Intangible assets and the cross-section of stock returns

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Abstract

We examine whether intangible assets are priced in the cross-section of stock returns. We find that intangible asset intensity has more explanatory power than size, value, profitability, and investment. An intangibles-based long-short factor has a higher Sharpe ratio than these established factors. Adding the intangible factor to the Fama-French five-factor model improves the description of average returns and makes the investment factor redundant. The intangible factor is distinct from traditional growth strategies, provides a hedge to value and quality strategies, and expands investors' opportunity sets. Intangible intensity as characteristic is more important than as risk factor, consistent with intangibles-based mispricing.

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

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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 important changes were driven by a rapid transition from a traditional economy dominated by physical assets and production processes to a knowledge economy powered by advancements in research, technology, human capital, and organization capital.

Despite the growing importance of intangible assets, the accounting and reporting rules for intangibles are outdated and provide limited information to investors (Lev, 2018).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 and earnings (Srivastava, 2014; Lev and Gu, 2016).

Naturally, such mismeasurement is likely to be most severe for firms with higher levels of intangibles. As investors commonly rely on fundamental characteristics to value companies and model stock prices, high intangibles firms may thus be associated with greater information asymmetries and/or mispricing. Consistent with the high information complexity of intangible assets, Gu and Wang (2005) find that analysts' earnings forecast errors are larger for more intangible-intensive firms. Palmon and Yezegel (2012) present empirical evidence that analysts' recommendation revisions are more valuable for firms with high Research & Development (R&D) intensity, which is consistent with the hypothesis that R&D intensity increases information asymmetry. Dugar and Pozharny (2021) find that the value relevance of book equity and earnings has declined only in high intangibles firms, and not in low intangibles firms.

Accounting and reporting issues related to intangibles can also affect the construction of factors used in asset pricing studies. Several recent papers study the impact of incorporating intangible assets on the Fama and French (1993) value factor (HML; High Minus Low book-to-market ratio). Park (2019), Lev and Srivastava (2020), Amenc, Goltz, and Luyten (2020), and Arnott, Harvey, Kalesnik, and Linnainmaa (2021) construct an intangible-adjusted HML factor by adding knowledge capital and organization capital to book equity, and show that the adjusted HML factor yields higher returns. These studies generally find that the mismeasurement of book equity partially contributes to the recent underperformance of the HML factor (and value strategies more generally).

Motivated by these considerations, in this paper, we examine whether intangible assets themselves provide explanatory power about the cross-section of stock returns. First, we hypothesize that firms' intangible intensity may be priced in the cross-section, because firms with higher levels of intangibles may be more susceptible to information asymmetries and/or mispricing. We measure intangible intensity as the ratio of internally created (off-balance-sheet) intangible assets relative to total assets. Following Peters and Taylor (2017), internally created intangible assets include knowledge capital and organization capital, which are estimated by accumulating past R&D expenditures and past Selling, General & Administrative Expense (SG&A) expenditures, respectively. Similar to Park (2019) and Amenc et al. (2020), we add knowledge capital and organization capital to total assets and deduct goodwill from it. These intangible assets are depreciated over time as in Peters and Taylor (2017).

To empirically study the relation between intangible intensity and average returns, we construct an intangible factor that is long high intangibles firms and short low intangibles firms over the sample period 1989-2020, using all U.S. stocks in the Russell 3000 index. We limit ourselves to the Russell index to exclude micro caps, which have an unduly impact on anomalies (Fama and French, 2008) and are also not considered by most institutional investors. We find that portfolios sorted on intangible intensity exhibit large variation in average returns, for both large stocks and small stocks. The intangible factor has an economically significant average return of 4.6% annually, 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.

As an alternative test of the association of intangibles with the cross-section of returns, we run Fama and MacBeth (1973) cross-sectional regressions of portfolio returns on value-weighted firm characteristics of the 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, among the key characteristics, intangible intensity is the strongest explanatory variable for the cross-section of returns both economically and statistically, followed by profitability. A one standard deviation change in intangible intensity is associated with an annualized return impact 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. Taken together, these findings suggest that intangible intensity is priced in the cross-section of U.S. stock returns.

