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# Intangible Capital as Sixth Factor in European Asset Pricing Model

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**Abstract**

A large part of a firm's value may reside in non-physical capital investments, such as branding or employee training. Intangible investments are usually expensed, making it difficult for investors to accurately price equity. While there is evidence supporting the inclusion of the intangible factor for US firms, the intangible factor for European firms has not been extensively researched. There are also structural differences in European and US research and development compositions that suggest different outcomes. This paper investigates the predictive power of the intangible factor to predict future returns in Europe, and whether investor mispricing drives the returns in intangibles. A dataset consisting of 40 European countries is used from 1999 July to December 2022. Using the Fama-Macbeth regression, the intangible risk premium was found to have a positive and significant effect on future portfolio returns. Gibbons-Ross-Shanken tests showed that including the intangibility factor improves Fama-French five-factor model. Lastly, Fama-Macbeth regression of gross profit and earnings growth on intangibility showed evidence that investors misprice firms with high intangibles leading to future price corrections. Robustness tests that include industry sorts and different time periods support results with variation.

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## 1 Introduction

The past decade has seen a significant increase in investment in knowledge-based activities that generate value for a firm in the long term (Gu & Lev, 2011). These activities include conducting research and development projects, investments in information technology (IT), creating unique organisational processes, or building brand value which provides a potential long-term benefit (Crouzet, Eberly, Eisfeldt, & Papanikolaou, 2022). According to Corrado, Carol A. and Hulten's (2010) study for the US, the average share of intangible capital of 17.4% for the 1948-1972 period increased to 33.9% for the 1995-2007 period. However, the high-risk profile of these investments causes managers to report them as expenses. Therefore, investors that rely on financial statements to value companies have difficulties pricing the market value of companies with high intangible capital (Crouzet et al., 2022; Eisfeldt & Papanikolaou, 2013; Eisfeldt, Kim, & Papanikolaou, 2020; Gu & Lev, 2011). Moreover, the mispricing of firms becomes more relevant as the share of capital-intensive physical activities in the economy is becoming smaller.

Studies conducted on the US financial markets show that research and development (R&D) and selling, general and administrative (SG&A) expenses play a relevant part in firm valuation. Several studies have shown that intangible intensity significantly affects the cross-sectional returns of US stocks (Bongaerts, Kang, & Van Dijk, 2022; Eisfeldt et al., 2020; Park, 2019). From interviews with sell-side analysts, Abhayawansa, Aleksanyan, and Bahtsevanoglou (2015) find that intangible capital is often reflected in the share price by analysts; however, its degree of inclusion depends on how measurable the intangible capital is. Banker, Huang, Natarajan, and Zhao (2019) conduct research on SG&A pricing in return for US firms between 1970-2011. They show that analysts tend to have more significant forecast errors with firms with higher SG&A expenses. Furthermore, they find that investors tend to overlook SG&A as the level of future abnormal returns is positively related to forecast errors. The book-market (BM) ratio has also lost its relevance, and alternative factors that adjust BM for intangibles have shown significant power to explain returns (Arnott, Harvey, Kalesnik, & Linnainmaa, 2021; Eisfeldt et al., 2020; Park, 2019).

Research on the effects of intangibility on returns has been mainly focused on the US, but the relationship with return patterns has not been extensively explored for European firms. On a macro level, the average level of intangibility as a percentage of GDP in EU14 is lower at 7.2% compared to the US average of 8.8% (Corrado, Carol, Haskel, Jona-Lasinio, & Iommi, 2016). Furthermore, accumulation in intangibles assets in Europe is slower than physical capital accumulation compared to the US, and European firms are less capable of translating

R&D investments into gains (Castellani, Piva, Schubert, & Vivarelli, 2019; Corrado, Carol et al., 2016). A relatively recent study of international cross-section returns with an intangible adjusted factor has shown that in Europe, an intangible adjusted value factor also provides an improvement over the traditional value factor for the 1983-2021 period (Vincenz, 2023).

Motivated by the lack of research on European cross-sectional returns and differences, I investigate the power of intangibles to explain the cross-sectional returns for European firms. The main research question of this paper is: "Does the intangible capital factor provide explanatory power in predicting European cross-sectional return, and does investor mispricing drive their return?" I investigate the theoretical arguments on how human capital is relevant to the firm's growth and review the current empirical studies made year to date on incorporating intangibility in asset pricing models. Furthermore, I examine the fundamental differences between the EU and US intangibles and investigate whether they are mispricing or perceived risk in the EU. I replicate the Fama and French (1993; 2015) (FF) factor model for European firms and incorporate intangible assets. In contrast to studies like Eisfeldt et al. (2020) and Park (2019), I follow the methodology of Peters and Taylor (2017) to derive intangible capital and follow Bongaerts et al. (2022) method where intangible intensity is added as an additional to the FF five-factor model. Using a dataset that includes 40 European countries between 1999 and 2022, intangibility significantly predicts future asset returns in cross-sectional regressions. Increasing intangible intensity portfolio exposure increases future portfolio returns on average by 0.941 percentage points when controlling for size, beta, value, investment, and operating profitability. Furthermore, including the intangible asset as an additional factor improves the model's explanatory power. Lastly, regressing the intangibility of firms against earnings and profitability growth indicates a mispricing explanation for intangibility in Europe because intangibility has a positive and significant effect on gross profit growth and a negative effect on earnings growth.

This study is socially relevant because the results suggest that participants should consider a firm's intangible capital when analysing its value. European stock markets also omit the value of intangible part assets in their stock valuation like in the US. This paper also shows that including intangible factor improves the model fit compared to the five-factor model, which can be helpful for European asset managers. Furthermore, evidence for mispricing in European firms indicates that asymmetric information exists in European financial markets. Bongaerts et al. (2022) mention that a correlation between intangible and value factors can create a valuable hedge strategy. The study is academically relevant because it contributes to the asset pricing model research by investigating the effects of adding the human capital factor to the FF multifactor model. The study's focus on human capital in financial markets also expands the research of anomalies centred on R&D and employees. Besides Vincenz (2023), empirical research is focused on US markets. This paper adds to the literature by looking at European stock returns and providing insight into whether there are differences in the effects of intangibles.

In the theoretical framework section, I describe past and current research in asset pricing modelling. I discuss the weaknesses in the original five-factor model and the most recent findings on the effects of intangible capital. In the results section, I provide average returns of 2 x 4 x 4 sorts, the results of Fama-Macbeth regressions, factor spanning and GRS test, and tests of mispricing. I additionally report the results from robustness checks, which use industry-sorted portfolios and runs the same tests for the pre-2007 and post-2007 period. Lastly, I conclude by discussing the results, the weaknesses of my analysis, and recommendations for future research.

## 2 Literature Review

In the theoretical framework, I review existing literature on asset pricing models and provide an overview of their development in the financial literature. The first sub-section of the literature review discusses the early attempts at predicting stock returns and how empirical finance transitioned to using the three- and five-factor models. Next, I discuss the weaknesses of the three and five-factor models and argue the relevance of intangible capital by reviewing the existing research on intangible capital in the US market. Afterwards, the differences in intangible capital characteristics are observed between Europe and US to gain insight into potential variances. In the final subsection, I conclude my literature review by developing the hypotheses using the literature.

### 2.1 Early Asset Pricing Models

The earliest studies on the determinants of stock value can be traced to Graham and Dodd's (1934) *Security Analysis* and William's (1938) *The Theory of Investment Value*. Graham and Dodd (1934) advocated more rigorous investment picking by searching for the value premium. The value premium exists in firms with high-quality accounting figures not reflected by the share price. As a result, they argued that investors under-priced the value of their shares, which should result in future price appreciation. Williams (1938) similarly stressed the importance of systematically valuing companies. He was among the first to encourage using the discounted valuation method. He urged investors to focus on the discounted value of dividends as the primary indicator of value.

In response to William's (1938) work, Markowitz (1952) argues that investors should also factor in the risk of the asset in addition to its future returns. According to Markowitz (1952), investors must first select shares based on assumptions about future performance and its correlation with other assets. In the second stage, he argues that investors facing uncertainty must diversify their portfolios by allocating their capital efficiently to maximise returns and minimise volatility. His work on portfolio theory provided individual investors with a quantitative method of arriving at an efficient portfolio and helped build the theoretical framework for academics.

Markowitz's (1952) portfolio selection theory was an essential building block for future asset pricing models that attempt to explain market equilibriums. The capital asset pricing model (CAPM) is a market equilibrium positive theory that assumes that all rational market participants have efficient portfolios with homogeneous expectations and may borrow or lend at a risk-free rate (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1961). Under the CAPM, all rational investors will have a portfolio on the capital market line, explaining expected returns as a positive linear relationship to expected risk. On the security level, this indicates that the return on individual equity is determined by its sensitivity to the market $\beta$ and the risk-free rate proxied by government bonds.

Both academic and financial analysts widely use the CAPM in companies' valuation; however, the model has several shortcomings that studies have raised. The main weaknesses lie in the model's assumptions and in predicting outcomes. For example, Basu (1977) investigated Fama's (1970) efficient market hypothesis theory by measuring the relationship between stock returns and the price-to-equity (P/E) ratio. Basu (1977) hypothesised that investor perception of the P/E ratio of a share leads to low P/E stocks outperforming high P/E ones. Using returns on 753 NYSE firms, Basu (1977) found evidence that portfolios of stocks with low P/E ratios have higher returns than high P/E ratio portfolios.

Banz (1981) investigated whether there is a relationship between the stock return and the firm's market value. His research showed that in 1936-1975, firms with smaller market capitalisation had higher risk-adjusted returns than larger firms, which he identifies as inefficiency in the market pricing model. Bhandari (1988) similarly found inconsistencies in the asset pricing model from CAPM. He investigated whether a firm's leverage affects its stock return. Bhandari (1988) used the firm's debt-to-equity ratio to proxy for a firm's leverage. He found that firms with high debt-equity ratios experience higher stock returns in addition to market beta. The findings of Black (1972) and Black, Jensen, and Scholes (1972) argue that the CAPM assumption of lending or shorting assets at the risk-free rate is unrealistic from an investor perspective. They found that returns for low beta portfolios in the 1926-1966 period was higher than the return predicted by the CAPM, and the returns for high beta portfolios were lower than the CAPM expected returns (Black et al., 1972).

## 2.2 Multifactor Approach

As academics began to encounter the shortcomings of CAPM, several economists began to alter the model by adding factors other than market sensitivity. For example, Black et al. (1972) proposed a two-factor CAPM model incorporating a zero-beta portfolio as a factor in which an investor may short-sell the risky asset instead of the risk-free one. They find that the coefficient of the zero-beta factor is significant. Moreover, they provide significant evidence for a positive linear relationship between returns and beta when there is no risk-free borrowing.

Ross (1976) developed the arbitrage pricing theory (APT), which states that the prices of assets can be explained by factors other than market sensitivity. The APT states that in a world with two assets, investors engage in arbitrage trading when one asset is mispriced. Investors sell overvalued assets and buy the undervalued asset with the proceeds. Compared to the CAPM, the APT is less restrictive by assuming that each stock's return may have a unique relationship with a risk factor. Examples of factors related to stock returns can be inflation, yield rates, or changes in the GNP (Chen, Roll, & Ross, 1986). Factors can also be stock related to the firm itself.

The most prominent asset pricing model theory within financial literature was the three and five-factor model by Fama and French (1992; 1993; 1996; 2015). The three-factor emerged as an additional way to explain the return pattern of equity. The three-factor model adds the size factor by using the market value as the proxy, and it is operationalised by measuring the difference between high and low-market capitalisation firms (Fama & French, 1992; Fama & French, 1993). This variable represents the economic driver that firms with smaller market value outperform larger firms in equity returns. Additionally, the value factor, proxied by the difference in high and low BM (HML), also represents the risk factor in stocks as (value) firms with high BM are perceived to have lower earnings prospects (Fama & French, 1993). As a result, the three-factor model was a significant improvement over the CAPM because it explained a higher portion of stock price variation.

