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The Effect of including Intangible Capital in the Value Factor of the Fama and French Capital Asset Pricing Framework

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Abstract

This paper explores the effect of including intangible capital in the construction of the Fama & French (1993) value factor on the asset pricing ability. Inspired by K. Eisfeldt & Papanikolaou (2020), this paper compares not only the inclusion of total intangible value into the value factor, as it is believed that it performs better than the traditional value factor, but also analyzes the components of intangible capital namely organizational capital and knowledge capital. Looking at the data from 1975 - 2017 we find that intangible value, as opposed to the traditional value factor, does have a substantial and significant better performance both in terms of asset pricing ability as well as yielding higher levels of return. Our results also indicate that the intangible value factor's outperformance holds overall subperiods. However, we find that to a very large extent the main driver of the intangible value's outperformance emerges from the organizational capital component. Our findings suggest that knowledge capital also provides significant outperformance but far less in comparison to organization capital. Finally, we were also able to construct a profitable investment strategy based on intangible value's outperformance relative to traditional value.

Contents

1 Introduction

In recent years the value factor has performed particularly badly, especially in the post-financial crisis era, as it lost its significance and even resulted in negative returns (Roisenberg, 2019). The creators of the three-factor model, and hence the value factor, have themselves even stated that the value factor has to an extend become 'redundant' (Fama & French, 2015). The fact that the value factor has recently even created negative returns gives rise to question whether the value factor is still able to price assets or if the way value is being measured is inaccurate.

An interesting observation is that nowadays intangible capital, which can be seen as the accumulation of research and development expenditure (R&D) and of selling, general and administrative expenditure (SG&A), have gained prominence. As (Corrado & Hulten, 2010) have shown that on average in recent times, intangible capital makes up about 34 percent of a firm's total capital. Hence not accounting for it as is currently the case could lead to divergence in the market value and the fair value of firms, thereby creating also investment opportunities to generate abnormal returns. Interestingly since around 1994 the expenditure rate on R&D has significantly increased as shown in Figure 4. Incidentally, this is also the same period in which Fama & French (1993) published their initial three-factor model which introduced the value factor at which point it was still strongly significant and had a high explanatory power. It could thereby be possible that the demise of the value factor could be to a certain extend linked to the increase in R&D expenditure and hence the rise of intangible capital. It has already been shown by Chan & Sougiannis (2001) that firms with high intensity of research and development expenditure especially ones that have been performing poorly in the past provide future abnormal returns on average. However, given that by generally adopted accounting standards, expenditure on research and development is not shown as an investment in the balance sheet but appears as an expense in the income statement. This has as a consequence that when valuations are solely based on book equity, it would mean that if two identical firms of which one would acquire physical goods, which would be accounted for as assets, while the other identical company that spends the same amount on research and development, would have a lower book value and hence thereby have a lower book to market value. Thereby firms that spend heavily on intangible assets as is the case with many companies these days, may appear to be expensive to value investors under the traditional measures of value. Given that the fundamental proxy to computing a firm's value has up till now been mainly derived from the book equity to market value ratio. It may be the case that the current way of measuring a firm's value is inaccurate and that value if rightly specified, may after all still help price assets correctly. By including intangible assets it in the book value and thereby creating an adjusted book-to-market ratio that accounts for the expenditure on intangible assets, may again reinstate the relevance of the value factor. This is substantiated by our findings which show that the intangible value factor offers significantly better asset pricing ability over the entire sample as well as in the subsamples. Moreover, the results further demonstrate the overperformance of the intangible value factor towards the traditional value factor in terms of returns, as we were able to come up with a profitable investment strategy that goes long in the intangible value factor and short in the traditional value factor. Our results thereby do imply that there exists a possible mispricing due to the exclusion of intangible capital in the computation of the value factor. In addition, we find that most of the outperformance seems to arise from the organizational component of intangible capital, hence SG&A expenditure. Meanwhile, we find that R&D seems to have a much smaller positive impact on the performance of intangible assets.

2 Literature Review

As the share of intangible capital in firms has increased in recent times so has intangible capital and research and development expenditure started to receive more attention in the economic literature. Corrado & Hulten (2010) have estimated that the rate of investment in intangible assets has strongly increased in recent years, from 5.9% in the period 1948 – 1972 to 12.8% in the most recent period 1995 – 2007. Moreover, they demonstrate that intangible assets on average make up for 33.9% of firms' total capital in the United States. Thus indicating that over time intangible capital has gained sizeable significance. In addition, (Choi & Lobo, 2000) analyzed the relationship between the reported value of intangible assets and the firms' equity valuations. Their empirical results indicate that the market tends to positively value reported intangible assets and that markets do not value them significantly different from other asset types reported on the balance sheet. These findings thereby suggest that intangible assets could be used in a similar way as traditional assets for the sake of market valuation. The work of Penman (2009) discusses the potential consequences and benefits of adding intangible asset component such as R&D and SG&A expenditure from the income statement to the balance sheet. The study points out the importance and helpfulness of using intangible assets co-jointly with the other assets to better evaluate a firm's fair value but also outlines the limits of solely focusing on intangible assets. Thereby motivating us to analyse both components of intangible capital namely knowledge as well as organizational capital.

In the research conducted by (Bosworth & Rogers, 1998), they analyze the effect of research and development expenditure on a firm's performance. Their results show that past research and development expenditure seems to have a positive effect on a firm's productivity level. Moreover, they find that firm size seems to have no relationship with research and development and that firms engaged in higher levels of research and development seem to be more specialized in their business segment and less diversified. Finally, their empirical analysis also indicates that current research and development expenditure is positively connected to a higher market value. Chan & Sougiannis (2001) further elaborates on stock price valuation of intangible assets by just focusing on research and development expenditure. They show that for firms that have high research and development to equity value, meaning companies with past low performances but high research and development tended to experience excess returns. Moreover, they found that research and development intensity was positively associated with higher stock volatility. On the other hand, there has also been evidence showing that the SG&A component of intangible capital has a beneficial effect both on firm level as well as on the firm's market valuation. As shown in the recent paper by Banker & Zhao (2019) they analyzed the relationship of SG&A expenditure on the market valuation and find that the market positively values increased SG&A expenditure, but that capital markets only partially value the intangible value created by SG&A expenditure, suggesting that it might still be undervalued. In addition, they find that higher SG&A expenditure, hence higher share of organizational capital leads to higher future growth on a firm level. Similarly in a very recent study by K. Eisfeldt & Papanikolaou (2020) attempts to incorporate intangible assets into the value factor of the Fama & French (1993) asset pricing model. To achieve this they add research and development and SG&A expenses to the book equity, which is then used instead for the computation of the value factor. Their results show that the intangible factor does as well and possibly better in terms of asset pricing ability, while also yielding higher returns compared to the traditional factor. Thereby proving that intangible value could be used to even improve asset pricing models to better capture investment risks. In our study, we only analyze the intangible value created by research and development expenditure as the work by (Sun, 2021) emphasizes the importance of analyzing the two major components of intangible capital namely SG&A and research and development expenditure separately. As Sun (2021) argues that combining both components as is often the case such as in the work of K. Eisfeldt & Papanikolaou (2020), could due to firms manipulating them differently cause differing valuation implications. Although some research has been conducted on the effect of intangible assets, overall little research has been done explicitly analyzing the effect of research and development expenditure on intangible capital, particularly in terms of capital asset pricing models such as the Fama & French (2015) factor model.

3 Methodology

3.1 Data

For our sample in this study, we consider monthly data starting from January 1975 until December 2017 and solely focuses on the US market and firms. The data to construct the intangible value factor has been sourced from the Wharton Research Data Service (WRDS), more specifically, accounting data from the Compustat database and stock price data from the CRSP database. In addition, we also use data from the WRDS's 'Peters and Taylor Total Q' library to construct the intangible value factor based only on SG&A and based on total intangible capital. Specifically, we use the *K_int_org* variable, which is the replacement cost of the firm's organization capital, the portion of intangible capital that comes from SG&A, based on Peters & Taylor (2016). The other factors namely market risk, size, standard value, profitability, investment, and momentum have all been sourced from the official series published on the website of Kenneth French (French, 2021). For the Fama-Macbeth regressions (Fama & MacBeth, 1973) we use 25 portfolios formed on firm size and book-to-market ratio and in addition to that 10 portfolios formed on momentum. Again the portfolio returns have been taken from Kenneth French's website (French, 2021).

