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APPLICATION OF CORE ACCOUNTING CONCEPTS AND ITS IMPACT ON FINANCIAL DISCLOSURE AMONG EURONEXT 100 FIRMS

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ABSTRACT

This study investigates the value relevance of accounting fundamentals in the Euronext 100 index; more specifically, it investigates the question of whether or not applying an accounting fundamental strategy to select stocks results in significant, positive excess market buy-and-hold returns after one and two years of portfolio formation. The purpose of this investigation is to determine whether or not accounting fundamentals can provide relevant information that can clarify firm value. This work offers a collection of accounting basic signals that represent information that might impact security prices, although the information may not necessarily be reflected in a timely way. This is accomplished by merging valuation theory with accounting research. After accounting for factors such as profits, the book-to-market ratio, and company size, annual financial and market data from companies included in the Euronext 100 index between the years 2000 and 2014 show that the basic approach offers investors information that is value-relevant. The connection between the accounting basic signals and the buy-and-hold market future returns (on a one- and two-year time horizon) is one that is both large and favourable. In other words, portfolios that are constructed on the basis of high scores on the signals have achieved a 13 percent market excess yearly return on average between the years 2000 and 2014. This study not only addresses the real-world issue of mispriced stocks, but it also makes a valuable contribution to the limited accounting research that has been conducted on European capital markets by elaborating on the "post-earnings" drift phenomenon that has been observed in the Euronext 100 index.

KEYWORDS: European capital markets; Accounting fundamentals; Stock returns; Earnings; Euronext 100 index; Portfolio formation

INTRODUCTION

An examination of a company's economic and financial records (such as profit-and-loss statements and balance sheets), including quantitative and qualitative information, is what's included in a fundamental analysis (FA), which is used to assess the worth of the company. This strategy, which is often used to determine the true worth of publicly traded equities, may be executed by analysts, brokers, and astute investors (Navas et al. 2018).

In the context of such an analysis, we will identify below a set of financial variables (fundamentals) that have been asserted by analysts to be helpful in stock valuation, and we will investigate these assertions by estimating the incremental value-relevance of these variables in relation to earnings (e.g., Dechow et al. 2010; Lev and Thiagarajan 1993; Piotroski, 2000; 2005; 2012).

After conducting a more comprehensive study on the role that fundamentals play in the valuation of companies, we will now concentrate on the significance of growth and earnings response coefficient. We have a theory that investors utilise the basic signals revealed in this research to evaluate the "quality" of reported profits. This theory is supported by the findings of the study.

This research may enable investors utilise accounting data to design hedging portfolios in which they may recognise the possibility of anomalous returns, so increasing their anticipated utility. This would be made feasible thanks to the findings of this study. As a result, they may be able to strike the ideal balance between the projected rewards and the risks posed by the market and the nation. Two important scores are presented by Piotroski (2000) and Lev and Thiagarajan (1993). These scores are the F-score and the L-score. They should relate positively to one- and two- year future stock returns, such that higher scores increase the likelihood of future market excess returns. To address the possibility of alternative explanations for these scores, including the potential that they instead measure factors that relate consistently to future returns (Kim and Lee 2014; Piotrsoki 2005; Amor-Tapia and Tascón 2016), this study relies on econometric models to show how the scores add value relevance beyond extantfactors, such as the book-to-market ratio, firm size, and earnings per share (e.g., Dosamantes 2013; Ohlson 1995, 2009).

The findings suggest that the F-score provides value-relevant information for investors who form portfolios. A significant relationship arises between the score for one-and two-year stock returns and excess market returns. A sensitivity analysis shows that simple, equally weighted portfolios constructed with high F-score stocks yield consistently positive returns. The L-score instead is significant only two years in the future. These results are robust, as confirmed by combine ordinary least squares (OLS) approach with a fixed effect model.

Our findings also support the incremental value-relevance of most of the identified fundamentals. We also show that the returns are correlated with fundamentals and adding year dummies to replace macroeconomic variables considerably strengths the relation to future returns.

The next section presents the literature review of empirical studies. Section 3 presents the methods for constructing fundamental scores; Section 4 describes the research design. Following the results in Section 5 and 6, Section 7 concludes.

1. Literature review

In theory, the stock price of a company should represent both the supply and demand sides of the market, which are often viewed as investors' perspectives on the value of a corporation. If the stock market is effective in reflecting all of the information that is currently available, then there is no other method that can exceed it in determining the worth of a company. However, since the acquisition of information is expensive, there may be certain groups of individuals who value the company more than the market (e.g., Laih et al. 2015). According to Khan (1986), after the disclosure of information on the positions held by significant traders, a futures market demonstrates moderate levels of efficiency. Borges (2010) found that the results of European indexes were consistent with the weak efficiency market hypothesis (EMH) between January 1993 and December 2007. As a result, he came to the conclusion that daily and weekly returns are not normally distributed. This is due to the fact that daily and weekly returns are negatively skewed, are leptokurtic, and display conditional heteroscedasticity. Borges rejects the EMH when considering daily data from Portugal and Greece because of the first-order positive autocorrelation in the returns; however, he also provides empirical tests that show that these two countries approached Martingale behaviour after 2003. Despite the fact that the evidence is mixed across countries, Borges concludes that the EMH cannot be supported. The statistics from France and the United Kingdom also contradict EMH, but in these instances, it is because there is evidence of mean reversion in the weekly data.

