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Revitalizing value investing: The inclusion of intangible assets in the book-to-market ratio

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Abstract

In this study a look is taken at the effectiveness of including intangible assets into the book-to-market calculation for investment purposes. This is done using two-way test for mean difference and an expanded Fama & French four-factor model. This paper adds to the literature by comparing different methodologies of calculating intangible assets and looking at the returns received from investing in portfolios based on an intangible book-to-market ratio. No evidence is found for the Eisfeldt, Kim & Papanikolaou (2020) intangible measure outperforming the Peters & Taylor (2017) measure. Adding intangible assets into the book-to-market ratio does significantly outperform the traditional book-to-market ratio. Value portfolios constructed on the intangible book-to-market earn significantly higher returns than portfolios constructed on the traditional book-to-market ratio. The results from the expanded Fama & French four-factor model indicate that intangible assets have statistically significant explanatory power. The momentum factor is found to play a small role in the returns of value portfolios.

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Section 1. Introduction

Can value investing be revitalized? Value investing strategies pick stocks based on fundamental measures like the book-to-market (BM) ratio or the price-to-earnings (PE) ratio. However, recently many of the traditional value investing strategies have begun to underperform the market. It is time to modernize value investing and bring it back as a profitable way of investing.

One way of improving on the value investing strategy would be to add intangible assets into the book value calculation. Intangible assets have steadily risen in importance in recent years, with a large amount of research now being dedicated to looking into the effects of intangible assets on both the firm specific as well as the macro-level. But what do intangible assets entail? The IFRS definition of an intangible asset is 'an identifiable nonmonetary asset without physical substance.' (IFRS - IAS 38 Intangible Assets, 2022). To make this more concrete, this includes a company's brand, human and knowledge capital. With the general development of technological knowledge, and especially the IT revolution, an increasing part of a company's assets are actually made up of these intangible assets. Research by Ewens, Peters, and Wang (2019) found that intangible capital now makes up half of corporate capital stocks. And research by the McKinsey Global Institute (2021) found that the share of intangibles in total new investments has risen enormously. It is also quite clear that intangibles play an important part in firm performance. For example, Eisfeldt and Papanikolaou (2013) found in their research that stocks of firms with high organizational capital outperform those with low organizational capital. All of this indicates that intangibles are a growing field of interest. Intangible assets are clearly important assets for companies, however currently intangible assets are not really considered when determining the value of a company. Fairly accounting for these intangible assets can perhaps help to more accurately value companies, which in turn can help value investing regain its former overperformance. We therefore arrive at the central research question of this paper:

Can a revised book-to-market ratio which includes intangible assets help improve the returns of value investing?

So, if intangible assets really are such important drivers of returns, why have they been overlooked? As discussed by Ballow, Burgman & Molnar (2004) part of the reason intangible assets for this oversight is because managing intangible assets is exceedingly difficult, since with current accounting standards they are often badly tracked and analyzed. Therefore, calculating intangible assets fairly and correctly is no easy matter. In fact, there are multiple ways of calculating a company's intangible assets. Two of these proposed calculations work in a similar way. They use the perpetual inventory method to accumulate these expensed investments in intangible capital. There is the Eisfeldt, Kim & Papanikolaou (EKP) (2020) measure and the Peters and Taylor (PT) (2017) measure. The EKP measure takes 100% of selling, general & administrative (SG&A) costs. The PT measure takes only 30% of yearly SG&A costs but adds 100% of research & development (R&D) costs. These are combined over a number of years to construct the intangible asset variable. For intangible assets to be a beneficial addition to value investing, the best way of calculating these intangible assets will have to be determined. Therefore both measures are compared in this paper.

Previous research finds robust evidence as to the benefits of adding intangible assets into value strategies. Most of the evidence seems to indicate that intangible assets can outperform the traditional value factor. To test if the intangible BM (IBM) ratio can outperform the traditional BM (TBM) ratio, two-way tests for mean difference are performed between high IBM and TBM portfolio returns over several different holding periods. These holding periods run for lengths of 1, 2, 5 ,10, 15 & 20 years. Returns are calculated as average yearly buy-and hold returns. Additional tests are performed to determine whether the equal or unequal variances version of the two-way test for mean difference is used. The test is upper one-sided, testing for if the high IBM portfolio has higher average returns than the high TBM portfolio. To make sure any results are based on causation and not just correlation, a F&F four-factor model regression is performed to determine the explanatory value of the IBM ratio. The momentum factor is added to this to improve the power of the tests.

As can be seen in the results in section 4, considerable evidence is found that supports the importance of intangible assets. No evidence is found for there being any difference between the calculations of the EKP and PT measures. These measures capture the same companies when used in portfolio construction. However, the EKP measure is easier to construct. Furthermore, its data is more complete and contains fewer missing values. This indicates that even though the EKP measure does not necessarily have better returns than the PT measure, it is the better method when considering ease of use and data quality. Further results indicate that the IBM ratio outperforms the TBM ratio when used in portfolio construction. The EKP IBM ratio outperforms the TBM ratio in most of the holding periods. A time-series regression in the style of an expanded Fama & French four-factor model indicates a significant relationship between intangible capital and stock returns. The Intangible High-Minus-Low (IHML) factor is found to significantly effect the returns of the six F&F portfolios at the 1% level. While the momentum variable has a small significant effect on the returns of value portfolios. With these results the main research question can be positively answered. The inclusion of intangible capital into the BM calculation is found to significantly increase investment returns from a simple value investing strategy based on the IBM ratio.

The relevance of this subject comes from multiple aspects. Firstly, there is the present underperformance of value investing, which has been discussed widely in both academia and media. This makes value investing in and of itself already quite the interesting and current topic for both practitioners and researchers to explore. Secondly, there is the newfound interest in intangibles in primarily academic circles. Any research that adds to the literature on the topic of intangibles will be making a valuable contribution to current research. This paper adds to the literature by replicating the construction of two different intangible capital measurements and comparing their relative effectiveness in predicting stock returns. Further contributions come from the evaluation of the value from adding intangible capital into the BM ratio in a new and divergent way from a majority of the current literature. The use of simple methods and calculations improves reliability and makes replication easier for future research. A traditional F&F 3-factor regression is performed to easier compare results to previous literature. The Momentum variable is added to this traditional F&F 3-factor regression to test for possible explanations of high (I)BM overperformance.

The main database used for retrieving data is the merged Compustat and Center for Research in Security Prices (CRSP) database provided by Wharton Research Data Services (WRDS). The firm-specific accounting data needed to construct the (I)BM ratios and the firm-specific stock returns are pulled from this merged database. For information on how to construct the Fama & French factors needed to determine the explanatory power of the intangible value factor, the Fama & French Data Library is used. In addition, Ken French's website is used for the Fama & French industry classification. Other data is retrieved from the Federal Reserve of St. Louis website and the Bureau of Economic Analyses.