Several reviews of the Fama and French (1993) three-factor model required them to adjust the model. The main criticism of the three-factor model was the exclusion of factors that explained previously unidentified anomalies at the time (Cohen, Gompers, & Vuolteenaho, 2002; Haugen & Baker, 1996). As a result, Fama and French (2015) expanded the model by including a measure of a firm's profitability and investments as additional drivers of equity returns. Theoretically, more profitable firms, as proxied by the difference in operating profitability, will experience higher returns (Fama & French, 2015). Similarly, firms with higher rates of investments, as measured by changes in total assets from the prior period, will experience higher returns in the future.

### 2.3 Additional Factor – Intangible Capital

Even with five factors, the model is criticised for having several weaknesses. Furthermore, there are concerns with the specification and measurement error of the FF model. The value factor, as measured by the BM ratio, has lost significance over time. According to Arnott et al. (2021), the HML factor has experienced a drawdown of -55% for the 2007 to 2022 period. Fama and French (2015) also find that the value factor has become redundant when the investment and profitability factors are included. This development requires a factor that provides better predictions for asset returns.

A significant component relevant to the growth of the firm is human capital. Investments in human capital within a firm generates intangible value that is difficult to track but is a significant component of stock returns. Firms can create value from physical assets in operations and non-physical assets such as training employees or building a brand (Corrado, Carol, Hulten, & Sichel, 2009; Corrado, Carol A. & Hulten, 2010; Crouzet et al., 2022). Campbell (1996) argues that the CAPM is flawed because it does not capture the time-variation in expected stock returns and human capital, and incorporating those would reduce the estimated risk of the stock market investment. He incorporates the return on human capital measured by real labour income growth along with the Fama and French factors, finding significant results for explaining returns. Jagannathan and Wang (1996) similarly investigate conditional CAPM and use human capital measured by the changes in labour income as a factor. The theoretical work by Lustig and Van Nieuwerburgh (2008) argues that human and financial wealth jointly influence aggregate wealth as measured by the sum of human capital and asset holdings. This paper will investigate the human capital factor in explaining average stock returns.

Maiti and Balakrishnan (2018) similarly investigated the addition of human capital as the sixth factor in the FF model in the Indian financial market. However, they use the q-factor model specification as per Hou, Xue, and Zhang (2014) for profitability and investment, and the growth of salary and wages is used as a proxy for human capital investments. They found that the human capital factor could capture the returns for most of the portfolios and was more efficient than the three and five-factor models.

The majority of studies on the intangible value topic follow the perpetual-inventory method. The perpetual-inventory method estimates the gross capital stock of countries and firms (Berlemann & Wesselhöft, 2014). Generally, the formula takes capital investments and assumes that it provides value indefinitely. The stock of capital decreases overtime through depreciation. Most studies that estimate intangibles via the factor model refer to Peters and Taylor (2017). Peters and Taylor (2017) investigate Tobin's *q*, which is the ratio of a firm's market value to its asset replacement cost. They adjust Tobin's *q* by incorporating intangible assets in the replacement cost. They proxy intangible capital by applying the perpetual-inventory method to R&D and SG&A expenses to estimate knowledge and organisational capital.

The relevance of the value factor has been slowly declining, prompting further research. Lev and Anup (2022) have researched the weakening value factors since 2007, investigating its driver. They claim that accounting practices contribute to the decline of value factors due to omitting intangible capital. They use a probit regression to model which characteristics determine a firm's probability to transition to a high market-to-book ratio (MB). They found that the ratio of intangible assets to total assets of firms that transitioned is significantly higher than firms that stayed as a value stock. Furthermore, they also argue that the banking crisis of 2007-2009 led to a contraction of lending and demand, making it difficult for value stocks to invest in intangible capital.

Park (2019) similarly investigates the loss in the relevance of the value factor. Park (2019) also claims that accounting standards that exclude the impact of intangibles are a driver of value factor decline. Using the BM factor adjusted for intangibles, he finds that the factor significantly outperforms the traditional BM factor using Fama-Macbeth's (1973) regression that predicts future returns. He also finds a positive and significant alpha on the returns of a portfolio constructed by a long position on the high intangible adjusted BM and short on the low intangible adjusted BM.

The research by Eisfeldt, Kim, and Papanikolaou (2020) argues that the value factor's underperformance is due to the omission of intangible capital, which does not appear on the firm's balance sheet. They investigated a modified FF model where the HML factor includes intangible assets, proxied by the firm's SG&A expenses and sorted on industries to account for within-industry effects for intangible capital and different accounting practices. They found that the intangible HML factor significantly outperforms the standard HML, with a 2.11% annual average return, by going long on the intangible factor and short on the value factor. They also found that the new factor has lower pricing errors than the value factor. Lastly, they attribute the driver for the returns to be the inherent risk of intangibles as a factor instead of mispricing.

Bongaerts et al. (2022) also expand on the study by Eisfeldt et al. (2020) to examine the inclusion of intangible value capital in the FF model. They also argue that valuations tend to exclude the effects of intangible capital, potentially creating mispricing in financial markets. They proxy for intangible capital as the sum of past R&D and SG&A expenditures to total assets (which includes knowledge and organisational capital and is net of goodwill). Using the GRS test, they found that the new model can explain expected returns better than the FF model. Additionally, they found that the returns come from the mispricing of high intangible firms rather than exposure to intangible risk by regressing 3 years earning and gross profit growth against intangibility.

### 2.4 Human Capital in Europe

Research on the differences in human capital investments between the US and Europe have been conducted and found several on intangible value accumulation. According to Wasmer (2006), European labour markets tend to have higher unemployment rates and duration than US markets. European markets are also more protected and have higher mobility costs. Firms in Europe tend to take fewer risks because of strict hiring regulations, and it is costlier to fire existing employees. These conditions developed a market in Europe where employees invest more in specific human capital than in the US. Firms in Europe, on average, have lower employee turnover and tend to be more specialised compared to US firms (Wasmer, 2006).

There are also differences R&D expenditures between the US and continental Europe. A gap exists between European and US labour productivity, attributable to decreases in EU productivity growth (Castellani et al., 2019; van Ark, O'Mahoney, & Timmer, 2008). Various factors drive the slowdown, one being the composition of economies. The US economy has a higher share of knowledge and high-tech industry than the EU(Castellani et al., 2019; Gómez Salvador, 2006). However, according to Erken and van Es (2007), the slowdown caused by the smaller economic composition of R&D intense industries of the EU compared to the US is only short-term. They argued that in the long term, the actual cause for the EU's productivity gap is institutional factors such as stringent intellectual property rights and government funding. Others have argued that in addition to lower R&D intensity, European firms are less capable of translating their R&D investments into productivity gains. Castellani et al. (2019) compared the R&D elasticity on the productivity of high, medium, and low-tech companies. Consistent with theory, they found that R&D has a higher effect at high-tech companies compared to lower levels. They compared this relationship between countries and found that while the R&D effect is significant and positive for both the US and the EU, the elasticity of the EU is only 35% of the US.

### 2.5 Hypothesis Development

Using the accumulated literature, I draw several hypotheses to answer the main research question. Past research found that including intangible intensity in the Fama and French (2015) five-factor model significantly improves the model's performance in explaining returns (Arnott et al., 2021; Bongaerts et al., 2022; Eisfeldt et al., 2020; Lev & Anup, 2022; Park, 2019). Furthermore, recent studies using international tests of the Fama and French (2015) five-factor model with an intangible adjusted value factor show evidence that intangible capital is priced in the cross-sectional returns. Therefore, I expect that when looking at the stock returns of European firms only, the intangible intensity characteristic will be priced in the cross-sectional returns.

Hypothesis 1: the intangible intensity of EU firms is priced in cross-sectional returns.

Furthermore, models that include intangible intensity have been shown to increase the predictive performance of average returns in the US relatively better than models that exclude it (Bongaerts et al., 2022). Eisfeldt et al. (2020) estimate the FF value factor with and without intangible factor adjustment. They found that the intangible adjusted value factor produced lower pricing errors compared to the traditional value factor. Therefore, I predict that Fama and French (2015) with the sixth-factor model as the intangible intensity provides an improvement over the traditional five-factor model in explaining average returns in Europe:

Hypothesis 2: the intangible capital factor, as the sixth factor, provides additional information for describing the return pattern of EU firms' shares over the traditional five-factor model.

Lastly, one of the issues is determining whether the return is caused by investors mispricing the shares of companies or the risk nature of intangibles. Empirical research so far has shown evidence that the return on intangibles is mainly driven by investor mispricing. For example, Bongaerts et al. (2022) find that intangible intensity has a significant relationship with future gross profit growth, which indicates that analysts misprice firms due to information complexity. Similarly, Banker et al. (2019) studied the returns of high SG&A firms. They find that returns of firms with high SG&A reverse in future years and that future returns are positively related to SG&A future value. These findings show evidence of mispricing risk as an explanation for returns. Therefore, I predict that returns for intangible intensity for European firms are driven by analyst mispricing:

Hypothesis 3: The intangible capital factor is caused by mispricing from accounting instead of intangibility risk in the EU.

# 3 Methodology

## 3.1 Data

The study aims to replicate the five-factor model per Fama and French's (2015) methodology for European stocks, including a sixth factor for intangible intensity as per Bongaerts et al. (2022). The return of European stocks is provided by Compustat Global Securities Daily via WRDS. The data is extracted for all stocks in the database from January 1st, 1997, until December 31st, 2022. The resulting output is a panel dataset on daily frequency for each company's stock issue (*GVKEY* and *IID* for company and stock issue identifier, respectively). Multiple stock issues are eliminated by only keeping primarily traded shares as identified by Compustat. The stocks are further filtered for firms with European headquarter and shares traded on European exchange codes. Lastly, only month-end close prices are used to obtain monthly returns, and only common shares (*TPCI*=0) are considered for this study.

The Compustat Global Fundamental database is used as a source for the fundamental accounting data for the same period. The dataset is also a panel with an annual frequency and company identifiers (*GVKEY*). The list of *GVKEY*s is created by extracting a unique list from the securities dataset that contains only European firms. After filtering, the dataset contains data for 10,470 unique companies. Similarly, the risk-free rates are extracted for the same periods via WRDS Fama-French Portfolios, which are daily one-month US treasury bill rates. Since the data is in multiple currencies, all figures are converted and reported in US dollars using month-end rates in the daily exchange rates from IBES.

### *3.1.1 Fundamental Data Processing*

The fundamental dataset acquired from Compustat is further processed. Duplicated company observations reported twice for the same fiscal year (e.g., due to a change in the fiscal reporting month) are eliminated by including the most recent observation. The variables relevant to the calculation of the return factors are obtained in the following way:

*Book Equity* – the book equity is used to obtain the book-to-market ratio to proxy for value firms. The book equity of a company is obtained using the firm's shareholder equity for the parent (excluding non-controlling and non-redeemable interest) plus deferred taxes and tax investment credit and excluding preferred capital (Fama & French, 2015). If the parent stockholder equity is missing, it is derived via 1) the difference between total assets and total liabilities excluding non-controlling non-redeemable interest, 2) total shareholders' equity excluding non-controlling interest, and 3) or common equity plus preferred capital.

*Total Assets* – the total asset amount is used to obtain the investment rate and the intangible asset intensity factors. The study excludes any firm observations that have a negative total asset amount. If the total asset amount is missing, the variable is proxied by taking the difference in total liabilities and total shareholders' equity.

*Investment Rate* – the investment factor is a proxy for firm growth, which takes the percentage change of total asset amount over the year (Fama & French, 2015). Observations at the beginning of the dataset are excluded from the study; otherwise, the factors will generate missing returns.