We then test empirically whether the intangible factor contains new information for describing average stock returns beyond the established asset pricing factors. In factor spanning tests, the intangible factor cannot be explained by the factors in the Fama-French five-factor model (market, size, value, profitability, and investment factors). The intangible 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 intangible factor. In addition, the significant return of the intangible factor cannot be captured by traditional growth strategies, such as the growth style indices.

Having established that the intangible factor is distinct from the known asset pricing factors, we proceed to examine whether adding this new factor may improve the performance of current factor models. To that end, we compare model performance of different factor models using the Gibbons, Ross and Shanken (1989) test that considers the joint significance of the alphas of a set of test assets across different factor models. Our GRS test results show that adding the intangible factor to the Fama-French three-factor and five-factor models improves the description of expected returns. In addition, a five-factor model with the market, size, value, profitability, and intangible 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 intangible factor.

Next, we conduct several tests on the alternative explanations of mispricing versus risk for the intangible premium. First, we follow Daniel and Titman (1997) and form test portfolios sorted by both characteristics (intangible intensity) and risk (intangible factor beta). Consistent with the mispricing explanation, we find that it is the characteristics of high or low intangible intensity, rather than the intangible risk, that explains average returns. Second, we find that intangible intensity is a strong predictor of future gross profit growth (which is a key driver of stock returns) in Fama-MacBeth regressions. Similar to the greater analysts' forecast errors documented by Gu and Wang (2005) on intangible-intensive firms, we conjecture that investors may underestimate the future profitability of these firms, due to the information complexity of intangible assets. Overall, our evidence suggests a plausible mispricing explanation based on the information asymmetries and behavioral biases associated with intangible assets.

Taking a more practical investor perspective, we then show that the intangible factor allows investors to harvest a significant factor premium while reducing the risk exposure to other factors. This is a desirable property for factor-based investment mandates in practice. Due to its strong negative correlation with value and quality strategies (-0.58 with HML, -0.26 with RMW, -0.32 with CMA), the intangible factor has the potential to provide a hedge to value and/or quality strategies. Value and quality investors can capture the economically large intangible premium while significantly reducing risks and increasing the Sharpe ratio. For instance, combining HML with the intangible factor increases the Sharpe ratio from -0.02 to 0.45 over our sample period, and combining HML and RMW with the intangible factor increases the Sharpe ratio from 0.16 to 0.43.

Our paper makes several contributions to the literature. First, it contributes to a growing body of recent work that examines the asset pricing implications of intangible assets. Park (2019), Lev and Srivastava (2020), Amenc, Goltz, and Luyten (2020), and Arnott, Harvey, Kalesnik, and Linnainmaa (2021) focus on the value factor alone, which cannot fully capture the impact of incorporating intangibles on asset pricing models. In contrast, by constructing a separate intangible factor, our study aims to incorporate the asset pricing impact of intangibles into any factor-based asset pricing model directly using a single factor. Importantly, this allows us to comprehensively analyze the relation between intangible intensity and the cross-section of average returns. In a contemporaneous study, Gulen, Li, Peters, and Zekhnini (2021) also aim to incorporate intangibles into the Fama-French five-factor model, e.g., by adding a separate value factor and a separate investment factor based on off-balance-sheet intangible assets only. Compared with Gulen et al. (2021), our intangible factor has more practical investment applications, for instance, as a potentially powerful hedge to value and quality strategies.

Second, our study contributes to the broad literature on the anomalies associated with R&D investments, organization capital, and intangible assets, as well as the mispricing versus risk explanations for these anomalies. The intangible factor is constructed based on the intensity of off-balance-sheet intangible assets. This is distinct from the R&D intensity or organization capital intensity used in other asset pricing studies, and can serve as a more comprehensive proxy for the reporting biases and potential information asymmetries in intangible-intensive firms. More importantly, our study 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. 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. Our findings suggest that it is the characteristic of intangible intensity, as opposed to intangible risk, that explains average returns in the cross-section. Overall, our evidence is consistent with a mispricing explanation based on the information complexity of intangible assets.