The paper is structured as follows. In section 2 the relevant literature is discussed, and the different hypotheses are substantiated. Section 3 explains the data retrieval process and provides descriptive statistics. It additionally discusses the methodology of the different calculations and tests used. In section 4 the result of the research is discussed for each hypothesis. Lastly, section 5 contains the conclusions of this paper as well as a discussion on possible improvements and ideas for future research. Section 6 includes the bibliography.

Section 2. Literature Review

2.1 Value Investing

In this paper I will look at the effect of adding intangible assets to the book-to-market (BM) calculations, and whether this improves the investment returns produced by high BM investing strategies. This research takes its place in a wide array of literature surrounding the subject of stock valuation and specifically value stocks. Both practitioners and academics have been searching for methods to consistently earn higher returns than the general stock market by selecting stocks based on certain criteria. Many of these investment strategies and pricing models exist. Some focus on investing based on the movement of the market, others try to calculate a company's value by looking at its future earnings. One of the more well-known strategies is called value investing. Value investing pertains to the selection of stocks that are trading for less than their intrinsic or fundamental value. This intrinsic value is based on a company's current business operations, profit, and assets on the balance sheet. Value investors believe that markets tend to overreact, causing stock prices to move in ways that do not seem validated by a company's actual long-term worth. Usually, certain metrics are looked at to determine whether a company is currently undervalued. Some of these metrics include the price-to-earnings (PE) ratio, debt-to-equity (DE) ratio and the book-to-market (BM) ratio. This last ratio has been seen by investors as a good indicator of whether a company is undervalued by simply comparing the assets on its balance sheet to the current market capitalization.

The earliest proponents of value investing were Graham & Dodd in their classic Security Analysis (1934). In this book, Graham & Dodd laid the intellectual foundation for value investing. They proposed that investors should be primarily focused on calculating the value of a firm’s current business operations instead of just focusing on future earnings. Scholars have also taken an interest in looking at value investing.

Particularly the BM ratio has been the subject of copious amounts of research since the 1980’s. For example, research by Rosenberg, Reid, and Lanstein (1985) found that the returns for portfolios that bought stocks with high BM ratios and sold stocks with low BM ratios showed significant outperformance. Other important research into the BM ratio comes from Fama & French (1992, 1995). In their research Fama & French looked at several different factors that could influence stock prices. These factors include the BM, (market)size, beta, investment pattern & profitability. They combined these factors into three- & five-factor asset pricing models (Fama & French, 1993, 2014). Both models include a so-called value factor. Which is constructed by subtracting the average returns of a portfolio of low BM stocks from the returns of a portfolio of high BM stocks.

The Fama & French research (1992) showed that U.S. firms with high BM ratios, so-called value stocks, outperformed 'growth' or low BM stocks. They found that on average the high BM portfolio outperformed the low BM portfolio by 0.99% per month over the sample period. This outperformance of value stocks overgrowth stocks was termed the value premium. Capaul, Rowley & Sharpe (1993) found that this value premium is also present internationally in other developed countries. These developed countries include the United Kingdom, Germany & Japan. The value factor is also present in emerging markets, as shown by Cakici, Fabozzi & Tan (2013). Research by Fama & French (1998) also found evidence for value stocks earning higher returns than growth stocks globally. All this research indicates that the value factor as proxied by the BM ratio is a valuable and consistent indicator of stock performance. Following the research from Fama & French (1992), academics have considered the BM ratio as the leading definition of value.

However, though most research does support the existence of the value premium, the reason behind its existence is less clear. Some academics follow the efficient market hypothesis (Fama, 1963), which states that the only way to increase returns is to expose yourself to more risk. So, when considering this view, high BM stocks must in some way be riskier to justify their higher returns. A possible explanation in this line of thinking comes from Chan and Chen (1991). They propose that the high BM outperformance comes from the fact that a high BM ratio is in fact a proxy for financial distress. In their view firms with high BM ratios have low stock prices because of bad future outlooks for these firms. This causes the market to price them lower to increase their expected stock returns, since investors must be compensated for the increased risks. Fama & French (1995) also maintain that the value premium is a compensation for value stocks being riskier in some way then growth stocks.

However not everybody agrees with the view that markets are efficient. Other researchers, like Lakonishok, Schleifer & Vishny (1994) think the overperformance of value can be linked to for example behavioral explanations. And that these behavioral factors result in market inefficiencies causing the (short-term) mispricing of stocks. Whatever the actual cause of value overperformance may be, a wide array of papers from Fama & French (2014) to Arnott et al (2021) do find evidence for high BM portfolios outperforming low BM portfolios. This stays true for most of the period from 1930 to the 1990's. Lately however, this overperformance has reversed. Since 2007, value has begun underperforming growth stocks by a wide margin. Arnott et al (2021) find that an annually rebalanced value portfolio would have had only 55% of the cumulative return of a growth portfolio from 2007 to 2020. Lev & Srivastave (2019), even find that the traditional high BM value investing strategy has been underperforming since before the dotcom bubble. Many explanations for this recent underperformance have been proposed, from low interest rates, to stranded assets or even the growth of private markets. Arnott et al, (2021) discount all these explanations. However, another explanation does seem to hold a lot of merit to them and others, namely the omission of intangible assets from the BM calculation.

2.2 Intangible Assets

In today's economy a company's intangible assets are a critical part of the company's ability to produce revenues and profits. Intangible assets or capital is defined by IFRS accounting standards as "an identifiable non-monetary asset without physical substance" (IFRS - IAS 38 Intangible Assets, 2022). Examples of intangible assets include human capital, patents, software, licenses, and brands. Intangible assets are now attracting a lot of interest from researchers due to their increased importance to businesses. Corrado et al (2012) find that in developed nations, investments in intangible capital make up around 40% of all capital investments. A report by the Mckinsay Institute (2021) finds that over the past 25 years the share of intangibles in new investments has increased by 29%. A paper by Marrocu, Paci & Pontis (2011) further underlines the importance of intangible capital. It shows that the productivity and output of firms in developed countries is heavily dependent on their accumulation of internal intangible capital. Roth & Thum (2013) find for a dataset of European businesses that investments in intangible capital increase labor productivity growth. Further research by Piekkola (2011) finds that intangible capital investments improve the profitability of firms and lead to increasing returns in intangible capital-intensive countries. The literature thus indicates that intangible capital is vital to companies. All this recent research shows the massive importance of intangible capital in today's capital mix. However, even though the importance of intangible assets is quite clear, often they are not fairly accounted for on balance sheets or financial statements. Investments in brand, knowledge or human capital are often accounted for as expenses instead of investments. Meaning they are at best partially represented on the balance sheet. Researchers have also noted this undercounting of intangibles, as Corrado et al (2012) discuss conventional calculations of business investments usually only consist of tangible assets like property, plant & equipment. This causes intangible assets to be vastly understated in the capital mix. Arnott et al, (2021) explain that the current measure of book value only captures traditional tangible capital, like real estate, machinery & financial assets. Intangible assets are almost entirely excluded from the accounting for book value. Only part of intangible investments ends up on the balance sheet as contributed capital or through goodwill in case of acquisitions. This lack of accounting for intangible assets on the balance sheet, also means that the intangible capital is not used in the BM calculations. By leaving out intangible capital from the BM ratio the true fundamental value of a business is severely understated. This undermines the effectiveness of value investing strategies that make use of the BM ratio. To counteract this understatement and to start to value firms more fairly, valuation methods need to change. Investors will need to construct a measure to account for the expenses in intangibles and combine them into a new intangible book-to-market or IBM ratio.