Besides performing our analysis based on the entire sample period, to gain further insights on the changes over time, we also perform it on some subsample. Our sample has been divided into three subperiods, the first from 1975 - 1994, which is meant to analyze the period in which research and development expenditures were rather low. The second subsample being 1995 - 2006 is meant to document the pre-crisis era in which research and development have picked up strongly as can be seen in 4. Finally, we consider the subperiod 2007 - 2017, which is meant to document the post-financial crisis era, in which the traditional value factor underperforms according to Fama & French (2015).

3.2 Construction of Intangible Value Factor

The construction of the intangible value factor HML_{int} follows the same methodology as used in Fama & French (1993) for the traditional factor except that for book equity we also include the stock of accumulated R&D, SG&A, and total intangible assets respectively. The computation of the monthly value factor is done using a modified version of the Python code published by the WRDS that replicates the Fama & French (1993) methodology. For our sample period, replicating the traditional value factor (HML_{FF}) series from the three-factor model (Fama & French, 1993), we get a very high correlation of 0.98 with the original series posted on Kenneth French's website (French, 2021). To construct, the intangible value we modified the Python code by accounting for companies' different types of intangible assets. On the firms' income statement Compustat only lists two variables of intangible expenditure namely research and development expenses (xrd) and selling, administrative and general expenses ($xsga$), which we interpret as knowledge capital and organizational capital respectively. In order to focus on the components of intangible capital, we perform our analysis using total intangible capital as well as knowledge capital given by R&D and organizational capital given by SG&A.

Hence, for research and development component of intangible capital we compute for company i at time t the intangible capital using the perpetual inventory model as follows:

$$Int_{it}^{R\&D} = (1-\delta)Int_{it-1}^{R\&D} + R\&D_{it} \tag{1}$$

Where in equation 1 we initialise $Int_{i0}^{R\&D} = R\&D_{i0}$ at time $t = 0$ where the research and development expense first appears in Compustat. Concerning the depreciation rate δ, in (Peters & Taylor, 2016) it has been shown that using the traditionally applied depreciation rate if 15% as opposed to the Bureau of Economic Analysis' R&D industry-specific depreciation rates results virtually in the same accumulated R&D figures. Consequently, we use a depreciation rate, hence a δ of 15% for all firms' R&D expenditures. Given the intangible capital Int_{it} we then add it to the firm's book equity to derive our augmented book equity, as shown below in equation 2:

$$BE_{it}^{int} = BE_{it} + Int_{it}^{R\&D} \tag{2}$$

Where in equation 2 for company i at time t, BE_{it} indicates the current standard book equity as given by Compustat and where $Int_{it}^{R\&D}$ stands for the intangible capital derived from the accumulated research and development expenditure. Finally, this gives BE_{it}^{int}, which is the updated book value that takes into account a firm's intangible value based on R&D. We subsequently use the updated book equity BE_{it}^{int} and replicate the Fama &

French (1993) methodology to compute the intangible value factor HML_{int}. Finally, we adjust the scale of our series of intangible factors so as to be at the same scale as the factors published on Kenneth French's website (French, 2021).

Meanwhile for the construction of the value factor of the SG&A component of intangible capital, which is interpreted as organizational capital. We follow the same procedure outlined above, but we do not use Compustat's *xsga* but instead use Peters & Taylor (2016)'s replacement cost of a firm's organizational capital K_int_org from the WRDS database, which accounts for the fact that Compustat's *xsga* often erroneously includes R&D in their *xsga* variable. Moreover, after excluding R&D the K_int_org only considers 30% of SG&A spending as an addition to a firm's intangible assets, as shown by Hulten & Hao (2008), Eisfeldt & Papanikolaou (2014), and Xiolan (2014). Finally we follow the work of Falato & Steri (2020) and use a depreciation rate for SG&A of 20%. This is shown below in equation 3:

$$Int_{it}^{SG\&A} = (1-\delta)Int_{it-1}^{SG\&A} + K\_int\_org_{it} \tag{3}$$

We then use the accumulated SG&A stock and add it to the augmented book equity BE_{it}^{int} as shown in equation 2, but using the accumulated SG&A stock $Int_{it}^{SG\&A}$ instead of $Int_{it}^{R\&D}$. Thereby we include the intangible capital component in our book equity and based on this follow the standard Fama & French (1993) methodology to compute the intangible value factor.

At last, in order to construct the value factor using the total value we combine our computed stock of organizational capital $Int_{it}^{SG\&A}$ and knowledge capital $Int_{it}^{R\&D}$ and at it to the book equity as shown in equation 4:

$$BE_{it}^{Total\_int} = BE_{it} + Int_{it}^{SG\&A} + Int_{it}^{R\&D} \tag{4}$$

Given our newly computed $BE_{it}^{Total\_int}$ we use it to compute our total intangible value factor HML_{int} again following the same Fama & French (1993) methodology.

3.3 Risk Parameters

To estimate the parameters for the intangible and standard value factor in both the three-factor model plus momentum and five-factor model plus momentum, we perform the Fama-Macbeth procedure from (Fama & MacBeth, 1973). The Fama-Macbeth procedure is a two-step procedure as follows:

1) Firstly, as shown in equation 5 for each asset i we regress its return at time t onto a constant and on each risk factor k, which in our case is Mkrtrf, SMB, HML and MOM for the Fama and French three-factor plus momentum, while for the Fama and French five-factor model RMW and CMA are added. Whereby at time t, each asset i's risk exposure for factor F_k is given by β_{i,F_k}. We perform such a regression for each asset i for each time period t.

$$R_{i,t} = \alpha_i + \beta_{i,F_1} F_{1,t} + ... + \beta_{i,F_k} F_{k,t} + \epsilon_{i,t} \tag{5}$$

2) Secondly, as can be seen in equation 6 regress for each asset i its returns for each time period t against the respective previously estimated factor loading $\hat{\beta}_{i,F_k}$ plus a constant in order to determine each factor's risk premium given by $\gamma_{t,k}$.

$$R_{i,t} = \gamma_{t,0} + \gamma_{t,1}\hat{\beta}_{i,F_1} + ... + \gamma_{t,k}\hat{\beta}_{i,F_k} + \epsilon_{i,t} \tag{6}$$

In the first step, we use as asset returns the return of 25 portfolios formed on size and book-to-market, and 10 portfolios formed on Momentum. All portfolios being the standard Fama and French portfolios sourced from Kenneth French's website (French, 2021). We run this procedure for all three computed intangible value factors namely for the SG&A, R&D, and total intangible capital component.

4 Analysis

4.1 Asset Pricing Ability

Here we compare the ability of intangible value to traditional value in terms of how well they can price standard test portfolios. To start off, we first compare the monthly returns of both intangible value (HML_{int}) and traditional value (HML_{FF}) by plotting them next to each other and computing their Pearson's correlation coefficient. Figure 1 shows the R&D based intangible factor against the traditional value factor, as can be seen from the figure both factors seem to mimic each other quite closely over time. This is confirmed by the very high Pearson correlation coefficient of 0.96, shown in Figure 1. This indicates that accounting for R&D expenditure in the book market value does not seem to change the intangible factor much compared to the original factor and that they still may have much in common. Thereby, given the low independent variation, we may expect the new factor to also capture the 'value effect' and offer some slight improvement compared to the traditional factor since the relationship is only slightly different from each other. Meanwhile, Figure 2 shows the SG&A based intangible factor, which also mimics the movement of the traditional, however, there seem to be fewer spikes hence volatility in the SG&A based intangible factor. This divergence from the traditional factor is substantiated by the relatively lower Pearson's correlation coefficient of 0.87, which is much lower than the one for the R&D based intangible factor which is 0.96. Thereby, the SG&A based intangible factor has a much higher level of independent variation, thereby also allowing for a more significant outperformance and better asset pricing test results, as opposed to the R&D based intangible factor. Finally, in Figure 3 the intangible factor based on total intangible capital and the traditional capital is shown, here we observe a slightly higher correlation coefficient of 0.88 compared to the one based solely on SG&A but still much lower than the one based only on R&D. This again seems to thereby provide sufficient independent variation in the newly computed intangible factor so as to still capture the traditional value effect but also offer the possibility for some outperformance.