Third, our paper contributes to the factor model literature and the practitioner literature on factor investing. We show that a five-factor model with the market, size, value, profitability, and intangible factors improves the descriptions of expected returns relative to the original Fama-French five-factor model, rendering the investment factor redundant for describing average returns in the sample period. Fama and French (2008) also recognize that the investment (asset growth) anomaly is less robust as it exists only in microcap and small stocks and not in big stocks. Finally, we show that the intangible factor is distinct from traditional factor based strategies and can significantly expand investors' opportunity set while considerably reducing risks.

2. Data and methods

This section describes our data and methods for measuring intangibles (Section 2.1), constructing the intangible 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. Advertizing 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:

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

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:

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

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.[1]

Lev and Radhakrishnan (2005), Hulten and Hao (2008), and Eisfeldt and Papanikolaou (2013) 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), and Peters and Taylor (2017) in counting 30% of SG&A 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. Correspondingly, a firm's internally created organization capital is constructed by accumulating 30% of past SG&A expenses using the perpetual inventory method as in Equation (1) and (2) with a depreciation rate of 20%:[2]

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

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

[1] 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 intangible factor.
[2] Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017) show that their results are robust to the choice of depreciation rate.

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).[3] 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*.

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 intangible factor and test assets

We follow similar procedures as those of Fama and French (2015) to construct the intangible 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 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

[3] Our results are robust to us using an alternative measure of intangibles intensity that does not correct for goodwill.

sorts on size and intangible intensity produce six portfolios. The Intangible factor INT is the average of the two high intangibles portfolio returns minus the average of the two low intangibles portfolios returns.

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 Intangible 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 intangible 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 3 x 3 x 3 x 3 or 2 x 4 x 4 x 4 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 x 4 x 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 expected returns. First, we analyze the risk and return characteristics of the intangible 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 intangible factor (sorts on intangible intensity)

Before we examine the performance of the intangible factor, we first analyze the six portfolios double sorted on size and intangible intensity that are used to construct the intangible 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 intangible factor (INT) constructed using the 2 x 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 intangible 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 intangible 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 intangible factor has been one of the strongest asset pricing factors in the past 30 years.

Table 2 also shows that the intangible 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 intangible 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 intangible 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 intangible factor seem to suggest that it is not a particularly risky factor.

One question that may arise is how the performance of the intangible 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.[4] 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 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 intangible factor delivered a large cumulative return of 270% during this period. During the burst of the technology bubble, the intangible 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 intangible factor occurred between October 2003 and June 2008, when it lost 38.2%. Since June 2008, the intangible 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 intangible 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 intangible 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 intangible factor.

[4] 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.

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 intangible 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(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.

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. In the next section, we examine whether the intangible factor has the potential to enhance the performance of existing factor models.

4. The intangible factor and asset pricing models

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

4.1 Factor spanning tests

While Table 2 and Figure 1 show that the average return of the intangible factor is both statistically and economically significant, they are not conclusive about whether the intangible 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 intangible 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 intangible factor, the five Fama-French factors (Market, SMB, HML, RMW, and CMA) and the momentum factor (MOM). The intangible 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 intangible factor can provide a hedge to value strategies and quality strategies such as profitability and investment. In addition, the intangible 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 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 intangible 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 intangible 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 intangible 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 intangible factor is not spanned by the other six factors and thus contains important new information for describing average returns. The intangible 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 intangible factor (-0.46, *t*-stat = -12.83). When the intangible 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 intangible factor. Controlling for the intangible 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 intangible factor (coefficient 0.24, *t*-stat = 5.27). After the intangible 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 intangible factor is not spanned by the established asset pricing factors and thus contains important new information for describing U.S. average returns. Furthermore, when the intangible 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 intangible 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 intangible factor

To examine whether the intangible factor may improve the performance of established factor models, we test asset pricing models that add the intangible 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 intangible factors (constructed as described in section 2.2).

Table 7 summarizes the impact of adding the intangible 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, combing 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.[5]

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 expected returns.

Taken together, our GRS test results show that adding the intangible 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 intangible 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.

[5] 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%).