Because investments in intangible assets have not been recorded on the balance sheet, but instead have been seen as expenses, there is no easily obtainable number like there is for book value. So, a measure will have to be used that takes historically expensed intangibles and combines them to construct an intangible asset variable. In the literature several different calculations and measures have been used for this purpose. This paper will look at two of such measures and will compare their effectiveness. These will be the Eisfeldt, Kim & Papanikolaou (EKP) (2013) and the Peters & Taylor (PT) (2017) measures. A brief description of both methods will follow, a more detailed view can be found in Section 3. The EKP measure takes 100% of SG&A costs, combines them each year into one intangible asset variable and depreciates them at a constant rate. The PT measure takes only 30% of yearly SG&A costs but adds 100% of R&D costs. These are combined over several years to construct an intangible asset post.

These intangible assets are depreciated at varying rates depending on the industry to which the firm belongs. EKP themselves find in a later paper that their original measure performs better than the PT measure when used in a Fama & French type HML regression (Eisfeldt, Kim & Papanikolaou, 2020). Research by Ewans, Peters & Wang (2019) finds that the inclusion of the PT measure into the HML calculation does increase the HML portfolio returns significantly. EKP argue in their paper that taking 100% of SG&A expenses provides a more reliable intangible capital estimate than the PT measure. Since, according to them, there is no reason to break out R&D expenses but not advertising or other intangible expenses. Furthermore, they argue that R&D expenses, and several other variables used in the PT measure, often have substantial amounts of missing observations. This is caused by the fact that many companies do not separately record R&D expenses. For this missing data, assumptions must be made, which impact the reliability of the intangible capital measurement produced by the PT method. However, because both measures do seem to produce improvements to the return of value portfolios, it is interesting to do further research on both measures to compare them. Because of the previous results from EKP (2020), the first hypothesis will be:

High IBM portfolios formed with the Eisfeldt, Kim & Papanikolaou (2013) intangibles measure earn higher returns than high IBM portfolios formed with the Peters & Taylor (2017) intangible measure.

Another interesting question to ask is whether the addition of intangibles to the BM ratio can improve the recent returns of value investing. Considering the increasing importance of intangible assets for businesses and the fact that intangible assets are undercapitalized on the balance sheet. The inclusion of intangibles could help improve the accuracy of the BM ratio in indicating a company's value. Improving the accuracy of a company's valuation should increase investment returns when following a high (I)BM value investing strategy. Since the strategy can then better select companies that are undervalued. A large amount of recent research shows this to be the case. In their 2020 paper Eisfeldt, Kim & Papanikolaou find that their IHML factor manages to significantly outperform the traditional HML factor by as much as 2.11% annually. Arnott et al (2021) also find in their research that if intangible assets had been included in the standard HML Factor, that this would also improve its annual return by 2.2%. Therefore, the second hypothesis is:

High IBM portfolios will perform better than High TBM portfolios and will earn higher average returns.

Looking at portfolios constructed from High IBM can give valuable insights in return characteristics and the added value of intangibles. However, since these portfolios only consider the level of the IBM ratios it is possible that there are other factors that are causing the return characteristics of the portfolios. Therefore, it is important to look at the explanatory power of intangibles in predicting stock returns while accounting for several other factors. One key factor that could very well be impacting any results is the (market)size factor, Fama & French (1992) show that smaller firms earn higher returns than larger ones, and that there is also an interaction effect between the value and size factor. Another important factor closely related to the value factor is momentum. The momentum factor is one of the most well-documented factors in finance. It is the tendency of past winner stocks to continue to outperform past loser stocks over a 6-to-12-month period (Rouwenhorst, 2022). Connected to the momentum factor there is also the reversal factor. This states that in the long-term past winners become losers and, vice versa, past losers become winners (Kelly, Moskowitz & Pruitt, 2021). The momentum, or momentum reversal, could be important in explaining the returns of value stocks. Because of this, including a momentum variable into a Fama & French 3-factor model might help improve predictive power. The papers of EKP (2020) and Park (2022) also test for the significance of intangible capital by performing a Fama-McBeth regression on the three-factor F&F model, including IHML instead of HML. They find that the IHML factor has statistically significant explanatory power when used in a F&F three-factor model. I expect these relationships to hold in this research. Furthermore, using the F&F three-factor model to test for the significance of the IHML factor will also allow for more accurate comparisons to previous papers, since most of the previous literature on this subject is done using the F&F factors. Therefore, the third hypothesis becomes:

The intangible value factor has significant explanatory power in explaining portfolio returns when using an expanded F&F four *-factor model including momentum.*

Section 3. Data & Methodology

3.1 Data

In this section the data retrieval process is described, as well as the methods used to filer the data. The portfolio formation is discussed and lastly the descriptive statistics of the sample are described.

3.1.1 Data Retrieval & Exclusion

The majority of the data is retrieved from the merged Compustat, and Center for Research in Security Prices (CRSP) database provided by Wharton Research Data Services (WRDS). The Compustat database contains quarterly and yearly company-level fundamental data. The CRSP database on the other hand contains security level data on stock prices and returns. For the period of 1990 to 2020 Compustat provides identifying information such as SIC & CUSIP codes. Compustat also adds balance sheet items like total assets, total liabilities, goodwill, R&D expenses, number of outstanding shares and SG&A expenses. Monthly stock prices and returns are retrieved from CRSP for a period of 2000 to 2021. The Fama & French Data Library is used for help with calculating the IHML panel data regression and for retrieving the industry specification list. Data for the yields on 1-month US treasury bills and consumer price index (CPI) levels are all retrieved from the FRED website of the St. Louis Federal Reserve Bank. Industry specific R&D depreciation rates are taken from the Bureau of Economic Analysis 2013 rapport.

