Master thesis submitted in partial fulfilment of the requirements for the degree

Master of Science

at the Technische Universität München

Multi-Factor Asset Pricing Models for the Spanish Stock Market

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Submitted on: April 10th, 2018

ABSTRACT

Tests on the five-factor model of Fama and French (2015) for the Spanish stock market from 1990-2016 (317 months), reveal that the *market*, *size* and *investment* factors do not contribute information about average stock returns. Analogous tests on the three-factor model of Fama and French (1993) are even more tragic, and reveal that none of the three factors contribute unique information to the model. Therefore alternative factor definitions are considered for the; *value*, *profitability* and *investment* factors. The performance of the three-factor model is significantly improved by using a *value* factor constructed on *E/P*. In order to improve the performance of the five-factor model, a modified six-factor model has been proposed. The proposal uses; a devil *B/M value* factor as suggested by Asness and Frazzini (2013), an *investment* factor based on *composite-equity-issuance*, and a sixth *momentum* factor as suggested by Carhart (1997). The *size*, *market* and profitability factors remain largely unchanged. All factors in the model proposal, except *size*, contribute unique, valuable information about average returns. Two new *risk* factors are also constructed, however their average returns prove to be captured by the here suggested six-factor model. *Size* is redundant for describing average returns for the studied sample.

Key words: Stock market, Spanish market, asset pricing, multi-factor model, five-factor, profitability, investment, momentum, risk.

ZUSAMMENFASSUNG

Tests zum Fünf-Faktoren-Modell von Fama and French (2015) für den spanischen Aktienmarkt von 1990-2016 (317 Monate) zeigen, dass der *Markt*-, die *Größen*- und die *Investitionsfaktoren* keine Informationen über durchschnittliche Aktienrenditen liefern. Analoge Tests aus dem Drei-Faktoren-Modell von Fama and French (1993) fallen noch tragischer aus und zeigen, dass keine der drei Faktoren einzigartige Informationen zu dem Modell beitragen. Daher werden alternative Faktordefinitionen für *Wert*-, *Rentabilität*- und *Investitionsfaktoren* berücksichtigt. Die Leistungen des Drei-Faktoren-Modells werden durch die Verwendung eines auf *Kurs-Gewinn-Verhältnis* (*E/P*) basierenden Wertfaktors deutlich verbessert. Um die Leistungen des Fünf-Faktoren-Modells zu erhöhen, wurde ein modifiziertes Sechs-Faktoren-Modell vorgeschlagen. Der Vorschlag verwendet einen auf Asness and Frazzini (2013) basierenden dämonischen (devil) *Buchwert-Marktwert* (*B/M*) *Wertfaktor*, einen auf den *zusammengesetzten Kapitalemissionen* (*CEI*) basierenden *Investitionsfaktor* und einen sechsten *Momentumfaktor*, wie in Carhart (1997). Die *Größen*-, *Markt*- und *Rentabilitätsfaktoren* bleiben weitgehend unverändert. Alle Faktoren im Modellvorschlag mit Ausnahme von dem Faktor *Größe* liefern einzigartige, wertvolle Informationen über durchschnittliche Renditen. Zwei neue Risikofaktoren werden konstruiert, aber in dem hier vorgeschlagenen Sechs-Faktoren-Modell werden ihre durchschnittlichen Erträge erfasst. Der *Größenfaktor* ist zur Beschreibung der durchschnittlichen Erträge für die untersuchte Stichprobe überflüssig.

Schlagworte: Aktienmarkt, spanischer Markt, Asset Pricing, Multifaktormodell, Fünf-Faktor, Rentabilität, Investition, Momentum, Risiko.

RESUMEN

Título: MODELOS MULTIFACTORIALES DE VALORACIÓN DE ACTIVOS PARA EL MERCADO DE VALORES ESPAÑOL

Ensayos realizados para el mercado de valores Español durante el periodo de 1990-2016 (317 meses), indican que los factores de *mercado*, *tamaño* e *inversión* del modelo de cinco factores de Fama and French (2015), no contribuyen en la explicación de los rendimientos medios de acciones. Ensayos análogos son aún más trágicos en el caso del modelo de tres factores de Fama and French (1993), dónde ningún factor aporta información única sobre los rendimientos medios de las acciones. Por consiguiente se han considerado definiciones alternativas para los factores; *valor*, *rentabilidad* e *inversión*. En el modelo de tres factores, se observa una mejora considerable si se utiliza un factor *valor* basado en el ratio *beneficio-precio* (*E/P*). Para mejorar el rendimiento del modelo de cinco factores, se propone un modelo modificado del mismo. El modelo propuesto utiliza; un factor *valor* “demónico” (devil) basado en el ratio *valor contable–precio* (*B/M*) como el sugerido por Asness and Frazzini (2013), un factor inversión basado en la emisión compuesta de capital (*CEI*), y un sexto factor de *inercia* como el sugerido por Carhart (1997). Los factores; *mercado*, *tamaño* y *rentabilidad* se conservan sin grandes cambios. Todos los factores del modelo propuesto, excepto el factor *tamaño*, contribuyen información única sobre rendimientos medios de acciones. Se construyen dos factores nuevos basados en *riesgo*, pero se observa que el modelo de seis factores aquí planteado captura sus rendimientos medios. El factor *tamaño* permanece redundante para la muestra de análisis.

Palabras clave: Mercado de valores, valoración de activos, mercado español, modelo multifactorial, cinco-factores, rentabilidad, inversión, riesgo, inercia.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AG	Asset growth
B/M	Market-to-book value
beta	Systematic risk
BV	Book value
CEI	Composite-equity-issuance
CMW	Conservative minus aggressive
Coef.	Coefficient
dev	Devil
DS	DataStream
E/P	Earnings-to-price
FF	Fama-French
HML	High minus low
Inv	Investment
LHS	Left-hand-side
Mom	Momentum
MV	Market value
NSI	Net stock issues
OP	Operating profitability
P	Price
PMV	Poised minus volatile
RF	Risk free rate
RHS	Right-hand-side
RM	Market return
RMRF	Market return minus risk free rate
RMW	Robust minus weak
ROE	Return on Equity
SMB	Small minus big
SR	Sharpe ratio
TR	Thomson Reuters
TRD	Thomson Reuters DataStream
TRW	Thomson Reuters WorldScope
Vol	Volatility
WML	Winner minus loser
WS	WorldScope

1. INTRODUCTION

The task of asset pricing has existed, intuitively at least, ever since the concept of private property was introduced to mankind. However, as pointed out by Dimson and Mussavian (1999), one of the earliest papers that addresses the task of asset pricing in modern finance, was presented by Daniel Bernoulli (1739). In said paper, Bernoulli covers some of the fundamental issues relevant to modern day financial economics and proposes that, “the determination of the value of an item must not be based on its price, but rather on the utility it yields”, Bernoulli (1739), p. 24.

There are many models currently used in the estimation of asset pricing to determine this “utility”. However, the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966), set the backbone for recent asset pricing, and has proven itself to be a valuable tool in the complex and demanding task of asset pricing. However, its modest approach and calculation also makes CAPM a flawed model, lacking many of the intricacies that add or subtract potential value to a modern firm.

More recently, multi-factor empirical pricing models have proven themselves to better explain the cross-sectional returns of stocks. Fama and French (2015) propose a new five-factor model to explain cross-sectional returns.

Due to its size, extensive documentation and relative superiority throughout the 20th century, the US capital market has been the focal point of most research, including Fama and French (2015). However, so far there is evidence that different markets, in different regions and with different economic and social backgrounds, can behave very differently. Hence models need to be tested for their efficacy in foreign markets. So far there is no evidence of the Fama-French five-factor model being tested on the Spanish capital market. This thesis will embrace said task.

The world is evolving, globalisation pushes for equilibrium; the Eurozone has empowered the European markets and what until very recently were emerging markets, are now global contenders. Furthermore, the increasing number of companies that choose to list their stock in foreign, stronger, exchanges makes it harder to discriminate between regions.

Will the multi-factor asset pricing model developed using US markets' empirical evidence be equally valid for Spain, Europe's fifth largest nation? Or will the models need "tweaking" in order to provide good cross-sectional coverage?

In Chapter 3, results on tests of the Fama-French five-factor model applied to Spain are presented and evaluated. Alternatives and variants of the model are explored and tested in Chapter 4, resulting in a final proposal for a more effective multi-factor model for the Spanish capital market.

1.1. MOTIVATION

The world of capital markets and financial products has grown more and more relevant over the last two decades. The internet and its increased global accessibility has unlocked the capital markets making it faster and easier for all people from all countries to invest on a worldwide scale. The products on offer have also evolved. The once traditional capital market, where shares on stocks and bonds are traded, is now hugely complemented by derivatives.

The three-factor asset pricing model, developed by Fama and French (1993), incorporates two additional factors, size and value, to the CAPM asset pricing model. In 2015, a further two factors, investment and operating profitability, were added to create the five-factor asset pricing model of Fama and French (2015).

Both models were developed and tested, initially at least, for the US stock markets. Tests on both models for other markets have exposed varying performance and weaknesses. This is no surprise, universally effective models seem, to date, inexistent. However, over the recent years globalisation is closing the breach between developed markets, the European and US markets are no longer divergent. On these grounds, there is a great interest in examining the potential compatibility of models between the US and the EU.

Fama and French (2017) found that both the Fama-French three-factor and Fama-French five-factor models perform poorly when the factors are applied globally and that, although with locally defined factors the five-factor model outperforms the three-factor model, one of its five factors is redundant for the EU. Currently, there are no studies that investigate the validity or accuracy of the five factor model applied specifically to the Spanish capital market.

Spain is the fifth largest nation in the European Union both by population and gross GDP[1]. Furthermore, with a market capitalisation of over $950 billion, the Spanish financial market ranks 5th in the European Union and 20th worldwide[2]. Consequently, it will be interesting to see how the established models perform in this region.

To date, the young five-factor model has yet to prove itself as a valid and valuable addition to the difficult task of asset pricing. Moreover, it has been heavily criticised by the sector for not including factors like momentum, a factor that has been widely accepted and used for over 15 years.

1.2. CURRENT STATE OF ART

The Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966), predicts that the estimated returns on an asset (or portfolio of assets) for month t, R_{it}, can be calculated as a function of the return on an alternative risk free investment, RF_t, and the expected market premium, RM_t, for the same month. According to CAPM, the relation between the expected returns of an asset and the expected market risk premium is merely dependant on the co-movement of asset i's price with that of the entire market portfolio.

$$R_{it} = RF_t + \beta_i RMRF_t + e_{it} \qquad (1)$$

In equation (1), $RMRF_t$ denotes the market return (RM_t) minus the risk free rate (RF_t) for month t. The co-movement of asset i is measured using beta, β_i, which is the standardized covariance of the asset's price with the market portfolio. Furthermore, the CAPM formula (1) determines β as the only measure for systematic risk, and concludes that further characteristics of the asset should not alter its expected return.

Black et al. (1972) and Fama and MacBeth (1973) study the validity of the CAPM model to explain the returns on stock portfolios, and find that, although the model does, to an extent, explain the returns of different portfolios, the relation is too flat. In doing so, they find that the CAPM model underestimates the

[1] Statistics collected from the European Commission's Eurostat website for 2017. See http://ec.europa.eu/eurostat.

[2] The World Federation of Exchanges: Monthly Reports, January 2018. See https://www.world-exchanges.org.

returns of stocks with low market covariances and overestimates the returns of those with high market covariances.

Basu (1977) further determined that the earnings-to-price ratio, *E/P*, played an important factor in the expected returns, finding securities with high *E/P* ratios to have a higher return yield than predicted by the CAPM model. Additionally, Banz (1981) and Rosenberg et al. (1985) show that the book-to-market value, *B/M*, of securities has an influence on the returns. These patterns, that seem to be unexplained by CAPM, are known as capital market anomalies.

Fama and French (1992) test the CAPM model on the cross-sectional returns of NYSE, AMEX and NASDAQ stocks, finding that “the relation between market β and average return is flat”, Fama and French (1992), p. 427. Additionally, they also find that even in the 50-year, 1941-1990 period, “the relation between β and average return is also weak”, Fama and French (1992), p. 428, thus confirming the shortcomings of CAPM to satisfactorily capture stock returns.

Fama and French (1992) go on to establish that the size, market equity, and book-to-market equity ratio variables confidently explain the cross-section of average returns on US stocks, during the 1963-1990 period. Moreover, they find and explain that said variables used in coalition, seem to absorb the effects of leverage and the earnings-to-price ratio, on average returns.

Fama and French (1993) use time-series regressions to test the relationship between individual characteristic variables of portfolios, such as book-to-market equity and size, and their average returns. They find that by adding risk factors related to size and *B/M* to the original CAPM model, improves its ability to explain the cross-sectional returns on US stocks. The resulting model is the now well-known Fama-French three-factor model.

$$R_{it} = RF_t + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + e_{it} \tag{2}$$

The Fama-French three-factor model time series regression, represented in equation (2), adds a size factor, *SMB,* and a value factor, *HML*, to the original CAPM model (1). SMB_t stands for “Small minus Big”, and represents the difference in returns between a diversified portfolio of small stocks and a diversified portfolio of large stocks. HML_t stands for “High minus Low”, and represents the difference in returns between a diversified portfolio with a high book-to-market equity ratio, *B/M*, and that of a diversified portfolio with a low

B/M. The factor exposures to SMB_t and HML_t of an asset i, are captured by s_i and h_i respectively.

Carhart (1997) expands on the Fama French three-factor model by adding a fourth momentum factor. Carhart uses this fourth term to explain the medium-term past performance of stocks, where the Fama-French three-factor model can only explain long-term past returns.

$$R_{it} = RF_t + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + w_i WML_t + e_{it} \qquad (3)$$

Equation (3) represents the Carhart four-factor time series regression. Here WML_t stands for "Winners minus Losers", and represents the difference in returns between a diversified portfolio with high momentum, winner, and a diversified portfolio with low momentum, loser. w_i represents the exposure of asset i to the *WML* factor.

Hanauer et al. (2014) test the Fama-French three-factor model on an international data set, and test an alternative proxy for expected returns – The implied cost of capital (ICC). They find the Fama-French three-factor model to be an adequate asset pricing model for the studied international markets when using regionally defined factors.

A new variant of the Fama-French three-factor model's *HML* factor was proposed by Asness and Frazzini (2013). They questioned the reason behind the annual construction for the *B/M* sorts for the traditional *HML* factor and proposed a new monthly construction for the factor, commonly known as *HMLdevil*. They found that *HMLdevil* is strongly negatively correlated to Carhart (1997)'s momentum factor, *WML*, and that when used in conjunction with the momentum factor, *HMLdevil* outperformed the traditional *HML* factor.

The Fama-French three-factor model and the Carhart four-factor model have been the industry standard in empirical asset pricing since their formulation. However, they are good, but not perfect. Hence, motivated by evidence of Novy-Marx (2013) and Titman et al. (2004), that their three-factor model was incomplete, in 2015 Fama and French released the paper "A five-factor asset pricing model", Fama and French (2015). Here they add a further two factors to their original three-factor model. The new factors are designed to capture the variation in average returns related to profitability and investment, and are thus labelled as profitability and investment factors.

$$R_{it} = RF_t + \beta_i RMRF_t + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{it} \quad (4)$$

The Fama-French five-factor model with its; market, size, value, profitability and investment factors, is represented in equation (4). Here the profitability, RMW_t, and investment, CMA_t, factors are added to the original three-factor model (2). RMW_t stands for "Robust minus Weak" and represents the difference in returns between a diversified portfolio with high profitability, robust, and a diversified portfolio with low profitability, weak. Similarly, CMA_t stands for "Conservative minus Aggressive" and represents the difference in returns between a diversified portfolio with low investment, conservative, and a diversified portfolio with high investment, aggressive. The factor exposures for *RMW* and CMA_t are captured by r_i and c_i respectively.

International performance tests of the Fama-French five-factor model are carried out by Fama and French (2017), where they study the model across different regions: North America, Europe, Asia Pacific and Japan. They find that in the most recent 1990-2015 period, there are large discrepancies between average returns on equal portfolio sorts between North American stocks, and European & Asia Pacific stocks. Similarly to their findings in Fama and French (2012), where they carry out international tests on their three-factor model, Fama and French (2017) find that a global version of their five-factor model fails to explain the regional expected returns. Hence Fama and French (2017) focus on locally defined models where the factors are constructed and tested for each region separately.

In their spanning tests they provide evidence that the investment factor, *CMA*, is redundant for the European and Japanese regions, stating that "dropping *CMA* from the five-factor model has little effect on the description of average returns, at least for 1990-2015.", Fama and French (2017), p. 458. They conclude that "local versions of the five-factor model absorb most of the value, profitability, and investment patterns in average returns", Fama and French (2017), p. 457.

The Fama and French (2017) study is of special significance for this thesis, as it demonstrates that the Fama-French five-factor model already has a different personality for the EU as for North America. Additionally, as will be explained in chapter 3, the studied period in Fama and French (2017) is almost the same as the period that will be used in this thesis.

The possibility of using risk; volatility and beta, to explain the cross-sectional returns is explored by Blitz and van Vliet (2007) and Frazzini and Pedersen (2014) respectively. Blitz and van Vliet (2007) focus on the long-term 36 month volatility of stocks and find that low-risk stocks tend to have good average returns, whereas high-risk stocks tend to have poor average returns.

Similarly Frazzini and Pedersen (2014) do international tests on potential beta factors on a variety of financial products. They find that in their tests of beta sorted portfolios, both for international and US equities, on average low beta stocks yield higher returns and Sharpe ratios than high beta stocks. In particular, for Spain, they find that their beta factor yields a statistically significant average monthly excess return of 0.59% over the 1984-2012 studied period, Frazzini and Pedersen (2014), p. 14, Table 5.

In regards to the Spanish capital market, there have been studies into the performance of the Fama-French three-factor model and other alternative models.

Nieto (2004) looks for empirical evidence of the performance of various multi-factor asset pricing models applied to the Spanish capital market in the period 1982-1998. Among her findings is that the CAPM model fails to explain cross-sectional returns. Furthermore, by carrying out Fama-Macbeth two-step cross-sectional regressions[3], Nieto (2004) tests the Fama-French three-factor model's performance, and finds that the negative relationship between return and size is supported by the betas, and that the R^2 of the regressions are high, at 85%.

A further study carried out by Nieto and Rodríguez (2005) provides empirical evidence that the Fama-French three-factor model performs well in the Spanish market, considerably outperforming the CAPM model. Nieto goes on to explain that the two Fama-French factors that replicate size and value, *SMB* and *HML* respectively, provide relevant information.