Yet the EMH does not consistently hold in less developed markets, compared with more developed markets (e.g., Aggarwal and Gupta 2009; Richardson et al. 2010; Sloan 1996; Xie 2001). According to the findings of the vast majority of academics, a capital market is considered to be more economically efficient as its level of development increases. Because of this, it is probable that stock prices in established markets effectively include all of the information that is currently accessible. However, a lack of market efficiency may occur when investors do not take into account all of the information that is disclosed in financial statements. According to Abarbanell and Bushee (1997, 1998), even highly skilled analysts routinely underestimate accounting signals when forecasting earnings, which causes stock prices to frequently be temporarily underestimated.

FA is aimed at determining the value of firms' securities by a careful examination of key-drivers, such as earnings, risk, growth and competitive position (e.g., Lev and Thiagarjan, 1993). The FA relies on financial reports, which provide fundamental data for calculating financial ratios. Each ratio provides an evaluation of different aspects of a firm's financial performance. Penman (2009) defines FA as the analysis of information that focuses on valuation and Kothari (2001) considers its use a powerful means to identify mispriced stocks relative to their intrinsic value. Richardson et al. (2010) highlight the research overlap between FA and accounting anomalies and note that recent FA research tends to focus on forecasting earnings, stock returns, or the firm's cost of capital. In addition, Financial Analysis looks at the sales, profits, growth potential, assets, debt, management, products, and competitiveness of a company in order to determine whether or not it is worthy of investment (Thomsett, 1998). This evaluation takes place on a fundamental financial level. This method may also include evaluating market activity in a way that takes into account the supply and demand dynamics that lie underneath the surface (Beneish et al. 2015; Doyle et al. 2003; Piotroski 2000). The goal is to gain a better abilityto predict future security price movements, then apply those improved predictions to the design of equity portfolios (Edirisinghe and Zhang 2007).

In particular, considerable research in U.S. markets offers strong empirical evidence of the value relevance of FA for explaining future market returns (e.g., Hirshleifer et al., 2008; Lev and Thiagarajan 1993; Abarbanell and Bushee 1998; Piotroski 2000; Bagella et al. 2005; Lev et al. 2010; Richardson et al. 2010; Drake et al. 2011). Research in European markets is comparatively scarce, though some notable exceptions offer insights (see table 1). For instance, Bagella et al. (2005) hypothesise that the majority of investors use a fundamental strategy when selecting stocks. Because of this, they construct discounted cash flow models, which they then evaluate using a sample of high-tech stocks to determine whether or not strong and weak versions receive support from the data collected from stock markets in the United States and Europe. Their empirical findings indicate that basic price earning (P/E) ratios are responsible for a large portion of the observed cross-sectional variance in P/E ratios, but other factors only play a marginal or insignificant role in the explanation of this variation. Their findings also suggest that there are major variations between the markets in Europe and the United States, such that there is a much weaker association between observable and underlying P/E ratios in Europe.

Walkshausl (2015) applies the findings of a research conducted in the United States by Bali et al. (2010) to the stock markets of Europe. Similar to the American value growth returns, the European value growth returns are heavily reliant on the valuation signals that are included in a company's equity fundraising operations. The high returns seen by value companies are caused by value buyers, and the poor returns seen by growth companies are caused by growth issuers. There is no existence of a value premium between growth buyers and value issuers. It is not possible to account for the significant return gap that exists between value buyers and growth issuers by referring to common risk characteristics. Nevertheless, the authors reach the conclusion that the observed value increase returns may be attributable to mispricing by using the market expectation mistakes technique proposed by Piotroski and So (2012). The most important research pertaining to FA is included in Table 1.

[insert table 1]

2. Construction of the fundamental scores: F-Score and L-Score

The F-score is calculated using 9 basic signals that were outlined by Piotroski (2000), while the L-score is calculated using 12 fundamental signals that were suggested by Lev and Thiagarajan (1993). The F-score as a whole provides information on yearly improvements in a company's profitability, financial leverage, and inventory turnover. The presence of a high F-score indicates the possibility of abnormally strong returns and future development. Despite the fact that the F-score was first established for businesses that had a high book-to-market ratio (BMR), it is also resilient to varying degrees of financial health, future company financial performance, asset growth, and future market value (e.g., Fama and French 2006). It has shown beneficial in distinguishing "winners" from "losers" among groupings of companies with varying degrees of previous profitability (Piotroski 2005), as well as in developing markets such as India (Aggarwal and Gupta 2009) and Mexico (Aggarwal and Gupta 2009). (Dosamantes 2013). The F-score may vary anywhere from 0 (indicating a very weak signal) to 9 (high signal). That is to say, Piotroski (2000) takes into consideration nine discrete accounting basic indicators at time t, which are outlined in Appendix 1. The sum of factors F1 through F9 is equal to the F-score.

Because of limitations in the available data, the present investigation bases its L-score calculations on nine key indications for each company (see Appendix 2).

Table 1. Relevant FA literature review.

Paper	Theoretical Perspective	Dependent Variable(s)	Independent Variable(s)	Country/ Market	Main Findings
Abarbanell and Bush ee(1998)	Valuation theory: Fundamental analysis should yield abnormal returns, because earnings are realized in the future if contemporaneous stock price reactions to the signals are incomplete	Future abnormal return	Contemporaneous earnings change, and accounti ngfundamentals	U.S.	An average 12-month cumulative size-adjusted abnormal return of 13.2% is earned according to a fundamental strategy based on Lev and Thiajaran. A significant portion of the abnormal returns is generated around subsequent earnings announcements.
Aggarwal and Gupta (2009)	Follows Piotroski (2000)	Future returns	Accounting fundamentals, BM ratio, size, accruals	India	The Piotroski strategy can separate winners from losers for two-year returns after portfolio formation. It generates 98.6% annual return for portfolios with high F-scores and 31.3% annual

					return for portfolios with low F-scores.
Al-Shubiri (2011)	Valuation theory and fundamental analysis	Share prices	Accounting fundamentals	Jordan (banks)	Positive significant relationship between market price of stock and net asset value per share (NAV), EPS and dividend percentage.
Bagella et al. (2005)	Fundamental analysis	Stock price	P/E and CAPM	U.S. Europe	A unique model that joins P/E and CAPM in a single formula.
Dehuan an dJin (2008)	Valuation theory and fundamental analysis	Stock returns	Accounting fundamentals	China	ROE, EPS, profit margin, ROA, changes in sales, and total asset turnover.
Dosamantes (2013)	Valuation theory, fundamental analysis and market under-reaction of high BM ratio firms	Future returns, earnings response coefficient and future earnings growth	Accounting fundamentals, BM ratio, size, accruals	Mexico	Mean return earned by a high book-to-market investor can be increased through selection of financially strong high BM firms.