Balance sheet data for all firms listed on the NYSE, NASDAQ and AMEX exchanges are retrieved from Compustat for a period from 1990 to 2020. Following EKP (2020) & PT (2017), certain industries are removed from the dataset, this includes regulated utilities (SIC 4900-4999), financial firms (6000 - 6999) and the category 'other' (9000+). Firms with fiscal years ending in any month other than December are also removed. Firms with missing, non-positive or book values below $5 million are also excluded. After this the return dataset from CRSP and the fundamental dataset from Compustat are merged based on CUSIP codes. This results in a dataset of about 2200 companies with fundamental data spanning over 30 years and return data for 20 years. The expense data used in the calculations is deflated by the CPI level, to set a standard level of expenses corrected for inflation. For SG&A, goodwill, COGS, R&D, and IR&D expenses the observation is set to zero if missing. After the calculation of the intangible capital, any firm with negative intangible capital is also removed from the sample. The IBM and TBM ratios are then winsorized at the 0.01% level to remove extreme outliers.

3.1.2 Portfolio Formation

Using the fundamentals from Compustat several different variables are constructed. The most important of these being the EKP and PT IBM ratios as well as the traditional BM (TBM) ratio. A precise description of this process can be found in section 4. These variables are used to form the firms into (I)BM portfolios. The highest 10% of firms in each measure are placed in separate 'High' (I)BM portfolios and the lowest 10% of firms are placed into 'Low' (I)BM portfolios for every year from 2000 to 2020. After portfolio formation the average annual 1, 2, 5-, 10-, 15- & 20-year returns are constructed using the CRSP stock prices for the different portfolios. Following the method of EKP (2020) the portfolio is formed in December of year t and the portfolio is 'bought' in the beginning of June the following year t + 1.

3.1.3 Descriptive statistics

Table 1 contains descriptive statistics concerning the most important variables used in the intangible capital calculation and portfolio formation.

Table 1:

Descriptive statistics

Variable	Median	Mean	Std. Dev.	Min	Max
SG&A[1]	71.18	541.18	1934.35	-292.50	86453.58
R&D	2.98	138.66	804.67	0.00	42740.00
Market value	617.84	6291.43	26882.48	0.02	1638236
Book value	258.82	2198.44	9207.84	5.01	222544.00
EKP Intangible Book Value	522.32	3826.91	14041.82	-12758.70	329710.90
PT Intangible Book Value	275.99	2168.51	9514.71	-46789.93	245856.20
EKP IBM	0.92	1.57	1.97	0.00	12.11
PT IBM	0.53	0.79	0.87	0.00	5.51
TBM	0.46	0.61	0.56	0.04	3.45

[1]: All numbers are in millions of dollars. Except for the EKP, PT IBM and TBM variables, those are ratios.

When looking at the results in Table 1 several aspects stand out. For most variables, the median is considerably lower than the mean. This indicates that this data sample is skewed towards smaller firms. The most striking example can be seen with the market value variable. Average market value is 6291.43 million, while the median market value is 617.84 million. The median value is only 1/10th of the mean value. Another interesting observation is that the EKP IBM is almost double the PT IBM in mean, median and standard deviation. This is most likely due to the way the initial capital of the PT measure is calculated. This calculation will be discussed in section 3.2.1. Since the (I)BM ratio should be used to most accurately see if a company is undervalued. Any overcounting of (intangible) assets would lead to a company looking more undervalued than it is. Leading to investments being made in the wrong companies, possibly resulting in poor performance. Because of this, the fact that the average, median & standard deviation of the PT IBM is lower than the EKP IBM should not have any effect on the results from the research.

3.2 Methodology

In this section the main variables of interest and the test model specifications are discussed. First, the main variables of interest will be discussed as well as the way in which they were calculated. After this the other variables will be discussed as well as the model specifications of the tests. The variable construction and test discussion will be centered around the different hypotheses formed in section 2.

3.2.1 Constructing EKP and PT

To answer the first hypothesis, two different measures of IBM are constructed. They follow a similar method for a large part of their calculations. The EKP and PT IBM measure differ primarily in what expenses they use to construct the intangible capital. EKP uses 100% of SG&A expenses, while PT uses 30% of SG&A expenses and 100% of R&D expenses. Additionally, EKP calculate initial intangible capital preceding the first year for which there is data by the following calculation:

$$Initial\ Capital = \left(\frac{SG\&A}{0.3}\right) \quad [1]$$

Where SG&A is the SG&A expense for the first year for which there is data, which is subdivided by a long-term average depreciation rate which they have set in their research at 30%. PT uses a different measure; in their original paper they calculate the initial intangible capital by trying to construct the probable SG&A spending before the first available data. They do this by calculating the average percentage increase of SG&A spending in the available data and using that to look back at pre-IPO data. However, they also look at a simpler method that sets initial capital to zero and find that for investing purposes this worked even better than their original method (PT, 2017). This last method is the one followed in this research because in this thesis the time-horizon is shorter than in the original PT paper. Calculating pre-IPO data on each firm going back 50 years would be both cumbersome and extremely difficult with the available data. Following this initial intangible capital, yearly intangible capital is constructed from the expense data, starting in 1990. For the EKP measure, the first yearly observation of intangible capital is calculated by adding the depreciated initial intangible capital to that year's SG&A, which results in equation 2.

$$EKP_{t=1} = (0.8 * Initial\ Capital) + SG\&A \quad [2]$$

For the following years, the intangible capital is calculated by depreciating last year's intangible capital by a set amount and adding that year's SG&A expense. The depreciation rate is set at 20% and is constant for every firm and throughout every year as can be seen in equation 3.

$$EKP_t = (0.8 * EKP_{t-1}) + SG\&A \quad [3]$$

The PT method is more complex because it uses two different expense posts in its intangible capital calculation. This results in two different intangible capital posts, organizational and knowledge capital, which are later combined to form the PT intangible capital. First yearly organizational expenses are calculated, shortened to PTO. These are calculated by the following equation:

$$PTO_t = (\ SG\&A_t - (R\&D_t * IR\&D_t)\ ) * 0.3 \quad [4]$$

Because in process R&D (IRD) is represented already in the book value of a company it must be subtracted from the R&D expenses to compensate for that. Unfortunately, in many cases the SG&A expenses from Compustat already contain R&D expenses, so to prevent double accounting R&D has to be subtracted from the SG&A expense. The resulting number is taken times 0.3 because PT maintains that only 30% of SG&A costs are investments into organizational capital (PT, 2017). However, in some cases R&D is not part of the SG&A expense post. To account for this possibility PT uses a method to screen for these occurrences. If the amount of cost of goods sold (COGS) is larger than R&D and R&D in turn is larger than SG&A expenses the PTO equation becomes:

$$PTO_t = SG\&A_t * 0.3 \quad [5]$$

Just like EKP, the PT measure then combines these yearly expenses into yearly intangible capital by adding them up and depreciating them. PT uses the same constant 20% yearly depreciation rate for organizational capital as EKP. The previous year's total PTOC is depreciated, and the current year's PTO is added to this depreciated organizational capital.