4.3 Potential explanations for the intangible 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 intangible 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 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 intangible 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 intangible factor beta of stocks. To strike a balance between increasing the number of test portfolios and avoiding poorly diversified portfolios, we form 2 x 2 x 2 x 2 sorts (16 portfolios) on size, intangible intensity, intangible factor beta,[6] and either book-to-market, operating profitability, or investment as the fourth sort variable. In total this produces 48 (16 x 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 intangible factor beta (high or low), corresponding to characteristics and risk respectively. Table 8 reports the average returns, intangible intensity, and intangible 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 intangible 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 intangible 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 intangible 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 intangible 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 intangible factor beta produces large and statistically significant variation in average returns between high and low intangible characteristics portfolios. Controlling for intangible 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

[6] The intangible factor betas are the exposure of stock returns to the intangible factor, obtained from linear regressions of stock returns on the returns of the intangible factor and the factors in the Fama-French five-factor model, using 36-month data prior to the formation of the test portfolios.

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 intangible factor loading that explains average returns. In short, the intangibles premium is associated with characteristics rather than risk. This is consistent with the mispricing explanation, in which high intangible intensity firms are more exposed to the reporting biases and information asymmetries that may create mispricing.

To further examine the mispricing explanation of the intangible 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 intangible 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*-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 intangible factor loadings 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 investors may underestimate the future profitability of intangible-intensive firms, our findings suggest a plausible mispricing explanation based on the information asymmetries and behavioral biases associated with intangible assets.

5. Investment applications of the intangible factor

In this section, we discuss and examine a number of practical investment applications of the intangible factor in factor investing and institutional investment processes.

Section 2 shows that the intangible 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. Thus, the intangible factor has the potential to expand the investment opportunity set of investors, while at the same time significantly reducing risk exposures. Table 10 illustrates the performance impact of combining the intangible 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: it reduces the volatility from 10.2% to 6.0%, and significantly increases Sharpe ratio from 0.16 to 0.43. This is because INT is strongly negatively correlated with HML and RMW (correlation of -0.58 and -0.26 respectively), while HML and RMW are positively correlated (correlation of 0.47). The implications of these observations are significant. The intangible 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 intangible factor has a much greater potential to improve investors' opportunity set and reduce risks.

While HML is considered a value strategy and RMW is considered a quality strategy, in practice investors typically use a composite of variables to construct both value and quality strategies. Table 10 shows the performance of a composite value strategy based on multiple variables (Book / Market, EBITDA / EV, Free CF / Price, Sales / Price, and Net Payout Yield), and a composite quality strategy based on multiple variables (Operating Profitability, Investment, Gross Profitability, Return on Equity, Return on Assets, and Accruals/Assets). The value strategy significantly improves performance relative to HML, with an average return of 2.2% versus -0.3% per annum, and a Sharpe ratio of 0.14 versus -0.02. However, combining the intangible factor with the value strategy further enhances the Sharpe ratio from 0.14 to 0.49, boosting the return to 3.4% and reducing the volatility from 15.9% to 7.0%. Similarly, despite that the quality strategy delivers much higher Sharpe ratio than RMW (0.66 versus 0.28), combining the intangible factor with the quality strategy further boost the Sharpe ratio to 0.85. In addition, combining the intangible factor with both value and quality strategies also substantially reduces the volatility from 11.5% to 7.2%, and increases the Sharpe ratio from 0.37 to 0.60. Finally, Table 10 also shows that adding INT to multi-factor portfolio of SMB, HML, RMW, and CMA increases the Sharpe ratio from 0.17 to 0.37.

The observations in Table 10 suggest that value and quality investors can capture an additional intangible premium while considerably reducing the overall risk. The intangible factor provides greater diversification to value and quality strategies than any factors in the Fama-French five-factor model and can significantly expand investors' opportunity set.

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 intangible 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 intangible factor cannot be explained by established asset pricing factors and thus contains important new information for describing average stock returns. We add the intangible 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 intangible 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 intangible factor is also distinct from traditional growth strategies. These characteristics suggest that the intangible 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 intangible 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 the information complexity of intangible assets. 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.