Drake et al. (2011)	Analysts tend to recommend stocks with high growth, high accruals, and low book-to- market ratios, despite these variables having a negative association with future returns	Stock returns	11 independent variables from accounting fundamentals	U.S.	Short interest is significantly associated in the expected direction with all 11 variables examined. There are abnormal returns from a zero- investment strategy that shorts firms with highly favorable analyst recommendations but high short interest and buys firms with highly unfavorable analyst recommendations but low short interest.
Elleuch and Trabelsi (2009)	Valuation theory:	Future returns	Accounting fundamentals	Tunisia	Fundamental accounting signals can be used to discriminate from an overall sample generated over a 15-month holding period, with negative returns of –11.6%, a winner portfolio generating positive return of 1.9%

					from a loser one generating negative return of –22,9% over thesame holding period.
Karathanassis and Philippas (1988)	Valuation theory: Fundamental analysis	Share prices	Accounting fundamentals	Greece (banks)	Dividends, retained earnings and size has showed a significant positive influence on share prices.
Lev and Thiagarajan (1993)	Valuation	Earnings response coefficient and future earnings growth	12 accounting signals, earnings per share	US.	the 12 fundamental signals proposed add approximately 70%, on average to the explanatory power of earnings with respect to excess returns.
Lev et al. (2010)	Valuation theory	Future cash flows and future earnings	Accounting fundamentals	U.S.	Accounting estimates beyond those in working capital items (excluding inventory) do not improve the prediction of cash flows. Estimates improve the prediction of the next year's earnings, though not of subsequent years' earnings.
Midani (1991)	Fundamental analysis	Share prices	Accounting fundamentals	Kuwait (industrial services & food)	In a sample of 19 Kuwaiti companies, EPS is adeterminant of share prices.

Nisa (2011)	Valuation	Share prices	Share prices	Pakistan	P/E Ratio, Net Profit after Tax, Inflation, DPS, GDP and Annual Turnover are determinants of stock price.
Piotroski (2000)	Valuation theory	Future returns	Accounting fundamentals: BM ratio, size, accruals	US	Mean return earned by a high book-to-market investor can be increased by at least 7.5% annually through selection of financially strong high BM firms.
Richardson et al. (2010)	Literature review on accounting anomalies and fundamental analysis	Future earnings and future stock returns	Accounting information	Mainly U.S.	Accounting anomaly information in forecasting future earnings and stock returns. Anomalous return patterns are commonly concentrated in a subset of small and less liquid firms with high risk.
Shen and Lin(2010)	Valuation	Stock returns	Accounting fundamentals: EPS and a vector of the corporate governance variables	Taiwan market	Corporate governance variables affects the relation between fundamental signals and stock returns. The study employs a endogenous switching model, which combines the response equation and governance index equation simultaneously.

Sunde and Sanderson (2009)	Fundamental analysis	Share prices	Accounting fundamentals	Zimbabwe	Corporate earnings, management, lawsuits, mergers and takeovers, market liquidity and stability, availability of substitutes, Government policy, macroeconomic fundamentals, investor sentiments, technical influences and analyst reports as factors influencing share prices.
Tsoukalas and Sil (1999)	Dividends	Future returns	Dividends ratios	United Kingdom (U.K.)	The dividend/price ratio predicts real stock returns for the UK stock market, and there was a strong relation between stock returns and dividendyields.
Walkshäusl (2015)	Valuation theory	Future ret urns, earnings response ,coefficient and future earnings growth	Accounting, fundamentals: BM ratio, size, accruals	Europe	As in the U.S., European value-growth returns strongly depend on the valuation signals contained in the firm's equity financing activities. The high returns of value firms are due to value purchasers; the low returns of growth firms are due to growthissuers.

Notes: US = United States; BM = book-to-market ratio; P/E = price-to-earnings ratio; CAPM = capital asset pricing model; DPS= Dividend per shares; DY = dividend yield; (EPS = earnings per share; GGP = growth in gross profit; A = total assets; ROA = Return on operating assets; ROE = return on equity; GM = gross margin; EBITDA = earnings before interest, taxes, depreciation, and amortization; NM = net margin; SGAE = selling, general and administrative expenses; GP = gross profit; DPS = dividends per share; GDP = gross domestic product.

Table 2. Sample description.