$$PTOC_t = (0.8 * PTOC_{t-1}) + PTO_t \quad [6]$$

For the PT knowledge capital or PTKC the calculation looks different. Here R&D expenses are used to construct the PTKC, furthermore PT also uses industry specific depreciation rates. Table 2, containing the different depreciation rates per industry, can be found in appendix A. PT considers 100% of R&D expenses as investments into knowledge capital. This results in equation 7:

$$PTKC_t = \ (DeprR\&D_i * R\&D_{t-1}) + R\&D_t \quad [7]$$

Adding up both PTOC and PTKC results in the total intangible capital for the PT measure. To construct the (I)BM ratios, some more variables are needed. First, market value is calculated by multiplying the number of shares outstanding with the end of the month share price of December. Further market value data was pulled from CRSP and added to this to fill in missing values.

This market value serves as the denominator in the (I)BM ratio seen in equation 8. Book value is calculated by subtracting total liabilities from total assets.
To calculate the traditional or TBM ratio book vale is divided by market value, as seen in equation 8.

$$TBM_t = \frac{Book\ Value_t}{Market\ Value_t} \quad [8]$$

Now to construct both the PT IBM and the EKP IBM respectively the intangible capital of both measures is added up to the respective book values each year while simultaneously subtracting goodwill. The resulting total capital is divided by the market value of the company to construct a yearly IBM ratio per company, this results in equation 9.

$$IBM_t = \frac{Intangible\ Capital_t + Book\ Value_t - Goodwill_t}{Market\ Value_t} \quad [9]$$

3.2.2 Comparing EKP & PT

Using these IBM ratios, each company is divided into portfolios in month 12 of each year. Taking the 10% highest and 10% lowest ratios each year to form High & Low portfolios for both measures. The average annual 1, 2, 5-, 10-, 15- & 20-year returns are calculated per portfolio. To see whether there is any difference in average results between the ‘High’ portfolios of both measures, a two-way test for mean difference is used. This test identifies whether there is a significant difference in means between the portfolios using standard deviation. Because the first hypothesis is formulated as EKP having higher average returns than PT the test is performed upper one-sided. It tests whether the High EKP portfolio performs better than the High PT portfolio for each of the average annual portfolio returns. The test for mean difference has the following null and alternative hypotheses:

$$H_0: \mu_1 = \mu_2$$
$$H_\alpha: \mu_1 > \mu_2$$

And rejects the null hypothesis in favor of the alternative hypothesis when:

$$t > t^{*Critical}$$

The t-statistic of the two-way test for mean difference is calculated using the following formula:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2})}}$$

To determine whether the two-way test for mean difference with unequal variance should be used a test for the difference in variance is performed. For those EKP and PT portfolios of the same years which have unequal variances the two-way test for mean difference with unequal variances is used. For those that could not be proven to have different variances the traditional test with equal variances is used. The results of this test for the difference in standard deviation between the EKP IBM and PT IBM portfolios can be found in Table 3.

Table 3:

Test for difference in Std. Dev for EKP BM and PT BM.

Holding period	Combined Standard Deviation
1 Year	1.382*
2 Year	0.539
5 Year	0.260
10 Year	0.152
15 Year	0.113
20 Year	0.084

* p<0.1; ** p<0.05; *** p<0.01

Only the 1 year holding period portfolios showed any sign of unequal variances, significant at the 10% level. The two-way test for mean difference is performed using both the equal and unequal variances for the 1 year holding period. No significant difference in results is found. Therefore, all the two-way tests for mean difference are performed with equal variances.

3.2.3 Comparing EKP & Traditional BM

To test the second hypothesis, first the traditional BM (TBM) is constructed by taking book-value and dividing it by that year's market value, like equation 8. Again, these TBM ratios are sorted into deciles and the top 10% highest ratios are formed into a High TBM portfolio and the lowest 10% into the Low TBM portfolio.

Two-way tests for mean difference are used on the High portfolios of the EKP IBM and the TBM, like the ones done for hypothesis 1. Another series of tests is performed to determine whether the standard deviations are unequal between the High IBM and TBM portfolios. The results can be found in Table 4. The portfolios with 5-, 15- & 20-year holding periods do not have significant differences in their variances. Therefore, their mean difference tests are performed with equal variances. The portfolios with 2- and 5-year holding periods have significant differences at the 5% level, the 1 year holding period portfolios have significant differences at the 1% level. For these portfolios, the mean difference test is performed with unequal variances.

Table 4:

Test for difference in Std. Dev for EKP BM and PT BM

Holding Period:	Combined Standard Deviation
1 Year	1.258***
2 Year	0.523**
5 Year	0.254
10 Year	0.144**
15 Year	0.108
20 Year	0.083

* p<0.1; ** p<0.05; *** p<0.01

3.2.4 IHML F&F Factor Model

To test the third hypothesis a F&F style regression is performed on the average monthly portfolio return of a group of 6 portfolios constructed on a 2x3 matrix sorted by Size and IBM. The companies are divided into three groups for the value factor, and two groups for size. The firms are sorted by the IBM variable, from small to large. Then observations above the 70th percentile are put into the value category. The observations between the 30th and 70th percentile is put into the ‘neutral’ category. Lastly the observations below the 30th percentile are added to the growth portfolio. For size two categories are made, observ^{at}ions ab^{ov}e the 50th percentile are put into the ‘big’ category, those below the 50th percentile are put into the ‘small’ category. This results in the portfolios found in Table 5.

Table 5:

2x3 portfolios on Size and IBM

	Value	Neutral	Growth
Big	Big Value (BV)	Big Neutral (BN)	Big Growth (BG)
Small	Small Value (SV)	Small Neutral (SN)	Small Growth (SG)

The F&F three-factor model uses several different factors to explain the returns of the portfolios. To allow for the correlation of the portfolios with the general market, a factor for the market risk premium is added to the regression. This market risk premium is constructed by taking the average return of the entire sample per period and subtracting the risk-free rate of that period. For the risk-free rate, the yield on the US 1-month treasury bill is used. To account for the fact that small firms outperform big firms a factor is included that accounts for the difference in returns between big and small firms. This small-minus-big (SMB) factor is constructed by subtracting the average returns of big firms from the average return of small firms for each period. The main variable of interest, the IHML factor, is constructed in a comparable way. It is constructed by subtracting the average return of growth firms from the average returns of value firms per period.