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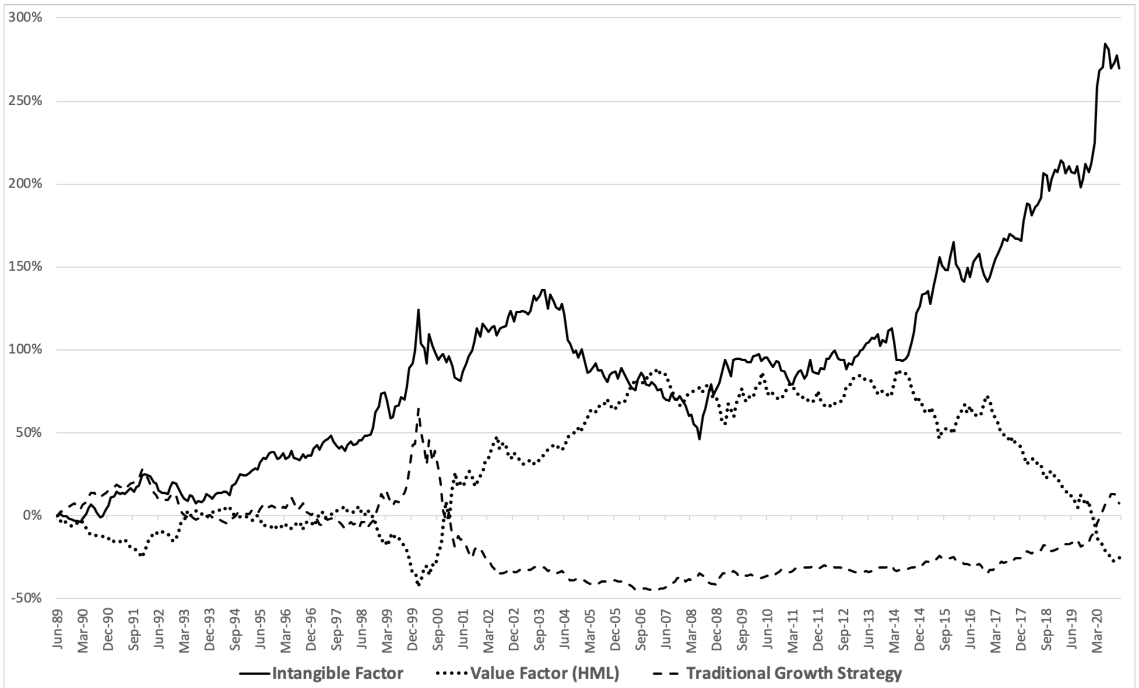
Figure 1: Cumulative Returns of the Intangible Factor vs. HML and Growth



Notes: This figure presents the cumulative returns for the Intangible factor, Value factor (HML), and Growth factor, for the period of June 1989 to November 2020. The Intangible 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

Large Cap Sorts	Average Return	Standard Deviation	Intangible Intensity	Book / Market	Operating Profitability	Investment
Low Intangibles	0.59%	4.35%	5%	46%	32%	21%
Medium	0.76%	4.76%	24%	30%	32%	18%
High Intangibles	0.87%	4.07%	43%	22%	37%	10%
High - Low	*0.28% (t-stat = 2.1)*					

Small Cap Sorts	Average Return	Standard Deviation	Intangible Intensity	Book / Market	Operating Profitability	Investment
Low Intangibles	0.53%	5.74%	5%	59%	18%	32%
Medium	0.71%	6.03%	24%	46%	17%	26%
High Intangibles	1.01%	6.63%	46%	39%	5%	17%
High - Low	*0.48% (t-stat = 2.8)*					

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

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

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

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	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	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				
Intangible			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

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

Notes: This table shows the correlations between the intangible 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**	
Market	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	
SMB	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	
HML	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	
RMW	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	
CMA	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	
MOM	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	
INT	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	
Market	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	
SMB	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	
HML	-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	
RMW	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	
CMA	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	
MOM	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 intangible 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

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

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 Intangible Factor Beta (Risk)

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

Notes: This table reports the average returns, intangible intensity, and intangible factor beta across 48 portfolios formed on 2 x 2 x 2 x 2 sorts on size, intangible intensity, intangible 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 intangible 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 intangible factor beta. The intangible factor betas are the exposure of stock returns to the intangible factor, obtained from linear regressions of stock returns on the returns of the intangible 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