The results of our Fama-Macbeth regressions are shown in Table 1, Table 2 and Table 3 for the value factor based on R&D, SG&A and total intangible capital respectively. Starting off with the three-factor model plus momentum, where the results are presented in columns one and two of each table, using once the traditional value factor and once the corresponding intangible value factor respectively. In the three-factor model plus momentum, we observe the smallest increase in the risk premium for value (HML) for the R&D component, while the largest increase is observed for the SG&A and a slightly less large increase by the total intangible value component. For the five-factor model plus momentum, we see a similar behavior except that the increases in the value factor's risk premium for both the SG&A and total component are much larger. While for the R&D component there is a slight decrease in the risk premium. This indicates that for both asset pricing models the relevance of the value factor increases when incorporating intangible assets especially for SG&A and total intangible assets.

Moving on to the models' explanatory power, we see that for the three-factor model plus momentum, the biggest increase in the adjusted R^2 is observed for SG&A closely followed by total intangible value. However, we observe a very slight decrease in the adjusted R^2 from 0.74 to 0.73 for the R&D component. For the five-factor model plus momentum, we again see a decrease in explanatory power for the model using R&D component from 0.80 to 0.77, while for both SG&A and the total component it also decreased but only from 0.80 to 0.79. Thereby, we see an increase in explanatory power for the three-factor model plus momentum, which seems to be driven mainly by the SG&A component, while for the five-factor model plus momentum the explanatory power decreases slightly, but again SG&A and total intangible capital seem to perform best.

Comparing the models' abnormal returns, for the three-factor model plus momentum, except for the R&D component, all alphas decrease when using the intangible value factor with the SG&A decreasing the strongest. However, the alpha seems to not have changed significantly at a 5% significance level as shown by the chi-squared test's p-value at the bottom of column 4. In contrast, for the five-factor model plus momentum, all alphas seem to increase for each component, especially for the SG&A component, however according to the chi-square tests the changes in the alphas are not significant at a 5% significance level.

All in all, for the three-factor model plus momentum we may conclude that in terms of asset pricing ability the intangible value factors seems to outperform the traditional value factor both in terms of a greater explanatory power and slightly decreased alphas as well as higher and more significant risk premium for intangible value. The outperformance is mainly driven by the SG&A component for all aspects, while not much significant change has been observed for the R&D component. Meanwhile, using intangible value factors in the five-factor model plus momentum did result in more significant increases in the value risk premium, however, the explanatory power decreased marginally for all components and the alphas did increase albeit not statistically significant, implying that the model gives higher levels of abnormal returns and hence less good pricing performance. The best performing intangible factor component was again SG&A followed by total intangible assets and R&D. Finally we may conclude that using intangible value factors does not seem to significantly underperform the traditional value factor and even seems to off superior pricing performances compared to the traditional value factor especially when using the three-factor model plus momentum.

4.2 Relative Performance over Time

In order to analyze the outperformance of the intangible factor compared to the standard value factor, we regress the monthly intangible value factor onto a constant and the traditional value factor as shown in equation 7. In addition, to adjust for heteroskedasticity, we use heteroskedasticity robust standard errors as shown by White (1980).

$$HML^{INT} = \alpha + \beta HML^{FF} + \epsilon \tag{7}$$

The results of the regression showing the outperformance of intangible value factor for the R&D, SG&A and total intangible capital components is given in Table 4, 5 and 6. Concerning the R&D component, we see in table 4 in column 1, the outperformance of the intangible value factor, for the full sample from 1975 to 2017. We observe an alpha is 0.09 and significant at a 5% significance level. Hence, the return on intangible value factor is on average 0.09 percent higher per month compared to the traditional value factor. Thereby indicating that intangible value seems to slightly but significantly outperform traditional value. Similarly, for the other components, we see an even stronger and significant outperformance with the strongest coming from the total intangible capital component with an alpha of 0.18, closely followed by the SG&A with 0.17. respectively.

For all the subperiods the alphas are positive for all components but not always significant at a 5% significance level. For the R&D component there is no clear trend in the change in alpha over time as it increases in the 1995 to 2006 period but then decreases again to the initial level in the 2007-2017 period. Concerning the beta for the full sample, we observe a highly significant beta of 0.87, which means that on average when the intangible value factor increases by one unit, the traditional value factor increases by 0.87 on average. The high beta thereby indicates that traditional and intangible values seem to correlate highly over the full sample. Meanwhile, for the SG&A and total intangible capital component, the strongest significance can be seen in the first subperiod, followed by a positive but statistically insignificant outperformance and ending with a strong positive outperformance in the final subperiod. Overall, the total intangible value component performs best in all subperiods, followed by the SG&A component and R&D component.

Concerning the betas, for all components we see that overall the betas are close to the value of 1, indicating a rather high level of covariance between the traditional value factor and the intangible value factors. Over time there is not much change in betas, however, there is also no clear relationship over time in the changes.

Now investigating the underperformance of the intangible factor compared to the standard value factor, we regress the monthly traditional value factor onto a constant and the intangible value factor as shown in equation 8:

$$HML^{FF} = \alpha + \beta HML^{INT} + \epsilon \tag{8}$$

In the results of equation 8 for the full sample and the subperiods for the components R&D, SG&A and total intangible capital are shown in the Table 7, 8 and 9 respectively.

For all components, we observe significant underperformance at a 5% significance level in the full sample. The strongest underperformance is experienced against the total intangible component with a negative alpha of -0.11 indicating that on average traditional value performs -0.11 percentage points lower per month than intangible value. Thereby, implying that traditional value seems to significantly underperform against all intangible value components and especially against the total intangible value factor. Looking at the subsamples, the underperformance of the traditional value factor seems to be mainly driven by the most recent subperiod of 2007 - 2017, where we observe large and strongly significant alpha values. This seems to be again indicating that the intangible factors seem to perform much better as opposed to the traditional value factor especially in recent times. In terms of betas, they are again highly significant and close to 1 indicating that there is a high correlation between the respective value factors.

4.3 Performance of Investment Strategies

For each constructed intangible value factor namely SG&A, R&D, and total intangible capital, the corresponding Tables 10, 11 and 12 present the performance results of three different investment strategies, namely going long in traditional value factor, long in the respective intangible value factor, and finally, an investment strategy that is long in the intangible value factor and short in the traditional value factor. For each strategy and time period, the tables present the expected annualized return in percent per year, the volatility, and the Sharpe ratio.

Starting with the analysis of the going long in the traditional value factor HML_{FF} strategy shown in the top panel of Table 10. We observe that over the entire sample period the annualized return is 3.88% per year, which is significantly different from zero at a 5% level. Over the subperiods, we see that initially in the 1975 - 1994 subsample, the expected return is quite high at 5.26% and increases in the subsequent subsample to 7.22% per year. However, in the most recent subperiod of 2007 - 2017, it turns negative to -2.05% per year. However, the negative return of -2.05% is not significantly different from zero at a 5% significance level, as opposed to the other subperiods. A similar observation can be made with the Sharpe ratio where the ratio initially remains stable increases slightly from 0.51 to 0.58 but then plunges strongly to -0.23. As the Sharpe ratio adjusts for volatility we may thereby infer that initially returns slightly increase but then strongly decrease and even turn negative in the most recent period of 2007 - 2017.

Moving on to the analysis of the performance of the investment strategy that goes long in the different components of intangible value factor namely R&D, SG&A and total intangible capital shown in the middle panels of Table 10, Table 11 and Table 12 respectively. The return for the total intangible value factor strategy is the highest over the full sample period with an average annualized return of 5.37% followed by SG&A with 5.32% and R&D with only 5.54%. Over time, we see that in the first two periods the returns are quite large and significant and increase slightly, but that in the most recent subperiod the returns decrease strongly and become not significantly different at a 5% significance level, although they still remain positive except for the value factor that is based on R&D. Moreover, the investment strategy not only strongly outperforms the long in traditional value strategy in the full sample but also outperforms over each subsample for each of the three intangible value components. This thereby shows that intangible value does not only perform better in the most recent period of 2007 - 2017 where intangible value provides negative returns but that it provides higher returns consistently overall sample periods.

In the last panel of the three Tables 10, 11 and 12 representing the results of R&D, SG&A, and total intangible value respectively, showing the performance of the investment strategy that goes long in the intangible value factor and short traditional factor investment strategy. Again over the entire sample period, the value factor based on total intangible capital performs best with an average annualized return of 1.44%, which is significant at a 5% significance level. This is followed by the SG&A based strategy with 1.31% and R&D with 0.64%, which are however not significantly different from zero. Over the different subperiods, there seems to be the trend that the average returns increase over time where in the first two subperiods the returns tended to be small but not significantly different from zero at a 5% significance level. However, it seemed that the higher returns are mainly driven by the substantially higher returns in the most recent subperiod of 2007 - 2017.