Added to this classic F&F 3-factor model is the momentum factor (MOM), this looks at the 12-month previous running returns of the portfolio. The momentum factor might be an important indicator of future stock performance. (Rouwenhorst, 2022) find that stocks that have had positive 6- to 12-month returns tend to keep outperforming stocks that have had underperformance for a previous 6- to 12-month period. The addition of all these variables results in the following regression:

$$R_p = \alpha + (R_m - R_f) + cIHML + dSMB + eMOM$$

Where the alpha 'α' is the constant, which measures the amount of overperformance of the portfolio, not captured by the different factors. This constant should be close to zero, since the three F&F factors account should account for all the returns.

Section 4. Results

4.1 The portfolio returns

In this section the results of the research will be discussed. The results are centered around the three hypotheses, so they will be looked at in that order. In Table 6 the average returns for the high and low portfolios of the different measures can be found, as well as the average returns of the entire sample.

Table 6:

Average annualized portfolio and sample returns

Portfolios	1 Year[1]	2 Year	5 Year	10 Year	15 Year	20 Year
			EKP			
High ratio	0.367[1]	0.197	0.130	0.104	0.108	0.107
(Std. Error)	(0.029)	(0.012)	(0.007)	(0.006)	(0.007)	(0.014)
Low ratio	0.089	0.034	0.029	0.039	0.051	0.014
(Std. Error)	(0.012)	(0.007)	(0.005)	(0.004)	(0.005)	(0.016)
			PT			
High ratio	0.344	0.187	0.118	0.100	0.104	0.093
(Std. Error)	(0.028)	(0.012)	(0.007)	(0.006)	(0.007)	(0.014)
Low ratio	0.093	0.061	0.055	0.061	0.067	0.038
(Std. Error)	(0.009)	(0.006)	(0.004)	(0.004)	(0.005)	(0.014)
			TBM			
High ratio	0.302	0.1738	0.107	0.094	0.095	0.087
(Std. Error)	(0.023)	(0.011)	(0.006)	(0.005)	(0.006)	(0.013)
Low ratio	0.136	0.064	0.047	0.052	0.057	0.028
(Std. Error)	(0.015)	(0.008)	(0.005)	(0.005)	(0.005)	(0.014)
			Sample			
Sample	0.159	0.094	0.069	0.064	0.074	0.068
(Std. Error)	(0.005)	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)

All number in the Table are percentages written as decimals

[1]: All holding period returns have been annualized

When looking at the average returns provided in Table 6 several interesting results can be seen. For both IBM measures the high portfolio outperforms the low portfolio every year. This supports the earlier evidence from EKP (2020) & Park (2022), who also find that the high IBM portfolios outperform low IBM portfolios. When looking at the 1 year holding period average returns some results stand out.

For both measures this is by far the highest average return across all the different holding periods. For the PT measure the average high IBM return is 34.43%, while for the EKP measure it is even higher at 36.74%. These high returns may be indicative of a momentum factor playing into the data. As discussed by Kelly, Moskowitz & Pruitt (2021), momentum happens when past losers continue to be losers and past winners continue to be winners for a period of time. Since the portfolios are made based on fundamental information released six months earlier in December, it is possible that investors have already recognized that these stocks are undervalued. Subsequently causing a period of overperformance, which is boosted by the momentum factor. This fits right into the value investing idea that value stocks have become temporarily undervalued by the market. Eventually these undervalued stocks will be recognized as such, leading to a period of overperformance. Overall, the average returns of the high (I)BM portfolios do appear to be larger than can be expected in reality. Part of this might be caused by survival bias present in the Compustat database, as discussed by Annaert, Crombez, Spinel & van Holle (2002). This survival bias artificially heightens the returns of value stocks since companies that go bankrupt or delist are not part of the database. This might impact the average returns of value stocks especially hard. According to the EMH, the value premium exists because it is a compensation for the increased riskiness of value stocks. The absence of delisted firms might therefore seriously impact the return characteristics of the sample.

4.2 Comparing the EKP & PT measures

When comparing both measures, what stands out is that the average yearly returns of the EKP measure are higher than the PT measure for every holding period. The difference ranges from 0.4% to 2.3%. However, this is not enough to determine whether the EKP measures have significantly higher portfolio returns. Therefore, the results from the two-way test for mean difference need to be discussed. These results can be found in Table 7.

Table 7:

Two Way test for Mean difference EKP and PT IBM portfolios

	1 Year	2 Year	5 Year	10 Year	15 Year	20 Year
EKP IBM	0.367	0.197	0.130	0.104	0.108	0.107
PT IBM	0.344	0.187	0.118	0.100	0.104	0.093
Difference	0.023	0.010	0.012	0.003	0.004	0.014
Significance	0.285	0.268	0.107	0.334	0.337	0.247

All number in the Table are percentages written as decimals

As can be seen in row three of Table 7, the difference between the EKP and PT measures is positive for every holding period. This means that the average yearly returns of the EKP measure are higher for every holding period. However, it cannot find any significant difference between the two measures after considering the standard errors and the confidence intervals. Only the difference of the 5-year holding period comes close to a 10% significance level. Based on this test we must reject the first hypothesis that: *High IBM portfolios formed with the Eisfeldt, Kim & Papanikolaou (2013) intangibles measure earn higher returns than high IBM portfolios formed with the Peters & Taylor (2017) intangible measure.* The mean difference tests found no statistical difference in the returns of the EKP and PT measures. The reason for the similarity in returns seems to be that, although their respective ways of calculating intangible capital differ significantly in some of its aspects, they result in similar portfolios. When comparing the high portfolios of the EKP and PT IBM, about 80% of the companies in the portfolios are the same. This would explain why the tests are unable to find differences in returns between the two measures.

However, when comparing both measures there are additional facts to take into consideration. The PT measure is more complicated to construct than the EKP measure, needing more data from various sources. Furthermore, often a large part of the needed data is missing. EKP (2020) find in their paper that almost half of the Compustat R&D expenses are either zero or missing. This paper finds comparable results, with the R&D data procured from Compustat returning zero or being missing for 44% of all observations. Similarly, the IRD variable is missing even more of its observations. Although we can find no evidence for the EKP measure performing better when looking at portfolio returns, for ease of use and accuracy we will set the EKP measure as the main IBM measure. Against which the other hypotheses are tested. Unless specified, mentions of IBM will now pertain to the EKP IBM ratio.

4.3 Comparing IBM & TBM

As with hypothesis 1, two-way mean tests for mean difference are performed on the high portfolios of the EKP IBM and TBM ratios. These tests are done to see whether using intangible assets in the BM calculation leads to a higher portfolio performance.

