645–80.
- Bongaerts, D., F. de Jong, and J. Driessens, 2017, An asset pricing approach to liquidity effects in corporate bond markets, *Review of Financial Studies* 30(4): 1229-1269
- Chan, L., J. Lakonishok, and T. Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56 (6): 2431–2456
- Daniel, K., and S. Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52(1): 1-33
- Daniel, K., S. Titman, and K.C.J. Wei, 2001, Explaining the cross-section of stock returns in Japan: Factors or characteristics?, *Journal of Finance* 56(2): 743-766
- Dugar, A., and J. Pozharny, 2021, Equity investing in the age of intangibles, *Financial Analyst Journal* 77(2): 21-42
- Eberhart, A.C., W.F. Maxwell, and A.R. Siddique, 2004, An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases, *Journal of Finance* 59(2): 623-650
- Eisfeldt, A., E.T. Kim, and D. Papanikolaou, 2021, Intangible Value, Working Paper
- Eisfeldt, A. and D. Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *Journal of Finance* 68 (4): 1365-1406
- Eisfeldt, A. and D. Papanikolaou, 2014, The value and ownership of intangible capital. *American Economic Review*, 104(5): 189–94
- Ewens, M., R. H. Peters, and S. Wang. 2020. Measuring intangible capital with market prices, National Bureau of Economic Research
- Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56
- Fama, E.F. and K.R. French, 2008, Dissecting anomalies, *Journal of Finance* 63(4): 1653-1678.
- Fama, E.F. and K.R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116: 1-22.
- Fama, E.F. and K.R. French, 2017, International tests of a five-factor asset pricing model, *Journal of Financial Economics* 123: 441-463.

- Gu, L., 2016, Product market competition, R&D investment, and stock returns, *Journal of Financial Economics* 119: 441-455
- Gu, F., and B. Lev, 2017, Time to change your investment model, *Financial Analyst Journal* 73(4): 23-33
- Gu, F., and W. Wang, 2005, Intangible assets, information complexity, and analysts' earnings forecasts, *Journal of Business Finance & Accounting* 32: 1673-1702
- Gulen, H., D. Li, R. H. Peters, and M. Zekhnini, 2021, Intangible capital in factor models, Working Paper
- Hou, K., C. Xue, and L. Zhang, 2020, Replicating anomalies, *Review of Financial Studies* 33(5): 2019-2133
- Hulten, C., Hao, X., 2008, What is a company really worth? Intangible capital and the “market-to-book value” puzzle, National Bureau of Economics Research, Working Paper
- Joshi, A., and D. M. Hanssens, 2010, The direct and indirect effects of advertising spending on firm value, *Journal of Marketing* 74 (1): 20–33
- Leung, W. S., Evans, K. P., & Mazouz, K., 2020, The R&D anomaly: Risk or mispricing?, *Journal of Banking & Finance*, 115, 105815.
- Li, D., 2011, Financial constraints, R&D investment, and stock returns, *Review of Financial Studies* 24: 2974-3007
- Li, Wendy C.Y., 2012, Depreciation of business R&D capital, US Bureau of Economic Analysis/National Science Foundation R&D Satellite Account Paper US Department of Commerce, Working Paper
- Li, W.C.Y. and B.H. Hall, 2018, Depreciation of business R&D capital, *Review of Income and Wealth* 66(1): 161-180
- Lev, B., 2018, Intangibles, Working Paper
- Lev, B., and F. Gu, 2016, *The end of accounting and the path forward for investors and managers*, Hoboken, NJ:John Wiley & Sons.
- Lev, B., and S. Radhakrishnan, 2005, The valuation of organization capital, in Carol Corrado, John Haltiwanger, and Dan Sichel, eds.: *Measuring Capital in the New Economy*, (National Bureau of Economic Research, Inc, Cambridge, MA).
- Lev, B., B. Sarath, and T. Sougiannis, 2005, R&D Reporting Biases and Their Consequences, *Contemporary Accounting Research* 22(4): 977-1026
- Lev, B., and T. Sougiannis, 1996, The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting and Economics* 21 (1): 107–138

- Lev. B., and A. Srivastava, 2020, Explaining the recent failure of value investing, Working Paper
- Palmon, D. and A. Yezegel, 2012, R&D intensity and the value of analysts' recommendations, *Contemporary Accounting Research* 29 (2): 621-654
- Park, Hyuna, 2019, An Intangible-adjusted Book-to-price Ratio Still Predicts Stock Returns, *Critical Finance Review* 25(1): 207-236.
- Penman, S., and X. Zhang, 2021, Accounting for asset pricing factors, Working Paper
- Peters, R., and L. Taylor, 2017. "Intangible capital and the investment-q relation." *Journal of Financial Economics* 123 (2): 251-272.
- Ramanna, K., and R. Watts, (2012). Evidence on the use of unverifiable estimates in required goodwill impairment. *Review of Accounting Studies* 17: 749-780.
- Srivastava, A., 2014, Why have measures of earnings quality changed over time?, *Journal of Accounting and Economics* 57: 196-217
- Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104:288-302
- Stambaugh, R. F., and Y. Yuan, 2017, Mispricing factors, *Review of Financial Studies* 30 (4): 1270-1315
- Wu, K., and S. Lai, 2020, Intangible intensity and stock price crash risk, *Journal of Corporate Finance* 64
- Zhang, L., 2005, The value premium, *Journal of Finance* 60: 67-103