*Operating Profit* – the operating profit is used to calculate the operating profitability factor. It is obtained by taking the difference in total revenue and cost of goods sold, selling, general and administrative expense, and interest expense, which is then divided by the book equity and the non-controlling interest (total balance sheet amount) (Fama & French, 2015; French, 2023). Observations with missing revenues are dropped from the study, and observations with at least one non-missing expense line are kept in the study.

### *3.1.2 Daily Return Processing*

The daily security returns are obtained by extracting all stocks from Compustat Global – Security Daily. The dataset contains observation for each company and their issued security. First, only common equity shares are kept in the dataset by including issue type code 0. Next, the returns are processed. The total returns are calculated by taking the end-of-month close prices, including the adjustment and daily total return factors. The adjustment and daily total return factors are used to obtain the total return on security (including dividend reinvestment). The simple returns are derived by taking the change in closing price only. Firms not traded on a European exchange or headquartered in Europe are excluded from the study. For comparison purposes, all prices are converted into USD. Only month-end close prices are observed to obtain monthly frequency.

*Simple Return* – Simple return is calculated by taking the change in the close price over a month. Simple returns exclude the effect of dividends and cash equivalent distributions. If a stock is delisted before the month's end, the return is adjusted by the delisting return.

*Total return* – total return is calculated by taking the change in adjusted close price over a month and adjusting the return by the daily return factor provided by Compustat. This return includes the effects of dividends and cash equivalent distributions.

*Market Equity* – market equity is derived by taking the close price at month end multiplied by the shares outstanding.

*(Excess) Market Return* – the market return is proxied by constructing a portfolio using all the stocks in the dataset. More specifically, I calculate the returns of a portfolio consisting of all stocks for each month, using lagged market equity as portfolio weights. The excess market return is obtained by subtracting the risk-free rate from the obtained market return.

*Market Beta* – the market beta is calculated for each stock by month to obtain the market exposure as a characteristic. Market beta is obtained by regressing excess returns on excess market returns. A rolling beta regression is performed using a 36-month window, including a minimum of 12 months of observations.

### 3.2 Replicating the Fama and French Five Factors Portfolio

The FF five-factor portfolios are constructed in the same way as the original authors. The portfolios are formed from July at year t and end in June at year t+1 (Fama & French, 2015). Portfolios are sorted into 2 x 3 and 2 x 4 x 4 portfolios. In the 2 x 3, stocks are sorted into portfolios based on the median market equity and the 30-70 percentile split using the London Stock Exchange (LSE) stocks as breakpoints. In the 32 portfolio sorts, firms are sorted based on median size and 25 percentiles breakpoints generated from stocks on the LSE. Then stocks are sorted into portfolios based on size, book-to-market, investment, profitability, or intangibility. The five factors are constructed in the following way:

*Small-Minus-Big (SMB)* – The SMB factor is the difference in the average portfolio returns of firms with low and high market capitalisation (Fama & French, 2015). The market equity used here is the June value at year t. The stocks are sorted into portfolios yearly based on the median size for the six and 32 portfolios.

*High-Minus-Low (HML)* – the HML factor represents the average difference in the portfolio returns of high BM and low BM stocks (Fama & French, 2015). BM is the ratio of book equity to market capitalisation. The book equity value for a portfolio formed in July year t equals the book equity at the fiscal close in year t-1, assuming that the financial closing year for all companies is in June. The market capitalisation is equal to the December value at t-1. Firms are sorted into three categories: high (above 70$^{th}$ percentile), low (below 30$^{th}$ percentile) and medium. For 32 portfolio sorts, firms are sorted based on four quartiles.

*Robust-Minus-Weak (RMW)* – The RMW factor is the difference between high operating profitability ratio (robust) firms and low operating profitability ratio (weak) firms (Fama & French, 2015). The operating profitability is calculated as the operating profit at year t-1 divided by book equity at year t-1. The stocks are sorted based on 30-70 percentiles for 2 x 3 sorts and four quartiles in the 32 portfolio sorts.

*Conservative-Minus-Aggressive (CMW)* – the CMW factor is the difference in portfolio returns between firms with low investment (conservative) and firms with high investment (aggressive). Investment growth is modelled as the change in total assets from the fiscal year ending t-2 to t-1 (Fama & French, 2015). Stocks are sorted similarly to the other accounting factors.

### 3.3 Construction intangible value factor

The construction of the primary factor variable for measuring the intangible asset intensity of a firm will be described in this section. As stated before, intangible assets are typically not stated on the balance sheet but are expensed (Crouzet et al., 2022; Eisfeldt et al., 2020). To properly reflect R&D and SG&A expenditures like investment in brand value and employees, the costs will be capitalised as per Bongaerts et al. (2022) who also follow Peters and Taylor (2017). By applying the perpetual-inventory method, they calculate the intangible value as the sum of knowledge and organisational capital.

*Knowledge capital* – knowledge capital is defined as the accumulated stock of R&D expenses depreciated by an R&D-specific depreciation rate. The formula for deriving a firm's knowledge capital is thus the following:

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

Where $G_{it}$ is knowledge capital at the end of the period, $\delta_{R\&D}$ is the depreciation rate of knowledge capital, $G_{i,t-1}$ is the prior period knowledge capital and $R\&D_{it}$ is the present R&D expenditure. $\delta_{R\&D}$ is set to a 15% rate because results should not be sensitive to this parameter (Peters & Taylor, 2017). The initial knowledge capital stock $G_{i0}$ is calculated the following way:

$$KC_{i0} = \frac{R\&D_{i0}}{g + \delta_{R\&D}}$$

Where $g$ is the average R&D growth rate, $R\&D_{i0}$ is the beginning R&D expenditure in the fundamental data. The rate for $g$ is set to 10%, as per Eisfeldt and Papanikolaou (2013).

*Organisational Capital* – This represents the accumulated knowledge from organisational activities such as employees and branding. Similarly to knowledge capital, the perpetual inventory method is applied to proxy for the organisational stock. The formula for calculating organisational capital is the following:

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

$OC_{it}$and $OC_{i,t-1}$ are end-of-period and prior-period organisational capital, $\delta_{SG\&A}$ is the depreciation rate for SG&A, and $\theta$ is the share of SG&A expenditure into human capital. As per the methodology of Peters and Taylor (2017), the share of SG&A $\theta$ that contributes to organisational capital will be 30%, whereas the rest are assumed to be operational costs.

Finally, the intangible asset intensity of a firm is calculated as per Bongaerts et al. (2022):

$$IAI_{it} = \frac{KC_{it} + OC_{it}}{KC_{it} + OC_{it} + AT_{it} - GW_{it}}$$

Which is the sum of knowledge and organisational capital divided by itself and the total assets $AT_{it}$ adjusted for goodwill $GW_{it}$.

*High Intangibility-Minus-Low Intangibility (HIMLI)* – As the last step, the intangible factor is calculated as the average difference in the returns of firms with high and low $IAI_{it}$.

### 3.4 Model Specification

The proposed model to analyse the effects of intangible intensity on European stock returns will be the Fama and French (2015) specification:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,SML}(SML_t) + \beta_{i,HML}(HML_t) + \beta_{i,RMW}(RMW_t) + \beta_{i,CMA}(CMA_t) + \beta_{i,HIMLI}(HIMLI_t)$$

The dependent variable is the return of an asset in excess of the risk-free rate. The six factors and their corresponding betas are on the right-hand side of the equation.

I test Hypothesis 1 using Fama-Macbeth (1973) (FMB) regression. The FMB regression is a two-step procedure. First, the return of assets is regressed against factors using time-series regressions. Then, in the second step, the returns are cross-sectionally regressed against the resulting factor betas to obtain the risk premium for each date. For Hypothesis 1, I use value-weighted *t*+1 returns of portfolios regressed against value-weighted portfolio characteristics in the first step, obtaining time-series averaged risk premiums for the portfolio characteristic in the second step:

$$R_{i,t+1} = \alpha_i + \lambda_t^{INT}(\beta_{i,t}^{INT}) + \lambda_t^{M}(\beta_{i,t}^{M}) + +\lambda_t^{Size}(\beta_{i,t}^{\text{Size}}) + \lambda_t^{BM}(\beta_{i,t}^{BM}) + \lambda_t^{OP}(\beta_{i,t}^{OP}) + \lambda_t^{INV}(\beta_{i,t}^{INV})$$

Where the dependent variable $R_{i,t+1}$ is future returns, and on the right-hand side, the $\lambda$ represents the risk premium at time *t* for the following portfolio characteristics: intangibility (*INT)*, market beta (*M*), natural log of lagged market equity (*Size*), book-market (*BM*), operating profitability (*OP*), and investment rate (*INV*).

For Hypothesis 2, I use a test of model efficiency developed by Gibbons, Ross, and Shanken (1989) (GRS) that tests the joint significance of the portfolio alphas. The null hypothesis of this test is the following:

$$H_0: \alpha_i = 0, \quad \forall i$$

Which states that the alphas for portfolio $i$ are jointly equal to zero. Rejecting the null hypothesis indicates that the model does not explain the returns well. Furthermore, the lower the GRS statistic, the more relatively effective the model is at explaining returns. Using a 2 x 4 x 4 sort, I perform a GRS test for the alphas of 32 portfolios and all 96 portfolio combinations.

Lastly, for Hypothesis 3, I follow Bongaerts et al. (2022) and Novy-Marx (2013) and perform a Fama-Macbeth regression to test for mispricing. Specifically, I regress the 3-year gross profit and earnings growth against portfolio characteristics. Gross profit growth is calculated the following as per Novy-Marx (2013):

$$\textit{3-Yr. Gross Profit Growth}_{i,t} = \frac{\textit{Gross Profit}_{i,t+3} - \textit{Gross Profit}_{i,t}}{\textit{Total Asset}_{i,t}}$$

Where gross profit is the difference between total revenue and cost of goods sold. Growth is then calculated as the difference between $\textit{Gross Profit}_{i,t+3}$, the gross profit in 3 years and $\textit{Gross Profit}_{i,t}$, current gross profit, scaled by current total assets. Similarly, earnings growth is calculated in the following way:

$$\textit{3-Yr. Earnings Growth}_{i,t} = \frac{IB_{i,t+3} - IB_{i,t}}{\textit{Book Equity}_{i,t}}$$

Where $IB_{i,t}$ is the income before extraordinary items (obtained from Compsutat). Earnings growth is calculated as the difference $IB_{i,t+3}$, income before extraordinary items in 3 years, and $IB_{i,t}$, the current income before extraordinary items scaled by book equity. The Fama-Macbeth second-stage regression is then specified as such:

$$\begin{aligned} 3 - Yr.Growth_{i,t} \\ &= \alpha_i + \lambda_t^{INT}\left(\beta_{i,t}^{INT}\right) + \lambda_t^{M}\left(\beta_{i,t}^{M}\right) + +\lambda_t^{Size}\left(\beta_{i,t}^{\text{Size}}\right) + \lambda_t^{BM}\left(\beta_{i,t}^{BM}\right) + \lambda_t^{OP}\left(\beta_{i,t}^{OP}\right) \\ &+ \lambda_t^{INV}\left(\beta_{i,t}^{INV}\right) \end{aligned}$$

Where the dependent variable is the 3-year gross profit and earnings growth, and the right-hand side consists of risks premia for intangibility (*INT)*, market beta (*M*), natural log of lagged market equity (*Size*), book-market (*BM*), operating profitability (*OP*), and investment rate (*INV*).

### 3.5 Descriptive Statistics

In this section, the return patterns of factors are examined. After data processing, the final dataset consists of returns from July 1999 to December 2022 and reports factors for 40 European countries (Appendix A). Table 1 reports the characteristics of the factors on six dimensions: value-weighted average monthly return and standard deviation, value at risk, maximum drawdown, skewness of returns, and the t-value for the test that the average is equal to zero. The factors are constructed using 2 x 3 sorts on size and the other characteristic.