5 How do Intangible Assets Impact the Value Factor

Comparing intangible value to traditional value starting with the asset pricing ability, for the intangible value factor constructed using total intangible capital, we do observe superior pricing errors as opposed to the model using the traditional value factor. Especially in the three-factor model plus momentum, where we observe a decreased alpha, a higher adjusted R^2, and a larger more significant risk premium for the value factor. Thereby reasserting and strengthening the significance and explanatory power of the value factor in the three-factor model plus momentum. In the five-factor model plus momentum, similar improvements are observed albeit on a bit smaller scale, thereby not performing worse and potentially slightly better. Moreover, by dissecting intangible capital into organizational capital hence SG&A and knowledge capital R&D and compute the intangible value factor base on those components, we do get a more in-depth view of the drivers of intangible value. In terms of pricing errors, the organizational capital value factor proves to have the highest outperformance producing very similar pricing errors to the total intangible value factor and even slightly outperforming it. Meanwhile, in comparison the knowledge capital value factor does not perform as well though also not performing significantly worse, this could be due to the very high correlation with the traditional value factor. Thereby indicating that the knowledge capital does not have much impact on the value factor in terms of pricing ability. On the other hand, organization capital does seem to be the main driver in terms of the better pricing errors for total intangible assets, thereby implying that intangible capital and especially the SG&A component strongly improves the asset pricing ability in our model.

Regarding the impact of intangible assets on the outperformance of intangible value compared to traditional value, we observe that the value factor based on total intangible assets as well as its components significantly outperforms the traditional value component significantly overall subperiods. The strongest outperformance arises from the total intangible asset value factor, the main driver of the outperformance among both components seems to be again the SG&A component performing much better than the R&D. Similarly, it is shown that the traditional value factor strongly underperforms in all subsamples against all intangible components. This thereby strongly suggests that adding intangible assets on average delivers significantly higher returns as opposed to the traditional value factor over all our studied subperiods.

In terms of investment strategies, going long in the intangible factor based on total intangible capital performs best with a large average annualized return of 5.23%. The outperformance holds again for all subsamples and most interestingly it delivers positive returns even in the most recent subperiod of 2007 - 2017, where traditional value had a negative annualized return of -2.05%. Although looking at the Sharpe ratios we do see that the returns adjusted for risk to decrease over time. For the two components of total intangible capital, both outperform traditional value in all subperiods, while again SG&A seems to do better. Overall we may state that intangible in terms of investment strategy also performs substantially better than traditional value.

Finally, given that on all aspects discussed total intangible capital seems to substantially outperform traditional value, we analyze the relative importance of the intangible capital components. Knowledge capital hence R&D expenditure seems to achieve the smallest positive impact on the value factor, considering that the correlation coefficient between the traditional and the R&D intangible value factor is extremely high at 0.96 over our entire sample period leaving little room for independent variation in the intangible value factor. Thereby also implying that traditional and intangible value based on R&D are very similar and that adding research and development expenditure only alters the intangible factor marginally. However, as shown in Figure 4, we see that research and development expenditure by firms in the United States increases over time initially increasing in 1994 and starting to strongly increase in 2004. The increase in research and development factor is observable in Table 4 where beta and decreases over time hence their relationship seems to decline over time. Moreover, the increase in research and development expenditure also seems to bring about better performances both in terms of relative outperformance as well as for the intangible investment strategy. Meanwhile, taking a close look at the SG&A component of intangible value we see in Figure 2 that the correlation between the SG&A based value factor and the traditional factor is 0.87, which is slightly lower than the correlation for the R&D component, which implies that SG&A has indeed a larger effect on the traditional value factor compared to R&D. However, the correlation coefficient is still large enough to capture the traditional value effect, and given this rather small change, it does seem to have a surprisingly large impact on the performance of the value factor. Given that SG&A value factor has very similar results compared to the total intangible value factor, and in terms of asset pricing ability even outperforms it, it may thereby suggest that SG&A has the largest impact among all intangibles on the Fama & French (1993) value factor.

6 Conclusion

The traditional value factor seems to have lost in significance in recent times and may have become even redundant Fama & French (2015). However, the traditional value factor only accounts for book equity which does not contain intangible assets, given the rise of intangibles in recent years it could be that the omission of it in the construction of the traditional value factor has caused it to lose its significance in recent times. Therefore, we tried to look at the different Fama & French (1993) value factors based on total intangible capital, organizational capital as well as knowledge capital, by including them in the book equity before sorting and compared them with the traditional value factor. We show that including intangibles in the construction of the value factor does lead to stronger performance over our entire sample as well in the subperiods we studied. We conclude that including total intangible capital seems not only to provide better pricing errors but also offers higher returns. Our results for the value factor that is based on total intangible value confirm the findings by K. Eisfeldt & Papanikolaou (2020) where they have very similar results showing the superior performance of including total intangible value. Interestingly in both their as well as our study, in terms of pricing ability adding intangible capital to the three-factor model plus momentum experiences the strongest increase in performance. The performance of the three-factor plus momentum model which uses intangible value is almost as strong as the traditional five-factor model plus momentum. This is an interesting observation as in Fama & French (2015) they show that including the two additional factors in the five-factor model leads to the redundancy of the value factor, they also show a negative correlation among the *CMA* factor and the value factor. However, when we use the intangible value factor, the value factor's risk premium increases in size and significance, while the *CMA* is insignificant and turns negative. This may be evidence that intangible value does capture part of the explanatory power of the factors in the five-factor model plus momentum. Thereby when including intangible assets in the value factor construction, using a three-factor model plus momentum could be viewed as a more parsimonious model with similar pricing ability. In addition, similar to K. Eisfeldt & Papanikolaou (2020) we find that the intangible capital value factor significantly outperforms the traditional value factor again in all subperiods, we were also able to construct a successful investment strategy that goes long in the intangible value factor and short in the traditional value factor. The long-short investment strategy emphasized and pinpointed the effect of including intangible capital on the value factor, especially as it provided a significant positive alpha. When it came to the different components of intangible capital, we did find that the SG&A component of intangible capital was the main driver of the superior performance of the intangible capital value factor. This confirms the findings of Banker & Zhao (2019), who found that capital markets only partly recognize the value of intangible value created through SG&A expenditure and that investing in firms with current high SG&A expenditures leads to future abnormal returns, which they suggest is probably due to mispricing of SG&A related intangible capital. This is shown by our results as SG&A related investment strategy did provide higher returns and that by including it in our asset pricing returns we could decrease the alphas. On the other hand, the R&D component of intangible capital did only provide a marginal outperformance on the R&D based value factor compared to the traditional value. Thus demonstrating that R&D seems to only deliver limited improvements to the value factor relative to the SG&A component. This is quite surprising as one would expect that investment into R&D would provide higher future returns as it would give firms a competitive advantage. However, Wang & Yang (2016) have demonstrated that high R&D expenditure have a significant relationship with enterprise risk and that the relationship is not linear but quadratic. Thereby, firms with high R&D capital and would also have proportionately larger firm risk. The consequence of higher R&D expenditure also has also been demonstrated to increase the firm's stock volatility (Chan & Sougiannis, 2001). On the other hand, SG&A expenditure could be relatively less risky as it is an investment into the organizational capital and hence human capital, which unlike R&D project is not so likely to fail, while also giving an competitive advantage on a firm level. This is substantiated by Li & Shen (2018) who in a merger and acquisition framework show that acquiring firms with higher organizational capital tend to stronger scale-down the cost of goods sold, increase innovative efficiency and achieve higher asset turnover. Thereby, showing that higher SG&A levels could offer better risk to performance compared to R&D and thereby perform better in terms of the intangible value factor.

All in all, although there still remains a lot of research to be done on measuring intangible capital and its effect on both market valuations and firms, our findings show that including intangible capital in the value factor does lead to better asset pricing models. Moreover, we find that traditional value investing strategies do not seem to have lost their edge in recent times but that by accounting for intangible assets, the significance of the value factor can be reasserted. Hence, by incorporating intangible capital we have shown that investors can construct profitable value-based investment strategies.