Panel A.			
Firms in the Euronext 100 by Stock Exchange			

Stock Exchange	**Number of firms listed in any period, 1990–2015**	**%**	**Average market capitalization as of 2014 (inEUR)**
Amsterdam	18	19%	31 052 906
Brussels	9	9%	21 562 959
Lisbon	5	5%	7 379 336
Paris	63	66%	29 354 532
Total/total/average	95	100%	27 675 550
Panel B.			
Firms in the Euronext 100 by industry			
Industry Classification	Number of firms listed in any period, 1990–2014	%	Average marke tcapitalization as of 2014 (inEUR)
Aerospace & Defense	4	4%	20 052 593
Automobiles & Parts	3	3%	4 977 051
Banks	6	6%	107 764 379
Beverages	4	4%	43 981 884
Chemicals	6	6%	12 435 688
Construction & Materials	3	3%	18 240 240
Electricity	3	3%	22 562 429
Electronic & Electrical Equipment	3	3%	17 526 019
Fixed Line Telecommunications	3	3%	11 643 943
Food & Drug Retailers	6	6%	10 937 394
Food Producers	1	1%	30 231 450
Gas, Water & Multi-utilities	3	3%	28 521 492
General Financial	4	4%	8 143 448
General Industrials	2	2%	28 110 825
General Retailers	1	1%	106 734 298
Health Care Equipment & Services	1	1%	15 980 741
Industrial Engineering	3	3%	6 491 717
Industrial Metals	2	2%	14 920 841
Industrial Transportation	3	3%	6 651 313
Life Insurance	4	4%	21 077 043
Media	5	5%	10 804 884
Mining	1	1%	5 099 906
Nonlife Insurance	2	2%	7 116 799
Oil & Gas Producers	3	3%	111 194 240
Oil Equipment, Services & Distribution	1	1%	3 496 385

Personal Goods	4	4%	72 674 339
Pharmaceuticals & Biotechnology	2	2%	9 316 301
Software & Computer Services	4	4%	11 227 598
Support Services	3	3%	9 005 573
Technology Hardware & Equipment	3	3%	27 110 749
Travel & Leisure	2	2%	9 916 094
Total/total/average	95	100%	27 675 550

Panel C.	
Listed firms in the Euronext 100 by year	
Year	Listed Firms
2000	71
2001	75
2002	75
2003	75
2004	76
2005	78
2006	81
2007	84
2008	85
2009	87
2010	92
2011	93
2012	95
2013	95
2014	95

Source: Euronext 100, European Classification System

Table 3. Descriptive statistics.

Variable	**Firm-year observations**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
R	1195	0,1443	0,1135	0,4989	-0,9287	5,1673
EPS	1224	2,3213	1,7940	6,4518	-122,10	50,4320
BMR	1159	0,7306	0,4146	1,2844	-0,3898	18,0290
Log A	1295	7,2445	7,1535	0,7449	4,7049	9,3163
F-Score	1330	5,3450	5	1,9448	0	9
L-Score	1330	3,9070	4	1,7714	0	8

Notes: R = annual returns; EPS = earnings per share; BMR = book-to-market ratio; Log A = log of total assets (size). F-score and L-score are as defined in Section 3.

Table 4. Correlation matrix.

	VIF	**R**	**EPS**	**BMR**	**Log A**	**F-Score**	**L-Score**
R		1					
EPS	1.062	0.051*	1				

BMR	1.171	-0.173***	-0.174***	1			
Log A	1.142	-0.069**	-0.023	0.243***	1		
F-Score	1.096	0.131***	0.077***	-0.193***	-0.097***	1	
L-Score	1.221	0.045	-0.092***	-0.245***	-0.266***	0.389***	1

Notes: R = annual returns; EPS = earnings per share; BMR = book-to-market ratio; Log A = log of total assets (size); VIF = variance inflation factor. F-score and L-score are as defined in Section 3. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 5. Value relevance of accounting signals.

	Model 1: Earnings	**Model 2:**	**Model 3: Value**	**Model 4: Value**	**Model 5: Value Relevance**	**Model 6: Value Relevance**
	response coefficient	Benchmark	Relevance of F-score	Relevance of L-score	of Fundamentals - Pooled Effects	of Fundamentals - Fixed Effects
Variable	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
EPS	0.003*	0.001	0.001	0.002	0.002	-0.001
t-statistic	1.76	0.76	0.75	0.88	0.78	-0.50
BMR		-0.041***	-0.036***	-0.040***	-0.036***	-0.069***
t-statistic		-4.18	-3.64	-4.03	-3.60	-4.77
Size		-0.088***	-0.091***	-0.087***	-0.090***	-0.219***
t-statistic		-3.59	-3.71	-3.55	-3.70	-3.20
F-score			0.029***		0.029***	0.031***
t-statistic			4.00		3.87	4.04
L-Score				0.008	0.002	0.018**
t-statistic				1.03	0.28	2.05
Intercept	0.747***	1.580***	1.481***	1.552***	1.475***	1.347***
t-statistic	13.08	7.13	6.69	6.95	6.62	2.75
N# obs.	1185	1135	1135	1135	1135	1135
Adjusted R^2	0.404	0.418	0.426	0.418	0.425	0.457

Notes: EPS = earnings per share; BMR = book-to-market ratio; Log A = log of total assets (size). F-score and L-score are as defined in Section 4.2. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 6: Buy-and-hold 12-month returns by F-score.