The momentum risk factor is put under scrutiny for the Spanish capital market by Font-Belaire and Grau-Grau (2007), here they question whether the size, value and momentum risk factors can explain the returns in the Spanish capital market. Their findings are that the factors; size, value and especially momentum,

[3] See Fama, E. F. & Macbeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of political economy,* 81**,** 607-636.

contribute significantly to explain the returns on assets in the Spanish capital markets for the January 1995 to December 2000 studied period.

De Pena et al. (2010) question the correct interpretation of the results obtained by the Fama-French three-factor model, to see if the *SMB* and *HML* factors are proxying for a rational underlying risk factor. They run regressions of monthly excess returns of six portfolios differentiated by size and book-to-market ratios on Fama-French; market, size and value factors, finding that the explanatory power of the model is high, with R^2 values between 0.73 and 0.86, during the January 1991 to June 2004 period.

To sum up, there is plenty of evidence showing that the Fama-French three-factors and the momentum factor are relevant for Spain for varying periods up to 2004. However, there have not been any specific studies for Spain that analyse the performance of the extended Fama-French five-factor model. This study will look for empirical evidence to support or reject the predictive power of the Fama-French five-factor model applied to the Spanish stock market for a more recent 26 year period. Insights will also be made into the performance of the original three-factor model for a more recent and extensive 26 year period. Alternatives and variants of this multi-factor model will also be evaluated, such as; the possible inclusion of the Carhart (1997) momentum factor, the inclusion of a risk factor like beta or volatility, and the use of an alternative *HML* factor, as described by Asness and Frazzini (2013).

1.3. STRUCTURE OF THE THESIS

The structure of this thesis will be the following. First a description into how data has been collected and screened will be carried out in chapter 2.1. Then, in chapter 2.2, the methods in factor construction and calculation will be detailed.

In chapter 3, the performance of the strict Fama-French five-factor and three-factor models will be evaluated for the Spanish capital market through the use of factor statistics, spanning tests and the calculation of the Sharpe ratio.

New variables and alternative factors will be evaluated in chapter 4. Here new factors, constructed using Fama-French methods, but using alternative characteristic variables will be constructed, and the resulting multi-factor models evaluated. In particular, the addition of Carhart (1997)'s momentum factor and Asness and Frazzini (2013)'s devil variation of the value factor will be assessed.

Chapter 5 is reserved for final conclusions followed by an appendix with robustness tests on single sorts and various other relevant tables and key figures.

2. FACTOR CONSTUCTION

2.1. SAMPLE DEFINITION

For the conduct of this thesis, data has been exclusively sourced from Thomson Reuters DataStream (TRD) and Thomson Reuters WorldScope (TRW) databases.

The initial sample has been collected using DEADES, WSCOPEES, FSPN, FSPNQ and FSPDOM Thomson Reuter (TR) constituent lists. The stocks have then been submitted to static screens to maintain only Spanish primary common equity listings as suggested by Ince and Porter (2006), Griffin et al. (2010) and Schmidt et al. (2011).

The sample for this study spans over the 26 year period from July 1990 to November 2016 (317 months). Market information of all common equity listings is gathered monthly at the end of each month, and book financials are collected at the end of December yearly. All data is collected and presented in Euros.

The listings of financial institutions such as banks or insurance companies make up an important segment of the Spanish stock market. Their contributions to the total market equity (ME) is moderate, with an average market share of 34.4%, and minimum and maximum values of 29.4% and 39.3% respectively for the sample period (calculated using yearly averages).

Furthermore, equities like the Santander bank or BBVA bank single-handedly make up a large percentage of the overall market equity. Such is the importance of financial institutions in the Spanish stock market, that if calculated by annual average market capitalisation, the Santander bank has been the largest stock on the Spanish market in three occasions, with a maximum average annual market share of 14.7% for the year 2014.

For these reasons, and due to the relatively reduced number of securities available on the Spanish stock market, the decision to include all financial institutions in the data sample has been made. Financial institutions are identified using the TRD identifier ICBSUC which displays the company's Industry

Classification Benchmark, all ICBSUC entries that start with the number “8” are classified as financials.

2.1.1. Data quality

To ensure that the cross-sectional returns of the data set are not influenced by survival bias, data is collected for the union of equities resulting from; DataStream lists, WorldScope lists and dead lists given by TR for Spain.

This way the returns resulting from high risk surviving stocks, characterised by certain aspects, will be appropriately compensated by the low returns resulting from similar stocks which have not survived. If only current constituents were considered, survival bias would lead to the incorrect overvaluation of risky variables.

Calculating the returns for stocks with small listing prices (e.g. $P < 1.00$) can lead to large margins of error due to TRD data being provided with an accuracy of 2 decimal places. Hence, in order to include all stock listings without having to assume large marginal errors, monthly stock returns are collected using TRD internally calculated percentage change in total index return “PCH#(X(RI),-1M)”.

As pointed out by Ince and Porter (2006) the data recovered from TR is not guaranteed to be error free, hence, the sample data is screened following the indications of Ince and Porter (2006), Griffin et al. (2010) and Schmidt et al. (2011).

2.1.2. Static screens

The union formed from the DEADES, WSCOPEES, FSPN, FSPNQ and FSPDOM constituent lists are screened to remove non-common equity listings, non-primary listings and listings of foreign companies.

Common equity is initially screened for by using the DataStream stock classification parameter. As such, only stocks with the TRD parameter, TYPE=“EQ”, are selected for the sample. The ISINID parameter has been used in order to limit the sample to primary listings only (ISINID=“P”). For the sample, only the major listing of any company has been considered, this equates to selecting only stocks with the DS parameter, MAJOR=“Y”.

To limit the sample to companies and equities located in Spain, the DataStream location parameters have been used (GEOLN=“SPAIN” & GEOGN=“SPAIN”).

Additionally, all securities with ISIN country code other than Spain[4] are rejected, GGISN="ES".

As reported by Ince and Porter (2006), and as becomes clearly observable after simple visual inspection, the TRD TYPE parameter does not always filter for strict common equities when equal to "EQ", and some non-common equities slip through. To amend this, filters for specific words and character chains contained in the security names are run, as suggested by Ince and Porter (2006), Griffin et al. (2010) and Hanauer (2014). The specific words and character chains, corresponding to typically used terms for indicating that the security is a duplicate, preferred stock, debt, etc., are listed in Table 1.

Table 1: **Generic character strings for detecting non-common equity**
In this table the generic character strings that have been used to filter out remnant non-common equity securities, after filtering using TRD's TYPE parameter equal to "EQ", are listed. The remaining securities' names are searched to see if they contain any of the listed character strings. All positive matches are manually revised and the non-common equities discarded.

Non-common equity	Character strings
Duplicates	"DUPLICATE" " DUPL" "DUP." "DUPE" "DULP" "DUPLI" "1000DUPL" "XSQ" "XETa" " DUP " "DUPL " "DUPL."
Depository Receipts	" ADR" "GDR"
Preferred Stock	"Stock" "PREFERRED" "PF." "PFD" "PREF" "'PF'" "PRF"
Warrants	"WARRANT" "WARRANTS" "WTS" "WTS2" "WARRT"
Debt	" DEB " " DB" "DCB" " DEBT " "DEBENTURES" "DEBENTURE" "BOND" "%"
Unit Trusts (2 words)	"RLST IT" "INVESTMENT TRUST" "INV TST" "UNIT TRUST" "UNT TST" "TRUST UNITS" "TST UNITS" "TRUST UNIT" "TST UNIT"
Unit Trusts (1 word)	" UT " ".IT"
ETF	"ETF" "ISHARES" "INAV" "X-TR" "LYXOR" "JUNGE" "AMUNDI"
Ince and Porter (2006)	"500" " BOND " "DEFER" " DEP " "DEPY" "ELKS" " ETF" "FUND" "FD" "IDX" "INDEX" " MIPS" "MITS" "MITS." " MITT " " MITT." "NIKKEI" "NOTE." " NOTE " "PERQS" " PINES " " PINES." "PRTF" "PTNS" "PTSHP" "QUIBS" " QUIDS" "RATE" "RCPTS" "RECEIPTS" "REIT" "RETUR" " SCORE" "SPDR" "STRYPES" "TOPRS" "WTS" "XXXXX" "YIELD" "YLD" " QUIDS"
Expired securities	"EXPIRED" "EXPD" "EXPIRY" "EXPY"

[4] Due to the elevated number of securities without ISIN country codes, GGISIN="NA", securities with no ISIN codes have been included in the sample, and their exclusion from the sample has been considered individually.

2.1.3. Dynamic screens

Thomson Routers' DataStream listing and WorldScope financial information has been retrieved for the remaining stocks. As pointed out by Ince and Porter (2006), the TRD information can distort variables and results. For example, the last listing information of a stock is maintained static once a stock is delisted, this could lead to a delisted stock to appear preferable in times of negative market returns.

In order to remove all data corresponding to dead stocks, TRD's total return index (RI) is collected in local currency and all monthly records with null returns are removed from the end of the time-series. At this stage all entries with no values for Price (P) and market value (MV) are removed.

Additionally, all records with a monthly return above 890% are removed from the sample, and listings that have an unadjusted listing price of more than 1´000´000 are removed.

In order to capture any stock splits that may not have been accounted for in TDS's total index return calculation, records with R_t or R_{t-1} greater than 300% and $(1 + R_t)(1 + R_{t-1}) - 1$ less than 50% are removed. R_t being the return for a stock for a month t.

Finally, all entries without a TRW common equity value (WC03501) are removed, as this is basic data the will be necessary throughout the study in order to calculate the securities' book values.

After the static and dynamic screening procedures, the total sample is reduced from 562 equities and 89'436 observations retrieved from the constituent's lists, to 315 equities and 44'599 observations. This equates to a maximum and minimum number of securities in the sample of 165 and 84, respectively, for any given month. For further details about sample size and composition see Table 15 in the appendix.

2.1.4. Thomson Reuters indexes

The TRD and TRW data identifiers that have been used for the conduct of this thesis are listed in Table 2.

Table 2: **List of Thomson Reuters DataStream and WorldScope identifiers**
In this table the identifiers used to collect data from TR are listed together with their corresponding TR short descriptions.

TRW Identifier	Description	TRD Identifier	Description
WC03501	COMMON SHAREHOLDERS' EQUITY	PCH#(X(RI),-1M)	ONE MONTH % CHANGE OF THE RETURN INDEX
WC01551	NET INC BEFORE EXTRA/PFD DIVS		
WC04860	NET CASH FLOW-OPERATING ACTIVS	RI	TOTAL RETURN INDEX
WC03263	DEFERRED TAXES	MV	MARKET VALUE
WC01001	NET SALES OR REVENUES	AF	ADJUSTMENTFACTOR
WC01501	MINORITY INTEREST	NOSH	NUMBER OF SHARES
WC02999	TOTAL ASSETS	P	PRICE
WC01051	COST OF GOODS SOLD (EXCL DEP)		
WC01101	SELLING, GENERAL & ADMINISTRAT		
WC01201	RESEARCH & DEVELOPMENT		
WC01251	INTEREST EXPENSE ON DEBT		
WC01151	DEPRECIATION/DEPLETION/AMORT		
WC02201	CURRENT ASSETS - TOTAL		
WC02001	CASH & SHORT TERM INVESTMENTS		
WC03101	CURRENT LIABILITIES-TOTAL		
WC03051	SHORT TERM DEBT & CURRENT PORT		
WC03063	INCOME TAXES PAYABLE		
WC01075	INTEREST EXPENSE - TOTAL		
WC01245	NON-INTEREST EXPENSE		
WC01271	PROVISION FOR LOAN LOSSES		

2.2. VARIABLE DEFINITION

In the following sections the definition and calculation of the variables used in the Fama-French five-factor model will be outlined. Additionally, the variables used for the analysis of alternative factor constructions and models will also be defined.

2.2.1. Fama-French five-factor model variables

The Fama-French five-factor model uses five factors constructed from 2 x 3 sorts on *Size* and Book-to-market value (*B/M*), Operating Profitability (*OP*) or Investment (*Inv*) variables.

These variables have been constructed similarly to Fama and French (2015) as such, for portfolios formed in June of year *t*:

- Risk-free-rate (*RF*) is estimated as the return on a one month T-bill.
- *Size* is easily defined as the market value (MV) of a security for June of year *t*, and is quantified by the TRD identifier MV.

- *B/M* is calculated as the book value (BV) of a firm divided by its MV, both measured at the end of December of *t-1*. BV is defined as common equity (WC03501) plus deferred taxes (WC03263) if available. In the case of devil versions, *B/M* is calculated monthly, using the most recent MV and BV values.
- *OP* is calculated as the annual revenues (WC01001) minus the cost of goods sold (WC01051), minus selling, general and administrative expenses (WC01101), minus interest expense on debt (WC01251)[5], all divided by book value at the end of December of *t-1*.

  OP is calculated differently for financial institutions, these are identified using Industry Classification Benchmark, (TR identifier: ICBSUC). The *OP* for financials is calculated as annual revenues (WC01001) minus total interest expense (WC010751), minus non-interest expense (WC01101), minus provision for loan losses (WC01271)[6], all divided by book value at the end of December of *t-1*.
- *Inv* is the growth of total assets (WC02999) from the end of December of *t-2* to the end of December of *t-1*.

2.2.2. Alternative variables

For the analysis of alternative factors, additional variables need to be defined.

For portfolios formed in June of year *t*:

- Earnings-to-price (*E/P*) is calculated as net income before extraordinary items (WC01551) divided by MV, both measured at the end of December of *t-1*. In the case of devil versions, *E/P* is calculated monthly, using the most recent MV and net income before extraordinary items values.
- Return on equity (*ROE*) is calculated as net income before extraordinary items (WC01551) divided by BV, all for the end of December of year *t-1*.
- Net share issues (*NSI*) is calculated following Pontiff and Woodgate (2008) as, the difference in natural logs of split adjusted shares outstanding between June of year *t-1* and June of year *t*. The split adjusted outstanding shares are obtained by dividing the number of shares (NOSH) by the adjustment factor (AF).

[5] All measured using accounting data for the end of December of year *t-1*
[6] All measured using accounting data for the end of December of year *t-1*

- Composite-equity-issuance (CEI) is calculated similarly to Daniel and Titman (2006) as (5):

$$CEI_t = log\left(\frac{MV_t}{MV_{t-1}}\right) - r(t-1,t) \tag{5}$$

Where *r(t-1,t)* is the cumulative log return calculated via the total return index (RI) from June of year *t-1* to June of year *t*.

- Systematic risk, *beta*, is estimated similar to Frazzini and Pedersen (2014), from rolling regressions of excess returns on market excess returns. Hence the *beta* is calculated as (6):

$$\beta_i = \rho_{i,m}\frac{\sigma_i}{\sigma_m} \tag{6}$$

Where σ_i and σ_m are the volatilities for stock *i* and the market, and $\rho_{i,m}$ is their correlation. *Beta* is updated yearly in June, using the past 36 months of the security's monthly returns when possible, and requiring a minimum of 12 months.

- Volatility (*Vol*) is calculated similarly to *beta*, as the standard deviation of a security's returns over the past 36 months, requiring a minimum of 12 months of data. Again, *Vol* is updated every year in June.
- Momentum (*Mom*) is defined, as in Fama and French (2008), as the cumulative monthly return of a security, from *t-12* to *t-2* (in this case *t* is measured in months). ***Mom* is updated monthly.**

2.3. FACTOR CONSTRUCTION

In this section, the processes used for the construction of factors will be outlined. All factors have been constructed following the guidelines given by Fama and French (1993), Fama and French (2015) and Fama and French (2017). The factors are by definition zero-cost portfolios, each related to their own characteristic variables. Every factor measures the variation in returns of portfolios formed based on a characteristic variable, and should be otherwise diversified with regards to any other characteristics.

2.3.1. Fama-French five-factor model RHS factors

The Fama-French five-factor model uses five risk factors; the market factor (*RMRF*), the size factor (*SMB*), the book-to-market value factor (*HML*), the profitability factor (*RMW*) and the investment (*CMA*) factor. See equation (4).

The market factor is simply calculated as the market return (*RM*) minus the risk free rate (*RF*) for any given month.

The remaining factors are constructed using portfolios resulting from 2 x 3 independent sorts on; *Size* and *B/M*, *Size* and *OP*, and S*ize* and *Inv*. At the end of June of year *t*, all equities are divided on market value into two sorts, big and small. Big equities are defined as those that cumulatively make up the top 90% of the total market equity. Small stocks make up the remaining 10%.

At the same time, all equities are also sorted into 3 sorts using their 30^{th} and 70^{th} percentiles for *B/M*, *OP*, and *Inv* as breakpoints. These breakpoints are calculated using big stocks only, in order to ensure that the resulting portfolios are balanced. As defined in section 2.2.1, the accounting data used is collected at the end of December of year *t-1*, as is the *MV* used for the calculation of *B/M*.

The intersection of the independent 2 x 3 sorts on *Size* and *B/M* result in six portfolios; BG, BN, BV, SG, SN and SV, where B and S stand for big or small, and V, N and G stand for value, neutral and growth (top 30%, middle 40% and bottom 30% of *B/M*) respectively. The value-weighted returns for each portfolio are then calculated and updated monthly.

The $SMB_{B/M}$ size factor is calculated monthly as the equal-weighted average of the returns of the three small stock portfolios, SV, SN and SG, minus the equal-weighted average of the returns of the three big stock portfolios, BV, BN and BG, as indicated in equation (7).

The *HML* factor is then calculated monthly as the equal-weighted average of the returns of the two high value portfolios, BV and SV, minus the equal-weighted average of the returns of the two low value portfolios, BG and SG, as indicated in equation (8)

$$SMB_{B/M} = \frac{(r_{SV} + r_{SN} + r_{SG}) - (r_{SV} + r_{SN} + r_{SG})}{3} \qquad (7)$$

$$HML = \frac{(r_{BV} + r_{SV}) - (r_{BG} + r_{SG})}{2} \tag{8}$$

Where *r* represents the value-weighted returns for each of the six previously mentioned portfolios.

For the remaining *RMW* and *CMA* factors, independent 2 x 3 sorts on; *Size* and *OP*, and S*ize* and *Inv*, respectively, are constructed following the same principles. The factors are then calculated in the same way as for *HML*, except now using Robust-minus-Weak for *RMW*, and Conservative-minus-Aggressive for *CMA*. Furthermore, two additional size factors SMB_{OP} and SMB_{Inv} are calculated.

The size factor used for the Fama-French five-factor model is the simple average of the individual size factors. As such the total SMB factor is calculated monthly as follows:

$$SMB = \frac{SMB_{B/M} + SMB_{OP} + SMB_{Inv}}{3} \tag{9}$$

All sorts and resulting portfolios of stocks are updated at the end of June each year, and the factors themselves are updated and recorded on a monthly basis.