**Figure 1: Cumulative Returns of the Intangibles factor vs. HML and Growth**



Notes: This figure presents the cumulative returns for the Intangibles factor, Value factor (HML), and Growth factor, for the period of June 1989 to November 2020. The Intangibles factor and Value factor are constructed using the Russell 3000 stock universe, following similar procedures to Fama and French (2015), as described in Section 2.2. The return of the Growth factor represents the relative performance of traditional growth versus value style indices. It is calculated as the average of the returns on Russell 1000 and Russell 2000 Growth indices, minus the average of the returns on Russell 1000 and Russell 2000 Value indices.

**Table 1: Returns and Characteristics of Six Portfolios Sorted on Intangibles and Size**

<u>Large Cap Sorts</u>	Average Return	Standard Deviation	Intangible Intensity	Book / Market	Operating Profitability	Investment
<b>Low Intangibles</b>	<b>0.59%</b>	<b>4.35%</b>	<b>5%</b>	<b>46%</b>	<b>32%</b>	<b>21%</b>
<b>Medium</b>	<b>0.76%</b>	<b>4.76%</b>	<b>24%</b>	<b>30%</b>	<b>32%</b>	<b>18%</b>
<b>High Intangibles</b>	<b>0.87%</b>	<b>4.07%</b>	<b>43%</b>	<b>22%</b>	<b>37%</b>	<b>10%</b>
<b>High - Low</b>	<i>0.28% (t-stat = 2.1)</i>					
<u>Small Cap Sorts</u>	Average Return	Standard Deviation	Intangible Intensity	Book / Market	Operating Profitability	Investment
<b>Low Intangibles</b>	<b>0.53%</b>	<b>5.74%</b>	<b>5%</b>	<b>59%</b>	<b>18%</b>	<b>32%</b>
<b>Medium</b>	<b>0.71%</b>	<b>6.03%</b>	<b>24%</b>	<b>46%</b>	<b>17%</b>	<b>26%</b>
<b>High Intangibles</b>	<b>1.01%</b>	<b>6.63%</b>	<b>46%</b>	<b>39%</b>	<b>5%</b>	<b>17%</b>
<b>High - Low</b>	<i>0.48% (t-stat = 2.8)</i>					

Notes: This table reports the value-weighted average monthly excess returns and standard deviations of six portfolios double sorted on intangibles and size, where the portfolios are rebalanced in June every year. It also shows the value-weighted average Intangible Intensity, Book/Market, Operating Profitability, and Investment of the six portfolios over the sample period. The sample covers the Russell 3000 stocks excluding financial firms over the period of June 1989 to November 2020.

**Table 2: Summary Statistics for Monthly Factor Returns Constructed using Russell 3000 Stocks**

	<b>Market</b>	<b>SMB</b>	<b>HML</b>	<b>RMW</b>	<b>CMA</b>	<b>MOM</b>	<b>INT</b>
<b>Mean</b>	<b>0.70%</b>	<b>0.01%</b>	<b>-0.02%</b>	<b>0.29%</b>	<b>0.10%</b>	<b>0.45%</b>	<b>0.38%</b>
<b>Standard Deviation</b>	<b>4.33%</b>	<b>3.01%</b>	<b>3.33%</b>	<b>3.55%</b>	<b>3.00%</b>	<b>5.45%</b>	<b>2.56%</b>
<i>t</i> -Statistics	<b>3.13</b>	<b>0.05</b>	<b>-0.13</b>	<b>1.60</b>	<b>0.67</b>	<b>1.59</b>	<b>2.88</b>
<b>Sharpe Ratio</b>	<b>0.56</b>	<b>0.01</b>	<b>-0.02</b>	<b>0.28</b>	<b>0.12</b>	<b>0.28</b>	<b>0.51</b>
<b>Max Drawdown</b>	<b>53.8%</b>	<b>42.3%</b>	<b>61.5%</b>	<b>47.0%</b>	<b>39.5%</b>	<b>65.9%</b>	<b>38.2%</b>
<b>Expected Shortfall</b>	<b>-10.0%</b>	<b>-6.0%</b>	<b>-7.1%</b>	<b>-7.3%</b>	<b>-6.4%</b>	<b>-13.4%</b>	<b>-4.6%</b>
<b>Skewness</b>	<b>-0.61</b>	<b>0.24</b>	<b>0.83</b>	<b>0.71</b>	<b>0.56</b>	<b>-1.34</b>	<b>0.46</b>

Notes: This table shows the performance of the intangibles factor (INT), the factors in the Fama-French five-factor model (Market, SMB, HML, RMW, CMA), and the momentum factor (MOM), all constructed using the Russell 3000 stocks excluding financial firms over the sample period of June 1989 and November 2020. The factor construction follows similar procedures to Fama and French (2015), as described in Section 2.2. Mean and Standard Deviation are the mean and standard deviation of the monthly returns, and *t*-stat is the ratio of Mean to its standard error. Expected Shortfall (95%) is the mean of monthly returns below the 5th percentile.