Average value-weighted returns in Table 1 show that the operating profitability ratio has the highest average return among all the factors, with a monthly return of 0.772% for the sample. These returns also significantly differ from zero at the 5% significance level (*t*-value=3.750). The value and the investment factor returns are also substantial, earning an average return of 0.576% and 0.474% on average, with significance at the 5% level (*t*-value=2.140 and *t*-value=3.261, respectively). The size market factor provides average returns of 0.559%, but it significantly differs from zero only at the 10% significance level (*t*-value=1.732). Lastly, the size and intangibility factors have average returns of only 0.262% and 0.193%, respectively. These effects are not statistically significant at 5%. This indicates that a portfolio long on high intangibles and short on low intangibles did not generate large monthly returns in Europe for the period.

For the volatility of the returns, the market factor has the highest standard deviation in monthly returns, followed by the value and intangibility factor. The investment factor experienced the lowest volatility for the sample. The intangibility and value factors had the most significant drawdown of 75% and 73% for the period, respectively, whereas the market factor markdown was only 41%. For the value at risk (VaR) metric, the market factor has the highest VaR of 9% for the period among all the other factors. Out of all the factors, the investment factor has the smallest volatility (2.441%), VaR (-2.817%) and maximum drawdowns (22.994%) for the period.

The summary statistic indicates that the intangible factor's risk is related to the value factor, but their returns differ. The average return for the value factor is 0.576%, while the intangible factor has a return of only 0.193%, yet their volatility, VaR, and drawdowns are similar. Their skewness is different because the value factor has a positive skew of 4.134, whereas the intangible factor has a negative skew of -6.676. In contrast to the value factor, the skew of the intangible factor indicates frequent small gains and occasional large losses.

Table 1. Factor Descriptive Statistics of 2 x 3 Portfolio Sort

| | Mean | SD | VaR | Drawdown | Skewness | t-value |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Market | 0.559 | 5.422 | -9.314 | 40.973 | -0.503 | 1.732 |
| SMB | 0.262 | 3.721 | -3.876 | 42.828 | 2.884 | 1.180 |
| HML | 0.576 | 4.522 | -3.918 | 73.172 | 4.134 | 2.140 |
| RMW | 0.772 | 3.455 | -4.312 | 34.867 | -1.870 | 3.750 |
| CMA | 0.474 | 2.441 | -2.817 | 22.994 | 0.793 | 3.261 |
| HIMLI | 0.193 | 4.326 | -3.757 | 75.547 | -6.676 | 0.749 |

*Note:* The table reports the descriptive statistics for 2 x 3 sorted portfolios formed on the market, size, BM, operating profitability, investment rate, and intangibility. The table shows monthly average value-weighted returns, standard deviation, value at risk (VaR), maximum drawdown, return skewness, and t-statistic for the test that returns are equal to zero. Returns are reported in percentages. The sample comprises firms across 40 European countries between July 1999 and December 2022.

The correlations of the value-weighted return of the factors formed by 2 x 3 sorts are presented in Table 2. The table below shows that most of the factors in Europe have a relatively low correlation with each other. The two factors with a high correlation are the operating profitability and size factor, which has a score of -0.390, and the intangibility and value factor, which has a correlation of -0.852. This correlation indicates that the return pattern for the intangibility factor is almost perfectly the negative inverse of the value factor returns. The correlation for the intangibility factor is as expected because the high intangibility firms tend to have smaller book-market ratios.

Table 2. Factor Correlation Matrix for 2 x 3 Portfolio Sort

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (1) Market | 1.000 | | | | | |
| (2) SMB | -0.049 | 1.000 | | | | |
| | (0.413) | | | | | |
| (3) HML | 0.025 | 0.129 | 1.000 | | | |
| | (0.670) | (0.031) | | | | |
| (4) RMW | -0.287 | -0.390 | 0.209 | 1.000 | | |
| | (0.000) | (0.000) | (0.000) | | | |
| (5) CMA | -0.238 | 0.068 | 0.194 | -0.028 | 1.000 | |
| | (0.000) | (0.254) | (0.001) | (0.640) | | |
| (6) HIMLI | -0.141 | -0.207 | -0.852 | -0.167 | 0.097 | 1.000 |
| | (0.018) | (0.000) | (0.000) | (0.005) | (0.105) | |

*Note:* The table reports the correlations between portfolios formed on the market, size, BM, operating profitability, investment rate, and intangible intensity from the 2 x 3 sort. The sample comprises firms across 40 European countries between July 1999 and December 2022. The *p*-value for significance is reported in parentheses.

# 4 Results

This section reports the results of the research paper for the hypotheses mentioned in the literature review. Hypothesis 1, which states that intangible intensity is priced in stock returns for European firms, is tested by analysing the characteristics of 2 x 3 sorted on intangible intensity and a 2 x 4 x 4 portfolio sort. Furthermore, I report the results of the Fama-Macbeth regression with lagged portfolio characteristics to estimate the predictive power of intangible intensity. I report the factor spanning, and GRS test results for Hypothesis 2, which tests whether intangible intensity improves model performance. Finally, hypothesis 3, which tests whether returns of intangible intensity are driven by mispricing, is investigated by running the Fama-Macbeth regression. Specifically, I regress the 3-year gross profit and earnings growth with intangible intensity and other characteristics following Bongaerts et al. (2022) and Novy-Marx (2013).

### 4.1 Results for Hypothesis 1

In this section, I discuss the findings of my analysis for Hypothesis 1. Table 3 shows the return patterns and characteristics of a 2 x 3 portfolio sort on size and intangible intensity. The table reports the average and standard deviation of the six portfolios' value-weighted monthly excess returns and value-weighted characteristics. For portfolios sorted on small-cap firms, the average excess return is higher than the large sort for all levels of intangibility. In the small-cap sort, average excess returns are 0.976% and 0.950% for low and high intangibility. The difference in returns for intangible sorts is higher for large-cap sorts. The average return for low intangibility portfolios is 0.391%, whereas the return for high intangibility sort is 0.803%.

For intangible intensity, the pattern of exposure is similar between both sizes. The average intensity for small and large sorts is 9.605% and 8.720% for low intangibility sorts and 58.654% and 50.598% for high intangibility sorts. However, there is a large difference in the exposure to the value characteristics. The average BM value is 188.638% for small-cap and low intangibility sort, whereas the value for large-cap and high intangibility sort is 73.314%. This difference indicates that small-cap firms with low intangibles tend to have high value, whereas large-cap firms tend to have growth firm characteristics and low-value ratios.

The operating profitability pattern is also different between small and large-cap stocks. For small-cap portfolios, the operating profitability is 9.529% for low-intangibility firms and -9.302% for firms with high intangibility. For large-cap sorts, the operating profitability is higher and increases with intangibility. Portfolios with large-cap and low intangibility sort have an average profitability of 35.807% and 66.078% for high intangibility sort. This indicates that large-cap firms have a higher ability to have high operating efficiency at any level of intangibility, and large firms are more capable of translating their gains to profit than small firms.

The sort on investment growth shows that for small cap portfolios with low intangibility, the asset growth is 429.151%, decreasing as intangibility increases. Compared to small-cap sorts, portfolios formed on large-cap sorts have smaller asset growth. The investment rate for low intangible portfolios is 85.958%, and for high intangibility, this rate is 7.678%. The volatility of the excess returns is higher for small-cap sorts than for large-cap sorts.

Table 3. Value-Weighted Monthly Average Return and Characteristics for 2 x 3 Portfolio Sort

| | | Mean | | | | Standard deviation |
|---|---|---|---|---|---|---|
| | Average Return | Intangible Intensity | Book/Market | Operating Profitability | Investment | Average Return |
| Size Sort | | | | | | |
| Small | | | | | | |
| Intangible Sort | | | | | | |
| Low | 0.976 | 9.605 | 188.638 | 9.529 | 429.151 | 8.668 |
| 2 | 0.668 | 30.775 | 158.141 | 8.323 | 51.754 | 5.805 |
| High | 0.950 | 58.654 | 72.633 | -9.302 | 22.438 | 6.875 |
| Big | | | | | | |
| Intangible Sort | | | | | | |
| Low | 0.391 | 8.720 | 73.314 | 35.807 | 85.958 | 5.504 |
| 2 | 0.634 | 31.685 | 44.713 | 43.161 | 14.444 | 5.478 |
| High | 0.803 | 50.598 | 27.617 | 66.078 | 7.678 | 4.715 |

*Note:* The table depicts the average monthly value-weighted return, volatility, and value-weighted characteristics of portfolios formed by 2 x 3 sort on size and intangible intensity. Returns and characteristics are reported in percentages. The sample comprises firms across 40 European countries between July 1999 and December 2022.

Before running Fama-Macbeth regressions, I report in Table 4 the return characteristic of 32 portfolios. The portfolio sorts are fixed on size and BM, while the third characteristic switches between operating profitability, investment, and intangibility. The returns are value-weighted excess monthly portfolio returns with a reported *p*-value for significance. The returns show that in the small-cap portfolio sort, the average return for low operating profitability portfolios is not significant at any BM levels. There are positive and significant returns at all BM levels only at robust profitability ratios. The average return for robust profitability ratio for low BM portfolios is 0.678%, and 1.067% for high BM ratio portfolios. Looking at the large-cap sort, the pattern of returns is similar; however, returns at high BM are lower than those for small-cap and high BM portfolios.

For investment growth in small-cap sort, the average return is also not significantly different from zero at lower BM ratios. The investment growth returns are positive and statistically significant at higher BM ratios but only for low investment rate portfolios. The average return for conservative and high BM portfolio sort is 1.063%, with a significant *p*-value at 5%. The average return exhibits a similar pattern for large-cap sorts, with significant returns for high BM sorts and low investment rates, albeit slightly lower than small-cap sort returns.

Lastly, looking at the intangibility sort for small-cap, the pattern is similar. Average returns are not significantly different from zero on low BM sorts. However, returns become significant at higher BM sorts. Moreover, the average returns for low intangible and high BM sort are 1.964% and significant at a 10% level, higher than the average return of high intangibility sort return of 1.150%. On the large-cap sort, the difference in the pattern is that high intangibility portfolios have significant returns at the 5% level for all value sorts. These returns are also higher compared to the small-cap and high intangible sort. The average returns are also not significant for high BM and low intangibility sorts for large-cap sorts.

Table 4. Value-Weighted Monthly Average Return for 2 x 4 x 4 Portfolio Sort

| | Size Sort | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Small | | | | Big | | | |
| | Book/Market Sort | | | | Book/Market Sort | | | |
| | Low | 2 | 3 | High | Low | 2 | 3 | High |
| Operating Profitability Sort | | | | | | | | |
| Weak | -0.206 | 1.268 | 0.181 | 0.725 | -0.609 | 0.279 | -0.059 | 0.675 |
| | (0.703) | (0.265) | (0.691) | (0.116) | (0.279) | (0.627) | (0.913) | (0.177) |
| 2 | 0.346 | -0.047 | 0.224 | 1.763 | -0.023 | 0.362 | 0.556 | 0.753 |
| | (0.539) | (0.916) | (0.504) | (0.045) | (0.962) | (0.357) | (0.103) | (0.054) |
| 3 | 0.104 | 0.780 | 0.945 | 1.511 | 0.343 | 0.709 | 0.831 | 0.886 |
| | (0.811) | (0.033) | (0.003) | (0.000) | (0.279) | (0.016) | (0.014) | (0.025) |
| Robust | 0.678 | 1.184 | 1.111 | 1.067 | 0.546 | 0.607 | 0.801 | 1.079 |
| | (0.096) | (0.000) | (0.001) | (0.003) | (0.076) | (0.072) | (0.030) | (0.017) |
| Investment Sort | | | | | | | | |
| Conservative | 0.498 | 0.529 | 0.543 | 1.063 | 0.500 | 0.724 | 0.729 | 0.956 |
| | (0.339) | (0.302) | (0.157) | (0.004) | (0.172) | (0.052) | (0.060) | (0.025) |
| 2 | 0.283 | 0.534 | 0.871 | 1.189 | 0.425 | 0.912 | 0.944 | 0.742 |
| | (0.532) | (0.152) | (0.012) | (0.000) | (0.180) | (0.004) | (0.008) | (0.064) |
| 3 | 0.377 | 1.593 | 0.746 | 2.201 | 0.514 | 0.643 | 0.726 | 0.806 |
| | (0.395) | (0.042) | (0.022) | (0.044) | (0.122) | (0.046) | (0.040) | (0.046) |
| Aggressive | -0.536 | 0.238 | 0.380 | 0.397 | 0.421 | 0.382 | 0.382 | 0.725 |
| | (0.226) | (0.606) | (0.315) | (0.347) | (0.235) | (0.277) | (0.305) | (0.127) |
| Intangible Intensity Sort | | | | | | | | |
| Low | -0.061 | -0.116 | 0.538 | 1.964 | 0.141 | 0.272 | 0.681 | 0.557 |
| | (0.915) | (0.782) | (0.130) | (0.066) | (0.719) | (0.405) | (0.051) | (0.159) |
| 2 | -0.414 | 0.814 | 0.542 | 1.021 | 0.548 | 0.810 | 0.736 | 0.845 |
| | (0.305) | (0.153) | (0.104) | (0.002) | (0.152) | (0.015) | (0.047) | (0.055) |
| 3 | 0.153 | 0.792 | 0.737 | 1.136 | 0.539 | 0.859 | 0.851 | 1.132 |
| | (0.736) | (0.105) | (0.024) | (0.001) | (0.108) | (0.008) | (0.015) | (0.004) |
| High | 0.261 | 1.671 | 1.006 | 1.150 | 0.721 | 1.009 | 1.316 | 1.350 |
| | (0.576) | (0.057) | (0.013) | (0.003) | (0.015) | (0.002) | (0.001) | (0.009) |