2.3.2. Alternative RHS factors

For the analysis of alternative factors, similar 2 x 3 independent sort constructions have been used as in Fama and French (1993). The alternative factors and how they have been calculated will be detailed in this section.

The *WML*, momentum factor, is created as described by Fama and French (2012) using 2 x 3 sorts on *Size* and *Mom*, and using the same breakpoint conventions as for the five-factor model's, *Size* - *B/M* sorts. This time for the second sort we obtain three momentum groups, Winner (W), Neutral (N) and Loser (L). *WML* sorts and their resulting portfolios are updated monthly, using the previous month's *Mom* and *MV* values to define the breakpoints.

$$WML = \frac{(r_{BW} + r_{SW}) - (r_{BL} + r_{SL})}{2} \tag{10}$$

The *WML* factor is then calculated using the same principles, as indicated in equation (10).

Two alternative risk factors, PMV_{Beta} and PMV_{Vol} (Poised-minus-Volatile), have been constructed using the same breakpoint conventions as for the *HML* sorts. For the second sort, three risk groups are now obtained based on the *Beta* or *Vol* characteristic variables, Poised (P, bottom 30%), neutral (N, middle 40%) and Volatile (V, top 30%). The sorts and resulting portfolios are updated yearly at the end of June using the *beta, Vol* and *Size* values for June of year *t*. The value-weighted return of each portfolio is updated monthly.

$$PMV = \frac{(r_{BP} + r_{SP}) - (r_{BV} + r_{SV})}{2} \tag{11}$$

The PMV_{Beta} and PMV_{Vol} factors are then calculated monthly as indicated in equation (11) by using either the *Size-Beta* sort or the *Size-Vol* sort for PMV_{Beta} and PMV_{Vol}, respectively.

Devil value factors will be constructed as defined by Asness and Frazzini (2013). 2 x 3 sorts will be created using *Size* as the first sort, big or small, and a characteristic value variable as the second sort. The sorts will be updated monthly using the most up to date information. The devil factors will then be calculated in the same way as *HML* (see equation (8)), and all devil factors will be labelled with the ending, *-dev*. For example, the construction of the devil version of the Fama-French *HML* factor, $HML_{B/M}dev$, is as follows. At the end of each month all equities are divided on market value into two sorts, big and small. At the same time, all equities are also sorted into three *B/M* groups. However, the calculation of *B/M* now uses the most current MV and BV. The breakpoints are the same as for the Fama-French factors. The $HML_{B/M}dev$ factor is then calculated monthly in the same way as defined in equation (8).

Finally, new variants of the existing factors will be created by altering the characteristic variable on which the factors' second sorts are constructed. The new characteristic variables will be; earnings-to-price ratio (*E/P*) for the value factor ($HML_{E/P}$), return-on-equity (*ROE*) for the profitability factor (RMW_{ROE}), and composite-equity-issuance (*CEI*) and net-stock-issues (*NSI*) for the investment factor (CMA_{CEI} and CMA_{NSI}). The policy on breakpoints for the resulting, 2 x 3, *Size*-variable sorts will be the same as described for the Fama-French factors. The sorts will also be updated yearly in June of year *t* using the accounting data for the end of December of year *t-1*, unless otherwise indicated or defined as a devil factor.

3. THE FAMA-FRENCH FIVE-FACTOR MODEL AND THE SPANISH STOCK MARKET

This chapter will focus on evaluating the performance of the Fama-French five-factor model when applied to the Spanish capital market. The studied period spans from July 1990 to November 2016 (317 months). All factors have been constructed using the methods described in section 2.3.1.

Additionally, the performance of the Fama French three-factor model will also be evaluated using the same data sample and evaluation methods. This will serve two purposes, firstly to check the three-factor model's performance for the Spanish stock market from July 1990 to November 2016, and secondly to provide a benchmark for the five factor model's performance.

Due to the reduced number of stocks available on the Spanish stock market, it makes no sense to try and replicate the 5 x 5 LHS (left-hand-side) portfolios which are used by Fama and French (2015) and Fama and French (2017) to test the five-factor model. Such sorting would result in very small portfolios, and even empty portfolios. In order for the LHS portfolios to be of a healthy size, the resulting sorts would not differ in great measure to the RHS 2x3 sorts. Hence it has been decided not to test the models using LHS portfolios, rather to evaluate using the factor returns themselves and use spanning tests to evaluate their ability to describe average returns.

3.1. SAMPLE REQUIREMENTS

The data sample for this chapter has been selected and filtered as described in section 2.1, however, further model specific filters have been applied as described by Fama and French (2015). Hence, to be included in the sample for July of year *t*, to July of year *t+1*, the listing must have in June of year *t*:

- A positive value for Book-Value and a valid Market-Value for December of year *t-1*.
- A value for annual revenues and at least one of the following; cost of goods sold, selling general and administration costs or interest expense on debt, all for December of year *t-1*. In the case of financial institutions, a value for annual revenues and at least one of the following; total interest expense, non-interest expense or provision for loan losses, is required for December of year *t-1*.

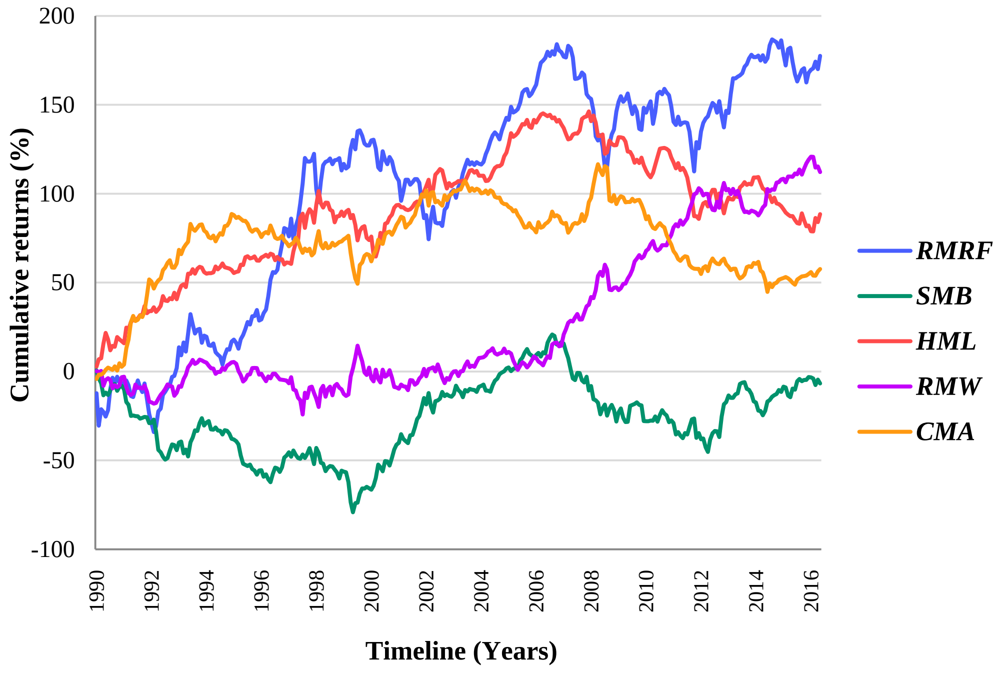
- Total asset data for years *t-1* and *t-2*.

After these final filters the sample is composed of 300 equities in total, with a minimum of 82, a maximum of 156 and a median of 131 equities per month over the studied 317 month period. For further details refer to Table 15 in the appendix.

3.2. SUMMARY STATISTICS

Figure 1 graphically demonstrates the monthly time-series of the returns on each of the five factors. Carrying out a simple visual inspection, it is easy to predict that none of the five factors have clear tendencies, and that they are of a volatile nature. The profitability factor (RMW), being the only exception, displaying very flat returns initially, followed by a clear positive slope from 2006 onwards. Both the value and investment premiums (HML and CMA, respectively) initially have positive tendencies and both reach their maximum cumulative return value in 2008, after which they start showing clear negative tendencies. The cross-sectional cumulative returns of the size factor (SMB) are also very interesting, three different tendencies are apparent; negative from 1990 to 1999, confidently positive from 1999 to 2007, and negative thereafter. In fact, if the average size factor returns are calculated for the 1999-2007 (96 month) period, a statistically relevant high average return (0.73%, t=2.25) is obtained.

Figure 1: Cumulative Fama-French factor returns
This figure plots the cumulative monthly returns of the Fama-French five factors for the Spanish capital market over the July 1990 to November 2016 (317 month) period.



The summary statistics for the factor returns are represented in Table 3. Panel A indicates that the market equity premium (*RMRF*) is high, however its statistical significance is questionable[7] (0.56%, t-stat=1.77). The results show that size is not priced for this sample period (-0.02% mean *SMB* returns). This is in line with the results obtained for Europe Fama and French (2017). Here too, the market equity premium was the highest of the five factors, but lacked statistical significance, and the size premium was also near to zero (0.05).

Although not listed in Table 3, the size factor for the Fama-French three-factor model ($SMB_{B/M}$), calculated using only the size-value sorts, has also been calculated. Its cross-sectional monthly returns are heavily correlated with the five factor model's size factor (*SMB*), having a correlation coefficient of 0.98. This in turn means that its average premium and standard error (-0.09 and t=-0.46) is also similar to that of *SMB*.

The value premium (mean *HML* returns) is priced at 0.23%, but at only 1.43 standard errors from zero, it lacks statistical significance. The profitability premium (mean *RMW* returns) is priced at 0.35%, and with a t-statistic of 1.98, is the only factor that has any sort of statistical significance. This is in line with the predictions from the visual inspection of Figure 1. The investment premium (mean *CMA* returns) is weak at 0.18% and 1.00 standard errors from zero.

Panel B of Table 3 shows the summary statistics (mean, standard deviation and t-statistic) for the average returns of each size component of the *HML*, *RMW* and *CMA* factors. The results show that, contrary to the results obtained by Fama and French (2017) for the European market and roughly the same time period, all factors for Spain have higher value premiums for big stocks (*HMLb*, *RMWb* and *CMWb*) than for small stocks (*HMLs*, *RMWs* and *CMWs*). However, none of these components have statistical significance, the best having 1.61 standard errors from zero, obtained for the profitability factor constructed with only big stocks (*RMWb*).

The average returns for all size components are positive. The average differences between returns on small and large components of each factor (*HMLs-b*, *RMWs-b* and *CMWs-b*) are very weak (t-statistics between 0.21 and 0.56).

[7] A standard level of confidence for this is 95%, requiring the t-statistic to be more than or equal to 2.

Hence, it cannot be said, with any legitimate level of confidence, that the premium of each factor is larger for small stocks than big stocks, or vice versa.

Table 3: **Summary statistics for the five Fama-French factors**
The table reports summary statistics for the returns on the five Fama-French factors applied to the Spanish capital market: July 1990-November 2016 (317 months). The factors are constructed as outlined by Fama and French (2015). The market factor (*RMRF*) is calculated as the sample's market return (*RM*) minus the risk free rate (*RF*). The value factor (*HML*) is calculated from portfolios formed in June of year *t*, by sorting stocks into two groups depending on market value (*MV*) and three groups depending on book-to-market value (*B/M*). Big stocks (*B*) are those that make up the top 90% of the total sample's market value, while small stocks (*S*) are those in the bottom 10%. Breakpoints on *B/M* are calculated using the 30th and 70th percentiles of big stocks only, and use the *B/M* values for December of year t-1. Six value-weighted portfolios are created from these independent sorts (2 x 3), *BV*, *BN*, *BG*, *SV*, *SN* and *SG*. *B* and *S* stand for Big and Small, and *V*, *N* and *G* stand for Value, Neutral and Growth (top 30%, middle 40% and bottom 30% of *B/M*). The HML factor is then calculated as the simple average returns of the two value portfolios (*BV* and *SV*) minus the simple average of the two growth portfolios (*BG* and *SG*). The profitability factor (*RMW*) and investment factor (*CMA*) are constructed in the same way as HML, except that the second sorts use breakpoints on either operating profitability (*OP*, measured as the operating profitability of a firm divided by its book value, sorted from robust to weak) or investment (*Inv*, measured as the rate of growth in total assets of a firm, sorted from conservative to weak), respectively. The result is a total of three 2 x 3 sorts on *Size* and *B/M*, *OP* or *Inv*, forming a total of eighteen portfolios. The size factor (*SMB*) is calculated as the sum of returns of the nine big stock portfolios, minus the sum of returns of the nine small stock portfolios, all divided by nine. For the *HML*, *RMW* and *CMA* factors, an additional size specific return is calculated, one with only big stocks and another with only small stocks. HML_B and HML_S are therefore calculated as the returns on *BV* minus *BG*, and *SV* minus *SG*, respectively. $HML_{S\text{-}B}$ is the simple average of HML_s minus HML_B. The size specific factor returns for *RMW* and *CMA* are calculated using the same approach. The value-weighted portfolio returns and resulting factor returns are updated monthly. Panel A reports the mean, standard deviation and t-Statistics for the returns of each factor. Panel B reports the mean, standard deviation and t-statistics for the returns on each size specific factor. Panel C reports the correlation between the five factors over the 317 month period.

Panel A: Means, standard deviations and t-statistics of factor returns

	RMRF	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.560	-0.02	0.28	0.35	0.18
Std Dev	5.65	3.42	3.48	3.18	3.24
t-Stat	1.77	-0.11	1.43	1.98	1.00

Panel B: Key statistics for small (S) and big (B) components of factor returns

	HML_B	HML_S	$HML_{S\text{-}B}$	RMW_B	RMW_S	$RMW_{S\text{-}B}$	CMA_B	CMA_S	$CMA_{S\text{-}B}$
Mean	0.38	0.17	-0.21	0.43	0.28	-0.15	0.21	0.15	-0.06
Std Dev	5.10	4.53	6.69	4.75	3.78	5.76	4.43	3.75	5.03
t-Stat	1.34	0.68	-0.56	1.61	1.32	-0.46	0.85	0.72	-0.21

Panel C: Correlations between factors

	RMRF	*SMB*	*HML*	*RMW*	*CMA*
RMRF	1.00	-0.34	0.00	0.00	-0.11
SMB	-0.34	1.00	0.05	-0.01	-0.02
HML	0.00	0.05	1.00	-0.51	0.08
RMW	0.00	-0.01	-0.51	1.00	-0.12
CMA	-0.11	-0.02	0.08	-0.12	1.00

Panel C of Table 3 shows the pairwise correlations between returns of each pair of factors. The market factor is negatively correlated to the size and investment factor by -0.34 and -0.11, respectively, both with certainties above the 2 standard errors from zero barrier (t=-6.45 and t=-2.01, respectively). There is a strong negative correlation between the value and profitability factors of -0.51 (t=-10.41). A weaker negative correlation is found between the profitability and investment factors of -0.12, but still with more than two standard errors from zero.

In general, the results of the factor returns are weak, none break the 5% significance level (although *RMW* comes very close t=1.98). The market and profitability premiums have the highest returns, and are the only significant factors at the 10% level. There is also not enough evidence to support that any average factor returns depend on the size of the stocks with which the factor is calculated, not even with a lower confidence interval of 90%.

Summary statistics do not suffice to determine whether individual factors contribute or not to the performance of the overall model. Hence, in the next sections, factor spanning tests (linear regressions of the returns of a factor regressed against the returns of the remaining factors) and Sharpe ratio tests will be conducted to see which factors contribute most to the overall performance of the model.

3.3. FACTOR SPANNING TESTS

To determine the extent to which each factor contributes to the overall performance of the Fama-French five-factor model, spanning tests on the model's factors are carried out. Additionally, results for spanning tests on the original Fama-French three-factor model using the same sample will be presented and analysed.

The spanning tests are done by running linear regressions of a single factor's monthly returns against the monthly returns of the remaining factors. For example, the spanning test regression for the market factor (*RMRF*) is calculated as indicated in equation (12).

$$\begin{aligned} RMRF_t = \alpha_{RMRF} + \beta_{RMRF,SMB} SMB_t + \beta_{RMRF,HML} HML_t \\ + \beta_{RMRF,RMW} RMW_t + \beta_{RMRF,CMA} CMA_t \end{aligned} \tag{12}$$

Where α indicates the intercept of *RMRF*, and the βs represent the slopes of *RMRF* with each of the other four remaining factors. The regression is repeated using different factors as the dependant variable each time (*SMB*, *HML*, *RMW* and *CMA* for the size, value, profitability and investment factors, respectively).

Table 4: **Spanning tests for the Fama-French five-factor model**
In this table, the results from regressing the monthly returns of each of the five factors against the monthly returns of the remaining four factors are displayed. *RMRF*, *SMB*, *HML*, *RMW* and *CMA* represent the market, size, value, profitability and investment factors, respectively. The table details the coefficients of the intercepts and slopes for each factor, together with the t-statistic of each coefficient. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	*RMRF*	*SMB*	*HML*	*RMW*	*CMA*	R^2
RMRF	Coef.	0.58		-0.57	0.03	-0.01	-0.21	0.12
	t-Statistic	*1.91*		*-6.52*	*0.34*	*-0.09*	*-2.28*	
SMB	Coef.	0.09	-0.21		0.06	0.01	-0.06	0.11
	t-Statistic	*0.47*	*-6.52*		*0.94*	*0.18*	*-1.13*	
HML	Coef.	0.46	0.01	0.05		-0.55	0.03	0.25
	t-Statistic	*2.69*	*0.34*	*0.94*		*-10.22*	*0.58*	
RMW	Coef.	0.50	0.00	0.01	-0.46		-0.07	0.25
	t-Statistic	*3.18*	*-0.09*	*0.18*	*-10.22*		*-1.51*	
CMA	Coef.	0.25	-0.08	-0.06	0.03	-0.10		0.02
	t-Statistic	*1.35*	*-2.28*	*-1.13*	*0.58*	*-1.51*		

An intercept of zero would indicate that the factor does not contribute to the model's outcome, and that its performance is captured entirely by a combination of the other factors. Hence, close to zero intercepts suggest that a factor is redundant in a model. On the other hand, if an intercept is reliably different from zero or strong, meaning that it has an intercept that is statistically significant[8], this indicates that the dependant variable contains unique information about average returns, not captured by the independent variables.

Table 4 shows the results for the spanning tests for the 317 month period from July 1990 to November 2016. The market, value and profitability factors have strong positive intercepts with good levels of significance. The profitability factor's intercept (0.50%) has the highest level of significance with more than 3

[8]A standard level of confidence for this is 95%, requiring the t-statistic to be more than or equal to 2.

standard errors from zero, followed by the value factor's intercept (0.45%) which has a certainty of 2.69 standard errors from zero. These economically and statistically strong intercepts, which exceed the factors' average returns, are largely due to strong negative slopes between both variables. The market factor has the highest intercept (0.58%) but has a slightly lower certainty of 1.91 standard errors from zero. The intercept for size is negligible (0.09%, t=0.47) and the intercept for the investment factor is also low and lacks significance (0.25%, t=1.35).