**Table 3: Average Monthly Returns of Portfolios Formed for Asset Pricing Tests**

Big				Small				
<b>Panel A: Portfolios formed on Size, B/M and OP</b>								
	Low B/M	2	3	High B/M	Low B/M	2	3	High B/M
Low OP	<b>0.57</b>	<b>0.17</b>	<b>0.16</b>	-	<b>0.36</b>	<b>0.60</b>	<b>0.51</b>	<b>0.65</b>
2	<b>1.13</b>	<b>0.49</b>	<b>0.56</b>	<b>0.56</b>	<b>0.73</b>	<b>0.73</b>	<b>0.64</b>	<b>0.71</b>
3	<b>0.78</b>	<b>0.62</b>	<b>0.73</b>	<b>0.76</b>	<b>0.54</b>	<b>0.75</b>	<b>0.73</b>	<b>0.85</b>
High OP	<b>0.85</b>	<b>0.81</b>	<b>0.87</b>	<b>0.74</b>	<b>0.86</b>	<b>0.87</b>	<b>0.84</b>	<b>0.79</b>
<b>Panel B: Portfolios formed on Size, B/M and INV</b>								
	Low B/M	2	3	High B/M	Low B/M	2	3	High B/M
Low INV	<b>0.80</b>	<b>0.81</b>	<b>0.76</b>	<b>0.69</b>	<b>0.76</b>	<b>0.83</b>	<b>0.86</b>	<b>0.75</b>
2	<b>0.76</b>	<b>0.67</b>	<b>0.67</b>	<b>0.65</b>	<b>0.74</b>	<b>0.90</b>	<b>0.68</b>	<b>0.76</b>
3	<b>0.81</b>	<b>0.71</b>	<b>0.92</b>	<b>0.77</b>	<b>0.79</b>	<b>0.76</b>	<b>0.91</b>	<b>0.81</b>
High INV	<b>1.03</b>	<b>0.72</b>	<b>0.18</b>	<b>0.70</b>	<b>0.40</b>	<b>0.64</b>	<b>0.36</b>	<b>0.69</b>
<b>Panel C: Portfolios formed on Size, B/M and INT</b>								
	Low B/M	2	3	High B/M	Low B/M	2	3	High B/M
Low INT	<b>0.62</b>	<b>0.61</b>	<b>0.48</b>	<b>0.60</b>	<b>0.17</b>	<b>0.48</b>	<b>0.51</b>	<b>0.71</b>
2	<b>0.72</b>	<b>0.62</b>	<b>0.64</b>	<b>0.76</b>	<b>0.45</b>	<b>0.52</b>	<b>0.68</b>	<b>0.78</b>
3	<b>0.94</b>	<b>0.82</b>	<b>0.93</b>	<b>0.80</b>	<b>0.55</b>	<b>0.87</b>	<b>0.80</b>	<b>0.84</b>
High INT	<b>0.84</b>	<b>0.92</b>	<b>1.05</b>	-	<b>0.93</b>	<b>1.09</b>	<b>0.97</b>	<b>0.86</b>

Notes: This table reports the average monthly excess returns (expressed in percentage points) for the 32 value-weighted portfolios formed on each of the three sorts: (A) Size, B/M, and OP, (B) Size, B/M, and INV, (C) Size, B/M, and INT, over the period of June 1989 and November 2020. At the end of June each year we form two Size groups (big and small) based on Russell 1000 and Russell 2000 stocks. Stocks in each Size groups are assigned independently to four B/M groups, four OP groups, four INV groups, and four INT groups. The average return is not available for the highest B/M and lowest OP quartile in big stock, and the highest B/M and highest INT quartile in big stocks, because these two quartiles are empty in part of the sample period.