*Note:* The table depicts the average monthly value-weighted excess return of portfolios formed by 2 x 4 x 4 sort on size and BM and either operating profitability, investment rate, or intangible intensity. Returns are reported in percentages. The sample comprises firms across 40 European countries between July 1999 and December 2022. The *p*-value for significance is reported in parentheses.

Table 5 reports the results of the Fama-Macbeth regression conducted to analyse the explanatory power of the intangible asset. Future value-weighted portfolios (1-month forward) returns are regressed against intangibility and other value-weighted characteristics. Specifically, the characteristics are beta, natural log of market capitalisation, BM, operating profitability, investment, and intangibility. The FMB regressions are run six times by adding each variable progressively. In model (1), the output shows that the value-weighted intangible intensity portfolio characteristic alone does not significantly affect future portfolio returns. Even after adding beta and market cap, the intangible intensity is still unable to explain returns. However, when the BM ratio is added to the model (4), the intangible intensity significantly and positively affects the future portfolio at the 1% level. Specifically, increasing intangible intensity risk premium by one percentage point will increase future portfolio returns by 1.371 percentage points, *ceteris paribus*. The return for model (5) is also positive and significant at the 1% level and shows that an increase in intangible intensity risk premium by one percentage point will increase future portfolio returns on average by 1.531 percentage points, *ceteris paribus*. Lastly, model (6) results are also positive and significant, but only at the 5% level. The effect is also lower compared to the previous two models. An increase in intangible intensity risk premium by one percentage point increases future portfolio returns on average by 0.941 percentage points. For the other characteristics, the beta factor is only significant in model (4) when the book market is added. When the investment rate is added, beta loses its explanatory power. Furthermore, including the operating profitability ratio and investment rate decreased the intangible intensity coefficient and increased the model R-squared to 34.2%.

Table 5. Results of Fama-Macbeth Regression of Future Portfolio Return on Characteristics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intangible Intensity | 0.730 | 0.575 | 0.678 | 1.371*** | 1.531*** | 0.941** |
| Beta | | -0.147 | -0.244 | -0.800** | -0.421 | -0.317 |
| ln(Market Equity) | | | -0.001 | 0.025 | -0.003 | -0.013 |
| Book/Market | | | | 0.543*** | 0.555*** | 0.473*** |
| Operating Profitability | | | | | 0.585*** | 0.462*** |
| Investment | | | | | | -0.456*** |
| R2 | 0.055 | 0.134 | 0.243 | 0.292 | 0.322 | 0.342 |

*Note:* The table depicts the Fama-Macbeth coefficients of value-weighted monthly future returns at t+1 against value-weighted portfolio characteristics. Portfolio characteristics at the individual firm level were winsorised using 1% and 99% levels. The sample comprises 96 portfolios formed from firms across 40 European countries between July 1999 and December 2022. *** p<.01, ** p<.05, * p<.1

I additionally perform two robustness checks, one with industry-sorted portfolios (Appendix B) and one with sub-periods (Appendix C), to control for industry differences and to separate significant financial events. When running industry-sorted portfolios, the FMB regression also showed that intangibility has a significant effect in predicting future stock returns. However, when controlling for investment, the coefficient became insignificant and decreased similarly in Column (6) of Table 5. This indicates that when portfolios are sorted on the industry, the investment, operating profitability, and BM together have a significant effect in predicting future returns instead of intangible intensity.

Furthermore, results differ depending on the period selected. When the FMB regression is run pre-2007, none of the characteristics significantly affects predicting future returns except for the investment characteristic, which is significant at 10%. However, using post-2007 data, intangibility was highly significant in the full model and had a larger coefficient (coefficient=1.242). This indicates that pre-2007 time period, most of the factors were not priced in the return patterns of European stocks, indicating that other unidentified anomalies were driving future returns.

Table 3, Table 4, and Table 5 presents the results of tests for Hypothesis 1. In summary, return patterns for intangibility in Europe vary considerably between sizes. Table 3 shows that the average return for intangibility increases with intensity for large-cap, while it stays constant in small sort. Table 4 also depicts the difference in return across patterns. Average returns for intangibility in small sort decreases in intensity at a high BM ratio, while it increases for large-cap sort. Moreover, returns at lower BM ratios are not statistically significant. Lastly, Table 5 shows that intangible intensity significantly affects future returns when controlling for beta and size. It also has the largest coefficient even when adding the BM and operating profitability. Therefore, these results indicate evidence to support Hypothesis 1, which states that intangibility is priced in the stock return of European firms. However, this finding is not robust when portfolios are industry-sorted and investment characteristic is included. Furthermore, this finding is sensitive to the period analysed.

### 4.2 Results for Hypothesis 2

Factor-spanning tests are performed by regressing each factor against the other factors to examine whether the intangible asset factor improves the model's explanatory power. This analysis would indicate the presence of multicollinearity or unnecessary factors. Table 6 presents the results of the factor-spanning test. The intercept in Table 6 for the intangibility factor is 0.591% and significant at the 1% level. This result indicates that the intangibility factor provides explanatory power and, therefore, is not unnecessary. Furthermore, the market, SMB, HML, and RMW factors are also positive and significant at the 1% level, which indicates that they also have explanatory power. Only CMA does not have a significant intercept, indicating that other factors span this factor. These results contrast the Fama-Macbeth regression in Table 5, where size and beta were not significant, and investment characteristic was significant in predicting future returns. Lastly, the intangible factor also has significant and negative loadings on the market ($p$<0.01), SMB ($p$<0.05), HML ($p$<0.01) and positive loading on the CMA ($p$<0.01) factors. The RMW factor does not significantly affect the returns of the HIMLI factor.

Table 6. Factor Spanning Test for 2 x 3 Portfolio Sort

| | Intercept | Market | SMB | HML | RMW | CMA | HIMLI | R2 |
|---|---|---|---|---|---|---|---|---|
| Market | 1.523*** | | -0.380*** | -0.130 | -0.672*** | -0.397*** | -0.429*** | 0.224 |
| SMB | 0.895*** | -0.163*** | | -0.190 | -0.534*** | 0.142 | -0.455** | 0.291 |
| HML | 0.506*** | -0.022 | -0.075 | | 0.047 | 0.517*** | -0.930*** | 0.811 |
| RMW | 1.046*** | -0.231*** | -0.426*** | 0.096 | | -0.125 | -0.158 | 0.345 |
| CMA | 0.138 | -0.070** | 0.058 | 0.536*** | -0.064 | | 0.522*** | 0.327 |
| HIMLI | 0.591*** | -0.065*** | -0.160** | -0.832*** | -0.070 | 0.450*** | | 0.815 |

*Note:* The table depicts the results of the factor-spanning test with robust standard errors. The row variables represent the dependent variable, while the column variables represent the coefficients and model R-squared. The sample is based on six portfolios formed from firms across 40 European countries between July 1999 to December 2022. *** p<.01, ** p<.05, * p<.1

Table 7 summarises GRS tests for the value-weighted excess returns for 96 portfolios and 32 portfolios sorted on size, BM, and operating profitability, investment, or intangible intensity. There are eight variations of regressions with different factor combinations. The table reports the $p$-value of the significance of the GRS test, the GRS statistic, and the average of the alpha and R-squared. For all sorts and factor combinations, the $p$-value<0.01 indicates there is evidence to reject the null hypothesis that the alpha is jointly equal to zero. In other words, the models do not entirely describe excess returns. However, model performance can be compared by looking at the GRS statistic, alphas, and R-squared. The lower the GRS statistic, the more efficient the model is to explain returns relative to others. A relatively more efficient model also has a lower average (absolute) alpha and higher R-squared.

Across 96 portfolios, the three-factor model has the highest GRS test statistic of 3.070 but has one of the lowest mean alpha of 0.049%. Adding the intangible and operating profitability factors reduces the GRS-statistic to 2.647 and 2.684. However, when the operating profitability factor is added, the average alpha is 0.178%, while for intangibility, the mean alpha decreases the -0.046%. The R-squared is the highest for the three-factor model with the intangibility factor. When looking at the five-factor model, the R-squared increases to 0.747 and the average alpha increases to 0.143%. A five-factor model that contains only the operating and intangibility factor decreases the GRS statistic to 2.185 and the average alpha to 0.095%. Changing the operating factor to the investment factor further decreases alpha return to -0.049%; however, the GRS-statistic increases to 2.628. Finally, when the intangibility factor is included, the GRS statistic decreases to 2.158, and the alpha equals 0.092%. The six-factor model also has the highest R-squared.

For the 32 portfolios sorted on operating profitability, the three-factor model has the highest GRS statistic and the lowest average alpha of -0.019%. Out of all the combinations of the three-factor models, the RMW factor has the lowest GRS statistic of 3.681 and the highest mean alpha of 0.162%. In contrast, the three-factor model with intangibility factor has a GRS score of 3.772 and mean alpha of -0.117%. For the five-factor model, the GRS score is 3.212, but the model improves by changing the last two factors to the RMW and IAI. The GRS statistic decreases to 2.900, and the mean alpha is at 0.087%. However, adding an investment rate instead of RMW increases GRS and the mean alpha to 3.771 and -0.118%. Lastly, the six-factor model explains excess returns relatively better than others because it has the lowest GRS statistic of 2.860 and the lowest average alpha of 0.086%. It also has the highest R-squared, equalling 0.752.

When the portfolios are sorted on the investment rate of firms, the pattern is similar. The GRS statistic shows that by adding the investment factor as an additional factor to the three-factor model, the GRS-statistic decrease to 2.422, and the average alpha is the lowest at 0%. The statistic and mean alpha are lower than the three-factor model with intangible intensity. The three-factor model with CMA also performs better than the five-factor model and the six-factor model with intangible intensity. The statistic and mean alpha are 2.710 and 0.095% for the five-factor model, and for the six-factor model, it is 2.777 and 0.040%, respectively.