Panel A: Raw returns							
F-score	Mean	N	Min	Max	25%	Median	75%
0	11.77%	2	-59.51%	83.05%	-59.51%	11.77%	83.05%
1	-0.91%	9	-83.79%	194.13%	-64.63%	-12.80%	10.44%
2	-6.50%	28	-92.87%	123.00%	-48.10%	-15.12%	27.39%
3	2.00%	119	-90.27%	157.01%	-25.60%	-0.14%	21.87%
4	9.56%	199	-80.73%	231.54%	-19.72%	6.76%	27.34%
5	12.43%	233	-79.89%	207.09%	-19.13%	8.02%	32.65%
6	17.35%	245	-74.30%	272.02%	-6.34%	13.43%	38.84%
7	25.48%	204	-86.89%	516.73%	-5.30%	17.09%	39.84%
8	20.12%	119	-80.88%	268.64%	-0.16%	16.66%	33.28%
9	14.37%	37	-36.60%	63.91%	-1.69%	18.57%	29.11%
Low F-score [0+1+2]	-4.27%	39	-92.87%	194.13%	-50.42%	-13.64%	27.39%
High F-score[8+9]	18.76%	156	-80.88%	268.64%	-1.11%	17.73%	32.61%
High-Low	23.03%		11.98%	74.51%	49.31%	31.37%	5.21%
t-statistic	4.58***						
Total	14.43%	1195	-92.87%	516.73%	-13.74%	11.50%	33.42%
Panel B: Market excess firm returns							
0	-25.93%	2	-93.76%	41.91%	-93.76%	-25.93%	41.91%
1	11.00%	9	-54.68%	152.99%	-36.98%	7.03%	25.21%
2	-3.39%	28	-70.85%	83.21%	-26.19%	-1.28%	16.63%
3	4.96%	119	-51.81%	122.75%	-12.78%	1.01%	17.06%
4	9.51%	199	-70.78%	197.28%	-9.01%	5.89%	24.42%
5	11.54%	233	-65.11%	188.85%	-8.92%	8.32%	25.68%
6	13.33%	245	-98.76%	281.97%	-6.77%	11.07%	26.70%
7	20.42%	204	-65.31%	492.27%	-6.12%	11.55%	31.75%
8	15.12%	119	-66.96%	234.39%	-4.30%	9.84%	26.35%
9	9.69%	37	-41.44%	55.07%	-6.91%	8.34%	27.97%
Low F-score[0+1+2]	-1.22%	39	-93.76%	152.99%	-29.89%	0.99%	20.38%
High F-score [8+9]	13.83%	156	-66.96%	234.39%	-5.58%	9.47%	27.63%
High-Low	15.05%		26.80%	81.39%	24.32%	8.47%	7.25%
t-statistic	3.46***						
Total	12.31%	1195	-98.76%	492.27%	-8.49%	7.81%	25.93%

Notes: The 12-month returns begin three months after the end of the fiscal year, which is December for all firms.Geometric means of the returns are computed.

***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7: Buy-and-hold 24-month returns by F-score.

Panel A. Raw returns							
F-score	Mean	N	Min	Max	25%	Median	75%
0	-63.42%	2	-80.15%	-46.70%	-80.15%	-63.42%	-46.70%

1	-17.07%	8	-68.17%	18.31%	-46.57%	-6.32%	9.54%
2	-20.98%	25	-78.06%	30.84%	-36.91%	-25.40%	-0.75%
3	-2.65%	112	-72.99%	87.11%	-20.32%	-2.27%	12.26%
4	2.38%	185	-69.65%	143.82%	-15.34%	3.57%	16.57%
5	4.14%	213	-59.99%	140.51%	-14.45%	2.82%	21.63%
6	11.69%	223	-64.51%	186.61%	-5.71%	11.47%	26.38%
7	20.98%	191	-74.75%	312.58%	-0.95%	15.35%	34.24%
8	20.93%	106	-48.57%	105.91%	6.11%	21.29%	36.54%
9	23.32%	35	-27.86%	80.30%	0.68%	26.11%	41.22%
Low F-score [0+1+2]	-22.51%	35	-80.15%	30.84%	-43.93%	-25.40%	0.65%
High F-score [8+9]	21.52%	141	-48.57%	105.91%	5.34%	23.37%	39.33%
High-Low	44.04%		31.57%	75.07%	49.27%	48.77%	38.68%
t-statistic	10.44***						
Total	8.99%	1100	-80.15%	312.58%	-10.75%	8.30%	25.67%
Panel B. Market excess firm returns							
0	-52.95%	2	-71.04%	-34.86%	-71.04%	-52.95%	-34.86%
1	1.07%	8	-38.48%	30.71%	-25.80%	12.61%	21.36%
2	-8.98%	25	-48.65%	27.68%	-23.83%	-10.45%	6.03%
3	3.47%	112	-52.31%	79.12%	-9.62%	3.27%	12.43%
4	6.03%	185	-50.43%	152.92%	-8.19%	5.45%	16.91%
5	6.82%	213	-46.26%	124.12%	-5.47%	6.60%	17.13%
6	10.23%	223	-61.02%	170.19%	-4.77%	10.32%	23.26%
7	15.38%	191	-50.05%	296.19%	-2.22%	10.60%	25.14%
8	13.63%	106	-33.96%	85.02%	-0.19%	10.90%	25.36%
9	14.40%	35	-34.34%	55.79%	2.74%	12.03%	27.12%
Low F-score [0+1+2]	-9.19%	35	-71.04%	30.71%	-27.97%	-10.45%	14.31%
High F-score [8+9]	13.82%	141	-34.34%	85.02%	1.29%	11.18%	25.80%
High-Low	23.02%		36.71%	54.31%	29.26%	21.64%	11.49%
t-statistic	6.21***						
Total	8.91%	1100	-71.04%	296.19%	-5.45%	7.70%	20.47%

Notes: The 24-month returns begin three months after the end of the fiscal year, which isDecember for all firms. Annualized means of the returns are computed.