**Table 4: Fama-MacBeth Regression of Portfolio Returns on Portfolio Characteristics**

Independent Variables	Specification (1)		Specification (2)		Specification (3)		Specification (4)		Specification (5)	
	Coefficient	t-stat								
Beta	-0.01	-0.01	-0.15	-0.18	-0.10	-0.13	-0.96	-1.00	-0.93	-0.97
ln(mcap)	-0.54	-0.61	-0.13	-0.15	-0.27	-0.32	-0.38	-0.42	0.11	0.13
Book-to-market	-0.35	-0.50	0.29	0.47	0.31	0.51	-0.70	-1.09	0.01	0.01
Profitability	0.66	1.52	0.89	2.29	0.78	2.28				
Investment	-0.98	-2.56	-0.49	-1.22	-0.46	-1.24				
Intangibles			1.57	2.83	1.36	2.68			1.76	3.19
Momentum					0.63	1.04				
R-Squared	85.1%		86.3%		87.2%		83.4%		84.8%	

Notes: This table reports the results of Fama-MacBeth regressions of portfolio returns on lagged portfolio characteristics that include Beta, ln(mcap), book-to-market, profitability, investment, momentum, and intangible intensity. Coefficients are annualized. The portfolios used in the cross-sectional regressions include 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios. For each portfolio, the independent variables of individual stocks in the portfolio are winsorized at the 1% and 99% level, and value weighted to calculate portfolio level characteristics. The portfolio characteristics of the 96 portfolios are standardized into  $z$ -scores for each of the monthly regressions. The sample covers the Russell 3000 stocks excluding financial firms over the period of June 1989 and November 2020.

**Table 5: Correlations between the Factors**

	<b>Market</b>	<b>SMB</b>	<b>HML</b>	<b>RMW</b>	<b>CMA</b>	<b>MOM</b>	<b>INT</b>
<b>Market</b>	1.00	0.30	-0.16	-0.47	-0.30	-0.24	0.02
<b>SMB</b>		1.00	-0.07	-0.47	-0.22	-0.04	0.19
<b>HML</b>			1.00	0.47	0.75	-0.21	-0.58
<b>RMW</b>				1.00	0.43	0.12	-0.26
<b>CMA</b>					1.00	-0.13	-0.32
<b>MOM</b>						1.00	0.19
<b>INT</b>							1.00

Notes: This table shows the correlations between the intangibles factor (INT) and the factors in the Fama-French five-factor model (Market, SMB, HML, RMW, CMA), all constructed using the Russell 3000 stocks excluding financial firms, over the sample period of June 1989 and November 2020. The factor construction follows similar procedures to Fama and French (2015), as described in Section 2.2.

**Table 6: Factor Spanning Test**

Panel A: With INT - Using Six Factors in Regressions to Explain the Average Returns on the Seventh Factor

	Coefficient								R Squared
	Intercept	Market	SMB	HML	RMW	CMA	MOM	INT	
<b>Market</b>	0.98%		0.10	0.24	-0.47	-0.43	-0.15	-0.07	0.30
T-stat	5.12		1.31	2.12	-6.59	-4.23	-4.04	-0.69	
<b>SMB</b>	0.00%	0.05		0.57	-0.44	-0.34	0.04	0.35	0.34
T-stat	0.02	1.31		7.98	-9.64	-5.04	1.71	5.59	
<b>HML</b>	0.00%	0.05	0.26		0.27	0.64	-0.05	-0.46	0.76
T-stat	-0.04	2.12	7.98		8.42	19.13	-3.01	-12.83	
<b>RMW</b>	0.39%	-0.22	-0.45	0.61		-0.13	0.08	0.13	0.51
T-stat	2.93	-6.59	-9.64	8.42		-1.85	3.32	1.98	
<b>CMA</b>	0.13%	-0.11	-0.19	0.78	-0.07		-0.01	0.24	0.63
T-stat	1.31	-4.23	-5.04	19.13	-1.85		-0.56	5.27	
<b>MOM</b>	0.50%	-0.29	0.18	-0.48	0.35	-0.08		0.10	0.14
T-stat	1.84	-4.04	1.71	-3.01	3.32	-0.56		0.77	
<b>INT</b>	0.32%	-0.02	0.22	-0.66	0.08	0.29	0.02		0.41
T-stat	3.00	-0.69	5.59	-12.83	1.98	5.27	0.77		

Panel B: Without INT - Using Five Factors in Regressions to Explain the Average Returns on the Sixth Factor

	Coefficient							R-Squared
	Intercept	Market	SMB	HML	RMW	CMA	MOM	
<b>Market</b>	0.96%		0.09	0.29	-0.48	-0.45	-0.15	0.30
T-stat	5.08		1.17	3.04	-6.73	-4.61	-4.08	
<b>SMB</b>	0.12%	0.04		0.37	-0.45	-0.26	0.05	0.28
T-stat	0.89	1.17		5.75	-9.41	-3.81	2.01	
<b>HML</b>	-0.22%	0.08	0.22		0.33	0.73	-0.08	0.65
T-stat	-2.06	3.04	5.75		8.81	18.67	-4.19	
<b>RMW</b>	0.44%	-0.23	-0.43	0.53		-0.09	0.09	0.51
T-stat	3.31	-6.73	-9.41	8.81		-1.38	3.43	
<b>CMA</b>	0.22%	-0.12	-0.14	0.67	-0.05		-0.01	0.61
T-stat	2.22	-4.61	-3.81	18.67	-1.38		-0.37	
<b>MOM</b>	0.54%	-0.29	0.21	-0.55	0.36	-0.05		0.14
T-stat	1.98	-4.08	2.01		3.43	-0.37		

Notes: This table reports the factor spanning tests for the intangibles factor (INT), the five factors in the Fama-French five-factor model (Market, SMB, HML, RMW, and CMA), and the momentum factor (MOM). In Panel A, the spanning regressions include INT and use six factors to explain the average returns of the seventh factor. In Panel B, the spanning regressions exclude INT and use five factors to explain the average returns of the sixth factor. The factors are all constructed using the Russell 3000 stocks excluding financial firms over the sample period of June 1989 and November 2020.