7 Figures

Figure 1: Monthly returns in percent for the R&D based intangible factor and the traditional factor

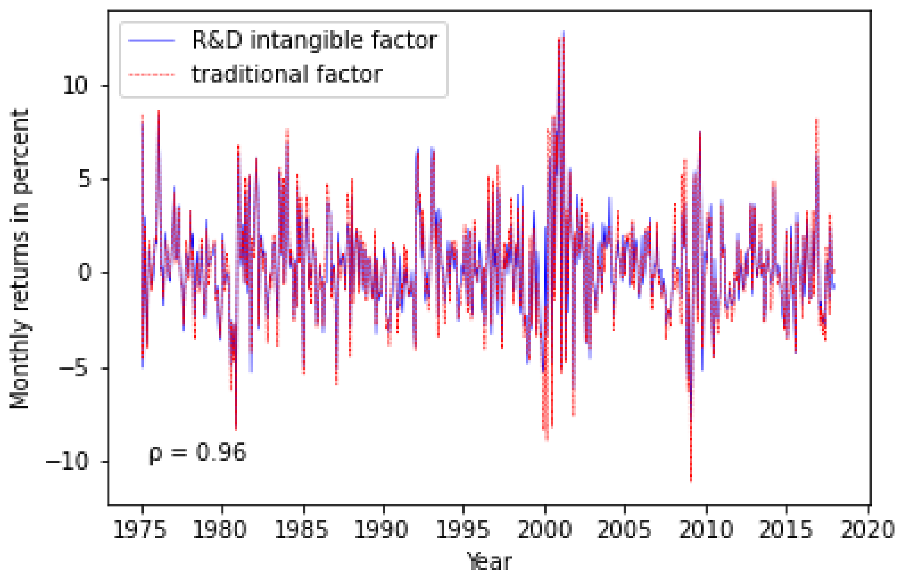


Figure 2: Monthly returns in percent for the SG&A based intangible factor and the traditional factor

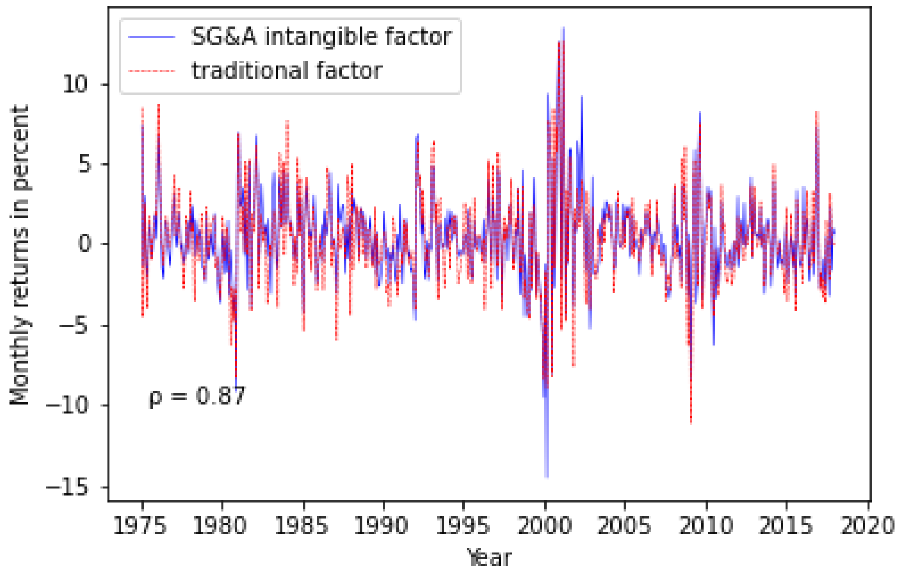


Figure 3: Monthly returns in percent for the intangible factor and the traditional factor

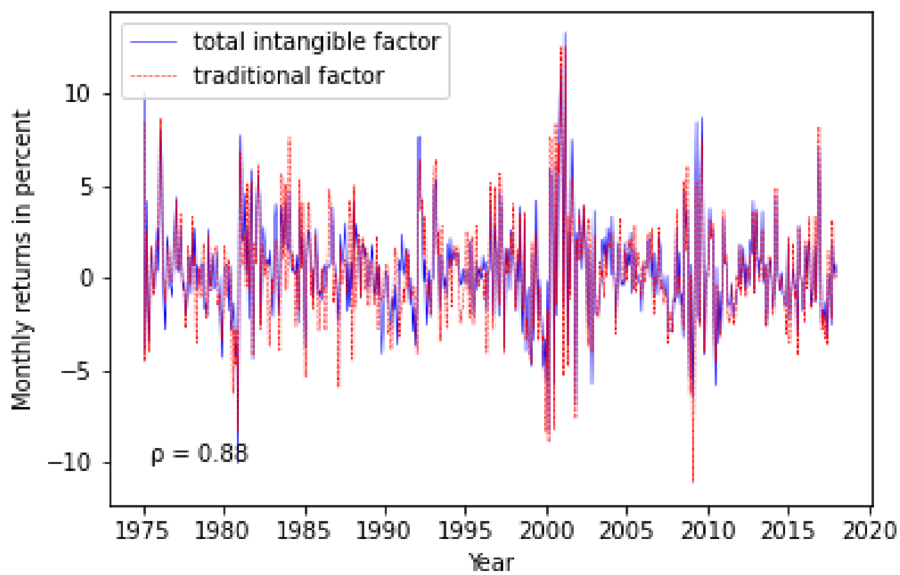
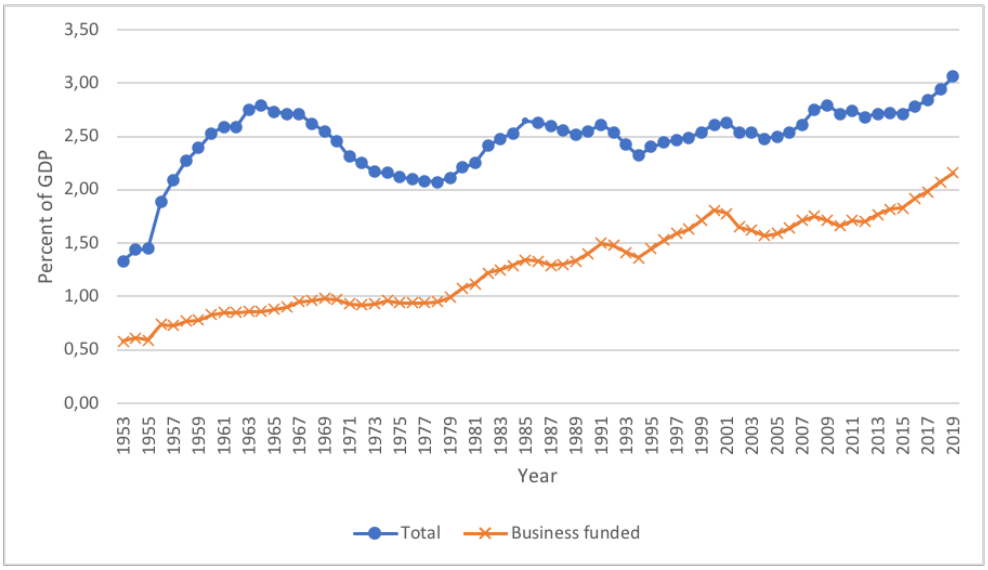


Figure 4: Ratio of U.S. R&D to gross domestic product, by source of funding for R&D



Note. The figure shows the increase in research and development as a share of GDP driven mainly by business funded research and development. National Center for Science and Engineering Statistics. 2021 (https://ncses.nsf.gov/pubs/nsf21324).