These intercepts are in line with the results obtained for Europe between 1990 and 2015 by Fama and French (2017). In their spanning tests, they also found that the only significant factors for Europe were value and profitability. This suggests that for the period from 1990 to 2015, the same factors are significant for Spain as for Europe, which both differ from the results obtained for North American stocks for the same time period.

The spanning tests in Table 4 reveal that for the studied time period, the value and profitability factors are important for describing average returns. This goes to show that factors that don't necessarily have promising summary statistics, such as *HML*, can carry marginal information that is crucial to the models overall performance. In light of the evidence found in Table 4, the size factor (*SMB*) is redundant and plays no role in describing the average returns of the Spanish stock market for the 1990-2016 studied time period.

Table 5: **Spanning tests for the Fama-French three-factor model**
In this table, the results from regressing the monthly returns of each of the three factors against the monthly returns of the remaining four factors are displayed. *RMRF*, $SMB_{B/M}$ and *HML* represent the market, size and value factors, respectively. The table details the coefficients of the intercepts and slopes for each factor, together with the t-statistic of each coefficient. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	*RMRF*	$SMB_{B/M}$	*HML*	R^2
RMRF	Coef.	0.52		-0.52	-0.03	0.10
	t-Statistic	*1.72*		*-6.03*	*-0.30*	
$SMB_{B/M}$	Coef.	0.03	-0.20		-0.04	0.10
	t-Statistic	*0.17*	*-6.03*		*-0.74*	
HML	Coef.	0.28	-0.01	-0.04		0.00
	t-Statistic	*1.43*	*-0.30*	*-0.74*		

Furthermore, spanning tests for the original Fama-French three factor model have also been carried out using the same sample stocks. The results are displayed in Table 5. It is immediately clear that size is also redundant for the three-factor model, and that only the market factor can be said to hold unique information if the certainty level is dropped to a 90% confidence interval.

The intercepts for the market and value factors are 0.52% and 0.28% respectively. However, with t-statistics of 1.72 and 1.43, they fail to break the 95% certainty barrier. Furthermore, the market and value intercepts are lower and weaker than for the five-factor model.

3.4. SHARPE RATIOS

In order to evaluate the performance of the model and its factors from an investor's point of view, the monthly time-series of factor returns are used to calculate optimal Sharpe ratios. For assessment, the optimum Sharpe ratios (*SR*) for the CAPM, Fama-French three-factor and Fama-French five-factor models have been calculated using the same data sample and time period. The comparison between Sharpe ratios for each model reflects the relative appeal of the different models from an investor's point of view.

The Sharpe ratio is calculated as follows:

$$SR = \frac{\sum_{i=1}^{N} w_i r_i}{\sqrt{\sum_{i=1}^{N}(w_i \sigma_i)^2 + \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}}}\ , \qquad for\ i \neq j \tag{13}$$

where r_i is factor *i*'s average monthly returns (minus the monthly risk free rates), w_i is its weight, σ_i is its variance and σ_{ij} is its covariance with factor *j*, over the 317 month period from July 1990 to November 2016. *N* is the total number of factors being considered. The Sharpe ratio is maximised by varying the weights of each factor.

Table 6 shows the results for the Sharpe ratio tests on the CAPM, Fama-French three-factor (*FF 3-Factors*) and Fama-French five-factor (*FF 5-Factors*) models. The table displays the maximised Sharpe ratio (*SR*) for each model, with the respective optimal factor weights, necessary to reach said *SR*. The tests have been carried out limiting the lower bound for the weight of each factor to 0, and the sum of all the factor weights to 1.

Table 6: **Sharpe tests for the Fama-French and CAPM models**
This table displays the maximised Sharpe ratios for the CAPM, Fama-French three-factor (*FF 3-Factors*) and Fama-French five-factor (*FF 5-Factors*) models. Monthly factor return data is used for the sample period from July 1990 to November 2016 (317 months). For the CAPM model test, only the market factor (*RMRF*), representing the sample's market premium has been considered. For the *FF 3-Factor* model, the original three Fama-French factors have been considered; market (*RMRF*), size ($SMB_{B/M}$) and value (*HML*). To calculate the $SMB_{B/M}$ (small-minus-big, *MV*) and *HML* (high-minus-low, *B/M*) factors, independent 2x3 sorts are created in June of year *t* depending on their relative size (*MV*) and value (*B/M*). Big (*B*) stocks are those which make up the top 90% of the total sample's *MV*, while small stocks make up the bottom 10%. Three sorts on *B/M* are created using the 30th and 70th percentile breakpoints on *B/M*, and labelled as Value (*V*), Neutral(*N*) and Growth(*G*) (top 30%, middle 40% and bottom 30%, respectively). The intersects of these sorts create six stock portfolios that are updated in June of every year. The value weighted returns of each portfolio are calculated monthly. The $SMB_{B/M}$ factor is calculated monthly as the difference between the simple-average returns of the three small stock portfolios minus that of the three large stock portfolios. The *HML* factor is calculated monthly as the difference between the simple-average returns of the two value portfolios minus that of the two growth portfolios from the *size-B/M* sorts. For the *FF 5-Factor* model, further 2 x 3 sorts are created on size and profitability(*OP*) or investment(*Inv*) to construct the profitability and investment factors, *RMW*(robust-minus-weak) and *CMA*(conservative-minus-aggressive), respectively. Breakpoint policy is maintained for all factors. The *RMW* and *CMA* factors are calculated similarly to *HML* as the difference in average returns of the robust and weak, and the conservative and aggressive portfolios resulting from the *size-OP* and *size-Inv* 2 x 3 sorts, respectively. The *SMB* factor used in the *FF 5-Factor* model is calculated as the sum of returns of the nine big stock portfolios, minus the sum of returns of the nine small stock portfolios, all divided by nine. The optimal Sharpe ratio (SR) and corresponding expected return (ER), standard deviation (Std Dev) and factor weights for each model are displayed. The factor weights for each model have a lower bound of 0, and the sum of all weights is limited to 1.

	SR	*ER*	*Std Dev*	*RMRF*	$SMB_{B/M}$	*SMB*	*HML*	*RMW*	*CMA*
CAPM	**0.10**	0.56	5.65	1.00					
FF 3-Factors	**0.13**	0.37	2.88	0.41	0.07		0.52		
FF 5-Factors	**0.23**	0.31	1.35	0.12		0.05	0.30	0.39	0.14

The Sharpe ratio calculated for the CAPM model is relatively low (0.10), even though the expected return is high, due to the high standard deviation of the market factor.

From Table 6 we can deduce that the original Fama-French three-factor model (*FF 3-Factors*) performs poorly in the Spanish market for the studied time period. With an SR ratio of 0.13, it only marginally outperforms the CAPM model. The size factor ($SMB_{B/M}$) is given a low weight (0.07) for the optimal *SR*, thus confirming evidence from the model's spanning tests in Table 5, that the size factor does not contribute to the performance of the three-factor model for this sample period. A large weight (0.52) is given to the value factor (*HML*) but this is not enough to significantly improve the *SR*.

The Fama-French five factor model (*FF 5-Factors*) performs significantly better than the other two models, achieving a *SR* ratio of 0.23. The distribution of weights confirms the evidence from the spanning tests that the size factor does not contribute to explaining average returns. The highest weight is given to the profitability factor (*RMW*, 0.39). This is no surprise as *RMW* was also deemed most significant in the spanning test. *HML* also holds a relatively high weight (0.30). Finally, the market and investment factors (*RMRF* and *CMA*) are given slight weights of 0.12 and 0.14, respectively, indicating that their contribution to the overall performance of the model is minor.

3.5. SUMMARY

All evidence indicates that the size factor (for the three-factor and five-factor model) does not help explain average returns for the Spanish capital market for this sample period. This is contradictory with the evidence found by; Nieto (2004), Nieto and Rodríguez (2005), Font-Belaire and Grau-Grau (2007) and De Pena et al. (2010), that size contributes in explaining average returns. This is most probably due to the differences in sampling periods, as mentioned in the analysis for Figure 1, the size factor has strong tendencies that alter abruptly over the sample period taken for this thesis. However, the sample period used in this thesis is considerably longer and more up-to-date than the previously mentioned papers, allowing for greater conviction.

The factor spanning tests indicate that only the value and profitability factors carry unique information about Spain's average returns from July 1990 to November 2016[9]. The remaining size, market and investment factors fail to contribute significant marginal information about average returns. This, in many ways, could be labelled as a model failure.

Overall, the five factor model performs significantly better than the three-factor model in the Sharpe ratio tests. This is almost entirely due to the profitability factor, which has a high average monthly return with a high level of certainty, and a strong negative correlation with the value factor.

The spanning and Sharpe tests reveal that the three-factor model fails to capture average returns for the studied time period, with none of its factors showing statistically significant intercepts in the spanning tests. The inclusion of

[9] For a 95% confidence interval.

the profitability factor in the five-factor model appears to be vital in improving the three-factor model's ability to describe average returns.

Although the five-factor model significantly outperforms the three-factor model in these tests, it still fails as a model, with only 2 of its 5 factors contributing information about average returns. Hence, the question remains whether the addition of a momentum factor, as indicated by Carhart (1997), and modification of the factor variables can improve the model's performance for the Spanish market.

4. ALTERNATIVE FACTORS

In this section, the main focus of the thesis will be addressed: Can the performance of the Fama-French five-factor model for Spain be improved by altering the factor variables and/or by adding new factors?

For this task, the Fama-French five-factor model has been taken as a starting point. The original five factors; market, size, value, profitability and investment have been conceptually conserved. However, their characteristic variables and construction techniques will be questioned and new proposals presented.

For the entirety of this chapter, the decision has been made to use the original Fama-French three-factor model's interpretation of the size factor ($SMB_{B/M}$), constructed using sorts on *size-B/M* only. The five-factor model's size factor uses a combination of the sorts used in all of the factors' construction, this is not possible here as it is uncertain which factors will be included in the final model. Nevertheless, as commented in section 3.2, paragraph 3, the correlation between the two versions of the size factor is extremely high at 0.98, thus the use of one or the other should be indifferent to the outcome of the model.

For the value, profitability and investment factors, between one and two alternative characteristic variables will be considered. Additionally, for the value factor, devil versions of the factor, used in combination with an additional momentum factor, will be analysed, as suggested by Asness and Frazzini (2013).

Two additional factors will be analysed to see if they can add value to the model. Firstly, the inclusion of a momentum factor, as suggested by Carhart (1997) will be evaluated. Secondly, a risk factor will be considered as suggested by Frazzini and Pedersen (2014) and Blitz and van Vliet (2007).

The modified model will be evaluated using empirical methods, similar to those used in chapter 3. First, summary statistics with average monthly factor returns and factor correlations will be evaluated. Then, each new factor will be tested for new information by regressing them against the original five factors.

Sharpe tests on the factors' past 26 year performance will reveal which factors would have been most appealing for an investor, and will be used to support the selection of favourite factors and variables for two new model proposals. The two proposals will then be submitted to spanning tests for final selection.

In the last section of this chapter, a final proposal of a modified Fama-French five-factor model adjusted for the Spanish stock market will be presented.

4.1. NEW VARIABLES AND FACTORS

The new variables and factors that will be considered in the proceeding analysis are detailed in this section. Ideas for the selection of potentially strong characteristic variables have been taken from Hanauer and Lauterbach (2018). Tests on single sorts, created using variable quintiles as breakpoints, have been preliminarily carried out to check for viability and also serve as robustness tests. The results of which are detailed in Table 16 of the appendix.

The earnings-to-price ratio (*E/P*) of a stock will be considered as an alternative to the book-to-market ratio for the formation of the Fama-French value factor. Earnings-to-price has been know and used historically for determining the value of a stock, indeed Fama and French (1992) found that used alone, *E/P* had explanatory power for the US stock market between 1963 and 1990. However, they also found that combinations of size and *B/M* captured the *E/P* variable, thus not including it in their three-factor model. Nevertheless, the explanatory power of *E/P* will be re-assessed in this thesis by constructing Fama-French's value factor (*HML*) using 30^{th} and 70^{th} percentile *E/P* breakpoints (for big stocks) instead of *B/M*.

The alternative value variable – Cash flow-to-price ratio (*CF/P*) has not been considered in this analysis due to a lack of WS data prior to the year 2000.

The characteristic variable for the profitability factor (*RMW*) will also be revised by evaluating the use of breakpoints (30^{th} and 70^{th} percentile based on big stocks) using Return-on-equity (*ROE*) instead of operating profitability to construct the factor's portfolios.

Composite-equity-issuance (*CEI*) and Net-stock-issues (*NSI*) will be considered as alternatives to asset growth in the construction of the investment variable (*CMA*). Hanauer and Lauterbach (2018) found that composite-equity-issuance alone has good explanatory power for average returns in emerging markets, finding that portfolios formed using low Composite-equity-issuance stocks have significantly higher value-weighted average returns than those formed with high *CEI*.

Two variants of a risk factor (*PMV*, Poised-minus-Volatile) will also be constructed and evaluated. The first variant will use the 36 month historical volatility (*Vol*) of stock returns as the characteristic variable for the breakpoints on the 2 x 3 sorts on *size-Vol*. The second variant of the factor will use systematic risk (*beta*) as the characteristic variable for the breakpoints on the 2 x 3 sorts on *size-beta*. Refer to sections 2.2.2 and 2.3.2 for more information about how these two risk factors have been constructed.

A past performance/momentum factor (*WML*) will be considered as an addition to the original five factors. This is common practice since the publication of Carhart (1997). Fama and French (2015) mention that they exclude the momentum factor from their five-factor model because it produced unimportant changes in the performance of their model for their tests on US stocks from 1963 to 2013. However, as pointed out by Asness and Frazzini (2013), when used in combination with a devil[10] version of the value factor, the explanatory power of the resulting model can be magnified significantly.

Finally, devil versions of the two value factors will be constructed and assessed. The combination of devil and momentum factors and their combined power to explain average returns will be tested in section 4.4.

4.2. SAMPLE REQUIREMENTS

The data sample used in chapter 3 (see section 3.1 for details) has been used as a starting point for this chapter’s data sample. Due to the evaluation of additional factors and characteristic variables in this chapter, the data sample has been further filtered to evaluate all factors using the same dataset.

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[10] Devil indicating that the 2 x 3 sorts and portfolios used in the calculation of the factor are updated monthly instead of yearly.

The additional conditions to section 3.1 for a stock to be included in the data sample for July of year *t*, up to July of year *t+1*, are that the listing must have in June of year *t*:

- A minimum of 12 months valid listing history data, including market value, stock returns, number of shares and adjusted stock price.
- Fiscal data for net income before extraordinary items.

After these final filters the sample is composed of 287 equities in total, with a minimum of 75, a maximum of 154 and a median of 128 equities per month over the studied 317 month period. For further details, refer to Table 15 in the appendix.

4.3. SUMMARY STATISTICS

The summary statistics for the previously mentioned alternative factors applied to the Spanish capital market from July 1990 to November 2016 are displayed in Table 7. Further, the original five factors are also included in the table.

Firstly, it is observed that the statistics for the original factors; market (*RMRF*), value (based on *B/M*, $HML_{B/M}$), profitability (based on *OP*, RMW_{OP}), and investment (based on *Inv*, CMA_{Inv}) represented also in Panel A of Table 3, vary slightly. This variation is merely due to the small change in sample data through the additional requirements applied in this chapter, explained in section 4.2. It is important to note that these changes are all relatively insignificant, insinuating that the sample has not been radically altered.

The value factors constructed using portfolios updated annually in June ($HML_{B/M}$ and $HML_{E/P}$), have very different premiums (mean monthly returns) and levels of significance depending on the variable used for the second sort. In isolation, the new *E/P* variant of the value factor, $HML_{E/P}$ (constructed using *size-E/P* 2 x 3 sorts), significantly out performs the original $HML_{B/M}$ factor (constructed using *size-B/M* 2 x 3 sorts), with a very high average monthly return of 0.69% (0.09% above the market premium). This alternative factor also boasts a very high level of significance of 3.48 standard errors from zero.

Table 7 displays summary statistics for two devil value factors considered for this analysis, ($HML_{B/M}dev$ and $HML_{E/P}dev$) constructed in accordance with Asness and Frazzini (2013) using monthly updated sorts. The results show that alone, the devil value factor constructed using *E/P* ($HML_{E/P}dev$) has both a higher premium and statistical significance (average monthly return = 0.38% and t=1.77), than the devil value factor constructed using *B/M* ($HML_{B/M}dev$). However, both devil factors fail to outperform their equivalent standard factors. Moreover, the $HML_{E/P}dev$ factor performs considerably worse in these summary statistics than $HML_{E/P}$.

The new variant of the profitability factor RMW_{ROE}, constructed using *ROE*, performs better in these tests than the original profitability factor RMW_{OP}, constructed using *OP*. The profitability premium for RMW_{ROE} is reasonable at 0.39% and has significance, breaking the 2 standard errors from zero barrier.

The premium for the alternative investment factor constructed using *CEI* (CMA_{CEI}), is very strong, having average monthly returns of 0.70% (0.10% above the market premium) and a very high level of significance (t=3.79) for this sample. The other alternative investment factor (CMA_{NSI}), constructed using NSI, performs better than the original CMA_{OP} factor, with a premium of 0.29%, but has low statistical significance (t=1.23).

Table 7 also displays the summary statistics for two alternatives of an additional risk factor (PMV_{beta} and PMV_{Vol}). PMV_{beta}, constructed using the systematic risk variable *beta*, has poor summary statistics, with insignificant average returns. PMV_{Vol}, on the other hand, has a more than reasonable premium of 0.47% and a t-statistic of 1.85.

Carhart's momentum factor (*WML*) has a high premium almost equal to that of the market, 0.59%, and with more than 2 standard errors from zero. This premium has significance.

Table 8 displays the correlations between all the alternative factors and five original factors. The market factor (*RMRF*) proves to have a notable negative correlation with the two alternative investment factors, CMA_{NSI} and CMA_{CEI} (-0.40 and -0.46 respectively). Furthermore, there is a very strong negative correlation towards the two new risk factors, PMV_{Vol} and PMV_{beta} (-0.53 and -0.72 respectively).

The momentum factor (*WML*) and the devil value factors ($HML_{B/M}dev$ and $HML_{E/P}dev$) have important negative correlations. This correlation is strongest between *WML* and $HML_{B/M}dev$ where the correlation is -0.50. Additionally the momentum factor has a -0.29 correlation with the market factor.