**Table 7: Summary Statistics of Tests of Different Models**

	<b>GRS</b>	<b>p(GRS)</b>	<b>A<math> a_i </math></b>	<b>A(<math>R^2</math>)</b>		<b>GRS</b>	<b>p(GRS)</b>	<b>A<math> a_i </math></b>	<b>A(<math>R^2</math>)</b>
<b>Panel A: 3 x 32 Size-BM-XXX portfolios</b>					<b>Panel B: 32 Size-BM-INT portfolios</b>				
FF3	<b>1.80</b>	<b>0.000</b>	<b>0.172</b>	<b>0.824</b>	FF3	<b>1.86</b>	<b>0.004</b>	<b>0.179</b>	<b>0.822</b>
FF3 + INT	<b>1.61</b>	<b>0.002</b>	<b>0.148</b>	<b>0.833</b>	FF3 + INT	<b>1.35</b>	<b>0.105</b>	<b>0.105</b>	<b>0.845</b>
FF3 + RMW	<b>1.65</b>	<b>0.001</b>	<b>0.150</b>	<b>0.833</b>	FF3 + RMW	<b>1.83</b>	<b>0.005</b>	<b>0.174</b>	<b>0.826</b>
FF3 + CMA	<b>1.75</b>	<b>0.000</b>	<b>0.164</b>	<b>0.830</b>	FF3 + CMA	<b>1.75</b>	<b>0.009</b>	<b>0.157</b>	<b>0.825</b>
FF5	<b>1.59</b>	<b>0.002</b>	<b>0.145</b>	<b>0.840</b>	FF5	<b>1.76</b>	<b>0.009</b>	<b>0.160</b>	<b>0.829</b>
FF3 + RMW INT	<b>1.49</b>	<b>0.007</b>	<b>0.137</b>	<b>0.843</b>	FF3 + RMW INT	<b>1.41</b>	<b>0.076</b>	<b>0.120</b>	<b>0.848</b>
FF3 + CMA INT	<b>1.60</b>	<b>0.002</b>	<b>0.149</b>	<b>0.839</b>	FF3 + CMA INT	<b>1.34</b>	<b>0.112</b>	<b>0.104</b>	<b>0.846</b>
FF5 + INT	<b>1.47</b>	<b>0.008</b>	<b>0.139</b>	<b>0.849</b>	FF5 + INT	<b>1.45</b>	<b>0.060</b>	<b>0.121</b>	<b>0.850</b>
<b>Panel C: 32 Size-BM-INV portfolios</b>					<b>Panel D: 32 Size-BM-OP portfolios</b>				
FF3	<b>2.13</b>	<b>0.001</b>	<b>0.139</b>	<b>0.836</b>	FF3	<b>1.42</b>	<b>0.073</b>	<b>0.199</b>	<b>0.812</b>
FF3 + INT	<b>1.88</b>	<b>0.003</b>	<b>0.133</b>	<b>0.839</b>	FF3 + INT	<b>1.57</b>	<b>0.031</b>	<b>0.206</b>	<b>0.816</b>
FF3 + RMW	<b>1.98</b>	<b>0.002</b>	<b>0.158</b>	<b>0.841</b>	FF3 + RMW	<b>1.01</b>	<b>0.454</b>	<b>0.118</b>	<b>0.833</b>
FF3 + CMA	<b>2.08</b>	<b>0.001</b>	<b>0.125</b>	<b>0.850</b>	FF3 + CMA	<b>1.46</b>	<b>0.059</b>	<b>0.212</b>	<b>0.814</b>
FF5	<b>1.91</b>	<b>0.003</b>	<b>0.147</b>	<b>0.856</b>	FF5	<b>1.01</b>	<b>0.461</b>	<b>0.126</b>	<b>0.836</b>
FF3 + RMW INT	<b>1.82</b>	<b>0.006</b>	<b>0.154</b>	<b>0.844</b>	FF3 + RMW INT	<b>1.26</b>	<b>0.165</b>	<b>0.137</b>	<b>0.837</b>
FF3 + CMA INT	<b>1.92</b>	<b>0.003</b>	<b>0.130</b>	<b>0.852</b>	FF3 + CMA INT	<b>1.58</b>	<b>0.029</b>	<b>0.212</b>	<b>0.818</b>
FF5 + INT	<b>1.84</b>	<b>0.005</b>	<b>0.156</b>	<b>0.857</b>	FF5 + INT	<b>1.24</b>	<b>0.181</b>	<b>0.139</b>	<b>0.839</b>