For the intangibility sort, the three-factor model has a GRS statistic of 3.826 and a mean alpha of 0.124%. When the intangible factor is added, the GRS statistic becomes 2.769 and the alpha return of 0.032%. When the RMW factor is used, the GRS statistic increases to 4.104, indicating the relatively inefficient model. Including the CMA factor improves the model compared to the three-factor model because the statistic and mean alpha decreases to 3.372 and 0.079%. However, the intangibility factor still significantly improves the FF explanatory power over the three-factor model. The five-factor model also improves over the three-factor model because the GRS statistic decreases to 3.476. However, using the five-factor model, the mean alpha increases to 0.195%. When RMW and IAI are used in the five-factor model, the GRS statistic substantially decreases to 2.688. Including only CMA and RMW also decreases the

GRS statistic to 2.747, but it is less efficient than the CMA and RMW combination. When using the six-factor model, the GRS statistic decreases to 2.664, the lowest among all the models.

Robustness checks using industry-sorted portfolios and different periods are also performed for Hypothesis 2. The robustness check showed a similar pattern in GRS-statistic. One crucial difference was that *p*-value>0.05 using a portfolio sorted on investment and the three-factor model with investment only, indicating enough evidence not to reject the null hypothesis of alphas jointly equalling zero. In Table 7, the GRS statistic was also the lowest for the investment factor when sorted on investment, but the *p*-value was significant at 1%. For the 96 portfolios, the results of the robustness checks were similar to the main results.

The GRS statistic under different periods also differs. For pre-2007 and intangibility sort, the three-factor model with investment factor had the lowest GRS statistic and *p*-value>0.10. This indicates that the three-factor model with an investment factor was relatively more efficient at predicting excess returns at intangibility sort. However, for the post-2007 period, the results are similar to the primary analysis, with higher R-squared statistics.

In summary, the results show that the intangibility factor adds explanatory power to the factor model. Table 6 shows from the factor spanning test that the intangibility factor is not redundant in explaining returns when regressed against other factors, as the intercept is significant at the 1% level. Furthermore, the GRS test overall shows that including intangibility as a factor decreases the GRS statistic and increases model R-squared. Therefore, this result provides evidence to support Hypothesis 2, which states that the intangible factor increases the explanatory power of the asset pricing model. These results are also robust when adjusting for industry sort. However, the result is not robust to the period used because, for the intangibility sort and the pre-2007 period, intangibility does not improve the model's explanatory power.

Table 7. Summary of GRS Test Statistic for Portfolios

| | p(GRS) | GRS | Mean Alpha | Mean R2 |
|---|---|---|---|---|
| 3 x 32 Size-BM-XX Portfolios | | | | |
| FF3 | 0.000 | 3.070 | 0.049 | 0.726 |
| FF3+IAI | 0.000 | 2.647 | -0.046 | 0.741 |
| FF3+RMW | 0.000 | 2.684 | 0.178 | 0.737 |
| FF3+CMA | 0.000 | 2.864 | 0.008 | 0.738 |
| FF5 | 0.000 | 2.420 | 0.143 | 0.747 |
| FF3+RMW IAI | 0.000 | 2.185 | 0.095 | 0.751 |
| FF3+CMA IAI | 0.000 | 2.628 | -0.049 | 0.747 |
| FF5+IAI | 0.000 | 2.158 | 0.092 | 0.757 |
| 32 Size x BM x OP Portfolios | | | | |
| FF3 | 0.000 | 4.458 | -0.019 | 0.723 |
| FF3+IAI | 0.000 | 3.772 | -0.117 | 0.733 |

| | | | | |
|---|---|---|---|---|
| FF3+RMW | 0.000 | 3.681 | 0.162 | 0.740 |
| FF3+CMA | 0.000 | 4.169 | -0.057 | 0.730 |
| FF5 | 0.000 | 3.212 | 0.138 | 0.745 |
| FF3+RMW IAI | 0.000 | 2.900 | 0.087 | 0.749 |
| FF3+CMA IAI | 0.000 | 3.771 | -0.118 | 0.737 |
| FF5+ IAI | 0.000 | 2.860 | 0.086 | 0.752 |
| 32 Size x BM x INV Portfolios | | | | |
| FF3 | 0.000 | 2.833 | 0.042 | 0.741 |
| FF3+ IAI | 0.000 | 2.632 | -0.054 | 0.756 |
| FF3+RMW | 0.000 | 3.322 | 0.136 | 0.748 |
| FF3+CMA | 0.000 | 2.422 | 0.000 | 0.758 |
| FF5 | 0.000 | 2.710 | 0.095 | 0.764 |
| FF3+RMW IAI | 0.000 | 2.806 | 0.044 | 0.762 |
| FF3+CMA IAI | 0.000 | 2.613 | -0.056 | 0.767 |
| FF5+ IAI | 0.000 | 2.777 | 0.040 | 0.772 |
| 32 Size x BM x IAI Portfolios | | | | |
| FF3 | 0.000 | 3.826 | 0.124 | 0.714 |
| FF3+IAI | 0.000 | 2.769 | 0.032 | 0.734 |
| FF3+RMW | 0.000 | 4.104 | 0.237 | 0.722 |
| FF3+CMA | 0.000 | 3.372 | 0.079 | 0.725 |
| FF5 | 0.000 | 3.476 | 0.195 | 0.731 |
| FF3+RMW IAI | 0.000 | 2.688 | 0.154 | 0.741 |
| FF3+CMA IAI | 0.000 | 2.747 | 0.028 | 0.739 |
| FF5+ IAI | 0.000 | 2.664 | 0.149 | 0.745 |

*Note*: The table depicts the GRS test results for all 96 portfolios and then for each sort based on size, value and either operating profitability, investment, or intangible intensity. The dependent variable is value-weighted returns in excess of the risk-free rate. The GRS *p*-value, statistics, mean alpha and mean R-squared are shown for all combinations of factors. The sample is based on six portfolios formed from firms across 40 European countries between July 1999 to December 2022.

### 4.3 Results for Hypothesis 3

Table 8 presents the results of the Fama-Macbeth regression of 3-year growth profit growth scaled by asset and 3-year earnings growth scaled by book equity on BM, operating profitability, investment and intangible intensity characteristics of firms. The controls used are beta and the natural log of lagged market equity. The regressions are constructed as per Bongaerts et al. (2022) who also follow the methodology of Novy-Marx (2013) to construct gross profit growth and earnings growth. The Fama-Macbeth regression shows that the beta of intangible intensity is significant at the 1% significance level and positively affects the 3-year gross profit growth. For other factors, the beta of the BM factor also has a significant and negative relationship between 3-year gross profit growth and operating profitability. The investment characteristic of the portfolio does not have a significant effect on the 3-year gross profit growth.

For the second regression with 3-year earnings growth as the dependent variable, the intangible intensity has a negative effect on the earnings growth. However, the effect is not significant at the 5% level but at the 10% level (*p*-value<0.1). The effect of value characteristics on the 3-year earnings growth is also negative and significant at the 5% level. Operating profitability is also negative but significant only at the 10% level. Compared to gross profit growth, the coefficients for earnings growth predictors are larger. Furthermore, the intangible intensity coefficient in the gross profit model is positive (coefficient=0.532) and highly significant (*p*-value<0.01), whereas, in the earnings regression, the coefficient is negative (coefficient=-27.742) and less significant (*p*-value<0.10).

Robustness checks were performed for this model using industry sorting (Appendix B) and running the regression FMB with different periods (Appendix C). The results of industry sorting are similar to the primary analysis in Table 8. Intangibility in the industry-sorted portfolio is no longer a significant predictor of 3-year earnings growth. This is also true when different sub-periods are used. In pre and post-2007 FMB regressions, the coefficients maintain their sign and significance.

In summary, Table 8 shows that current intangible intensity strongly predicts future gross profit growth. Firms that heavily invest in R&D operate may have increased production measured by gross profit, but their total income may be decreased, hence the negative coefficient for intangible intensity in Column (2) (coefficient=-27.742) (Bongaerts et al., 2022). Additionally, investors may misprice firms that invest heavily in intangibles due to the unpredictable nature of such investments. Since gross profit growth strongly predicts stock returns, a significant coefficient indicates that prices are correct in the future for high intangible firms due to information complexity (Bongaerts et al., 2022; Gu & Wang, 2005). Therefore, this result provides evidence to support Hypothesis 3, which states that the return for intangible firms is due to investor mispricing. The result was also robust to industry sort and different subperiods.

Table 8. Fama-Macbeth Regression of 3-Year Gross Profit and Earnings Growth

| | (1)<br>3-Year Gross Profit Growth | (2)<br>3-Year Earnings Growth |
|---|---|---|
| Book/Market | -0.147*** | -15.917** |
| Operating Profitability | -0.404** | -37.644* |
| Investment | -0.074 | -10.890 |
| Intangible Intensity | 0.532*** | -27.742* |

*Note:* The table depicts the Fama-Macbeth results of regressing 3-year gross profit (scaled by assets) and earnings growth (scaled by book equity) against portfolio characteristics. The characteristics are beta, natural log of lagged market equity, BM, operating profitability, investment, and intangible intensity. All characteristics are value-weighted. The sample comprises 96 portfolios formed from firms across 40 European countries between July 1999 and December 2022. Newey-West standard errors are used with three lags. *** p<.01, ** p<.05, * p<.1

## 5 Discussion and Conclusion

This section will discuss the findings and compare them to existing literature. Firstly, Hypothesis 1 stated that the intangible factor is priced in the cross-sectional returns in Europe, for which I found supporting evidence using FMB regression. This finding agrees with past empirical findings focused on the US and international tests of intangibility (Banker et al., 2019; Bongaerts et al., 2022; Eisfeldt et al., 2020; Park, 2019; Vincenz, 2023). However, compared to US findings, I found that the BM factor was priced in the cross-sectional returns and was not redundant in the factor-spanning test. In addition, the average returns of stocks were increasing and significant at higher levels of BM in general. This indicates that a portfolio strategy based on the value characteristics of a firm has significant returns in addition to the intangibility factor, which contradicts the conclusions of Lev and Anup (2022) and Park (2019) that the value factor's relevance is declining. Moreover, sorting portfolios based on industry as per Bongaerts et al.'s (2022) and Eisfeldt et al.'s (2020) methodology makes the intangible statistically not significant when using the full model, which contrasts with Bongaerts et al.'s (2022) findings where they found that industry sorting has no effect. This may provide evidence that European stock returns for intangibility may be sensitive to industry differences.

Hypothesis 2 tested whether the intangibility factor improves the explanatory power of the returned model. The factor-spanning test depicted a significant intercept for the intangible factor, indicating that the factor's returns are not explained by other factors in the model. These results correspond with the research by Vincenz's (2023) and Bongaerts et al.'s (2022) findings. However, the factor spanning also showed a significant intercept for all other factors except CMA, which indicates the relevance of other factors to explain returns in European firms. This is in contrast to research by Bongaerts et al. (2022) that finds significant intercept for RMW and intangibles only in the US. The GRS statistic found that for all portfolio sorts, the intangibility factor, as the sixth factor, improves explaining returns except for investment-sorted portfolios. The GRS test results align with Bongaerts et al.'s (2022) findings, which also find a decrease in GRS-statistic across all portfolio sorts. The contrast to my findings is that the investment sort intangible factor does not improve the GRS statistic, and models with CMA improve the model.

Lastly, I find significant evidence for Hypothesis 3, which states that the nature of returns for the intangibility factor is due to investor mispricing. The regressions replicated the models of Bongaerts et al.'s (2022) research for US stocks. I similarly find a positive and significant effect of intangibility on predicting future gross profit growth, while the effect of intangibility on earnings growth is negative and less significant. Again, these results agree with

Bongaerts et al.'s (2022) research which similarly reported a positive coefficient on profitability growth and a negative coefficient on earning growth.