As is only normal, all versions of the value factor have strong positive correlations between each other, including devil versions. There is a strong negative correlation between the two *B/M* versions of the value factor ($HML_{B/M}dev$ and $HML_{B/M}$), and the two versions of the profitability factor (RMW_{OP} and RMW_{ROE}), with negative correlations between -0.47 and -0.53. There is also a smaller, but still significant negative correlation between RMW_{OP} and the two *E/P* versions of the value factor ($HML_{E/P}dev$ and $HML_{E/P}$, -0.31 and -0.29 respectively). $HML_{E/P}$ has a particularly strong positive correlation towards CMA_{CEI} and PMV_{Vol}, 0.60 and 0.47, respectively.

The alternative version of the profitability factor (RMW_{ROE}) has a negative correlation with the original investment factor (CMA_{Inv}, -0.29), but positive correlations varying between 0.26 and 0.36 with the momentum, risk and remaining investment factors.

The new alternative investment factors, CMA_{NSI} and CMA_{CEI}, and the two new risk factors, PMV_{beta} and PMV_{Vol}, have relatively strong correlations between them. In particular, CMA_{CEI}, has a very strong correlation of 0.58 and 0.56 with the risk factors, PMV_{Vol} and PMV_{beta}, respectively.

From the summary statistics analysis it can be deduced that working alone, the new/alternative *WML*, $HML_{E/P}$, RMW_{ROE} and CMA_{CEI} factors have the most substantial and significant premiums for Spain in the period from 1990 to 2016. Furthermore, it is worth underlining the fact that $HML_{E/P}$ and CMA_{CEI} both have premiums above the market premium, and have very high levels of certainty, well above 3 standard errors from zero.

Table 7: **Summary statistics for alternative factors**

The table reports summary statistics for the monthly returns on variants of the five Fama-French factors, a momentum factor and two risk factors applied to the Spanish capital market: July 1990-November 2016 (317 months). The factors are constructed as outlined by Fama and French (2015). The market factor (*RMRF*) is calculated as the sample's market return (*MR*) minus the risk free rate (*RF*). The value factor ($HML_{B/M}$) is calculated from portfolios formed in June of year *t*, by sorting stocks into two groups depending on market value (*MV*) and three groups depending on book-to-market value (*B/M*). Big stocks (*B*) are those that make up the top 90% of the total sample's market value, while small stocks (*S*) are those in the bottom 10%. Breakpoints on *B/M* are calculated using the 30th and 70th percentiles of big stocks only, and use the *B/M* values for December of year t-1. Six value-weighted portfolios are created from these independent sorts (2 x 3), *BV*, *BN*, *BG*, *SV*, *SN* and *SG*. *B* and *S* stand for Big and Small, and *V*, *N* and *G* stand for Value, Neutral and Growth (top 30%, middle 40% and bottom 30% of *B/M*). The $HML_{B/M}$ factor is then calculated as the simple average returns of the two value portfolios (*BV* and *SV*) minus the simple average of the two growth portfolios (*BG* and *SG*). The $HML_{E/P}$, RMW_{OP}, RMW_{ROE}, CMA_{Inv}, CMA_{NSI}, CMA_{CEI}, PMV_{Vol}, and PMV_{beta} factors are calculated in a similar way. They all use independent 2 x 3 sorts, with the first sort on size, to create six value weighted portfolios. The second sort uses the 30th and 70th percentile breakpoints based on big stocks of the variable indicated by the sub-indices, e.g. for CMA_{NSI}, the second sort uses the 30th and 70th percentiles of net-stock-issues based on big stocks for breakpoints. Sorts are updated annually in June, except factors marked with the suffix *-dev* (short for devil) and *WML*, which have their sorts updated monthly using the most recent data available (*MV*, *B/M and E/P*). The *RMW* factors are calculated as the averages of the two robust profitability portfolios minus the two weak profitability portfolios. The *CMA* factors are calculated as the averages of the two conservative investment portfolios minus the two aggressive investment portfolios. The *PMV* factors are calculated as the averages of the two poised risk portfolios minus the two volatile risk portfolios. The size factor ($SMB_{B/M}$) is calculated using the *size-B/M* sorts as; the sum of returns of the three big stock portfolios, minus the sum of returns of the three small stock portfolios, all divided by three. The momentum factor, *WML*, is calculated using monthly independent 2 x 3 sorts on size-momentum, and is calculated as the averages of the two winner momentum portfolios minus the two loser momentum portfolios (breakpoint strategy is the same as for *HML*). The value-weighted portfolio returns and resulting factor returns are updated monthly. Panel A reports the mean, standard deviation and t-Statistics for the returns of each factor.

	RMRF	*WML*	$SMB_{B/M}$	$HML_{B/M}$	$HML_{B/M}dev$	$HML_{E/P}$	$HML_{E/P}dev$	RMW_{OP}	RMW_{ROE}	CMA_{Inv}	CMA_{NSI}	CMA_{CEI}	PMV_{Vol}	PMV_{beta}
Mean	0.60	0.59	-0.15	0.27	0.28	0.69	0.38	0.29	0.39	0.16	0.27	0.70	0.47	0.15
Std Dev	5.60	4.88	3.38	3.46	3.57	3.51	3.83	3.20	2.96	3.19	3.89	3.28	4.47	5.06
t-Stat	1.92	2.17	-0.78	1.39	1.39	3.48	1.77	1.60	2.36	0.91	1.23	3.79	1.85	0.53

Table 8: **Correlations between alternative factors**
The table reports the correlations between the monthly returns on variants of the five Fama-French factors, a momentum factor and two risk factors applied to the Spanish capital market: July 1990-November 2016 (317 months). The factors in consideration are the following: market factor (*RMRF*), momentum factor (*WML*), size factor (*SMB*), value factors (*HML*), profitability factors (*RMW*), investment factors (*CMA*) and risk factors (*PMV*), all (except *RMRF*) formed using 2 x 3, size-x sorts, where x is indicated by the sub-indices. Sorts are updated annually in June, except factors marked with the suffix *-dev* (short for devil) and *WML*, which have their sorts updated monthly. All factors returns are calculated monthly.

	$RMRF$	WML	$SMB_{B/M}$	$HML_{B/M}$	$HML_{B/M}$ dev	$HML_{E/P}$	$HML_{E/P}$ dev	RMW_{OP}	RMW_{ROE}	CMA_{Inv}	CMA_{NSI}	CMA_{CEI}	PMV_{Vol}	PMV_{beta}
$RMRF$	1.00	-0.29	-0.32	-0.02	0.10	-0.19	0.05	0.01	-0.15	-0.11	-0.40	-0.46	-0.53	-0.72
WML	-0.29	1.00	0.08	-0.08	-0.50	0.14	-0.34	0.23	0.28	0.05	0.22	0.25	0.30	0.48
$SMB_{B/M}$	-0.32	0.08	1.00	0.00	0.03	-0.06	-0.06	0.03	-0.08	-0.02	-0.05	-0.07	-0.04	0.10
$HML_{B/M}$	-0.02	-0.08	0.00	1.00	0.71	0.53	0.41	-0.50	-0.47	0.09	-0.02	0.20	0.13	0.01
$HML_{B/M}$ dev	0.10	-0.50	0.03	0.71	1.00	0.31	0.59	-0.47	-0.53	0.08	-0.14	0.03	-0.08	-0.22
$HML_{E/P}$	-0.19	0.14	-0.06	0.53	0.31	1.00	0.65	-0.29	0.21	0.01	0.28	0.60	0.45	0.26
$HML_{E/P}$ dev	0.05	-0.34	-0.06	0.41	0.59	0.65	1.00	-0.31	0.04	-0.02	0.08	0.33	0.18	-0.10
RMW_{OP}	0.01	0.23	0.03	-0.50	-0.47	-0.29	-0.31	1.00	0.33	-0.12	0.03	-0.09	-0.06	0.05
RMW_{ROE}	-0.15	0.28	-0.08	-0.47	-0.53	0.21	0.04	0.33	1.00	-0.25	0.29	0.31	0.36	0.26
CMA_{Inv}	-0.11	0.05	-0.02	0.09	0.08	0.01	-0.02	-0.12	-0.25	1.00	0.05	0.16	-0.02	0.20
CMA_{NSI}	-0.40	0.22	-0.05	-0.02	-0.14	0.28	0.08	0.03	0.29	0.05	1.00	0.46	0.33	0.42
CMA_{CEI}	-0.46	0.25	-0.07	0.20	0.03	0.60	0.33	-0.09	0.31	0.16	0.46	1.00	0.58	0.56
PMV_{Vol}	-0.53	0.30	-0.04	0.13	-0.08	0.45	0.18	-0.06	0.36	-0.02	0.33	0.58	1.00	0.69
PMV_{beta}	-0.72	0.48	0.10	0.01	-0.22	0.26	-0.10	0.05	0.26	0.20	0.42	0.56	0.69	1.00

From this analysis, it is also worth noting that the devil factors don't have particularly interesting premiums for 1990-2016, however, they do have strong negative correlations with the momentum factor. In particular, the $HML_{B/M}dev$ factor has a negative correlation with momentum of -0.50. Additionally, the risk factors have strong positive correlations with CMA_{CEI}, and, as is expected, strong negative correlations with the market factor. The PMV_{Vol} seems to be the best performing alternative risk factor, having a premium of 0.47% (t=1.85).

Finally, it is important to re-emphasise that this summary statistics analysis can give good indications about factor premiums, but in a multi-factor model, what counts is a factor's marginal information about average returns. Hence, in the next sections, spanning tests and further regressions will help to identify the truly important factors to include in an empirical multi-factor model adapted for the Spanish capital market.

4.4. EXPOSURES OF ALTERNATIVE FACTORS TO THE ORIGINAL FIVE-FACTOR MODEL

To determine whether any of the alternative factors carry unique information, not already captured by the original five-factor model, each alternative factor's returns are regressed against the returns of the original five factors. By analysing the intercept of each regression, it is possible to determine to what extent the alternative factor would add information to the original five-factor model. If the intercept is strong, this would suggest that the alternative factor would add unique information about average returns to the five-factor model if it were incorporated. A small intercept, statistically no different from zero, would indicate the opposite. The results of these regressions are displayed in Table 9.

The new alternative to the value factor constructed using *E/P* ($HML_{E/P}$) has a very strong intercept of 0.64, and 3.88 standard errors from zero. As expected, it shares a substantial positive slope with the original value factor ($HML_{B/M}$), but this is not enough to eliminate the intercept. The economic importance of the intercept, is however, reduced in comparison to the factor's average returns.

The profitability factor constructed using *ROE* (RMW_{ROE}) has a considerable intercept of 0.55 with a certainty well above 95% (t=3.89). This intercept, well above the factor's average returns, is mainly due to significant negative slopes (t-statistics between -3.46 and -7.46) with all original factors except the original profitability factor (RMW_{OP}), where the slope is slightly positive (0.10).

The two alternative investment factors (CMA_{NSI} and CMA_{CEI}) both have significant intercepts. However, once again, the CMA_{CEI} alternative shines above the CMA_{NSI} alternative, having both a higher intercept, and a much higher level of significance, with an intercept of 0.78 with almost 5 standard errors from zero.

Carhart's momentum factor (*WML*) proves to contribute marginal information to the original five factor model, with an intercept of 0.59 and a t statistic of 2.29.

Both versions of the new risk factor hold unique information to the five factor models factors. Once again, the risk factor constructed using past returns' volatility (PMV_{Vol}) outperforms the beta construction factor (PMV_{beta}), with a very strong and significant intercept of 0.70 and a t-statistic of 3.38. Both versions of the risk factor hold very strong negative slopes with the market factor.

The devil versions of the value factors have also been regressed ($HML_{B/M}dev$ and $HML_{E/P}dev$). These are the only two new factors that fail to have intercepts with a confidence interval of 95%. In particular, $HML_{B/M}dev$ has a trivial intercept, insinuating that it adds no new information to the five factor model. However, these results were to be expected, as there is a very high correlation between the original value factor ($HML_{B/M}$) and its devil version.

These results show that the addition of any one of the alternative factors, with the exception of the devil factors, would increase the explanatory power of the resulting model to explain average returns between July 1990 and November 2016.

The results from this analysis should be interpreted with caution, as they only describe the marginal information about average returns of the alternative factors when added, individually, to the original model, not the effects of changing one factor for another. Furthermore, if a factor is changed in the model, other alternative factors, that here do not contribute significantly, such as the devil factors, may become relevant.

Table 9: **Regressions of new alternative factors against the original five-factors**[11]
In this table, the results from regressing the monthly returns of each of the new alternative factors against the monthly returns of the original Fama-French five-factors are displayed. *RMRF*, $SMB_{B/M}$, $HML_{B/M}$, RMW_{OP} and CMA_{Inv} represent the original market, size, value, profitability and investment factors, respectively. The size factor is the exception, as $SMB_{B/M}$ represents the original size factor from the three-factor model, constructed using sorts on *size-B/M*. The monthly returns of each alternative factor ($HML_{B/M}dev$, $HML_{E/P}$, $HML_{E/P}dev$, RMW_{ROE}, CMA_{NSI}, CMA_{NSI}, *WML*, PMV_{Vol} and PMV_{beta}) have been regressed against the original five factors. For each regression, the coefficients of the intercepts and slopes for each factor, together with the t-statistic of each coefficient, are displayed. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	*RMRF*	$SMB_{B/M}$	$HML_{B/M}$	RMW_{OP}	CMA_{Inv}	R^2
$HML_{B/M}dev$	Coef.	0.11	0.09	0.08	0.65	-0.17	0.02	0.53
	t-Statistic	*0.76*	*3.32*	*1.92*	*14.16*	*-3.39*	*0.48*	
$HML_{E/P}$	Coef.	0.64	-0.15	-0.14	0.51	-0.05	-0.08	0.32
	t-Statistic	*3.88*	*-4.77*	*-2.79*	*9.45*	*-0.83*	*-1.58*	
$HML_{E/P}$ *dev*	Coef.	0.32	0.02	-0.05	0.38	-0.18	-0.09	0.18
	t-Statistic	*1.63*	*0.58*	*-0.88*	*5.89*	*-2.56*	*-1.41*	
RMW_{ROE}	Coef.	0.55	-0.13	-0.15	-0.34	0.10	-0.21	0.32
	t-Statistic	*3.89*	*-4.91*	*-3.46*	*-7.46*	*2.05*	*-4.90*	
CMA_{NSI}	Coef.	0.42	-0.33	-0.23	-0.01	0.04	0.00	0.19
	t-Statistic	*2.10*	*-8.67*	*-3.68*	*-0.17*	*0.60*	*-0.03*	
CMA_{CEI}	Coef.	0.78	-0.31	-0.23	0.18	0.02	0.08	0.30
	t-Statistic	*4.96*	*-10.48*	*-4.71*	*3.48*	*0.38*	*1.57*	
WML	Coef.	0.59	-0.25	-0.02	0.07	0.41	0.08	0.13
	t-Statistic	*2.27*	*-5.15*	*-0.27*	*0.77*	*4.40*	*0.93*	
PMV_{Vol}	Coef.	0.70	-0.50	-0.32	0.16	-0.01	-0.15	0.35
	t-Statistic	*3.38*	*-12.83*	*-5.07*	*2.31*	*-0.07*	*-2.29*	
PMV_{beta}	Coef.	0.44	-0.67	-0.21	0.05	0.15	0.19	0.54
	t-Statistic	*2.23*	*-18.45*	*-3.46*	*0.76*	*2.16*	*3.15*	

4.5. THE MOMENTUM – DEVIL SYMBIOSIS

In this section the relationship between the two devil value factors *(*$HML_{E/P}dev$ *and* $HML_{B/M}dev$) and Carhart's momentum factor (*WML*) will be explored. Asness and Frazzini (2013) and Asness et al. (2015) find that the combination of a momentum factor and devil value factor improves the performance of the Fama-French models. The devil versions of the value factors are created using the same calculations and criteria, except that their sorts are updated monthly (like *WML*) using the most recent data, instead of annually in June.

[11] Except the size factor which is constructed as in the three-factor model, $SMB_{B/M}$.

Asness et al. (2015) find that by including a momentum factor in the Fama-French five-factor model, and changing the normal value factor for a devil version of itself, improves the power of the resulting model to explain average returns. Moreover, they find that the normal value factor is redundant in the five-factor model for the US between 1963 and 2014, but that by using a devil value factor in its place and including a momentum factor, the devil value factor becomes relevant, carrying unique information about average returns. They fittingly refer to this phenomenon as resurrecting value.

In order to try and determine if this behaviour is also observed for Spain between July 1990 and November 2016, linear regressions have been carried out using monthly factor returns of both alternatives of the here scrutinised devil value factors as independent variables, $HML_{B/M}dev$ and $HML_{E/P}dev$. The regressions test if the non-devil versions, alone or in combination with the momentum factor, can span the devil factor in question.

The first and second rows of Table 10 place $HML_{E/P}dev$ as the dependant variable in the regressions. In the first row, $HML_{E/P}dev$ is regressed against $HML_{E/P}$, the regular version of itself. The resulting trivial intercept indicates that $HML_{E/P}dev$ contains no unique information not already captured by $HML_{E/P}$. The second row incorporates the momentum factor (*WML*) as an additional independent variable, here it is observed that the negative exposure to *WML* manages to change the sign of $HML_{E/P}dev$'s intercept, but still it fails to be significant (0.05, t=0.37).

The third and fourth rows of Table 10 are somewhat more interesting, placing $HML_{B/M}dev$ as the dependant variable in the regressions. Once again, in the first row, $HML_{B/M}dev$ is regressed against $HML_{B/M}$, the regular version of itself, and once again, the intercept is trivial due to the massive exposure to $HML_{B/M}$. However, in the fourth row, with the addition of *WML* as an independent variable, $HML_{B/M}dev$'s intercept suddenly becomes significant (0.28, t=2.54), triggered by a large negative correlation with *WML.*

From Table 10, it is clear that the *E/P* alternative construction value factor being considered in this chapter ($HML_{E/P}$), shows no affinity to the phenomenon described by Asness et al. (2015). As here the devil version of $HML_{E/P}$ showed no evidence of containing unique information not already present in the regular version of $HML_{E/P}$, even when a momentum factor is added.