***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8. Buy-and-hold 12-month returns by L-score.

Panel A. Raw returns							
L-score	Mean	N	Min	Max	25%	Median	75%
0	-13.21%	22	-83.79%	60.89%	-30.02%	-12.51%	6.55%
1	13.05%	80	-90.27%	212.75%	-14.74%	11.49%	28.50%
2	16.19%	116	-92.87%	319.15%	-12.01%	13.98%	36.82%
3	14.64%	215	-67.69%	272.02%	-12.37%	8.79%	33.55%

4	13.68%	277	-80.73%	379.46%	-16.85%	11.47%	33.11%
5	13.15%	244	-86.89%	516.73%	-13.09%	8.14%	29.98%
6	18.18%	180	-78.01%	157.26%	-3.39%	20.97%	39.71%
7	17.96%	54	-64.59%	233.16%	-13.98%	3.16%	43.30%
8	32.12%	7	11.13%	52.01%	25.22%	33.08%	39.08%
Low L-score [0+1+2]	12.07%	218	-92.87%	319.15%	-16.01%	10.78%	31.06%
High L-score 8+9]	19.58%	61	-64.59%	233.16%	-11.59%	11.13%	42.90%
High-Low	7.51%		28.27%	-85.98%	4.42%	0.34%	11.85%
t-statistic	1.54						
Total	14.43%	1195	-92.87%	516.73%	-13.74%	11.50%	33.42%
Panel B. Market excess firm returns							
0	0.70%	22	-38.86%	42.49%	-14.99%	-1.04%	16.03%
1	10.91%	80	-70.85%	171.61%	-9.92%	6.54%	24.66%
2	10.78%	116	-93.76%	329.10%	-9.87%	4.20%	30.44%
3	12.15%	215	-54.68%	281.97%	-9.41%	7.81%	25.78%
4	12.41%	277	-98.76%	370.62%	-10.85%	7.21%	24.63%
5	11.23%	244	-66.96%	492.27%	-7.99%	6.64%	21.97%
6	14.48%	180	-46.26%	117.77%	-2.24%	13.77%	29.82%
7	19.53%	54	-50.00%	243.39%	-8.24%	7.55%	26.07%
8	17.24%	7	-8.06%	43.89%	2.40%	20.58%	29.74%
Low L-score[0+1+2]	9.81%	218	-93.76%	329.10%	-12.27%	4.62%	26.61%
High L-score [8+9]	19.26%	61	-50.00%	243.39%	-7.11%	8.14%	26.07%
High-Low	9.45%		43.76%	-85.71%	5.16%	3.53%	-0.54%
t-statistic	1.55						
Total	12.31%	1195	-98.76%	492.27%	-8.49%	7.81%	25.93%

Notes: The 12-month returns begin three months after the end of the fiscal year, which isDecember for all firms. Geometric means of the returns are computed.

***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9. Buy-and-hold 24-month returns by L-score.

Panel A. Raw returns							
L-score	Mean	N	Min	Max	25%	Median	75%
0	2.83%	22	62.19%	76.85%	-19.89%	9.01%	30.71%
1	3.39%	75	-72.99%	57.37%	-12.16%	2.05%	27.04%
2	5.73%	107	-80.15%	96.91%	-13.99%	6.28%	24.95%
3	9.07%	197	-61.90%	166.34%	-10.58%	7.94%	25.55%
4	6.44%	252	-69.65%	213.05%	-13.42%	5.24%	20.47%
5	9.77%	225	-74.75%	312.58%	-6.39%	7.24%	23.02%
6	15.31%	164	-64.51%	92.05%	-2.74%	16.89%	32.55%
7	12.62%	51	-50.40%	138.74%	-15.58%	9.18%	32.62%
8	27.49%	7	-0.36%	67.55%	6.88%	17.99%	46.74%
Low L-score [0+1+2]	4.56%	204	-80.15%	96.91%	-15.44%	5.36%	25.98%

High L-score [8+9]	14.42%	58	-50.40%	138.74%	-13.75%	10.32%	33.94%
High-Low	9.86%		29.75%	41.83%	1.69%	4.96%	7.95%
t-statistic	3.20***						
Total	8.99%	1195	-80.15%	312.58%	-10.75%	8.30%	25.67%
Panel B. Market excess firm returns							
0	7.63%	22	-32.50%	52.34%	-11.70%	10.27%	24.81%
1	4.63%	75	-48.65%	44.30%	-8.62%	7.09%	17.72%
2	4.29%	107	-71.04%	74.93%	-7.24%	5.24%	16.81%
3	8.94%	197	-61.02%	145.45%	-4.03%	8.10%	21.26%
4	7.29%	252	-59.91%	192.17%	-7.23%	4.70%	16.05%
5	9.14%	225	-47.17%	296.19%	-5.96%	6.59%	19.55%
6	14.22%	164	-52.11%	67.55%	2.76%	13.52%	26.57%
7	14.01%	51	-26.16%	120.10%	-2.13%	12.42%	22.35%
8	17.86%	7	1.51%	43.04%	5.24%	21.43%	24.29%
Low L-score [0+1+2]	4.78%	204	-71.04%	74.93%	-8.47%	6.41%	17.79%
High L-score [8+9]	14.47%	58	-26.16%	120.10%	0.53%	12.50%	23.67%
High-Low	9.69%		44.88%	45.17%	9.00%	6.09%	5.88%
t-statistic	3.42***						
Total	8.91%	1195	-71.04%	296.19%	-5.45%	7.70%	20.47%

Notes: The 12 and 24-month returns begin three months after the end of the fiscal year, whichis December for all firms. Annualized means of the returns are computed.