Table 8:

Two Way test for Mean difference EKP IBM and TBM portfolios

	1 Year	2 Year	5 Year	10 Year	15 Year	20 Year
EKP IBM						
Mean	0.367	0.197	0.130	0.104	0.108	0.107
TBM Mean	0.302	0.174	0.107	0.094	0.095	0.087
Difference	0.065	0.023	0.023	0.009	0.013	0.012
Probability	0.039	0.076	0.006	0.102	0.067	0.147

All number in the Table are percentages written as decimals, e.g 0.367 is 36.7%.

The results for the two-way test for mean differencTabe can be found in Table 8. When looking at the mean differences in the third row of Table 8, the IBM ratio has higher average portfolio returns than the TBM ratio. This stays true for every holding period. The highest difference can be found in the 1 year holding period, where the IBM ratio outperforms the TBM ratio with 6.5% yearly. The lowest difference can be found under the 10-year holding period, with a 0.94% yearly overperformance by the IBM ratio. However, not all these differences are statistically significant. The difference for the 2- and 15-year holding period returns are significant at the 10% level. The 10-year holding period return closely approaches the 10% significance level with an alpha of 0.102. The 1 year holding period return is significant at 5% and lastly, the 5 year holding returns is significant at 1%.

Overall, this evidence does seem to indicate that the IBM ratio outperforms the TBM ratio. The second hypothesis states: *High IBM portfolios will perform better than High TBM portfolios and will earn higher average returns.* From the results in Table 8 there is enough evidence to accept the second hypothesis. These results are supported by much of the current literature. Arnott et al (2021) also find that adding intangible capital to book value performs better than traditional book value in selecting stocks. Another paper finds that the addition of intangible capital improves the accuracy of the BM ratio. Causing the IBM factor to outperform TBM portfolios (Park, 2022).

4.4 The IHML F&F Factor Model

To further substantiate the results from the two-way test for mean difference, a time-series regression is performed on the F&F factors, inlcuding IHML and momentum. The results of the different regressions on the portfolio returns can be found in Table 9.

Table 9:

Time series regression on F&F 4-factor model including IHML and Momentum

Portfolios	Constant	Market Risk	IHML	SMB	Momentum	Adj. R^2
Small Growth(SG)	0.001 (0.001)	1.008*** (0.021)	-0.529*** (0.023)	0.700*** (0.032)	-0.008 (0.007)	0.969
Small Neutral(SN)	0.001 (0.001)	0.962*** (0.021)	0.044** (0.023)	0.356*** (0.031)	-0.004 (0.007)	0.955
Small Value(SV)	-0.001** (0.000)	0.961*** (0.018)	0.483*** (0.019)	0.442*** (0.027)	0.013** (0.003)	0.975
Big Growth(BG)	-0.000 (0.001)	1.010*** (0.019)	-0.458*** (0.021)	-0.643*** (0.029)	0.008 (0.006)	0.924
Big Neutral(BN)	-0.001* (0.001)	0.865*** (0.019)	-0.075*** (0.021)	-0.474*** (0.029)	0.006 (0.006)	0.915
Big Value(BV)	0.002*** (0.001)	1.125*** (0.019)	0.530*** (0.020)	-0.385*** (0.028)	-0.013** (0.006)	0.970

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 9 provides the results from regression on the expanded F&F four-factor model. The constant is close to zero for all portfolios and significant at the 1% level for the BV portfolio. It is also significant at the 5% level for the SV portfolio and significant at 10% BN portfolio. A significant constant in a Fama & French model indicates that there is alpha, or overperformance, possible with these strategies. In this case that means that there is a positive alpha possible of 0.002% for the BV portfolio and negative alphas of -0.001% for the SV and BN portfolios. However, these are all so close to zero that it is doubtful whether there is any actual alpha possible in a real investment scenario. This is certainly the case when accounting for transaction costs for example.

The market excess return variable, or (market beta), is strongly significant at the 0.01% level for all different portfolios. Standard deviations of the beta factor are quite similar at around 0.020 for all the portfolios. This is to be expected since the coefficients of the beta factor also fall in quite a narrow range. The beta factor's coefficients fall between 0.865 to 1.125 for every portfolio. With the BN portfolio having the lowest correlation and the BV portfolio the highest. These numbers mean that the portfolios move very similarly to the general stock market. Both growth portfolios have a beta higher than 1, meaning their movements larger than the movements of the general market. This is similar to the evidence found in the research by F&F (1992). Interestingly, the BN portfolio has the lowest correlation with the overall market, a suitable explanation for this is missing. However, this still falls in a believable beta range.

Similar to the beta factor, the SMB variable is significant at the 1% level for all six portfolios as well. The results found here corroborate earlier research. With the small portfolios all having significant positive exposure of between 0.356 and 0.700, while the big portfolios all have significant negative exposure of between -0.385 and -0.643. According to the F&F papers (1992, 1993) small firms earn excess returns over larger firms. The fact that the small portfolios in Table 9 all have positive exposure to the SMB factor is a sign that the results from the regression can be considered dependable. The adjusted R^2 for all six regressions is in the high 90% range. For example, the regression on the SG portfolio has an adjusted R^2 of 0.969. This means that the 4 factors in this regression on the returns of the SG portfolio together explain about 96.9% of the variances. These results indicate that the models are quite accurate and have a good fit.

To look at the effect of Momentum as an explanation of the returns of value stocks, a momentum variable was added to the classic F&F three-factor model. As can be seen in Table 9 the Momentum variable has low explanatory power in most of the portfolios, with the Momentum factor having no significant effect on the SG, SN, BG, and BN portfolios. The coefficients of the Momentum factor are also low and quite close to zero for all portfolios. The direction of Momentum is mixed, with the coefficients being negative for the SG and SN portfolios and positive for the SV and BG portfolios. Therefore, no real conclusions can be drawn on the effect of Momentum on these portfolios. Interestingly however, the Momentum variable is significant at the 5% level for both the SV and BV portfolios. With the SV and BV coefficients being 0.013 and -0.013 respectively. These results do indicate that the Momentum factor might play a role, albeit small, in the returns of value portfolios. Momentum positively affects the returns of the SV portfolio, and negatively affect the returns on the BV portfolio.

Adding in the Momentum variable did increase the adjusted R^2 and the significance of most of the variables compared to the original F&F three-factor model. These results corroborate with earlier research by Carhart (1997) who finds that adding Momentum to the F&F three-factor model improves its explanatory power.