Table 10: **Regression tests for devil - momentum symbiosis**

This table displays the results from regressing each devil value factor against its non-devil equivalent factor, with and without including the momentum factor. The monthly returns of both versions of the devil value factors ($HML_{E/P}dev$ and $HML_{B/M}dev$) have firstly been regressed against the monthly returns of the non-devil versions of themselves ($HML_{E/P}$ and $HML_{B/M}$, respectively). Secondly, they have been regressed against their non-devil versions of themselves and the momentum factor (*WML*). Devil factors and *WML* are constructed using sorts that are updated monthly instead of annually. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	$HML_{E/P}$	$HML_{B/M}$	*WML*	R^2
$HML_{E/P}dev$	Coef.	-0.11	0.71			0.42
	t-Statistic	*-0.64*	*15.26*			
$HML_{E/}dev$	Coef.	0.05	0.78		-0.34	0.61
	t-Statistic	*0.37*	*20.10*		*-12.32*	
$HML_{B/M}dev$	Coef.	0.08		0.73		0.50
	t-Statistic	*0.57*		*17.75*		
$HML_{B/M}dev$	Coef.	0.28		0.70	-0.33	0.70
	t-Statistic	*2.54*		*21.61*	*-14.31*	

However, the results for the traditional *B/M* construction value factor ($HML_{B/M}$) replicate those described by Asness et al. (2015). As such, the use of a devil $HML_{B/M}$ factor together with the *WML* factor can magnify the explanatory power of the resulting model, above that obtained using the regular $HML_{B/M}$ factor or momentum alone. Hence, if $HML_{B/M}$ is to be considered for the model for Spain, it would make sense for the model to include the devil version of the $HML_{B/M}$ factor together with the momentum factor.

As a robustness test, regressions of each of the four value factor alternatives have been regressed against the original; market, size, profitability and investment factors, with and without the addition of the *WML* factor. These tests confirm that the use of $HML_{B/M}dev$ in combination with *WML*, adds considerable information about average returns. Whereas the use of $HML_{E/P}$, with or without the *WML* factor, adds more information about average returns than when the $HML_{E/P}dev$ factor is used. The regressions are presented in Table 17 of the appendix.

4.6. *B/M, ROE* AND *E/P*: SHARED INFORMATION

In this section, the relationship between the two value factors and the *ROE* construction version of the profitability factor (RMW_{ROE}) will be analysed. These factors show high correlations, both positive and negative.

Due to the way in which these factors are constructed, it is only normal that they should share tendencies. The *B/M* breakpoints used in the construction of $HML_{B/M}$ have company book value (*BV*) as a numerator, whereas the *ROE* breakpoints used in the construction of RMW_{ROE} use company *BV* in the denominator. Hence the returns on these two factors have a large negative correlation. The alternative value factor, $HML_{E/P}$, uses the *E/P* ratio for its breakpoints on its second sorts. This *E/P* ratio shares the numerator (net income) with *ROE*, and the denominator (*MV*) with *B/M*.

This leads to the following question: Do the $HML_{B/M}$ and the RMW_{ROE} factors capture the returns of the $HML_{E/P}$ factor? To find out, a series of regressions have been carried out to test if combinations of the $HML_{B/M}$ and RMW_{ROE} factors can subsume the $HML_{E/P}$ factor, making it redundant, the results of which are displayed in Table 11.

The first row of Table 11 displays the results from regressing the monthly returns of the annual $HML_{E/P}$ factor against the returns of $HML_{B/M}$ and RMW_{ROE}. The results show a small and statistically insignificant intercept value (0.20, t=1.44) due to large positive slopes with $HML_{B/M}$ and RMW_{ROE}.

The second row of Table 11 shows the results from executing the same regression using the devil versions of the value factors. Here an enhanced exposure of $HML_{E/P}dev$ to $HML_{B/M}dev$ reduces the intercept further to -0.12. Finally, row three repeats this last regression adding the momentum factor (*WML*) as an additional independent variable. This action reduces $HML_{E/P}dev$'s intercept to a completely insignificant -0.08 (t=-0.52).

In light of these results, the answer to the question posed previously is yes. Used combined, the $HML_{B/M}$ and RMW_{ROE} factors do capture the returns of $HML_{E/P}$. This also proves to be true when considering the devil versions of the value factors, moreover, the coverage is increased. For these reasons, it is logical that a multifactor-model that contains the RMW_{ROE} factor should also contain a value factor constructed using *B/M* and not *E/P*.

Table 11: **Exposures of $HML_{E/P}$ to $HML_{B/M}$ and RMW_{ROE}**
This table shows the results from regressions with the monthly returns of $HML_{E/P}$ and $HML_{E/P}dev$ as the dependant variables, and combinations of $HML_{B/M}$, $HML_{B/M}dev$, RMW_{ROE}, *and WML* as independent variables. The suffix *–dev* indicates a devil factor, devil factor and momentum sorts are updated monthly instead of annually. The coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	$HML_{B/M}$	$HML_{B/M}dev$	RMW_{ROE}	*WML*	R^2
$HML_{E/P}$	Coef.	0.20	0.81		0.69		0.54
	t-Statistic	*1.44*	*18.46*		*13.43*		
$HML_{E/P}dev$	Coef.	-0.12		0.91	0.64		0.51
	t-Statistic	*-0.80*		*18.34*	*10.69*		
$HML_{E/P}dev$	Coef.	-0.08		0.87	0.64	-0.06	0.52
	t-Statistic	*-0.52*		*15.93*	*10.74*	*-1.58*	

4.7. Sharpe tests

To find out which factors are most appealing from an investors point of view, the optimal factor weights in order to maximise the Sharpe ratio have been calculated for multiple combinations of factors.

The Sharpe ratio has been calculated as described in section 3.4. Here, once again, the factor weights have a lower bound of 0 and the sum of all weights has an upper bound of 1. If a factor included in the model is assigned a weight near to zero, when maximising the Sharpe ratio, it is said to be unselected, and its inclusion has little to no effect on the model's performance. The results of the tests are displayed in Table 12.

The first three rows of Table 12 report maximised Sharpe ratios for the Fama-French three-factor model (*FF 3F*) and model variants. The first row indicates the *R* for the original Fama-French three-factor model. Neither the *SR* ratio nor the factor weights are seen to vary significantly from the results obtained for the same test in Table 6. The slight differences are due to small changes in the sample data, described in section 4.2.

The second row of Table 12 incorporates the *E/P* construction version of the value factor ($HML_{E/P}$) into the model, the result is remarkable. The maximised Sharpe ratio increases from 0.134 to 0.246, above the maximum Sharpe ratio achieved from the original five-factor model (see row 4), and all the weight is removed from the traditional *B/M* construction version of the value factor ($HML_{B/M}$).

To further investigate the effects of changing the value factor's variable to *E/P* on the performance of the three-factor model, spanning tests have been carried out using the $HML_{E/P}$ factor. The intercepts of the market and value factor regressions are statistically and economically significant (*RMRF*: 0.76, t=2.54 and $HML_{E/P}$: 0.75, t=3.90). These results indicate that, for said modified three-factor model, the market and value factors now contribute unique valuable information about the average returns of Spanish stocks. The results of the spanning test can be found in the appendix, Table 18.

A Sharpe test with all the alternatives for the value factor and the momentum factor (*WML*) are considered in row three of Table 12. Here, a combination of *WML* and the devil version of the $HML_{B/M}$ factor ($HML_{B/M}dev$), add further value, increasing the *SR* ratio to 0.295. The $HML_{B/M}$ and $HML_{E/P}dev$ factors attain no weight in this model. This is in line with the evidence found in section 4.5, that $HML_{B/M}dev$ together with *WML* delivers more information than $HML_{B/M}$, and that in the same circumstances, $HML_{E/P}dev$ remains redundant to $HML_{E/P}$.

Rows four through seven of Table 12 report maximised Sharpe ratios for the Fama-French five-factor model (*FF 5F*) with factor alternatives and additional factors. The first row indicates the *SR* for the original[12] Fama-French five-factor model. Once again, neither the *SR* ratio nor the factor weights are seen to vary significantly from the results obtained for the same test in Table 6.

Row five of Table 12 includes all of the alternatives to the original five factors in the calculation to maximise *SR*. A rise in the *SR* to 0.386 is reported, but this is expected, the true point of this test model is to see which factors are most important. From the results it is visible that $HML_{B/M}dev$ is favoured to the other value factors, even in this model where momentum has not yet been added. This is likely due to its superior negative correlation with both profitability factors (see Table 8) and $HML_{E/P}$'s large positive correlation with CMA_{CEI}. The test model also reveals a tie between both profitability factors, assigning a healthy 0.15 weight to each of them. Finally, there is a clear preference for the *CEI* version of the investment factor (CMA_{CEI}), which is assigned an optimal weight of 0.21.

The test model in row six contains all the factors from row five, plus the momentum factor (*WML*), which increases the *SR* to 0.414. The addition of

[12] Except the size factor which is constructed as in the three-factor model, $SMB_{B/M}$.

momentum increases the affinity to $HML_{B/M}dev$ over the other value factors, by increasing its weight to 0.21, and setting all other value factor weights to 0. The weight distribution for the profitability factors now shifts slightly towards RMW_{ROE} (0.15), but still remains high for RMW_{OP} (0.12). The investment factors remain relatively unchanged, with CMA_{CEI} still very much in the lead. The newly added momentum factor is also selected, having an assigned optimal weight of 0.10.

All alternatives and additional factors are considered to maximise the *SR* in row seven. All weights remain rather unchanged with respect to the previous row. However, here, for the first time the two risk factors are included. The results show that the beta construction risk factor (PMV_{beta}) is not selected at all, and the volatility construction risk factor (PMV_{Vol}) receives a weight of only 0.04, setting its level of importance relatively low. It's also important to point out that the *SR* ratio barely changes from 0.414 to 0.418. This rise is insignificant and insinuates that the inclusion of a risk factor does not significantly improve the performance of the model.

The market and size factors are included throughout the tests. The market factor is consistently assigned a relatively high weight in the maximisation process, whereas size consistently receives a relatively low weight.

From these tests it is observable that there is a clear preference for $HML_{B/M}dev$ as a value factor and CMA_{CEI} as an investment factor. It is also clear that adding *WML* as a sixth factor improves the performance of the model. Still unclear is the optimum profitability factor, as both options are selected for the maximum *SR* when included in the model. Lastly, the necessity for a seventh risk factor is still unclear, although PMV_{Vol} is selected when included in the model, it is assigned a very small weight, producing only slight changes in the maximum *SR*.

The last three rows of Table 12 report the optimum weights and maximum Sharpe ratios for three model proposals. The factors included in the proposals have been carefully selected, taking into account their performance throughout this thesis. The proposals are constructed on the original Fama-French five-factor model, as such, they all include versions of the five; market, size, value, profitability and investment factors.

Table 12: **Sharpe tests on alternative factors**

This table displays the maximised Sharpe ratios for the Fama-French three-factor (*FF 3F Original*) and Fama-French five-factor (*FF 5F Original*) models in combination with alternative value, profitability and investment factors. Additionally, the models have been augmented in some tests by the addition of the momentum factor and risk factors. The market factor (RMRF) is calculated as the sample's market return (*MR*) minus the risk free rate (*RF*). All other factors use independent 2 x 3 sorts, with the first sort on size, to create six value weighted portfolios. The second sort uses the 30th and 70th percentile breakpoints based on big stocks of the variable indicated by the sub-indices, e.g. for CMA_{NSI}, the second sort uses the 30th and 70th percentiles of net-stock-issues based on big stocks for breakpoints. The value factors that have been considered are $HML_{B/M}$, $HML_{B/M}dev$, $HML_{E/P}$, and $HML_{E/P}dev$, and are calculated as the averages of the two high value portfolios minus the two low value portfolios. The profitability factors being considered are RMW_{OP}, and RMW_{ROE}, and are calculated as the averages of the two robust profitability portfolios minus the two weak profitability portfolios. The investment factors being considered are CMA_{Inv}, CMA_{NSI}, and CMA_{CEI}, and are calculated as the averages of the two conservative investment portfolios minus the two aggressive investment portfolios. The risk factors being considered are PMV_{Vol} and PMV_{beta}, and are calculated as the averages of the two poised risk portfolios minus the two volatile risk portfolios. The momentum factor, *WML*, is calculated using monthly independent 2 x 3 sorts on size-momentum, and is calculated as the averages of the two winner momentum portfolios minus the two loser momentum portfolios. The size factor ($SMB_{B/M}$) is calculated using the *size-B/M* sorts as; the sum of returns of the three big stock portfolios, minus the sum of returns of the three small stock portfolios, all divided by three. Sorts are updated annually in June, except factors marked with the suffix *-dev* (short for devil) and *WML*, which have their sorts updated monthly using the most recent data available (*MV, B/M and E/P*). The value-weighted portfolio returns of all factors are updated monthly. The optimal Sharpe ratio (*SR*) and corresponding factor weights for each model are displayed. The factor weights for each model have a lower bound of 0, and the sum of all weights is limited to 1. All tests are carried out with monthly factor returns for the sample period; July 1990-November 2016 (317 months).

	SR	*RMRF*	$SMB_{B/M}$	*WML*	$HML_{B/M}$	$HML_{B/M}dev$	$HML_{E/P}$	$HML_{E/P}dev$	RMW_{OP}	RMW_{ROE}	CMA_{Inv}	CMA_{NSI}	CMA_{CEI}	PMV_{Vol}	PMV_{beta}
FF 3F Original	0.134	0.46	0.00		0.54										
FF 3F + $HML_{E/P}$	0.246	0.28	0.06		0.00		0.65								
FF 3F + alternatives + WML	0.295	0.22	0.02	0.27	0.00	0.19	0.31	0.00							
FF 5F Original	0.212	0.14	0.00		0.32				0.38		0.15				
FF 5F + alternatives	0.386	0.14	0.06		0.06	0.11	0.02	0.00	0.15	0.15	0.08	0.02	0.21		
FF 5F + alternatives + WML	0.414	0.14	0.04	0.10	0.00	0.21	0.00	0.00	0.12	0.15	0.06	0.02	0.18		
ALL	0.418	0.14	0.05	0.09	0.00	0.20	0.00	0.00	0.12	0.13	0.06	0.02	0.15	0.04	0.00
Proposal 1	0.387	0.17	0.06	0.14		0.21				0.19			0.23		
Proposal 2	0.391	0.17	0.05	0.12		0.19			0.17				0.31		
Proposal 3	0.398	0.18	0.06	0.11		0.18			0.16				0.25	0.07	

In all three model proposals, $HML_{B/M}dev$ is chosen as the alternative to the original value factor and CMA_{CEI} is chosen as the alternative to the original investment factor. Additionally, all proposals include the momentum factor (*WML*) as the sixth factor in the model. The models vary in the selection choice of profitability factor and in the inclusion or not of PMV_{Vol} as a seventh risk factor.

Proposal 1 considers RMW_{ROE} as the alternative to the original profitability factor. In the maximisation of *SR* for this model proposal, weights are relatively evenly distributed across all factors, all having weights above 0.14 and below 0.21 (with the exception of the size factor which receives a smaller 0.06 weight). The maximum *SR* is 0.387, almost double the ratio achieved for the original five factor model.

Proposal 2 considers the original profitability factor RMW_{OP}. Here the weights of the factors are not as even as in proposal 1, with CMA_{CEI} receiving over 30% of the total weight allocation. The maximum *SR* for this proposal is equally good, slightly higher even than for proposal 1 (0.391).

Lastly, proposal 3 takes the same factors as considered in proposal 2 and adds PMV_{Vol} as a seventh risk factor. The maximum *SR* achieved with the inclusion of this seventh factor is only marginally better than for the other two, six factor, proposals (0.398). Only a small weight of 0.07 is assigned to the PMV_{Vol} factor. All remaining factors retain healthy weights between 0.11 (*WML*) and 0.25 (CMA_{CEI}), with the CMA_{CEI} retaining the largest portion.

From the results obtained in Table 12, proposal 3 can be preliminarily discarded as a candidate for an augmented version of the five-factor model. This is due to the miniscule effect that the inclusion of the seventh risk factor has on the performance of the model. Further tests in section 4.8 will determine if the risk factor is captured by proposals 1 and 2.

The model proposals 1 and 2 seem to have almost analogous results in the Sharpe tests. Both have high Sharpe ratios and relatively even weight spreads across factors. Proposal 2 has a marginally higher Sharpe ratio, but nothing of obvious significance. For this reason, both models will be escalated as final propositions and analysed further in the next section.

4.8. EXPOSURES OF DISMISSED FACTORS TO THE NEW MODEL PROPOSALS

This section will focus on further analysing the two new model proposals escalated from the previous section. In particular, this section concentrates on determining their abilities to explain the average returns of the factors not included in said models.

To determine whether or not the two new model proposals can capture the average returns of the unused factors and deem them redundant, a series of linear regressions have been carried out. For each model proposal, regressions are run with the dismissed factors as dependant variables and the model factors as the independent variables. If a dismissed factor's average returns are captured by the model, the intercept from its regression will be statistically no different from zero, making the factor redundant.

Panel A of Table 13 reports regressions on proposal 1. Proposal 1 contains $RMRF$, $SMB_{B/M}$, $HML_{B/M}dev$, RMW_{ROE}, CMA_{CEI} and WML as its model factors, therefore these are the independent variables in all of the regressions. Each row places a factor not included in the model as the dependant variable. The results show that factors $HML_{B/M}$, $HML_{E/P}$, CMA_{NSI}, PMV_{Vol} and PMV_{beta}, all have very small intercepts ranging from 0.09 to -0.12, which are statistically no different from zero. This indicates that these factors' average returns are successfully captured by the model and that they would be redundant in the model. This is especially important when you consider that the $HML_{E/P}$ factor has a statistically and economically significant average monthly return (0.69%, t=3.48), and not capturing this in the model would be unacceptable.

Panel A also reveals a slightly negative intercept for $HML_{E/P}dev$ of -0.26, although it fails to be significant at the 5% significance level, it is significant at a level of 10%. This intercept is mainly due to a spread of positive slopes to all factors, especially $HML_{B/M}dev$, RMW_{ROE} and CMA_{CEI}, with the exception of WML. The CMA_{Inv} regression reveals a slightly positive intercept (0.20) due to a large negative factor loading with RMW_{ROE}, still, with only 1.12 standard errors from zero, this intercept still deems the factor redundant.

The most important finding of panel A is the positive and statistically significant intercept in the RMW_{OP} regression (0.36, t=2.12). As expected, this factor has a positive slope with its profitability counterpart RMW_{ROE}, however, a negative slope with CMA_{CEI}, and an even more negative slope with $HML_{B/M}dev$ is enough to make its intercept significant. This failure of proposal 1 to capture the average returns of the RMW_{OP} factor is a let-down.

Panel B of Table 13 reports regressions on proposal 2. Proposal 2 is identical to proposal 1, except for the profitability factor, which in proposal 2 is RMW_{OP}, therefore the independent variables in the regressions for panel B, are; *RMRF*, $SMB_{B/M}$, $HML_{B/M}dev$, RMW_{OP}, CMA_{CEI} and *WML*.

The results from panel B show that the $HML_{B/M}$, $HML_{E/P}$, $HML_{E/P}dev$, CMA_{Inv}, CMA_{NSI} and PMV_{beta} factors are successfully spanned by the factors contained in proposal 2. They all display intercepts in the regressions between 0.11 and -0.10, that are statistically insignificant, all with less than 0.82 standard errors from zero.