Notes: This table reports the summary statistics on the ability of different factor models to explain monthly excess returns on 32 Size-B/M-INT portfolios (Panel B), 32 Size-B/M-INV portfolios (Panel C), 32 Size-B/M-OP portfolios (Panel D), and the combined 96 portfolios (Panel A). For the 96 regressions in Panel A and each set of the 32 regressions in Panel B, C and D, the table shows the factors that augment Market and SMB in the regressions, the GRS statistic testing whether the expected values of all 96 or 32 intercepts are zero, the p-value of the GRS statistic, the average absolute value of the intercepts  $A|a_i|$ , and the average  $R^2$  of the regressions. The sample covers the Russell 3000 stocks excluding financial firms over the period of June 1989 and November 2020.

**Table 8: Portfolio Sorts on both Intangible Intensity (Characteristics) and Intangibles factor Beta (Risk)**

Average Intangible Intensity			
	High intangible characteristics ptfs	Low intangible characteristics ptfs	<i>High - Low intangibles</i>
<b>High intangible risk ptfs</b>	<b>0.38</b>	<b>0.12</b>	<b>0.25 (<i>t-stat</i> = 37.3)</b>
<b>Low intangible risk ptfs</b>	<b>0.36</b>	<b>0.10</b>	<b>0.26 (<i>t-stat</i> = 42.4)</b>
<i>High - Low intangible risk</i>	<i>0.01 (<i>t-stat</i> = 8.4)</i>	<i>0.02 (<i>t-stat</i> = 14.3)</i>	
Average Intangibles Factor Beta			
	High intangible characteristics ptfs	Low intangible characteristics ptfs	<i>High - Low intangibles</i>
<b>High intangible risk ptfs</b>	<b>1.13</b>	<b>0.89</b>	<b>0.24 (<i>t-stat</i> = 11.2)</b>
<b>Low intangible risk ptfs</b>	<b>-0.90</b>	<b>-1.10</b>	<b>0.21 (<i>t-stat</i> = 13.0)</b>
<i>High - Low intangible risk</i>	<i>2.02 (<i>t-stat</i> = 13.1.)</i>	<i>1.99 (<i>t-stat</i> = 15.4)</i>	
Average Return (%)			
	High intangible characteristics ptfs	Low intangible characteristics ptfs	<i>High - Low intangibles</i>
<b>High intangible risk ptfs</b>	<b>1.14</b>	<b>0.80</b>	<b>0.34 (<i>t-stat</i> = 6.2)</b>
<b>Low intangible risk ptfs</b>	<b>1.09</b>	<b>0.86</b>	<b>0.23 (<i>t-stat</i> = 5.9)</b>
<i>High - Low intangible risk</i>	<i>0.05 (<i>t-stat</i> = 0.9)</i>	<i>-0.06 (<i>t-stat</i> = -2.7)</i>	

Notes: This table reports the average returns, intangible intensity, and intangibles factor beta across 48 portfolios formed on  $2 \times 2 \times 2 \times 2$  sorts on size, intangible intensity, intangibles factor beta, and either book-to-market, operating profitability, or investment as the fourth sort variable. We split the 48 portfolios into four groups of 12 portfolios, based on intangible intensity (high or low) and intangibles factor beta (high or low). For the two pairs of high versus low intangible characteristics groups and two pairs of high versus low intangible risk groups, we also report for each pair the difference in the average returns, intangible intensity, and intangibles factor beta. The intangibles factor betas are the exposure of stock returns to the intangibles factor, obtained from linear regressions of stock returns on the returns of the intangibles factor and the factors in the Fama-French five-factor model, using 36-month data prior to the formation of the test portfolios.

**Table 9: Fama-MacBeth Regression of 3-Year Growth in Gross Profit and Earnings on Key Characteristics**

Independent Variables	3Y gross profit growth as dependent variable		3Y earnings growth as dependent variable	
	Coefficient	t-statistics	Coefficient	t-statistics
Book-to-market	-3.62	-15.00	-2.06	-3.73
Profitability	0.40	1.43	-1.93	-2.08
Investment	2.46	4.88	-2.71	-4.34
Intangibles	2.04	8.08	-0.14	-0.28

Notes: This table reports the results of Fama-MacBeth regressions of three-year gross profit growth (scaled by total assets) and earnings growth (scaled by book equity) on lagged fundamental firm characteristics including book-to-market, profitability, investment, and intangible intensity. Regressions include controls for beta, ln(mcap), and momentum. Coefficients are annualized and in percentage. t-statistic are Newey-West adjusted using three lags. The portfolios used in the cross-sectional regressions include 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios. For each portfolio, the independent variables of individual stocks in the portfolio are winsorized at the 1% and 99% level, and value weighted to calculate portfolio level characteristics. The portfolio characteristics of the 96 portfolios are standardized into z-scores for each of the monthly regressions. The sample covers the Russell 3000 stocks excluding financial firms over the period of June 1989 and November 2020.