Several weaknesses need to be addressed in this study. Firstly, the measure of organisational and knowledge capital, as per Peters and Taylor (2017), is an imperfect proxy, and since many firms may report do not report R&D expenses or may have missing R&D, this may indicate bias in the estimation of intangibles (Eisfeldt et al., 2020; Vincenz, 2023). The assumption of 30% SG&A spend is also arbitrary and may be based on research that used outdate information  (Eisfeldt et al., 2020). Furthermore, the assumptions for the growth and depreciation rate of R&D and SG&A were arbitrary and were taken from Bongaerts et al.'s (2022), Peters and Taylor (2017) and Eisfeldt and Papanikolaou  (2013). It is difficult to estimate an accurate rate for these figures, and no assumed figures for Europe were available. Additionally, the assumptions were not varying over time and by industry, leading to an inaccurate proxy. Future research could focus on deriving accurate rates for depreciation and growth rates for firms and industries to have a more accurate estimation of organisation and knowledge capital. Lastly, a further approach that incorporates the prediction by analysts would reveal more insight into the mispricing explanation for intangible returns.

In conclusion, the main research question that this research investigated was: "Does the intangible capital factor provide explanatory power in predicting European cross-sectional return, and is their return driven by investor mispricing?" Using Compustat data for 40 European firms, I find that intangible intensity is priced in the returns, as it had a significant effect in predicting future growth. Furthermore, including the intangible factor provides significant gain in explanatory power over the five-factor model for European equity market. Lastly, I find evidence that support investor mispricing explanation for the returns in intangibility characteristic.

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# Appendices

## Appendix A

Table A1. Distribution of European Countries

| | Sub-Region | | | | |
|---|---|---|---|---|---|
| | Eastern Europe | Northern Europe | Southern Europe | Western Europe | Total |
| Country | | | | | |
| Austria | | | | 77 | 77 |
| Belgium | | | | 132 | 132 |
| Bulgaria | 78 | | | | 78 |
| Croatia | | | 82 | | 82 |
| Czechia | 24 | | | | 24 |
| Denmark | | 222 | | | 222 |
| Estonia | | 27 | | | 27 |
| Faroe Islands | | 1 | | | 1 |
| Finland | | 194 | | | 194 |
| France | | | | 811 | 811 |
| Germany | | | | 852 | 852 |
| Gibraltar | | | 2 | | 2 |
| Greece | | | 257 | | 257 |
| Guernsey | | 7 | | | 7 |
| Hungary | 40 | | | | 40 |
| Iceland | | 19 | | | 19 |
| Ireland | | 104 | | | 104 |
| Isle of Man | | 6 | | | 6 |
| Italy | | | 441 | | 441 |
| Jersey | | 14 | | | 14 |
| Latvia | | 30 | | | 30 |
| Lithuania | | 45 | | | 45 |
| Luxembourg | | | | 51 | 51 |
| Malta | | | 18 | | 18 |
| Monaco | | | | 2 | 2 |
| Netherlands | | | | 192 | 192 |
| North Macedonia | | | 1 | | 1 |
| Norway | | 355 | | | 355 |
| Poland | 833 | | | | 833 |
| Portugal | | | 51 | | 51 |
| Romania | 129 | | | | 129 |
| Russian Federation | 263 | | | | 263 |
| Serbia | | | 38 | | 38 |
| Slovakia | 9 | | | | 9 |
| Slovenia | | | 30 | | 30 |
| Spain | | | 178 | | 178 |
| Sweden | | 1,035 | | | 1,035 |
| Switzerland | | | | 258 | 258 |
| Ukraine | 29 | | | | 29 |
| United Kingdom of Great Britain and Northern Ireland | | 2,787 | | | 2,787 |
| Total | 1,405 | 4,846 | 1,098 | 2,375 | 9,724 |

*Note*: The table depicts the distribution of unique firm observations across countries and regions.

## Appendix B

Table B1. Results of Fama-Macbeth Regression of Future Portfolio Return on Characteristics with Industry Sort

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intangible Intensity | 0.670 | 0.469 | 0.559 | 0.921** | 0.865** | 0.355 |
| Beta | | 0.149 | 0.099 | -0.127 | 0.017 | 0.085 |
| ln(Market Equity) | | | 0.007 | 0.025 | 0.004 | -0.004 |
| Book/Market | | | | 0.272*** | 0.309*** | 0.259** |
| Operating Profitability | | | | | 0.533*** | 0.452*** |
| Investment | | | | | | -0.400*** |
| R2 | 0.040 | 0.114 | 0.219 | 0.262 | 0.289 | 0.309 |

*Note:* The table depicts the Fama-Macbeth coefficients of value-weighted monthly future returns at t+1 against value-weighted portfolio characteristics. Portfolio characteristics at the individual firm level were winsorised using 1% and 99% levels. Industry sorting was applied. The sample consists of 96 portfolios formed from firms across 40 European countries between July 1999 to December 2022. *** p<.01, ** p<.05, * p<.1

Table B2. Factor Spanning Test for 2 x 3 Portfolio Sort with Industry Sort

| | Intercept | Market | SMB | HML | RMW | CMA | HIMLI | R2 |
|---|---|---|---|---|---|---|---|---|
| Market | 0.752*** | | -0.404*** | 0.563*** | -0.668*** | -0.536*** | 0.047 | 0.205 |
| SMB | 0.233 | -0.086** | | -0.058 | -0.501*** | 0.141** | 0.048 | 0.259 |
| HML | 0.218 | 0.115*** | -0.055 | | -0.077 | 0.272*** | -0.362*** | 0.193 |
| RMW | 0.445*** | -0.117*** | -0.410*** | -0.066 | | 0.121** | -0.285*** | 0.334 |
| CMA | 0.104 | -0.100*** | 0.122* | 0.247*** | 0.129** | | 0.231** | 0.151 |
| HIMLI | 0.306** | 0.007 | 0.036 | -0.282*** | -0.260*** | 0.198* | | 0.219 |

*Note:* The table depicts the results of the factor-spanning test with robust standard errors. The row variables represent the dependent variable, while the column variables represent the coefficients and model R-squared. Industry sorting was applied. The sample is based on six portfolios formed from firms across 40 European countries between July 1999 to December 2022. *** p<.01, ** p<.05, * p<.1

Table B3. Summary of GRS Test Statistic for Portfolios with Industry Sort

| | p(GRS) | GRS | Mean Alpha | Mean R2 |
|---|---|---|---|---|
| 3 x 32 Size-BM-XX Portfolios | | | | |
| FF3 | 0.000 | 2.304 | 0.104 | 0.703 |
| FF3+IAI | 0.000 | 2.239 | 0.046 | 0.708 |
| FF3+RMW | 0.000 | 2.090 | 0.185 | 0.711 |
| FF3+CMA | 0.000 | 2.209 | 0.072 | 0.710 |
| FF5 | 0.000 | 1.934 | 0.154 | 0.718 |
| FF3+RMW IAI | 0.000 | 1.921 | 0.135 | 0.716 |
| FF3+CMA IAI | 0.000 | 2.228 | 0.043 | 0.714 |
| FF5+IAI | 0.000 | 1.903 | 0.130 | 0.722 |
| 32 Size x BM x OP Portfolios | | | | |
| FF3 | 0.000 | 3.746 | 0.097 | 0.701 |

| | | | | |
|---|---|---|---|---|
| FF3+IAI | 0.000 | 3.232 | 0.036 | 0.706 |
| FF3+RMW | 0.000 | 3.474 | 0.214 | 0.713 |
| FF3+CMA | 0.000 | 3.537 | 0.065 | 0.707 |
| FF5 | 0.000 | 3.074 | 0.189 | 0.717 |
| FF3+RMW IAI | 0.000 | 2.800 | 0.168 | 0.717 |
| FF3+CMA IAI | 0.000 | 3.228 | 0.033 | 0.709 |
| FF5+IAI | 0.000 | 2.761 | 0.165 | 0.720 |
| 32 Size x BM x INV Portfolios | | | | |
| FF3 | 0.043 | 1.518 | 0.090 | 0.706 |
| FF3+IAI | 0.031 | 1.571 | 0.042 | 0.713 |
| FF3+RMW | 0.005 | 1.857 | 0.149 | 0.713 |
| FF3+CMA | 0.073 | 1.424 | 0.053 | 0.717 |
| FF5 | 0.039 | 1.533 | 0.110 | 0.723 |
| FF3+RMW IAI | 0.017 | 1.673 | 0.106 | 0.719 |
| FF3+CMA IAI | 0.029 | 1.583 | 0.038 | 0.722 |
| FF5+ IAI | 0.020 | 1.642 | 0.098 | 0.728 |
| 32 Size x BM x IAI Portfolios | | | | |
| FF3 | 0.000 | 2.297 | 0.127 | 0.701 |
| FF3+ IAI | 0.004 | 1.878 | 0.061 | 0.707 |
| FF3+RMW | 0.000 | 2.618 | 0.192 | 0.708 |
| FF3+CMA | 0.002 | 2.000 | 0.098 | 0.707 |
| FF5 | 0.000 | 2.210 | 0.164 | 0.714 |
| FF3+RMW IAI | 0.006 | 1.836 | 0.130 | 0.713 |
| FF3+CMA IAI | 0.005 | 1.861 | 0.059 | 0.711 |
| FF5+IAI | 0.006 | 1.818 | 0.127 | 0.717 |

*Note*: The table depicts the GRS test results for all 96 portfolios and then for each sort based on size, value and either operating profitability, investment, or intangible intensity. The dependent variable is value-weighted returns in excess of the risk-free rate. The GRS *p*-value, statistics, mean alpha and mean R-squared are shown for all combinations of factors. Industry sorting was applied. The sample is based on six portfolios formed from firms across 40 European countries between July 1999 to December 2022.

Table B4. Fama-Macbeth Regression of 3-Year Gross Profit and Earnings Growth with Industry Sort

| | (1)<br>3-Year Gross Profit Growth | (2)<br>3-Year Earnings Growth |
|---|---|---|
| Book/Market | -0.183*** | -10.391** |
| Operating Profitability | -0.347** | -28.459* |
| Investment | -0.061 | -10.287* |
| Intangible Intensity | 0.702*** | -5.082 |

Note: The table depicts the Fama-Macbeth results of regressing 3-year gross profit (scaled by assets) and earnings growth (scaled by book equity) against portfolio characteristics. The characteristics are beta, natural log of lagged market equity, BM, operating profitability, investment, and intangible intensity. All characteristics are value-weighted. Industry sorting was applied. The sample consists of 96 portfolios formed from firms across 40 European countries between July 1999 to December 2022. Newey-West standard errors are used with three lags. *** p<.01, ** p<.05, * p<.1

## Appendix C

Table C1. Results of Fama-Macbeth Regression of Future Portfolio Return on Characteristics pre-2007

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Intangible Intensity | 1.209 | 0.973 | 0.687 | 1.130 | 1.261 | 0.247 |
| Beta | | 0.057 | -0.298 | -1.111 | -0.992 | -0.699 |
| ln(Market Equity) | | | -0.074 | -0.065 | -0.068 | -0.069 |
| Book/Market | | | | 0.408 | 0.447 | 0.374 |
| Operating Profitability | | | | | 0.169 | -0.081 |
| Investment | | | | | | -0.491* |
| Constant | 0.901 | 1.271*** | 1.839*** | 1.302 | 1.171 | 1.588* |
| R2 | 0.054 | 0.176 | 0.259 | 0.305 | 0.331 | 0.359 |

*Note:* The table depicts the Fama-Macbeth coefficients of value-weighted monthly future returns at t+1 against value-weighted portfolio characteristics. Portfolio characteristics at the individual firm level were winsorised using 1% and 99% levels. The sample consists of 96 portfolios formed from firms across 40 European countries between July 1999 to December 2006. *** p<.01, ** p<.05, * p<.1

Table C2. Results of Fama-Macbeth Regression of Future Portfolio Return on Characteristics post-2007

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intangible Intensity | 0.492 | 0.371 | 0.670 | 1.461*** | 1.634*** | 1.242*** |
| Beta | | -0.268 | -0.235 | -0.686* | -0.183 | -0.171 |
| ln(Market Equity) | | | 0.035 | 0.068* | 0.029 | 0.014 |
| Book/Market | | | | 0.590*** | 0.590*** | 0.503** |
| Operating Profitability | | | | | 0.782*** | 0.718*** |
| Investment | | | | | | -0.441*** |
| Constant | 0.262 | 0.548 | 0.239 | -0.195 | -0.640 | -0.283 |
| R2 | 0.055 | 0.114 | 0.236 | 0.285 | 0.318 | 0.335 |