The intercept in the PMV_{Vol} regression of panel 2 shows a slightly higher value (0.24). This is due to large negative slopes with *RMRF* and $SMB_{B/M}$. Previously these same slopes were compensated by a positive factor loading on RMW_{ROE} in proposal 1. Here instead, the correlation with RMW_{OP} is in fact slightly negative, thus increasing the intercept. However, with a t-statistic of 1.20, this positive intercept is statistically no different from zero, therefore PMV_{Vol} is redundant.

Finally, and most interestingly, panel B reveals that the profitability counterpart factor, RMW_{ROE}, not included in proposal 2's model, has an insignificant intercept for a 5 % significance level. Specifically, the regression of RMW_{ROE} against proposal 2 yields an intercept of 0.26 (t=1.87), which is both smaller economically and statistically than the intercept witnessed for the regression of RMW_{OP} on proposal 1. This improvement is greatly due to the positive correlation between RMW_{ROE} and CMA_{CEI}, which is not shared by RMW_{OP}. In any case, this intercept, statistically no different from zero (at a 5% level of significance), is an improvement in performance when compared to proposal 1.

The results for both proposal 1 and 2 show that the inclusion of a seventh risk factor would not improve the performance of either model. This supports the decision to reject proposal 3 in the previous section. It is also worth noting that although alternative factors such as $HML_{E/P}$ can have outstanding summary statistics for average factor returns, their inclusion in the proposals would not contribute anything to the overall model performances. Once again, this highlights the importance of marginal information over individual performance in multi-factor models.

Overall, these test results show that, while proposal 1 successfully spans the returns of all but one alternative factor, proposal 2 successfully captures the returns of absolutely all alternative factors. This quality of proposal 2 to make all other factors redundant for the sample and studied time period, grants it superiority over the model in proposal 1. Therefore, the model in proposal 2 is selected as the best model, and will be analysed in more detail in the following section.

Table 13: **Dismissed factor exposures to new model proposals**
This table reports regressions on two model proposals of factors that have not been included in said models. Panel A shows regressions with the factors included in proposal 1 as independent variables (*RMRF*, $SMB_{B/M}$, $HML_{B/M}dev$, RMW_{ROE}, CMA_{CEI} and *WML*). Panel B shows regressions with the factors included in proposal 2 as independent variables (*RMRF*, $SMB_{B/M}$, $HML_{B/M}dev$, RMW_{OP}, CMA_{CEI} and *WML*). In each panel, the dependant variables are all the factors that have been considered in this chapter that are not included in the panel's independent variables. For each regression, the coefficients of the intercepts and slopes for each factor, together with the t-statistic of each coefficient, are displayed. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

Panel A: Dismissed factor exposures to Proposal 1

		Intercept	*RMRF*	$SMB_{B/M}$	$HML_{B/M}dev$	RMW_{ROE}	CMA_{CEI}	*WML*	R^2
$HML_{B/M}$	Coef.	-0.12	0.02	-0.05	0.72	-0.25	0.19	0.23	0.63
	t-Statistic	*-0.94*	*0.85*	*-1.21*	*15.48*	*-4.88*	*3.98*	*7.67*	
$HML_{E/P}$	Coef.	-0.10	0.05	-0.02	0.57	0.37	0.49	0.18	0.53
	t-Statistic	*-0.69*	*1.61*	*-0.43*	*10.77*	*6.32*	*9.19*	*5.26*	
$HML_{E/P}dev$	Coef.	-0.26	0.10	0.03	0.76	0.50	0.34	-0.10	0.56
	t-Statistic	*-1.68*	*3.09*	*0.68*	*13.48*	*8.08*	*5.98*	*-2.81*	
RMW_{OP}	Coef.	0.36	0.02	0.05	-0.31	0.20	-0.13	0.04	0.23
	t-Statistic	*2.12*	*0.67*	*0.92*	*-4.92*	*2.90*	*-2.11*	*0.90*	
CMA_{NSI}	Coef.	0.07	-0.19	-0.12	-0.04	0.16	0.33	0.02	0.28
	t-Statistic	*0.34*	*-4.65*	*-2.05*	*-0.52*	*2.02*	*4.55*	*0.49*	
CMA_{Inv}	Coef.	0.20	-0.03	-0.06	-0.12	-0.45	0.25	0.02	0.13
	t-Statistic	*1.12*	*-0.90*	*-1.03*	*-1.76*	*-6.19*	*3.71*	*0.49*	
PMV_{Vol}	Coef.	0.09	-0.31	-0.19	0.20	0.38	0.37	0.12	0.48
	t-Statistic	*0.47*	*-7.70*	*-3.24*	*2.72*	*4.73*	*5.17*	*2.69*	
PMV_{beta}	Coef.	0.06	-0.51	-0.12	-0.08	0.00	0.36	0.25	0.64
	t-Statistic	*0.34*	*-13.31*	*-2.23*	*-1.12*	*0.05*	*5.28*	*5.70*	

Panel B: Dismissed factor exposures to Proposal 2

		Intercept	*RMRF*	$SMB_{B/M}$	$HML_{B/M}dev$	RMW_{OP}	CMA_{CEI}	*WML*	R^2
$HML_{B/M}$	Coef.	-0.10	0.02	-0.03	0.75	-0.23	0.09	0.25	0.64
	t-Statistic	*-0.82*	*0.88*	*-0.86*	*17.89*	*-5.44*	*2.01*	*8.47*	
$HML_{E/P}$	Coef.	0.08	0.06	-0.02	0.33	-0.15	0.61	0.16	0.49
	t-Statistic	*0.53*	*1.95*	*-0.38*	*6.44*	*-3.02*	*11.68*	*4.53*	
$HML_{E/P}dev$	Coef.	-0.09	0.11	0.03	0.50	-0.02	0.50	-0.13	0.47
	t-Statistic	*-0.53*	*3.17*	*0.49*	*8.85*	*-0.44*	*8.77*	*-3.30*	
RMW_{ROE}	Coef.	0.26	0.02	-0.02	-0.44	0.13	0.35	-0.06	0.41
	t-Statistic	*1.87*	*0.69*	*-0.50*	*-9.54*	*2.90*	*7.35*	*-1.92*	
CMA_{NSI}	Coef.	0.11	-0.19	-0.13	-0.11	0.02	0.39	0.01	0.27
	t-Statistic	*0.55*	*-4.54*	*-2.09*	*-1.65*	*0.29*	*5.68*	*0.28*	
CMA_{Inv}	Coef.	0.10	-0.04	-0.05	0.07	-0.09	0.09	0.05	0.03
	t-Statistic	*0.51*	*-1.06*	*-0.79*	*1.11*	*-1.46*	*1.33*	*1.11*	
PMV_{Vol}	Coef.	0.24	-0.30	-0.19	-0.02	-0.08	0.49	0.10	0.44
	t-Statistic	*1.20*	*-7.18*	*-3.17*	*-0.34*	*-1.20*	*7.15*	*2.19*	
PMV_{beta}	Coef.	0.06	-0.51	-0.12	-0.08	0.00	0.36	0.25	0.64
	t-Statistic	*0.34*	*-13.31*	*-2.23*	*-1.24*	*0.04*	*5.70*	*5.72*	

4.9. FINAL PROPOSAL

With the evidence and analyses carried out in this chapter, and in culmination of this thesis, it is now time to define a final proposal for an empirical multi-factor asset pricing model, based on the Fama-French five-factor model, which specifically attends to the behaviour of the Spanish capital market.

4.9.1. Description

The final model proposal includes all of the types of factors (market, size, value, profitability and investment) included in the Fama-French five-factor model, with the addition of a momentum factor, making the final proposal a six-factor model.

$$R_{it} = RF_t + \beta_i RMRF_t + s_i SMB_{B/M,t} + h_i HML_{B/M} dev_t + r_i RMW_{OP,t} + c_i CMA_{CEI,t} + w_i WML_t + e_{it} \tag{14}$$

Equation (14) represents the time series regression for the final model proposal. Where, for month t, R_{it} is the return of asset i, RF_t is the risk-free rate of return, $RMRF_t$ is the excess market return, and $SMB_{B/M}$, $HML_{B/M}dev$, RMW_{OP}, CMA_{CEI}, and *WML*, are the; size, value, profitability, investment and momentum factor returns respectively.

The market factor (*RMRF*) and the profitability factor (RMW_{OP}) have been conserved as described by Fama and French (2015) in their original five-factor model. The size factor ($SMB_{B/M}$) for the final proposal is identical to the size factor in the original three-factor model, Fama and French (1993).

The value factor used in the final proposal ($HML_{B/M}dev$) is constructed similarly to the value factor in the original five-factor and three-factor models. The only difference being that its sorts/portfolios are updated monthly instead of annually, as described by Asness and Frazzini (2013).

The investment factor used in the final proposal (CMA_{CEI}) is constructed in a similar way to the original Fama-French investment factor. However, CMA_{CEI} uses size–composite-equity-issuance 2 x 3 sorts in its construction, instead of the size–asset-growth sorts used for the original factor. The breakpoints and timeliness of the factor remain the same.

The sixth momentum factor incorporated in the final model proposal (*WML*) is constructed similarly to Fama and French (2012), using independent 2 x 3 sorts on size-momentum. As for $HML_{B/M}dev$, the sorts/portfolios for the *WML* factor are updated monthly instead of annually.

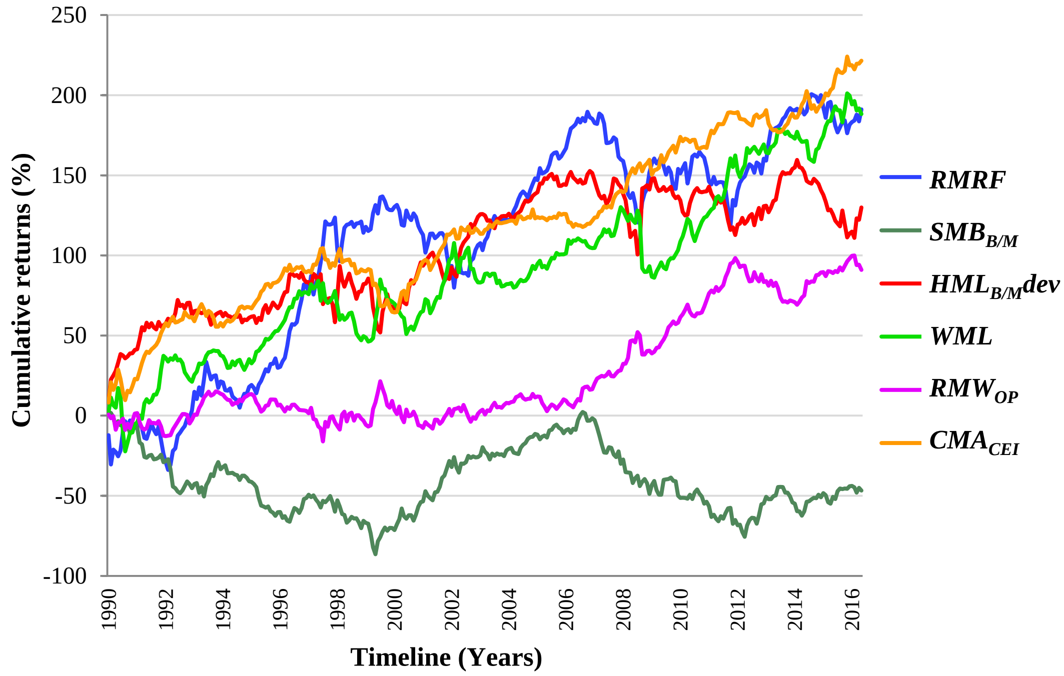
For further details on how each factor is constructed see sections 2.2 and 2.3 of the thesis.

4.9.2. Performance

The average premiums for the factors included in the final model for 1990-2016 (317 months) can be found in Table 7. Said table shows that the equity premium (average monthly *RMRF* return) is high, with a level of certainty between 90 and 95% (0.60%, t=1.91). The average returns for the value and profitability factors are relatively low and lack statistical significance ($HML_{B/M}dev$: 0.29%, t=1.39, RMW_{OP}: 0.29%, t=1.60). On a more positive note, the investment and momentum premiums are large, both economically and statistically (CMA_{CEI}: 0.70%, t=3.79, *WML*: 0.59%, t=2.17). Finally, the size premium ($SMB_{B/M}$) appears to be slightly negative, but without any statistical significance (-0.15%, t=-0.78).

The cumulative performance of each factor is represented in Figure 2. From the figure, the clear positive tendencies of the new CMA_{CEI} and additional *WML* factors are easily appreciable. Strong, stable and seemingly permanent tendencies such as these are vital to the credibility of empirical models.

Figure 2: Cumulative factor returns for final model proposal
This figure plots the cumulative monthly returns of the six factors included in the final model proposal for the Spanish capital market, over the July 1990 to November 2016 (317 month) period.



The factors' standalone average returns can be interesting, however, in a multi-factor model, such as the one proposed, a factor's contribution to the overall performance of the model is more important. To determine the marginal information about average returns that each factor contributes to the model, factor spanning tests have been conducted.

Table 14 reports spanning regressions of the factors included in the final model proposal. Each factor has been regressed against the other five factors. If the intercept of the regression is statistically different to zero, the factor contains unique information about average returns, its inclusion in the model is therefore important. If the intercept of a factor's spanning regression is statistically no different from zero, the other five factors are said to span the factor in question, making it redundant.

All regression intercepts in Table 14, with the exception of the $SMB_{B/M}$ factor, are statistically different from zero with at least a 5% significance level. The market factor appears to carry the most information about average returns, with a very large intercept, both economically and statistically speaking (1.08%, t=4.09), partially achieved due to a huge negative exposure to CMA_{CEI}. A strong negative correlation between *WML* and $HML_{B/M}dev$ is enough to give both factors a strong intercept in the spanning tests. The regression of RMW_{OP} has a healthy intercept, well above its average returns, which is thanks to a considerable negative factor exposure to $HML_{B/M}dev$. The regression of CMA_{CEI} reveals a negative exposure to the *RMRF* and $SMB_{B/M}$ factors. The $SMB_{B/M}$ factor's intercept lacks any sort of significance.

From the spanning tests in Table 14 some clear conclusions can be made. Firstly, the new alternatives to the traditional factors and the additional momentum factor work very well together. Secondly, when comparing the spanning tests for the original five-factor model (Table 4) with the new model proposal, it's soon clear that the new model resuscitates the market and investment factors, and then some. They go from being redundant to the most economically and statistically relevant factors in the model. Lastly, it is also clear that the new model fails to resuscitate the size factor. The large negative correlations between *RMRF* and CMA_{CEI} boost the factors returns 0.30%, from -0.15% to +0.15%, but unfortunately this is still not enough to make it significant.

Table 14: **Spanning tests for the Fama-French five-factor model**
In this table, the results from regressing the monthly returns of each of the six proposal factors against the monthly returns of the remaining five factors are displayed. *RMRF*, $SMB_{B/M}$, $HML_{B/M}dev$, RMW_{OP}, CMA_{CEI} and *WML* represent the market, size, value, profitability, investment and momentum factors, respectively. The table details the coefficients of the intercepts and slopes for each factor, together with the t-statistic of each coefficient. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	*RMRF*	$SMB_{B/M}$	$HML_{B/M}dev$	RMW_{OP}	CMA_{CEI}	*WML*	R^2
RMRF	Coef.	1.08		-0.57	0.13	0.07	-0.78	-0.13	0.35
	t-Statistic	*4.09*		*-7.54*	*1.39*	*0.79*	*-9.51*	*-2.02*	
$SMB_{B/M}$	Coef.	0.14	-0.27		0.14	0.05	-0.31	0.06	0.16
	t-Statistic	*0.74*	*-7.54*		*2.23*	*0.86*	*-4.99*	*1.44*	
$HML_{B/M}dev$	Coef.	0.46	0.05	0.11		-0.39	0.16	-0.32	0.39
	t-Statistic	*2.74*	*1.39*	*2.23*		*-7.69*	*2.81*	*-9.10*	
RMW_{OP}	Coef.	0.42	0.03	0.04	-0.40		-0.06	0.02	0.21
	t-Statistic	*2.48*	*0.79*	*0.86*	*-7.69*		*-1.09*	*0.60*	
CMA_{CEI}	Coef.	0.72	-0.29	-0.24	0.15	-0.06		0.15	0.30
	t-Statistic	*4.49*	*-9.51*	*-4.99*	*2.81*	*-1.09*		*4.07*	
WML	Coef.	0.61	-0.10	0.11	-0.66	0.05	0.33		0.33
	t-Statistic	*2.56*	*-2.02*	*1.44*	*-9.10*	*0.60*	*4.07*		

The maximum Sharpe ratio achieved by the new model proposal is 0.391, well above that achieved by the original five factor model (0.212). The maximum ratio is achieved with a portfolio with the following factor composition: 17% *RMRF*, 5% $SMB_{B/M}$, 14% *WML*, 19% $HML_{B/M}dev$, 17% RMW_{OP} and 31% CMA_{CEI}. See Table 12, Proposal 2.

From the results collected throughout this thesis, it would seem that the size factor is redundant for Spain, and hence its removal from the final proposal would have little to no effect on the model's descriptive power about average returns. However, as this is an exercise of enhancement, of an existing model, to the needs of the Spanish capital market, the decision was made to keep the essence of all five factors in the new model proposal.

Overall, the new model proposal is an unquestionable improvement on the performance of the original five-factor model for the Spanish capital market.

5. CONCLUSIONS

For the studied time period from July 1990 to November 2016 (317 months), both the Fama-French three-factor and five-factor models perform poorly in explaining the average returns of Spanish stocks.

No correlation between the size factor and average returns has been found, this is in line with the findings of Fama and French (2015) for the European market. Spanning tests on the three-factor model reveal that none of the factors contribute unique information about the average returns of Spanish stocks.

From the original five-factor model, only the profitability factor has a strong positive relationship with average returns. Furthermore, spanning tests on the five-factor model show that, the only two factors that hold unique information about Spanish average returns are the profitability and value factors[13]. The original size and investment factors are proven to be redundant.

The Fama-French five-factor model, does however, substantially outperform the three-factor model. This is almost entirely due to the inclusion of the profitability factor, and its strong negative correlation with the value factor. The improvement is clearly visible in the maximum Sharpe ratios of each model, the five-factor model achieving a 77% improvement over the three factor model.

In the pursuit of a more comprehensive empirical multi-factor asset pricing model, adjusted for the Spanish capital market, multiple alternatives to the original Fama-French five-factor model's factors have been considered. All alternatives have been constructed using the same 2 x 3 sorts, size-variable, construction method described by Fama and French. For the value, profitability and investment factors, at least one alternative characteristic variable has been considered. The market factor has remained untouched, and the size factor has been constructed as in the Fama-French three-factor model. Two additional types of factors have also been considered, a momentum factor and two risk factors.