***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 10. New Scores: Buy-and-hold returns.

Panel A: New F-Score							
	Mean	N	Min	Max	25%	Median	75%
One-Year returns							
Raw Returns							
Mean all firms	14,43%	1195	-92,87%	516,73%	-13,74%	11,50%	33,42%
Low F-Score [0+1+2]	-4,27%	39	-92,87%	194,13%	-50,42%	-13,64%	27,39%
New High F-Score [7+8+9]	22,57%	360	-86,89%	516,73%	-3,94%	17,31%	35,75%
High - Low	26,84%		5,97%	322,60%	46,49%	30,96%	8,36%
T-statistics	4,58***						
Market-Adjusted							
Mean all firms	12,31%	1195	-98,76%	492,27%	-8,49%	7,81%	25,93%
Low F-Score [0+1+2]	-1,22%	39	-93,76%	152,99%	-29,89%	0,99%	20,38%
New High F-Score [7+8+9]	17,57%	360	-66,96%	492,27%	-6,02%	10,88%	29,53%
High - Low	18,79%		26,80%	339,28%	23,87%	9,89%	9,15%
T-statistics	3,46***						
Two-Year returns							

Raw Returns							
Mean all firms	8,99%	1100	-80,15%	312,58%	-10,75%	8,30%	25,67%
Low F-Score [0+1+2]	-22,51%	35	-80,15%	30,84%	-43,93%	-25,40%	0,65%
New High F-Score [7+8+9]	21,21%	332	-74,75%	312,58%	0,57%	18,74%	35,49%
High - Low	43,72%		5,40%	281,74%	44,50%	44,15%	34,84%
T-statistics	10,44***						
Market-Adjusted							
Mean all firms	8,91%	1100	-71,04%	296,19%	-5,45%	7,70%	20,47%
Low F-Score [0+1+2]	-9,19%	35	-71,04%	30,71%	-27,97%	-10,45%	14,31%
New High F-Score [7+8+9]	14,72%	332	-50,05%	296,19%	-0,21%	10,85%	25,46%
High - Low	23,91%		20,99%	265,47%	27,76%	21,31%	11,15%
T-statistics	6,21***						
Panel B: New L-Score							
	Mean	N	Min	Max	25%	Median	75%
Raw Returns							
Mean all firms	14,43%	1195	-92,87%	516,73%	-13,74%	11,50%	33,42%
Low L-Score [0+1+2]	12,07%	218	-92,87%	319,15%	-16,01%	10,78%	31,06%
New High L-Score [7+8+9]	18,54%	241	-78,01%	233,16%	-6,71%	19,41%	39,75%
High - Low	6,47%		14,85%	-85,98%	9,31%	8,63%	8,69%
T-statistics	1,54						
Market-Adjusted							
Mean all firms	12,31%	1195	-98,76%	492,27%	-8,49%	7,81%	25,93%
Low L-Score [0+1+2]	9,81%	218	-93,76%	329,10%	-12,27%	4,62%	26,61%
New High L-Score [7+8+9]	15,69%	241	-50,00%	243,39%	-5,49%	12,90%	29,71%
High - Low	5,88%		43,76%	-85,71%	6,78%	8,28%	3,10%
T-statistics	1,55						
Two-Year returns							
Raw Returns							
Mean all firms	8,99%	1195	-80,15%	312,58%	-10,75%	8,30%	25,67%
Low L-Score [0+1+2]	4,56%	204	-80,15%	96,91%	-15,44%	5,36%	25,98%
New High L-Score [7+8+9]	15,08%	222	-64,51%	138,74%	-4,10%	15,79%	33,75%
High - Low	10,52%		15,64%	41,83%	11,34%	10,44%	7,77%
T-statistics	3,20***						
Market-Adjusted							
Mean all firms	8,91%	1195	-71,04%	296,19%	-5,45%	7,70%	20,47%
Low L-Score [0+1+2]	4,78%	204	-71,04%	74,93%	-8,47%	6,41%	17,79%
New High L-Score [7+8+9]	14,29%	222	-52,11%	120,10%	2,30%	13,28%	25,59%
High - Low	9,51%		18,94%	45,17%	10,77%	6,87%	7,80%
T-statistics	3,42***						

Notes: The 24-month returns begin three months after the end of the fiscal year, which is

December for all firms. Annualized means of the returns are computed.
***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

3. Research design

3.1 Econometric models

The following regression is proposed as a benchmark model to test the earnings effect on firm returns, with and without the BMR and firm size as control variables (e.g., Campbell and Shiller 1988; Midani 1991; Ohlson 1995; Dosamontes 2013). In other words, At the end of March in the year after t, the financial statements for year t will be accessible. The dividends paid, stock splits, and reverse stock splits are all included into the calculation of the returns; however, taxes is not taken into account, and the results are shown in their unadjusted (gross) form. The following formula was used to calculate the yearly returns:

$$R_t = \frac{P_t}{P_{t-1}} - 1 \quad (2)$$

The earnings per share for the company I adjusted for the price of the shares at the beginning of the year, are represented by the variable EPS_{it}. The following regressions are used to assess the value significance of the basic signals “for example, Piotroski 2000; Nawazish 2008; Dosamantes 2013; Amor-Tapia and Tascón, 2016”:

$$R_{it} = \alpha + \beta_1 EPS_{it} + \beta_2 BMR_{it} + \beta_3 SIZE_{it} + \varepsilon_{it}. \quad (3)$$

$$R_{it} = \alpha + \beta_1 EPS_{it}\ \beta_2 BMR_{it} + \beta_3 SIZE_{it} + \beta_4 Fscore_{it} + \varepsilon_{it}. \quad (4)$$

$$R_{it} = \alpha + \beta_1 EPS_{it} + \beta_2 BMR_{it} + \beta_3 SIZE_{it} + \beta_4 Lscore_{it} + \varepsilon_{it}. \quad (5)$$

$$R_{it} = \alpha + \beta_1 EPS_{it} + \beta_2 BMR_{it} + \beta_3 SIZE_{it} + \beta_4 Fscore_{it} + \beta_5 Lscore_{it} + \varepsilon_{it}. \quad (6)$$

In these equations, "BMR" stands for "book-to-market ratio," and "SIZE" refers to "the size of the business as measured by the logarithm of the firm's total assets." BMR and SIZE both relate to the book value of the company's assets relative to its current market value. Both the F-score and the L-score were calculated in a manner that was in compliance with the instructions given in Section 3.