	3Y gross profit grwoth as dependent variable		3Y earnings growth as dependent variable	
Independent Variables	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
Intangible	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 Intangible Factor with Multi-Factor Portfolios

Factor Portfolio	Average Return	Annual Volatility	Sharpe Ratio	Factor Portfolio + 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
Value Strategy	2.2%	15.9%	0.14	Value Strategy + INT	3.4%	7.0%	0.49
Quality Strategy	6.2%	9.4%	0.66	Quality Strategy + INT	5.4%	6.3%	0.85
Value + Quality	4.2%	11.5%	0.37	Value + Quality + INT	4.3%	7.2%	0.60
SMB+HML+CMA+INV	1.1%	6.8%	0.17	SMB+HML+CMA+INV	1.8%	5.0%	0.37

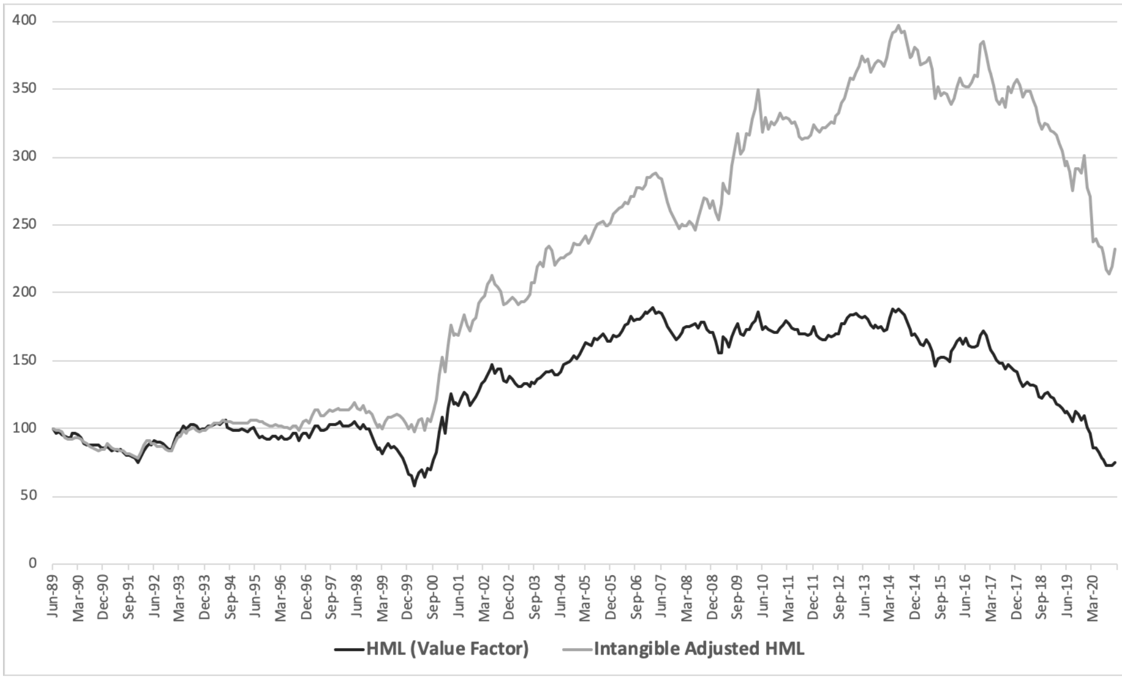
Notes: This table shows the performance statistics of various factor portfolios and combination of these portfolios with the Intangible factor. Average returns are annual mean returns. Factors are equally weighted in all multi-factor portfolios (i.e., the weight of INT is 1/3 in HML + RMW + INT and 1/5 in SMB + HML + CMA + INV + INT). 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. The Value strategy is constructed by sorting the stocks by a composite factor that equal-weights Book / Market, EBITDA / EV, Free CF / Price, Sales / Price, and Net Payout Yield. The Quality strategy is the constructed by sorting the stocks by a composite factor that equal-weights Operating Profitability, Investment, Gross Profitability, Return on Equity, Return on Assets, and Accruals/Assets.

Appendix

Figure A1: Impact of excluding Big Tech on the Performance of Intangible Factor

Notes: This figure presents the cumulative performance for the intangible 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 intangible Factor. The intangible 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%.