*Note:* The table depicts the Fama-Macbeth coefficients of value-weighted monthly future returns at t+1 against value-weighted portfolio characteristics. Portfolio characteristics at the individual firm level were winsorised using 1% and 99% levels. The sample consists of 96 portfolios formed from firms across 40 European countries between January 2007 to December 2022. *** p<.01, ** p<.05, * p<.1

Table C3. Factor Spanning Test for 2 x 3 Portfolio Sort pre-2007

| | Intercept | Market | SMB | HML | RMW | CMA | HIMLI | R2 |
|---|---|---|---|---|---|---|---|---|
| Market | 1.706*** | | -0.202 | -0.211 | -0.578*** | -0.236 | -0.013 | 0.291 |
| SMB | 1.147*** | -0.118 | | -0.498*** | -0.231* | 0.257 | 0.029 | 0.403 |
| HML | 0.506*** | -0.022 | -0.075 | | 0.047 | 0.517*** | -0.930*** | 0.811 |
| RMW | 1.279*** | -0.387*** | -0.264* | 0.077 | | -0.254 | 0.197 | 0.310 |
| CMA | 0.468 | -0.101 | 0.189* | 0.586*** | -0.163 | | 0.567*** | 0.412 |
| HIMLI | 0.026 | -0.004 | 0.016 | -0.578*** | 0.093 | 0.417*** | | 0.572 |

*Note:* The table depicts the results of the factor-spanning test with robust standard errors. The row variables represent the dependent variable, while the column variables represent the coefficients and model R-squared. The sample is based on six portfolios formed from firms across 40 European countries between July 1999 to December 2006. *** p<.01, ** p<.05, * p<.1

Table C4. Factor Spanning Test for 2 x 3 Portfolio Sort post-2007

| | Intercept | Market | SMB | HML | RMW | CMA | HIMLI | R2 |
|---|---|---|---|---|---|---|---|---|
| Market | 1.482*** | | -0.994*** | 0.423 | -1.104*** | -0.812*** | -0.324 | 0.373 |
| SMB | 0.664*** | -0.234*** | | 0.388*** | -0.754*** | -0.161 | -0.148 | 0.632 |
| HML | 0.443*** | 0.038 | 0.148*** | | 0.148*** | 0.433*** | -0.828*** | 0.909 |
| RMW | 0.876*** | -0.239*** | -0.693*** | 0.357*** | | -0.171 | -0.110 | 0.583 |
| CMA | -0.014 | -0.095*** | -0.080 | 0.566*** | -0.093 | | 0.477*** | 0.314 |
| HIMLI | 0.677*** | -0.033 | -0.065 | -0.953*** | -0.053 | 0.420*** | | 0.903 |

*Note:* The table depicts the results of the factor-spanning test with robust standard errors. The row variables represent the dependent variable, while the column variables represent the coefficients and model R-squared. The sample is based on six portfolios formed from firms across 40 European countries between January 2007 to December 2022. *** p<.01, ** p<.05, * p<.1

Table C5. Summary of GRS Test Statistic for Portfolios pre-2007

| | p(GRS) | GRS | Mean Alpha | Mean R2 |
|---|---|---|---|---|
| 3 x 32 Size-BM-XX Portfolios | | | | |
| FF3 | . | -3.591 | -0.134 | 0.668 |
| FF3+IAI | . | -7.623 | -0.149 | 0.683 |
| FF3+RMW | . | -6.076 | 0.062 | 0.687 |
| FF3+CMA | . | -2.126 | -0.154 | 0.687 |
| FF5 | . | -7.791 | 0.051 | 0.705 |
| FF3+RMW IAI | . | -5.923 | 0.046 | 0.702 |
| FF3+CMA IAI | . | -9.830 | -0.158 | 0.699 |
| FF5+IAI | . | -4.674 | 0.050 | 0.717 |
| 32 Size x BM x OP Portfolios | | | | |
| FF3 | 0.000 | 3.134 | -0.189 | 0.681 |
| FF3+IAI | 0.000 | 3.242 | -0.209 | 0.688 |
| FF3+RMW | 0.001 | 2.679 | 0.070 | 0.705 |
| FF3+CMA | 0.000 | 3.704 | -0.203 | 0.693 |
| FF5 | 0.000 | 3.149 | 0.074 | 0.717 |
| FF3+RMW IAI | 0.000 | 2.828 | 0.049 | 0.713 |
| FF3+CMA IAI | 0.000 | 3.615 | -0.212 | 0.701 |
| FF5+IAI | 0.000 | 3.091 | 0.071 | 0.725 |
| 32 Size x BM x INV Portfolios | | | | |
| FF3 | 0.019 | 1.891 | -0.099 | 0.667 |
| FF3+IAI | 0.025 | 1.828 | -0.121 | 0.681 |
| FF3+RMW | 0.009 | 2.074 | 0.046 | 0.684 |
| FF3+CMA | 0.029 | 1.795 | -0.118 | 0.690 |
| FF5 | 0.015 | 1.963 | 0.033 | 0.706 |
| FF3+RMW IAI | 0.012 | 2.014 | 0.025 | 0.698 |
| FF3+CMA IAI | 0.031 | 1.781 | -0.126 | 0.700 |
| FF5+IAI | 0.015 | 1.965 | 0.031 | 0.716 |
| 32 Size x BM x IAI Portfolios | | | | |
| FF3 | 0.092 | 1.501 | -0.114 | 0.657 |

| | | | | |
|---|---|---|---|---|
| FF3+IAI | 0.120 | 1.436 | -0.118 | 0.680 |
| FF3+RMW | 0.023 | 1.848 | 0.070 | 0.673 |
| FF3+CMA | 0.122 | 1.432 | -0.142 | 0.678 |
| FF5 | 0.038 | 1.736 | 0.048 | 0.692 |
| FF3+RMW IAI | 0.031 | 1.786 | 0.065 | 0.695 |
| FF3+CMA IAI | 0.137 | 1.401 | -0.137 | 0.697 |
| FF5+IAI | 0.043 | 1.709 | 0.048 | 0.710 |

*Note*: The table depicts the GRS test results for all 96 portfolios and then for each sort based on size, value and either operating profitability, investment, or intangible intensity. The dependent variable is value-weighted returns in excess of the risk-free rate. The GRS *p*-value, statistics, mean alpha and mean R-squared are shown for all combinations of factors. The sample is based on six portfolios formed from firms across 40 European countries between July 1999 to December 2006.

Table C6. Summary of GRS Test Statistic for Portfolios post-2007

| | p(GRS) | GRS | Mean Alpha | Mean R2 |
|---|---|---|---|---|
| 3 x 32 Size-BM-XX Portfolios | | | | |
| FF3 | 0.000 | 2.514 | 0.041 | 0.794 |
| FF3+IAI | 0.000 | 2.047 | -0.044 | 0.806 |
| FF3+RMW | 0.000 | 2.226 | 0.127 | 0.802 |
| FF3+CMA | 0.000 | 2.407 | 0.021 | 0.803 |
| FF5 | 0.000 | 2.073 | 0.108 | 0.809 |
| FF3+RMW IAI | 0.005 | 1.722 | 0.050 | 0.813 |
| FF3+CMA IAI | 0.000 | 2.017 | -0.041 | 0.810 |
| FF5+IAI | 0.006 | 1.704 | 0.051 | 0.817 |
| 32 Size x BM x OP Portfolios | | | | |
| FF3 | 0.000 | 3.895 | -0.038 | 0.777 |
| FF3+IAI | 0.000 | 3.773 | -0.112 | 0.787 |
| FF3+RMW | 0.000 | 3.041 | 0.114 | 0.791 |
| FF3+CMA | 0.000 | 3.829 | -0.056 | 0.782 |
| FF5 | 0.000 | 2.886 | 0.106 | 0.796 |
| FF3+RMW IAI | 0.000 | 2.807 | 0.064 | 0.801 |
| FF3+CMA IAI | 0.000 | 3.722 | -0.109 | 0.789 |
| FF5+IAI | 0.000 | 2.791 | 0.064 | 0.803 |
| 32 Size x BM x INV Portfolios | | | | |
| FF3 | 0.001 | 2.105 | 0.021 | 0.809 |
| FF3+IAI | 0.000 | 2.421 | -0.061 | 0.821 |
| FF3+RMW | 0.001 | 2.102 | 0.087 | 0.814 |
| FF3+CMA | 0.004 | 1.956 | -0.000 | 0.822 |
| FF5 | 0.009 | 1.822 | 0.063 | 0.825 |
| FF3+RMW IAI | 0.001 | 2.115 | 0.007 | 0.824 |
| FF3+CMA IAI | 0.000 | 2.463 | -0.057 | 0.828 |
| FF5+IAI | 0.001 | 2.163 | 0.007 | 0.831 |
| 32 Size x BM x IAI Portfolios | | | | |
| FF3 | 0.000 | 3.817 | 0.139 | 0.797 |
| FF3+IAI | 0.000 | 2.432 | 0.043 | 0.810 |
| FF3+RMW | 0.000 | 3.596 | 0.181 | 0.801 |
| FF3+CMA | 0.000 | 3.599 | 0.119 | 0.803 |
| FF5 | 0.000 | 3.248 | 0.156 | 0.806 |
| FF3+RMW IAI | 0.002 | 2.053 | 0.080 | 0.813 |
| FF3+CMA IAI | 0.000 | 2.395 | 0.045 | 0.813 |
| FF5+IAI | 0.002 | 2.050 | 0.081 | 0.816 |

*Note*: The table depicts the GRS test results for all 96 portfolios and then for each sort based on size, value and either operating profitability, investment, or intangible intensity. The dependent variable is value-weighted returns in excess of the risk-free rate. The GRS *p*-value, statistics, mean alpha and mean R-squared are shown for all combinations of factors. The sample is based on six portfolios formed from firms across 40 European countries between January 2007 to December 2022.

Table C7. Fama-Macbeth Regression of 3-Year Gross Profit and Earnings Growth pre-2007

| | (1) | (2) |
|---|---|---|
| | 3-Year Gross Profit Growth | 3-Year Earnings Growth |
| Book/Market | 0.057 | -49.301** |
| Operating Profitability | 0.389 | -117.115* |
| Investment | 0.300*** | -36.969* |
| Intangible Intensity | 0.783*** | -83.311* |

*Note:* The table depicts the Fama-Macbeth results of regressing 3-year gross profit (scaled by assets) and earnings growth (scaled by book equity) against portfolio characteristics. The characteristics are beta, natural log of lagged market equity, BM, operating profitability, investment, and intangible intensity. All characteristics are value-weighted. The sample consists of 96 portfolios formed from firms across 40 European countries between July 1999 to December 2006. Newey-West standard errors are used with three lags. *** p<.01, ** p<.05, * p<.1

Table C8. Fama-Macbeth Regression of 3-Year Gross Profit and Earnings Growth post-2007

| | (1) | (2) |
|---|---|---|
| | 3-Year Gross Profit Growth | 3-Year Earnings Growth |
| Book/Market | -0.241*** | -0.531 |
| Operating Profitability | -0.778*** | -0.994 |
| Investment | -0.249*** | 1.147 |
| Intangible Intensity | 0.416*** | -2.132** |

*Note:* The table depicts the Fama-Macbeth results of regressing 3-year gross profit (scaled by assets) and earnings growth (scaled by book equity) against portfolio characteristics. The characteristics are beta, natural log of lagged market equity, BM, operating profitability, investment, and intangible intensity. All characteristics are value-weighted. The sample consists of 96 portfolios formed from firms across 40 European countries between January 2007 to December 2022. Newey-West standard errors are used with three lags. *** p<.01, ** p<.05, * p<.1