The alternative value factor constructed using *E/P* ($HML_{E/P}$), instead of *B/M*, proves to have a large positive relation with average returns. Strong relations with average returns are also held with; the alternative *CEI* variant of the investment factor (CMW_{CEI}), the *ROE* alternative to the profitability factor (RMW_{ROE}) and the momentum factor (*WML*).

[13] For a 95% confidence interval.

Tests when enhancing the three-factor model show that simply by changing the value variable to *E/P*, the maximum Sharpe ratio sees an 84% improvement with respect to the original three-factor model. Additionally, with this small change, spanning tests indicate that the market and value factors both become relevant, carrying unique information about average returns.

The devil *B/M* version of the profitability factor ($HML_{B/M}dev$) and the momentum factor have strong negative correlations for Spain, in line with Asness and Frazzini (2013). However, no such alliance has been found for the devil *E/P* version of the profitability factor and *WML*.

Of the two proposed alternative risk factors, based on historical volatility and systematic risk (*Vol* and *beta* respectively), a positive relation between the volatility construction risk factor and average returns was found for a 90% confidence level, while no relation was found for the *beta* construction risk factor. Both factors were found to be captured by combinations of the traditional factors and momentum.

Finally, an adapted and augmented version of the five-factor model has been presented based on the empirical evidence for the Spanish stock market between 1990 and 2016. The new six-factor model incorporates the momentum factor and uses alternative versions of the value and investment factors. The new value factor ($HML_{B/M}dev$), based on Asness and Frazzini (2013), uses *B/M* as the characteristic variable and has its portfolios updated monthly. The new investment factor (CMW_{CEI}) uses *CEI* as its characteristic variable, and is otherwise unchanged.

Spanning tests on the new six-factor model reveal that all factors, except the size factor, contribute with unique information about average returns to the model. Size is still redundant. The maximum Sharpe ratio for the new model is 84% higher than for the original five factor model. The fact that the new model proposed in this thesis, meaningfully outperforms the original five-factor model in describing average returns for Spanish stocks, over the 26 year period from July 1990 to November 2016, is indisputable.

However, a word of caution, this is an empirical asset pricing model, hence although the model's performance is unquestionable for the studied sample and time period: 1990-2016 (317 months). Tendencies can change, and one can never take these models as future fact. This said, I am confident that the sample quality and time period are suffice to warrant the model credibility and recognition.

Appendix

Table 15 shows details about the composition of the data sample used in the various test carried out in this thesis.

Table 16, Panel A and B, displays the average monthly returns on sorts constructed using variable quintiles as breakpoints. The breakpoints are only on large stock in order to keep the 5 portfolios more balanced. For the *NSI* sorts, the five portfolios are formed as follows, all stocks with zero *NSI*, are placed in sort Nº3, then the stocks with negative *NSI* are divided in 2 using the median of negative *NSI* as the breakpoint. The most negative portfolio is assigned to sort Nº1 and the other to sort Nº2. The process is repeated for the positive *NSI* stocks, with the most positive portfolio being assigned to sort Nº5. All sorts are updated annually in June, except for the variables with the *–dev* suffix and Mom, which are updated monthly. The returns of each portfolio are updated monthly. In Panel A, the returns of the portfolios are calculated using simple averages, while in Panel B, the returns are value weighted. The tables also display the long-short portfolio returns, along with the CAPM alphas and alpha t-statistics that result from the following regression: $R_{it} = \alpha_i + \beta_i RMRF_t + e_{it}$, where R_{it} are the returns of variable *i*'s long-short portfolio for month *t*.

From the results, it is interesting to see that the long-short portfolio returns of the *E/P*, *E/Pdev*, *CEI*, *Mom* and *Vol* variables, all have significant CAPM alphas in both value weighted and equal weighted sorts. In the case of *E/P*, *E/Pdev* and *Mom*, the average returns are positively correlated with the variable, whereas with *CEI* and *Vol,* the correlation is negative.

The ROE variable outperforms the OP variable in Panel A and B, however its CAPM alpha fails to reach a confidence interval of 95% in both panels. *NSI* and *Beta* show a significant negative correlation in Panel A, but lose strength in the value weighted sorts in panel B. *B/M*, *B/Mdev*, *Inv* and *Size*, show no clear relation with average returns.

Panel C of Table 16 shows the maximised Sharpe ratios for combinations of the value weighted long-short portfolios. Of the value variables, *E/Pdev* seems to shine, having the largest weight allocation. *Vol* is preferred over *Beta*. The Sharpe test on the profitability variables reveals a tie, and the Sharpe test on the investment variables sets CEI as the favourite. In the last Sharpe test, all variables are thrown into the pool. Here, the most loaded variables from each category are *B/Mdev*, *ROE*, *Inv* and *Vol*. However, the loadings of *Inv* and *Vol* are relatively low. The *Mom* and *RMRF* variables are selected throughout, and the size variable is consistently not selected.

It's also interesting to point out, that none of the Sharpe tests in Table 16, not even the one that includes all variables, achieve an *SR* ratio as high as the ratio achieved by the final model proposal of section 4.9. (0.391). This is a testament to the importance of the portfolio construction technique. The 2 x 3, size-variable, sorts described by Fama and French (1993), clearly are better at capturing average returns than the simpler single sorts applied in Table 16.

Table 17 displays the results from spanning devil and non-devil value factors against the five-factor model, with and without the inclusion of the momentum factor. Panel A displays the behaviour of the *B/M* value factors. The intercepts for $HML_{B/M}$ are relatively unchanged with the addition of the WML factor. The $HML_{B/M}dev$ factor's intercept without the inclusion of WML is weaker than for its non-devil counterpart. However, when $HML_{B/M}dev$ is regressed against the other four factors and the WML factor, a huge negative slope with the *WML* factor boosts its intercept economically and statistically well above any of the *B/M* regressions. This completely supports the theory that *WML* and $HML_{B/M}dev$ work well together, put forward by Asness and Frazzini (2013).

Panel B of Table 17 displays the behaviour of the *E/P* value factors. Here the intercept of $HML_{E/P}$ is reduced with the inclusion of *WML*. Although the $HML_{E/P}dev$ intercept improves with the addition of the *WML* factor, its intercept is still significantly weaker than either of the $HML_{E/P}$ intercepts. This supports the idea that the devil value-momentum improvement is not shared with all value factor constructions, and definitely not with the *E/P* value factor.

Table 18 displays the spanning tests for an alternative three-factor model that uses a value factor constructed using *E/P*, instead of *B/M*. From the table, it is clear that the *RMRF* and $HML_{E/P}$ factors have large negative correlations. This is enough to give both factors large intercepts, both economically and statistically speaking. When compared to the results from the original three factor model's spanning tests in Table 5, it is clear that the new, simple, alternative model resurrects the market and value factors, giving them significant marginal information about average returns. The Size factor remains redundant.

Table 15: **Data sample composition details**

This table displays information about the data sample's composition. The information is split into three sections. Firstly, information about the data sample after the initial screening process, described in Chapter 2, is displayed. The *Average Total ME* and *Financials' ME* are each year's average total market capitalisation for all stocks and financial stocks respectively, measured in millions of euros. The *Largest Stock* is taken as the listing with the highest annual average market value for any given year. Secondly, information about the data samples after the specific filters applied in Chapters 3 and 4 is displayed. Here the *Nº Stocks* and *Nº Big Stocks* represents the number of stocks in July of each year, in total, and that fall into the big stock category, respectively. Big stocks are those that make up the top 90% of the market equity.

	Data sample after initial screening (Chapter 2)					Data sample Chapter 3			Data sample Chapter 4		
Year	Average Total ME	Financials' ME (mean)	Minimum Nº Stocks	Maximum Nº Stocks	Largest Stock	Nº Stocks	Nº Big Stocks	Average Total ME	Nº Stocks	Nº Big Stocks	Average Total ME
1990	54147	20449	84	96	TELEFONICA	82	43	50055	75	39	48630
1991	61148	22729	97	103	TELEFONICA	96	47	59123	95	47	58218
1992	61252	20557	103	111	TELEFONICA	100	40	59461	99	40	58453
1993	80078	28769	111	123	TELEFONICA	109	41	75166	104	40	73934
1994	96774	31474	121	123	TELEFONICA	113	47	92183	113	47	91750
1995	96039	32401	123	126	ENDESA	118	46	92924	117	46	92890
1996	119608	38518	125	126	TELEFONICA	122	42	118129	121	42	118095
1997	180789	62267	125	144	TELEFONICA	121	44	178285	121	44	178282
1998	268609	102723	143	162	TELEFONICA	138	46	263283	131	45	262612
1999	300841	108575	151	161	TELEFONICA	143	39	291775	130	38	290431
2000	381245	131010	151	156	TELEFONICA	147	34	359635	142	31	348481
2001	381035	131706	154	165	TELEFONICA	154	38	352111	148	36	343433
2002	345151	113122	156	161	TELEFONICA	156	43	319019	154	43	317176
2003	334783	102501	145	154	TELEFONICA	145	40	333121	143	39	332102
2004	412941	128977	140	145	TELEFONICA	135	37	406826	133	37	404405
2005	512436	170753	136	140	TELEFONICA	133	40	504819	131	39	500705
2006	623723	229403	135	144	BANCO SANTANDER	126	41	612855	124	41	610249
2007	747881	262070	142	149	TELEFONICA	136	44	724768	131	41	719333
2008	589340	192986	146	153	TELEFONICA	144	39	556050	137	37	545429
2009	479144	166660	144	147	TELEFONICA	142	35	470561	141	35	464398
2010	471930	164908	141	145	TELEFONICA	133	33	469658	131	32	469319
2011	463758	153015	141	147	TELEFONICA	134	29	458304	131	29	458083
2012	377809	128430	145	147	BANCO SANTANDER	136	28	373414	130	26	370765
2013	465510	166308	139	145	INDITEX	123	26	459313	123	26	451888
2014	583737	229611	138	145	BANCO SANTANDER	119	25	568389	118	25	568335
2015	629003	223674	143	155	INDITEX	125	27	604332	121	27	603041
2016	546714	160866	145	159	INDITEX	140	31	527451	131	31	525324

Table 16: **Single sorts on characteristic variables**

Panel A and B display the average monthly returns of portfolios formed using the quintile breakpoints of the corresponding characteristic variables, similar to those described by Hanauer and Lauterbach (2018). Portfolios are formed annually in June, except for devil (indicated by the suffix *–dev*) and M*om* variables which have their portfolios updated monthly. Definitions of the variables can be found in section 2.2. The breakpoints are calculated using big stocks only (big stocks make up the top 90% of the total ME). The tables also display the long-short portfolio returns, along with the CAPM alphas and alpha t-statistics that result from the following regression: $\boldsymbol{R_{it} = \alpha_i + \beta_i RMRF_t + e_{it}}$, where R_{it} are the returns of variable *i*'s long-short portfolio for month *t*. In panel A, the average monthly returns of each portfolio are calculated as the equally weighted returns of the stocks it contains. Panel B on the other hand, uses value weighted portfolio returns. Panel C displays the maximised Sharpe ratios resulting from using the different value weighted long-short portfolios described for panel A and B. The sum of all factor weights is restricted to 1 and each individual factor weight has a lower bound of 0. All calculations use monthly factor returns from July 1990 to November 2016 (317 months).

Panel A: Equally weighted single sort portfolio returns

Variable	1	2	3	4	5	5-1	*alpha*	*t-Statistic*
B/M	0.21	0.26	0.58	0.84	0.57	0.36	0.39	1.85
B/Mdev	0.39	0.43	0.47	0.48	0.65	0.26	0.27	1.20
E/P	0.17	0.35	0.63	0.72	1.08	0.91	1.03	5.23
E/Pdev	0.20	0.51	0.59	0.77	0.93	0.73	0.78	3.75
ROE	0.40	0.66	0.62	0.71	0.73	0.34	0.33	1.74
OP	0.53	0.35	0.46	0.91	0.87	0.34	0.14	0.63
Inv	0.62	0.68	0.50	0.55	0.41	-0.20	-0.22	-1.02
NSI	0.69	0.66	0.66	0.56	0.21	-0.48	-0.68	-2.14
CEI	0.95	0.89	0.49	0.35	0.25	-0.70	-0.88	-4.09
Mom	0.22	0.36	0.45	0.95	1.10	0.88	1.07	3.64
Size	0.49	0.59	0.52	0.33	0.68	0.19	0.06	0.26
Beta	0.61	0.66	0.55	0.36	0.45	-0.15	-0.61	-2.72
Vol	0.76	0.66	0.67	0.31	0.42	-0.34	-0.68	-2.97

Panel B: Value weighted single sort portfolio returns

Variable	1	2	3	4	5	5-1	*alpha*	*t-Statistic*
B/M	0.41	0.52	0.66	0.87	0.72	0.32	0.33	1.12
B/Mdev	0.40	0.68	0.54	0.64	0.95	0.55	0.51	1.68
E/P	0.06	0.56	0.59	0.79	0.94	0.88	0.94	3.49
E/Pdev	0.24	0.49	0.47	0.65	1.19	0.95	0.88	2.98
ROE	0.25	0.89	0.43	0.51	0.74	0.49	0.49	1.89
OP	0.24	0.42	0.31	0.93	0.76	0.52	0.35	1.60
Inv	0.64	0.74	0.66	0.47	0.47	-0.17	-0.26	-1.04
NSI	0.64	0.53	0.78	0.69	0.42	-0.22	-0.41	-1.18
CEI	0.83	0.76	0.64	0.34	0.33	-0.50	-0.70	-3.08
Mom	0.34	0.25	0.54	0.95	0.89	0.55	0.72	2.08
Size	0.38	0.58	0.49	0.36	0.65	0.27	0.11	0.45
Beta	0.47	1.01	0.60	0.60	0.34	-0.13	-0.51	-1.76
Vol	0.96	0.87	0.39	0.33	0.19	-0.77	-0.97	-3.33

Panel C: Sharpe ratios for value weighted long-short portfolios

	SR	*RMRF*	*Size*	*Mom*	*B/M*	*B/Mdev*	*E/P*	*E/Pdev*	*ROE*	*OP*	*Inv*	*NSI*	*CEI*	*Beta*	*Vol*
Value vars.	0.31	0.19	0.01	0.33	0.00	0.10	0.03	0.34							
Profitability vars.	0.19	0.28	0.00	0.25					0.21	0.26					
Investment vars.	0.23	0.35	0.03	0.13							0.13	0.00	0.36		
Risk Vars.	0.23	0.42	0.00	0.17										0.00	0.41
ALL	0.37	0.15	0.00	0.14	0.00	0.23	0.03	0.03	0.20	0.01	0.09	0.03	0.00	0.03	0.06

Table 17: **Spanning devil value factors for the five factor model with momentum**
This table shows the results from regressions with the monthly returns of different value variables as the dependant variables, and the remaining 4 factors from the original five-factor model as independent variables. Panel A shows the results from running the regressions with the *B/M* construction value factors. Analogously, panel B shows the results from running the regressions with the *E/P* construction value factors. Every regression is run twice, once with, and once without, the inclusion of the *WML* factor as an additional independent variable. The suffix *–dev* indicates a devil factor, devil factor and momentum sorts are updated monthly instead of annually. The coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

Panel A: B/M value factors		*Intercept*	*RMRF*	*$SMB_{B/M}$*	*RMW_{OP}*	*CMA_{Inv}*	*WML*	*R^2*
$HML_{B/M}$	Coef.	0.42	-0.01	0.01	-0.54	0.03		0.24
	t-Statistic	*2.46*	*-0.16*	*0.12*	*-10.01*	*0.64*		
$HML_{B/M}$	Coef.	0.40	0.00	0.01	-0.55	0.03	0.03	0.24
	t-Statistic	*2.33*	*0.06*	*0.13*	*-9.88*	*0.60*	*0.77*	
$HML_{B/M}dev$	Coef.	0.38	0.08	0.09	-0.52	0.04		0.22
	t-Statistic	*2.14*	*2.49*	*1.57*	*-9.32*	*0.77*		
$HML_{B/M}dev$	Coef.	0.57	0.01	0.08	-0.41	0.07	-0.31	0.38
	t-Statistic	*3.54*	*0.22*	*1.62*	*-7.83*	*1.33*	*-8.72*	
Panel B: E/P value factors		*Intercept*	*RMRF*	*$SMB_{B/M}$*	*RMW_{OP}*	*CMA_{Inv}*	*WML*	*R^2*
$HML_{E/P}$	Coef.	0.86	-0.15	-0.14	-0.32	-0.06		0.13
	t-Statistic	*4.62*	*-4.28*	*-2.41*	*-5.58*	*-1.10*		
$HML_{E/P}$	Coef.	0.78	-0.12	-0.14	-0.37	-0.07	0.13	0.16
	t-Statistic	*4.21*	*-3.27*	*-2.39*	*-6.29*	*-1.29*	*3.23*	
$HML_{E/P}dev$	Coef.	0.49	0.02	-0.05	-0.39	-0.07		0.10
	t-Statistic	*2.34*	*0.50*	*-0.80*	*-5.96*	*-1.14*		
$HML_{E/P}dev$	Coef.	0.63	-0.04	-0.06	-0.30	-0.06	-0.23	0.16
	t-Statistic	*3.11*	*-0.96*	*-0.91*	*-4.69*	*-0.90*	*-5.18*	

Table 18: **Spanning tests for alternative three-factor model with E/P value factor**
In this table, the results from spanning the monthly factor returns of a modified three-factor model, that uses a value factor constructed using *E/P* instead of the traditional *B/M*, are displayed. Each factor is regressed against the remaining 2 factors. *RMRF*, *$SMB_{B/M}$* and *$HML_{E/P}$* represent the market, size and value factors, respectively. The table details the coefficients of the intercepts and slopes for each factor, together with the t-statistic of each coefficient. Additionally, the coefficient of determination (R^2) has been adjusted for degrees of freedom. The regressions are calculated for the monthly factor returns from July 1990 to November 2016 (317 months).

		Intercept	*RMRF*	*$SMB_{B/M}$*	*$HML_{E/P}$*	*R^2*
RMRF	Coef.	0.76		-0.55	-0.34	0.14
	t-Statistic	*2.55*		*-6.39*	*-4.10*	
$SMB_{B/M}$	Coef.	0.06	-0.21		-0.13	0.11
	t-Statistic	*0.35*	*-6.39*		*-2.41*	
$HML_{E/P}$	Coef.	0.75	-0.15	-0.14		0.05
	t-Statistic	*3.90*	*-4.10*	*-2.41*		

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