8 Tables

Table 1: Pricing Ability: Traditional Value vs Intangible Value based on R&D

	(1)	(2)	(3)	(4)
α	1.14	1.17	0.92	0.97
	(3.87)	(3.94)	(2.58)	(2.76)
β_{mkt-rf}	-0.39	-0.41	-0.22	-0.28
	(-1.37)	(-1.42)	(-0.65)	(-0.83)
β_{SMB}	0.19	0.19	0.33	0.33
	(4.32)	(4.19)	(5.48)	(5.66)
$\beta_{HML_{FF}}$	0.33		0.29	
	(5.38)		(4.57)	
$\beta_{HML_{INT}}$		0.35		0.27
		(5.74)		(4.28)
β_{MOM}	0.53	0.53	0.51	0.51
	(6.01)	(5.98)	(6.05)	(6.20)
β_{RMW}			0.37	0.43
			(2.35)	(2.58)
β_{CMA}			0.02	-0.08
			(0.07)	(-0.34)
adj. R^2	0.74	0.73	0.80	0.77
Prob. $< \chi^2$		0.02		0.04

Table 2: Pricing Ability: Traditional Value vs Intangible Value based on SG&A

	(1)	(2)	(3)	(4)
α	1.14	0.95	0.92	1.14
	(3.87)	(3.31)	(2.58)	(3.30)
β_{mkt-rf}	-0.39	-0.21	-0.22	-0.43
	(-1.37)	(-0.78)	(-0.65)	(-1.30)
β_{SMB}	0.19	0.22	0.33	0.31
	(4.32)	(5.20)	(5.48)	(5.73)
$\beta_{HML_{FF}}$	0.33		0.29	
	(5.38)		(4.57)	
$\beta_{HML_{INT}}$		0.38		0.46
		(6.34)		(6.49)
β_{MOM}	0.53	0.52	0.51	0.51
	(6.01)	(6.56)	(6.05)	(6.57)
β_{RMW}			0.37	0.33
			(2.35)	(2.55)
β_{CMA}			0.02	-0.14
			(0.07)	(-0.75)
adj. R^2	0.74	0.78	0.80	0.79
Prob. $< \chi^2$		0.86		0.82

Table 3: Pricing Ability: Traditional Value vs Intangible Value based on Total Intangible Capital

	(1)	(2)	(3)	(4)
α	1.14	1.03	0.92	0.99
	(3.87)	(3.60)	(2.58)	(3.02)
β_{mkt-rf}	-0.39	-0.29	-0.22	-0.29
	(-1.37)	(-1.04)	(-0.65)	(-0.93)
β_{SMB}	0.19	0.20	0.33	0.33
	(4.32)	(4.78)	(5.48)	(5.96)
$\beta_{HML_{FF}}$	0.33		0.29	
	(5.38)		(4.57)	
$\beta_{HML_{INT}}$		0.37		0.43
		(5.66)		(5.98)
β_{MOM}	0.53	0.53	0.51	0.52
	(6.01)	(6.45)	(6.05)	(6.58)
β_{RMW}			0.37	0.42
			(2.35)	(2.92)
β_{CMA}			0.02	-0.07
			(0.07)	(-0.69)
adj. R^2	0.74	0.77	0.80	0.79
Prob. $< \chi^2$		0.92		0.94

Table 4: Outperformance of the Intangible Value Factor based on R&D compared to the Traditional Value Factor

	Full sample	1975 - 1994	1995 - 2006	2007 - 2017
	(1)	(2)	(3)	(4)
α	0.09	0.07	0.14	0.07
	(2.81)	(1.8)	(1.61)	(1.32)
β	0.87	0.92	0.83	0.85
	(46.8)	(58.3)	(20.32)	(29.26)
adj. R^2	0.92	0.95	0.89	0.93

Table 5: Outperformance of the Intangible Value Factor based on SG&A compared to the Traditional Value Factor

	Full sample	1975 - 1994	1995 - 2006	2007 - 2017
	(1)	(2)	(3)	(4)
α	0.17	0.23	0.05	0.18
	(2.75)	(2.64)	(0.37)	(1.82)
β	0.81	0.70	0.95	0.78
	(26.41)	(17.55)	(18.12)	(15.76)
adj. R^2	0.75	0.66	0.84	0.77

Table 6: Outperformance of the Intangible Value Factor based on Total Intangible Capital compared to the Traditional Value Factor

	Full sample	1975 - 1994	1995 - 2006	2007 - 2017
	(1)	(2)	(3)	(4)
α	0.18	0.25	0.10	0.19
	(3.39)	(2.71)	(1.06)	(2.35)
β	0.79	0.73	0.83	0.84
	(31.24)	(15.45)	(22.99)	(16.26)
adj. R^2	0.77	0.64	0.86	0.86

Table 7: Underperformance of the Traditional Value Factor compared to the Intangible Value based only on R&D

	Full sample	1975 - 1994	1995 - 2006	2007 - 2017
	(1)	(2)	(3)	(4)
α	-0.07	-0.05	-0.09	-0.09
	(-2.00)	(-1.17)	(-0.88)	(-1.48)
β	1.06	1.03	1.07	1.09
	(63.95)	(62.39)	(31.45)	(28.12)
adj. R^2	0.92	0.95	0.89	0.93

Table 8: Underperformance of the Traditional Value Factor compared to the Intangible Value based only on SG&A

	Full sample	1975 - 1994	1995 - 2006	2007 - 2017
	(1)	(2)	(3)	(4)
α	-0.08	-0.08	0.05	-0.22
	(-1.19)	(-0.76)	(0.47)	(-1.92)
β	0.93	0.95	0.88	0.99
	(29.52)	(22.86)	(17.82)	(18.01)
adj. R^2	0.75	0.66	0.84	0.77

Table 9: Underperformance of the Traditional Value Factor compared to the Intangible Value based on Total Intangible Capital

	Full sample	1975 - 1994	1995 - 2006	2007 - 2017
	(1)	(2)	(3)	(4)
α	-0.11	-0.07	-0.02	-0.22
	(-1.74)	(-0.67)	(-0.212)	(-2.45)
β	0.97	0.88	1.04	1.01
	(36.02)	(21.97)	(24.80)	(16.62)
adj. R^2	0.77	0.64	0.86	0.86

Table 10: Performance of Investment Strategies based on Intangible Value using only the R&D Component

		Full sample	1975-1994	1995-2006	2007-2017
		(1)	(2)	(3)	(4)
	E[R]	3.88	5.26	7.22	-2.05
		(2.50)	(2.53)	(2.05)	(-0.74)
$\mathbf{HML_{FF}}$	stdev	10.00	9.08	11.80	9.29
	Sharpe ratio	0.35	0.51	0.58	-0.23
	E[R]	4.54	5.68	7.78	-0.87
		(3.21)	(2.89)	(2.50)	(-0.35)
$\mathbf{HML_{INT}}$	stdev	9.08	8.57	10.42	8.23
	Sharpe ratio	0.46	0.59	0.72	-0.11
	E[R]	0.64	0.40	0.52	1.20
		(1.45)	(0.83)	(0.46)	(1.52)
$\mathbf{HML_{INT} - HML_{FF}}$	stdev	2.87	2.15	3.95	2.60
	Sharpe ratio	0.09	-0.09	0.05	0.44

Table 11: Performance of Investment Strategies based on Intangible Value using only the SG&A Component

		Full sample	1975-1994	1995-2006	2007-2017
		(1)	(2)	(3)	(4)
	E[R]	3.88	5.26	7.22	-2.05
		(2.50)	(2.53)	(2.05)	(-0.74)
$\mathbf{HML_{FF}}$	stdev	10.00	9.08	11.80	9.29
	Sharpe ratio	0.35	0.51	0.58	-0.23
	E[R]	5.23	6.56	7.47	0.52
		(3.58)	(3.66)	(2.03)	(0.21)
$\mathbf{HML_{INT}}$	stdev	9.38	7.79	12.30	8.21
	Sharpe ratio	0.52	0.77	0.58	0.06
	E[R]	1.31	1.24	0.23	2.62
		(1.70)	(1.04)	(0.16)	(1.93)
$\mathbf{HML_{INT} - HML_{FF}}$	stdev	5.00	5.29	4.99	4.46
	Sharpe ratio	0.19	0.12	-0.02	0.57

Table 12: Performance of Investment Strategies based on Intangible Value using total Intangible Capital

		Full sample	1975-1994	1995-2006	2007-2017
		(1)	(2)	(3)	(4)
	E[R]	3.88	5.26	7.22	-2.05
		(2.50)	(2.53)	(2.05)	(-0.74)
$\mathbf{HML_{FF}}$	stdev	10.00	9.08	11.80	9.29
	Sharpe ratio	0.35	0.51	0.58	-0.23
	E[R]	5.37	7.03	7.18	0.52
		(3.81)	(3.67)	(2.29)	(0.20)
$\mathbf{HML_{INT}}$	stdev	9.03	8.30	10.50	8.47
	Sharpe ratio	0.55	0.78	0.65	0.05
	E[R]	1.44	1.69	-0.04	2.62
		(1.97)	(1.36)	(-0.03)	(2.44)
$\mathbf{HML_{INT} - HML_{FF}}$	stdev	4.76	5.50	4.39	3.51
	Sharpe ratio	0.22	0.20	-0.08	0.73