Moving on to the main variable of interest, the IHML factor is strongly significant at the 1% level for all six portfolios. It is coefficients, however, do vary significantly between the six portfolios. With the lowest correlation being -0.529 for the SG portfolio, and the highest correlation being 0.530 for the BV portfolio. As expected, the IHML factor plays almost no role in the neutral portfolios. Both SN and BN have small coefficients of 0.044 and -0.075 respectively. This is in line with the F&F research (1993,1995), this can be explained by the fact that the neutral portfolios are portfolios made up of stocks that are centered around the median of the IBM ratio. These are thus stocks that are neither considered growth or value stocks. The effect of the IHML factor on these two portfolios is therefore correspondingly close to zero. Both growth portfolio returns show a strong negative relation with the IHML factor. With the SG portfolio having a -0.529 IHML factor coefficient and the BG portfolio having a -0.458 coefficient. This is again in line with the earlier results from F&F. Since value normally outperforms growth, growth stocks are expected to have a negative correlation with the IHML factor. The IHLM factor has strongly positive coefficients on the value portfolios. With the SV portfolio having a coefficient of 0.483 and the BV portfolio having a coefficient of 0.530. Meaning that the returns of both value portfolios are heavily influenced by the IHML factor. Interestingly, the BV portfolio is more correlated with the IHML factor than the SV portfolio. Taking all the above results into account, the third hypothesis can now be accepted: *The intangible value factor has significant explanatory power in explaining portfolio returns when using an expanded F&F four-factor model including momentum.* The results from Table 9 show that the IHML factor does have significant explanatory power for (value) stock returns. This supports the evidence found in EKP (2020) and Park (2022) that the IHML factor has statistically significant explanatory power.

Section 5. Conclusion & Discussion

5.1 Conclusion

This paper tests whether the inclusion of intangible capital into the BM calculation can help improve value investing returns. Three different hypotheses are tested on Compustat data over a 20-year period from 2000 to 2020 to try and answer this main research question. Using two different measures to calculate intangible capital, the first hypothesis looks at whether the EKP or PT measure is more effective at the construction of an intangible capital variable.

As seen in the results section of this research, the first hypothesis can be rejected. The results in Table 7 show no evidence for the EKP IBM measure performing better than the PT IBM measure when used in portfolio selection. The tests used cannot find any significant difference in returns between the two measures for any holding period. However, the EKP measure is found to be easier to construct, with less missing data. The different result in this paper as compared to the EKP (2020) paper can be explained by the different way in which they calculated the PT IBM and the different way in which the difference is tested in their paper.

The second hypothesis regarding the overperformance of IBM compared to the TBM ratio is accepted. The results in Table 8 show that the IBM measure earns higher average portfolio returns than the TBM measure in both the short- as well as long-term holding periods. Even though the difference is not significant for all the holding periods, most holding periods do show an overperformance by the EKP IBM measure. There are enough of these significant differences to conclude that the IBM ratio performs better than the TBM ratio in predicting stock returns.

The third hypothesis looks at the explanatory power of adding intangible capital to the BM calculation. In addition to adding a Momentum factor into the F&F three-factor model as a possible explanation for value stock overperformance. Results from these regressions in Table 9 confirm the explanatory power of the IHML factor in predicting stock returns. The IHLM factor has a strong effect on the returns of both growth and value portfolios. With the IHLM factor being especially important in explaining the returns of the value portfolios. Furthermore, the results show that the momentum factor plays a small role in determining the returns of value portfolios. The momentum factor is, however, found to have no significant affect on either neutral or growth portfolios.

With these results in hand the main research question can be positively answered. The inclusion of intangible capital does help improve the returns from value investing. Following a simple value investing strategy that tries to identify undervalued stocks by looking at their IBM ratio. This increased performance from the IBM ratio over the TBM ratio can be explained by several factors. Primarily the increasing importance of intangible capital in businesses, which is undercounted by conventional accounting rules. This leads the TBM to undervalue certain firms. This author suggests, based on both the results in this paper and previous research, that the inclusion of intangible capital into the BM calculation helps improve the accuracy of the BM ratio by more correctly valuing businesses and their assets. Therefore, allowing investors to follow a simple value investing method to predict more correctly which stocks are under- and overvalued.

5.2 Discussion

There are several limitations that affect the results from this paper. In general, the average returns of the high (I)BM portfolios do appear to be larger than can be expected in reality. Part of this might be caused by survival bias present in the Compustat database, as discussed by Annaert et al (2002). This might have a bigger impact on high BM or value stocks since theory says that these are distressed stocks with correspondingly higher risk premia. If some of the risky firms that go bankrupt are taken out, that could increase the returns quite drastically. For future research, using a dataset that compensates for this survival bias would help improve the reliability of the research. Another dataset driven limitation is the high number of missing values for certain variables, including R&D, Goodwill, and IR&D.

Following the research by EKP (2020) and PT (2017) missing variables are set to zero. However, this is sure to have an impact on the results. More precise data on expense and balance sheet posts would also help improve the reliability of this paper. A third limitation is the fact that only stocks listed on US exchanges are included in this paper. Research that looks at international stocks of both developed nations and emerging markets might add valuable information on whether the increased accuracy of IBM ratios is a global phenomenon. Further research into the relationship between the momentum factor and the (intangible) value factor could also be of great interest. With the momentum factor seeming to play a role in the returns of value portfolios. To further the research in this field, developing new ways of calculating intangible assets could also help improve the results of future papers. Since this paper only looks at the high B/M ratios, the effectiveness of the two IBM measures and the TBM measure hasn’t been compared for low B/M ‘growth’ stocks. Further research should be done to examine the effectiveness of intangibles in correctly valuing growth stocks. A possible weakness of this research is that the methods used to compare the results for hypothesis 1 and 2 only look at average portfolio returns. Future research would do well to also look at, for example, Sharpe ratios or Information ratios. Using these ratios will allow the returns to be corrected for volatility. Future research should focus on taking a deeper look into the effects of adding intangibles to the book-value.

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Appendix

Table 2:

R&D depreciation rate per industry

Industry	SIC Codes[1]	Depreciation Rates[2]
Computers and peripheral equipment	3570-3579, 3680-3689, 3695	0.287
Software	7372	0.373
Pharmaceuticals	2830, 2831, 2833-2836	0.174
Semiconductor	3661-3666, 3669-3679	0.314
Aerospace products and parts	3720, 3721, 3724, 3728, 3760	0.233
Communication equipment	3576, 3661, 3663, 3669, 3679	0.195
Computer system design	7370, 7371, 7373	0.255
Motor vehicles, bodies, trailers, and parts	3585, 3711, 3713-3716	0.313
Navigational measuring, electromedical and control instruments	3812, 3822, 3823, 3825, 3826, 3829, 3842, 3844, 3845	0.181
Scientific research and development	8731	0.214
Other	N/A	0.15

[1]: SIC codes are 4 number identifying codes used to sort companies into industries.

[2]:Depreciation rates are percentages written as decimals