**Table 10: Combining the Intangibles factor with Fama-French Factors**

FF Factor	Average Return	Annual Volatility	Sharpe Ratio	FF Factor + INT Factor	Average Return	Annual Volatility	Sharpe Ratio
HML	-0.3%	11.5%	-0.02	HML + INT	2.1%	4.8%	0.45
RMW	3.5%	12.3%	0.28	RMW + INT	4.0%	6.6%	0.61
HML + RMW	1.6%	10.2%	0.16	HML + RMW + INT	2.6%	6.0%	0.43

Notes: This table shows the performance statistics of various factor portfolios and combination of these portfolios with the Intangibles factor. Average returns are annual mean returns. Factors are equally weighted in all multi-factor portfolios. All factors are constructed using the Russell 3000 stocks excluding financial firms, over the sample period of June 1989 and November 2020. The factor construction follows similar procedures to Fama and French (2015), as described in Section 2.2.

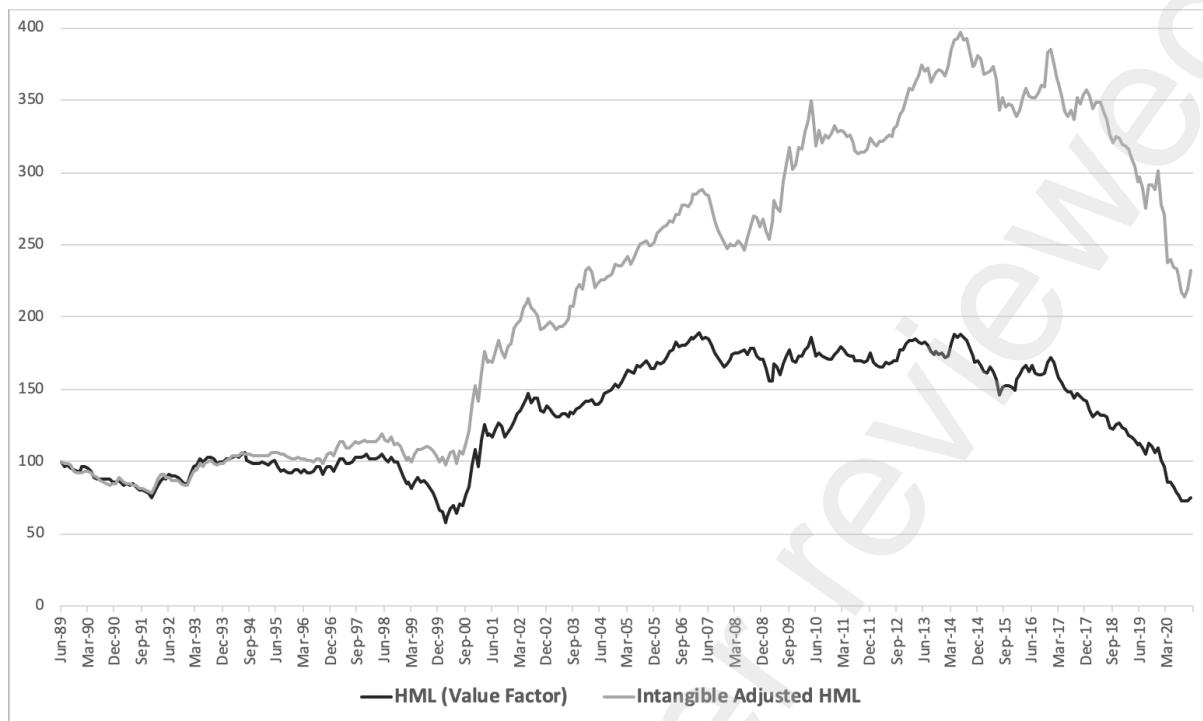
## Appendix

**Figure A1: Impact of excluding Big Tech on the Performance of Intangibles factor**



Notes: This figure presents the cumulative performance for the intangibles factor for the period of June 1989 to November 2020. It also shows the impact of excluding FAANG (Facebook, Amazon, Apple, Netflix, and Google), Microsoft, and Tesla on the performance of the intangibles factor. The intangibles factor is constructed using the Russell 3000 stock universe, following similar procedures to Fama and French (2015), as described in Section 2.2.

**Figure A2: Performance Impact of Adjusting HML for Intangibles**



Notes: This figure presents the cumulative performance of HML and intangibles-adjusted HML, both constructed using the Russell 3000 stocks excluding financial firms over the sample period of June 1989 and November 2020. The factor construction follows similar procedures to Fama and French (2015), as described in Section 2.2. The intangibles-adjusted HML is constructed by adding knowledge capital and organization capital to the firms' book equity (similar to Park (2019), Amenc et al. (2020) and Arnott et al. (2021)). This adjustment significantly improved the annualized return of HML over the sample period from -0.9% to 2.7%.