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9 Appendix

Listing 1: Modified code from the WRDS website used for the construction of intangible value factor

```
import pandas as pd
import numpy as np
import datetime as dt
import wrds
import psycopg2
import matplotlib.pyplot as plt
from dateutil.relativedelta import *
from pandas.tseries.offsets import *
from scipy import stats

###################
# Connect to WRDS #
###################
conn=wrds.Connection()

###################
# Compustat Block #
###################
comp = conn.raw_sql("""
                    select gvkey, datadate, at, pstkl,
                        txditc,
                    pstkrv, seq, pstk, xrd
```

```
                    from comp.funda
                    where indfmt='INDL'
                    and datafmt='STD'
                    and popsrc='D'
                    and consol='C'
                    and datadate >= '01/01/1959'
                    """)

comp['datadate']=pd.to_datetime(comp['datadate'])
#convert datadate to date fmt
comp['year']=comp['datadate'].dt.year

# create preferrerd stock
comp['ps']=np.where(comp['pstkrv'].isnull(), comp['pstkl'],
    comp['pstkrv'])
comp['ps']=np.where(comp['ps'].isnull(),comp['pstk'], comp[
    'ps'])
comp['ps']=np.where(comp['ps'].isnull(),0,comp['ps'])

comp['txditc']=comp['txditc'].fillna(0)

#
    ###################################################################

#ADDING R&D and depreciating it
#
    ###################################################################
```

```
import math
comp['depr_xrd'] = 0 #initiate new r&d column

comp['xrd'] = comp['xrd'].fillna(0) #convert Nan into zeros
    for xrd

#create double cursor
prev_comp = comp['gvkey'][0]
prev_RD = 0

for index, row in comp.iterrows():

    if prev_comp == row['gvkey']:

        comp.loc[index, 'depr_xrd'] = round(row['xrd'] +
            prev_RD*0.85, 3)

        prev_RD = round(row['xrd'] + prev_RD*0.85, 3)

    else:
        #newly initialise
        prev_comp = row['gvkey']
        #prev_RD = 0
```

```
        #compute
        comp.loc[index, 'depr_xrd'] = row['xrd']
        prev_RD = row['xrd']


#
    ############################################################

#My part stops here
#
    ############################################################



#here I now change book equity
# create book equity
comp['int_be']=comp['seq']+comp['txditc']+comp['depr_xrd']-
    comp['ps']
comp['int_be']=np.where(comp['int_be']>0, comp['int_be'],
    np.nan)

# number of years in Compustat
comp=comp.sort_values(by=['gvkey','datadate'])
comp['count']=comp.groupby(['gvkey']).cumcount()

comp=comp[['gvkey','datadate','year','int_be','count']]
```

```
###################
# CRSP Block        #
###################
# sql similar to crspmerge macro
crsp_m = conn.raw_sql("""
                        select a.permno, a.permco, a.date, b.
                           shrcd, b.exchcd,
                        a.ret, a.retx, a.shrout, a.prc
                        from crsp.msf as a
                        left join crsp.msenames as b
                        on a.permno=b.permno
                        and b.namedt<=a.date
                        and a.date<=b.nameendt
                        where a.date between '01/01/1959' and
                             '12/31/2017'
                        and b.exchcd between 1 and 3
                        """)

# change variable format to int
crsp_m[['permco','permno','shrcd','exchcd']]=crsp_m[['
    permco','permno','shrcd','exchcd']].astype(int)

# Line up date to be end of month
crsp_m['date']=pd.to_datetime(crsp_m['date'])
crsp_m['jdate']=crsp_m['date']+MonthEnd(0)

# add delisting return
```

```
dlret = conn.raw_sql("""
                    select permno, dlret, dlstdt
                    from crsp.msedelist
                    """)
dlret.permno=dlret.permno.astype(int)
dlret['dlstdt']=pd.to_datetime(dlret['dlstdt'])
dlret['jdate']=dlret['dlstdt']+MonthEnd(0)

crsp = pd.merge(crsp_m, dlret, how='left',on=['permno','
   jdate'])
crsp['dlret']=crsp['dlret'].fillna(0)
crsp['ret']=crsp['ret'].fillna(0)
crsp['retadj']=(1+crsp['ret'])*(1+crsp['dlret'])-1
crsp['me']=crsp['prc'].abs()*crsp['shrout'] # calculate
   market equity
crsp=crsp.drop(['dlret','dlstdt','prc','shrout'], axis=1)
crsp=crsp.sort_values(by=['jdate','permco','me'])

### Aggregate Market Cap ###
# sum of me across different permno belonging to same
   permco a given date
crsp_summe = crsp.groupby(['jdate','permco'])['me'].sum().
   reset_index()
# largest mktcap within a permco/date
crsp_maxme = crsp.groupby(['jdate','permco'])['me'].max().
   reset_index()
# join by jdate/maxme to find the permno
```

```
crsp1=pd.merge(crsp, crsp_maxme, how='inner', on=['jdate','
    permco','me'])
# drop me column and replace with the sum me
crsp1=crsp1.drop(['me'], axis=1)
# join with sum of me to get the correct market cap info
crsp2=pd.merge(crsp1, crsp_summe, how='inner', on=['jdate',
    'permco'])
# sort by permno and date and also drop duplicates
crsp2=crsp2.sort_values(by=['permno','jdate']).
    drop_duplicates()

# keep December market cap
crsp2['year']=crsp2['jdate'].dt.year
crsp2['month']=crsp2['jdate'].dt.month
decme=crsp2[crsp2['month']==12]
decme=decme[['permno','date','jdate','me','year']].rename(
    columns={'me':'dec_me'})

### July to June dates
crsp2['ffdate']=crsp2['jdate']+MonthEnd(-6)
crsp2['ffyear']=crsp2['ffdate'].dt.year
crsp2['ffmonth']=crsp2['ffdate'].dt.month
crsp2['1+retx']=1+crsp2['retx']
crsp2=crsp2.sort_values(by=['permno','date'])

# cumret by stock
crsp2['cumretx']=crsp2.groupby(['permno','ffyear'])['1+retx
```

```
    '].cumprod()
# lag cumret
crsp2['lcumretx']=crsp2.groupby(['permno'])['cumretx'].
    shift(1)

# lag market cap
crsp2['lme']=crsp2.groupby(['permno'])['me'].shift(1)

# if first permno then use me/(1+retx) to replace the
    missing value
crsp2['count']=crsp2.groupby(['permno']).cumcount()
crsp2['lme']=np.where(crsp2['count']==0, crsp2['me']/crsp2[
    '1+retx'], crsp2['lme'])

# baseline me
mebase=crsp2[crsp2['ffmonth']==1][['permno','ffyear', 'lme'
    ]].rename(columns={'lme':'mebase'})

# merge result back together
crsp3=pd.merge(crsp2, mebase, how='left', on=['permno','
    ffyear'])
crsp3['wt']=np.where(crsp3['ffmonth']==1, crsp3['lme'],
    crsp3['mebase']*crsp3['lcumretx'])

decme['year']=decme['year']+1
decme=decme[['permno','year','dec_me']]
```

```
# Info as of June
crsp3_jun = crsp3[crsp3['month']==6]

crsp_jun = pd.merge(crsp3_jun, decme, how='inner', on=['
    permno','year'])
crsp_jun=crsp_jun[['permno','date', 'jdate', 'shrcd','
    exchcd','retadj','me','wt','cumretx','mebase','lme','
    dec_me']]
crsp_jun=crsp_jun.sort_values(by=['permno','jdate']).
    drop_duplicates()

#######################
# CCM Block           #
#######################
ccm=conn.raw_sql("""
                  select gvkey, lpermno as permno, linktype
                     , linkprim,
                  linkdt, linkenddt
                  from crsp.ccmxpf_linktable
                  where substr(linktype,1,1)='L'
                  and (linkprim ='C' or linkprim='P')
                  """)

ccm['linkdt']=pd.to_datetime(ccm['linkdt'])
ccm['linkenddt']=pd.to_datetime(ccm['linkenddt'])
# if linkenddt is missing then set to today date
ccm['linkenddt']=ccm['linkenddt'].fillna(pd.to_datetime('
```

```
    today'))

ccm1=pd.merge(comp[['gvkey','datadate','int_be', 'count']],
    ccm,how='left',on=['gvkey'])
ccm1['yearend']=ccm1['datadate']+YearEnd(0)
ccm1['jdate']=ccm1['yearend']+MonthEnd(6)

# set link date bounds
ccm2=ccm1[(ccm1['jdate']>=ccm1['linkdt'])&(ccm1['jdate']<=
    ccm1['linkenddt'])]
ccm2=ccm2[['gvkey','permno','datadate','yearend', 'jdate','
    int_be', 'count']]

# link comp and crsp
ccm_jun=pd.merge(crsp_jun, ccm2, how='inner', on=['permno',
     'jdate'])
ccm_jun['beme']=ccm_jun['int_be']*1000/ccm_jun['dec_me']

# select NYSE stocks for bucket breakdown
# exchcd = 1 and positive beme and positive me and shrcd in
     (10,11) and at least 2 years in comp
nyse=ccm_jun[(ccm_jun['exchcd']==1) & (ccm_jun['beme']>0) &
     (ccm_jun['me']>0) & (ccm_jun['count']>1) & ((ccm_jun['
    shrcd']==10) | (ccm_jun['shrcd']==11))]
# size breakdown
nyse_sz=nyse.groupby(['jdate'])['me'].median().to_frame().
    reset_index().rename(columns={'me':'sizemedn'})
```

```python
# beme breakdown
nyse_bm=nyse.groupby(['jdate'])['beme'].describe(
    percentiles=[0.3, 0.7]).reset_index()
nyse_bm=nyse_bm[['jdate','30%','70%']].rename(columns={'30%
    ':'bm30', '70%':'bm70'})

nyse_breaks = pd.merge(nyse_sz, nyse_bm, how='inner', on=['
    jdate'])
# join back size and beme breakdown
ccm1_jun = pd.merge(ccm_jun, nyse_breaks, how='left', on=['
    jdate'])


# function to assign sz and bm bucket
def sz_bucket(row):
    if row['me']==np.nan:
        value=''
    elif row['me']<=row['sizemedn']:
        value='S'
    else:
        value='B'
    return value

def bm_bucket(row):
    if 0<=row['beme']<=row['bm30']:
        value = 'L'
    elif row['beme']<=row['bm70']:
```

```
            value='M'
        elif row['beme']>row['bm70']:
            value='H'
        else:
            value=''
        return value

# assign size portfolio
ccm1_jun['szport']=np.where((ccm1_jun['beme']>0)&(ccm1_jun[
    'me']>0)&(ccm1_jun['count']>=1), ccm1_jun.apply(
    sz_bucket, axis=1), '')
# assign book-to-market portfolio
ccm1_jun['bmport']=np.where((ccm1_jun['beme']>0)&(ccm1_jun[
    'me']>0)&(ccm1_jun['count']>=1), ccm1_jun.apply(
    bm_bucket, axis=1), '')
# create positivebmeme and nonmissport variable
ccm1_jun['posbm']=np.where((ccm1_jun['beme']>0)&(ccm1_jun['
    me']>0)&(ccm1_jun['count']>=1), 1, 0)
ccm1_jun['nonmissport']=np.where((ccm1_jun['bmport']!=''),
    1, 0)

# store portfolio assignment as of June
june=ccm1_jun[['permno','date', 'jdate', 'bmport','szport',
    'posbm','nonmissport']]
june['ffyear']=june['jdate'].dt.year

# merge back with monthly records
```

```python
crsp3 = crsp3[['date','permno','shrcd','exchcd','retadj','
    me','wt','cumretx','ffyear','jdate']]
ccm3=pd.merge(crsp3,
        june[['permno','ffyear','szport','bmport','posbm','
            nonmissport']], how='left', on=['permno','ffyear
            '])

# keeping only records that meet the criteria
ccm4=ccm3[(ccm3['wt']>0)& (ccm3['posbm']==1) & (ccm3['
    nonmissport']==1) &
          ((ccm3['shrcd']==10) | (ccm3['shrcd']==11))]

############################
# Form Fama French Factors #
############################

# function to calculate value weighted return
def wavg(group, avg_name, weight_name):
    d = group[avg_name]
    w = group[weight_name]
    try:
        return (d * w).sum() / w.sum()
    except ZeroDivisionError:
        return np.nan

# value-weigthed return
vwret=ccm4.groupby(['jdate','szport','bmport']).apply(wavg,
```

```
    'retadj','wt').to_frame().reset_index().rename(columns
    ={0: 'vwret'})
vwret['sbport']=vwret['szport']+vwret['bmport']

# firm count
vwret_n=ccm4.groupby(['jdate','szport','bmport'])['retadj'
    ].count().reset_index().rename(columns={'retadj':'
    n_firms'})
vwret_n['sbport']=vwret_n['szport']+vwret_n['bmport']

# tranpose
ff_factors=vwret.pivot(index='jdate', columns='sbport',
    values='vwret').reset_index()
ff_nfirms=vwret_n.pivot(index='jdate', columns='sbport',
    values='n_firms').reset_index()

# create SMB and HML factors
ff_factors['WH']=(ff_factors['BH']+ff_factors['SH'])/2
ff_factors['WL']=(ff_factors['BL']+ff_factors['SL'])/2
ff_factors['int_WHML'] = ff_factors['WH']-ff_factors['WL']
ff_factors['int_WHML'] = 100*ff_factors['int_WHML'] #
    rescale

ff_factors['WB']=(ff_factors['BL']+ff_factors['BM']+
    ff_factors['BH'])/3
ff_factors['WS']=(ff_factors['SL']+ff_factors['SM']+
    ff_factors['SH'])/3
```

```
ff_factors['WSMB'] = ff_factors['WS']-ff_factors['WB']
ff_factors['WSMB'] = 100*ff_factors['WSMB'] #rescale
ff_factors=ff_factors.rename(columns={'jdate':'date'})

# n firm count
ff_nfirms['H']=ff_nfirms['SH']+ff_nfirms['BH']
ff_nfirms['L']=ff_nfirms['SL']+ff_nfirms['BL']
ff_nfirms['HML']=ff_nfirms['H']+ff_nfirms['L']

ff_nfirms['B']=ff_nfirms['BL']+ff_nfirms['BM']+ff_nfirms['
    BH']
ff_nfirms['S']=ff_nfirms['SL']+ff_nfirms['SM']+ff_nfirms['
    SH']
ff_nfirms['SMB']=ff_nfirms['B']+ff_nfirms['S']
ff_nfirms['TOTAL']=ff_nfirms['SMB']
ff_nfirms=ff_nfirms.rename(columns={'jdate':'date'})

#saving into a .csv document

ff_factors.to_csv('intangible_FF_factor_SCALED.csv')
```

Listing 2: Computation of Fama Macbeth regression (1973)

```
from numpy import mat, mean
from pandas import read_csv
import statsmodels.api as sm
```

```
import pandas as pd
import numpy as np



factors = read_csv('int_FF5_MOM_FINAL.csv')
rf = read_csv('OFFICIAL_FF5_trimmed.CSV')

port10 = read_csv('trimmed_port10.csv')
port25 = read_csv('trimmed_port25.csv')



# Split using both named colums and ix for larger blocks
dates = factors['Date'].values
factors = factors[['Mkt-RF','SMB','int_WHML','RMW','CMA','
    MOM']].values
riskfree = rf['RF'].values
port_A = port25.iloc[:,1:].values
port_B = port10.iloc[:,1:].values

# Use mat for easier linear algebra
factors = mat(factors)
riskfree = mat(riskfree)
portfolio_A = mat(port_A)
portfolio_B = mat(port_B)
```

```
portfolios = np.concatenate((portfolio_A, portfolio_B),
    axis=1)


# Shape information
T,K = factors.shape
T,N = portfolios.shape
# Reshape rf and compute excess returns
riskfree.shape = T,1
excessReturns = portfolios - riskfree

# Time series regressions
X = sm.add_constant(factors)
ts_res = sm.OLS(excessReturns, X).fit()
alpha = ts_res.params[0]
beta = ts_res.params[1:]
avgExcessReturns = mean(excessReturns, 0)
# Cross-section regression
cs_res = sm.OLS(avgExcessReturns.T, sm.add_constant(beta.T)
    ).fit()
print(cs_res.summary())
riskPremia = cs_res.params

rmse_multiple = np.sqrt(1/cs_res.nobs * sum(np.square(
    cs_res.resid)))
```

```
print(rmse_multiple)
```