**Table A1: Fama-MacBeth Regression of Portfolio Returns on Portfolio Characteristics (Robustness Test)**

Independent Variables	Specification (1)		Specification (2)		Specification (3)		Specification (4)		Specification (5)	
	Coefficient	t-stat								
Beta	-0.01	-0.01	0.00	0.00	0.15	0.20	-0.96	-1.00	-0.72	-0.73
ln(mcap)	-0.54	-0.61	-0.09	-0.11	-0.21	-0.25	-0.38	-0.42	0.11	0.13
Book-to-market	-0.35	-0.50	0.26	0.41	0.23	0.37	-0.70	-1.09	-0.11	-0.17
Profitability	0.66	1.52	0.92	2.33	0.84	2.35				
Investment	-0.98	-2.56	-0.38	-0.91	-0.44	-1.09				
Intangibles			1.22	2.55	1.04	2.41			1.22	2.66
Momentum					0.84	1.53				
R-Squared	85.1%		85.8%		86.6%		83.4%			

Notes: This table conducts a robustness test for Table 4, where the sorts on intangible intensity is done within industries when we construct the test assets. It reports the results of Fama-MacBeth regressions of portfolio returns on lagged portfolio characteristics that include Beta, ln(mcap), book-to-market, profitability, investment, momentum, and intangible intensity. Coefficients are annualized. The portfolios used in the cross-sectional regressions include 32 Size-B/M-OP portfolios, 32 Size-B/M-INV portfolios, and 32 Size-B/M-INT portfolios. For each portfolio, the independent variables of individual stocks in the portfolio are winsorized at the 1% and 99% level, and value weighted to calculate portfolio level characteristics. The portfolio characteristics of the 96 portfolios are standardized into z-scores for each of the monthly regressions. The sample covers the Russell 3000 stocks excluding financial firms over the period of June 1989 and November 2020.

**Table A2: Portfolio Sorts on both Organization Capital Intensity (Characteristics) and Organization Capital Factor Beta (Risk)**

Average OrgCap Intensity			
	High OrgCap characteristics ptfs	Low OrgCap characteristics ptfs	<i>High - Low OrgCap</i>
<b>High OrgCap risk ptfs</b>	<b>1.09</b>	<b>0.28</b>	<b>0.80 (t-stat 14.6)</b>
<b>Low OrgCap risk ptfs</b>	<b>1.05</b>	<b>0.26</b>	<b>0.78 (t-stat 13.9)</b>
<i>High - Low OrgCap risk</i>	<i>0.04 (t-stat 4.9)</i>	<i>0.02 (t-stat 4.1)</i>	
Average Organization Capital Factor Beta			
	High OrgCap characteristics ptfs	Low OrgCap characteristics ptfs	<i>High - Low OrgCap</i>
<b>High OrgCap risk ptfs</b>	<b>1.43</b>	<b>1.31</b>	<b>0.12 (t-stat 4.5)</b>
<b>Low OrgCap risk ptfs</b>	<b>-1.26</b>	<b>-1.51</b>	<b>0.25 (t-stat 5.3)</b>
<i>High - Low OrgCap risk</i>	<i>2.69 (t-stat 11.5)</i>	<i>2.82 (t-stat 14.4)</i>	
Average Return (%)			
	High OrgCap characteristics ptfs	Low OrgCap characteristics ptfs	<i>High - Low OrgCap</i>
<b>High OrgCap risk ptfs</b>	<b>1.07</b>	<b>0.97</b>	<b>0.10 (t-stat 1.9)</b>
<b>Low OrgCap risk ptfs</b>	<b>1.04</b>	<b>0.90</b>	<b>0.14 (t-stat 3.5)</b>
<i>High - Low OrgCap risk</i>	<i>0.03 (t-stat 0.9)</i>	<i>0.07 (t-stat 2.1)</i>	

Notes: This table reports the average returns, organization capital (OrgCap) intensity, and organization capital factor beta across 48 portfolios formed on  $2 \times 2 \times 2 \times 2$  sorts on size, OrgCap intensity, OrgCap factor beta, and either book-to-market, operating profitability, or investment as the fourth sort variable. We split the 48 portfolios into four groups of 12 portfolios, based on OrgCap intensity (high or low) and OrgCap factor beta (high or low). For the two pairs of high versus low OrgCap characteristics groups and two pairs of high versus low OrgCap risk groups, we also report for each pair the difference in the average returns, OrgCap intensity, and OrgCap factor beta. The OrgCap factor betas are the exposure of stock returns to the OrgCap factor, obtained from linear regressions of stock returns on the returns of the OrgCap factor and the factors in the Fama-French five-factor model, using 36-month data prior to the formation of the test portfolios.