If the basic signals are value relevant, then the coefficient 4 in Equations 4 and 5 should be positive and statistically significant. This would indicate that the fundamental signals are value relevant. In Equation 6, in addition to the coefficients 4 and 5, the coefficients 1 and 2 should be statistically significant in the positive, and the coefficient 3 should be statistically significant in the negative.

For instance, according to Piotroski (2000), the primary mechanism behind momentum strategies (such as Chan et al. 1996), which can predict future stock returns, is an underreaction to historical information and financial events. This underreaction is the ultimate mechanism behind the success of the F-score, which Piotroski (2000) identifies as the ultimate mechanism behind the success of the F-score. According to our findings, BMR represents a ratio of the momentum. As a result, it is vital to show that a technique for analysing financial statements can detect financial trends, above and beyond the impacts of other, previously proven effects. This is because it is important to demonstrate that the approach can.

In the second step of this process, firm-year observations are classified according to F-score and L-score to on-year and two-years raw returns, as well as market-excess firm returns. The purpose of this step is to investigate the possibility of using fundamental signals to understand future returns.

Data collection and the Euronext 100 stock market

Prices that were adjusted for the market and financial data were retrieved from the Datastream database on an annual basis for all active companies trading on the Euronext 100 stock exchange between the years of 2000 and 2014. The calculation of market returns is informed by daily data as well as yearly data pertaining to the market index. Sample descriptions may be found in Panel A of Table 2, organised according to the stock exchange (Panel A), industry (Panel B), and year (Panel C). Sixty-six percent of the companies listed on the Euronext 100 are French companies; these companies are evenly spread across all sectors, and the number of companies listed has increased steadily from 2000 (71 businesses) to 2014 (100 firms) (95 firms). [insert table 2]

The blue chip index maintained by Euronext N.V. is called the Euronext 100, and it includes around eighty percent of the top corporations that trade on the platform. It differs from the majority of other indexes in that it includes firms from a number of nations located within Europe. More specifically, it covers the biggest and most liquid equities that are listed on the stock markets of Amsterdam, Brussels, Lisbon, and Paris. Each stock must trade more than twenty percent of its total issued shares in order to be considered active.

The descriptive statistics for the variables are in Table 3, showing that the mean annual return is 14.13%; the average annual returns are small relative to the standard deviation, which indicates high volatility in the returns in the period under analysis. The average EPS is 2.3213; the BMR is below the unit, indicating that on average, the stocks listed in Euronext 100 were overvalued during the period of analysis; the average firm size is 7.2445; and the average F- and L-scores are 5.3450 and 3.9070, respectively. [insert table 3]

Table 4 reports the correlation matrix and collinearity statistic. The F-score is significantly correlated with all the model variables: returns, EPS, BMR, size (log A), and the L-score. The correlations among the independent variables do not produce a multicollinearity problem though, because the variance inflation factor fluctuates between 1.1 to 1.2 (Gujarati 2004). Regarding the variable returns, BMR, and size show negative correlations. The correlation of EPS is marginal, at the 10% level, and that with the L- score is not even statistically significant; for F-score is statistically significant at 1% level.The negative correlation of BMR differs from findings in capital market literature (e.g., Piotroski 2000). For size, the negative correlation could arise because small firms often provide higher expected returns as a liquidity premium (e.g., Fama and French 1992, 1995). [insert table 4] Results

5.1. Explanatory power of accounting signals: F and L-scores

Table 5 reports the OLS results for the five proposed models from Equations 1, 3 - 5, which were estimated using time dummy variables, to control for time effects (e.g., macro-economic conditions) and industry dummies. [insert table 5]

In Model 1, the EPS variable provides relevance to investors. It is statistically significant at the 10% level. Adding the BMR and size variables in Model 2 causes EPS to lose its statistical significance though. The BMR and size variables are statistically significant at the 1% level; they relate negatively to 12-month firm returns in the period three months after the end of the fiscal year. The predictions offered previously indicated that size should relate negatively with returns, but BMR was not expected to show this link. One possible explanation is, this variable works better for companies with low book value (BV), such as small companies, so BMR becomes something like a size ratio too. A similar result was reported by Dosamantes (2013).

Models 3 - 5 show evidence of the value relevance of the F- and L-scores. Beyond the value relevance of EPS, BMR, and firm size, the F-score is statistically significant atthe 1% level in

Models 3 and 5; the L-score is not statically significant in either Model 4or Model 5. Model 5 affirms the additional explanatory power of the F-score after controlling for all other variables. The coefficient of the F-score indicates that a one-unit increase in this metric is associated with an increase in the subsequent annual return of about 2.9%, keeping the size, BMR, EPS, and L-score constant. For the size variable, a one-unit decrease is associated with an increase in subsequent annual returns of about 9.0%. Thus, investors prefer to buy shares from smaller firms, likely because small companies generate higher returns, as a premium related to their low liquidity. In theory,the returns of so-called small caps outperform those of larger companies (e.g., Piotroski 2000; Dosamantes 2013; Holloway et al. 2013).

Because OLS cannot control for individual heterogeneity (e.g., Livbevan and Danbolt 2004), the robustness checks estimates Model 6 using panel data linear estimators, that is, random effects and fixed effects model. The random effects model assumes that individual heterogeneity is not correlated with the independent variables. A Hausman (1978) test considers the null hypothesis that there is no correlation between individual heterogeneity and the independent variables. By rejecting the null hypothesis, this study reveals that individual heterogeneity is correlated with the independent variables; therefore, the fixed effects method can estimate Model 6. After controlling for individual heterogeneity, the results of Model 6 compared with Model 5 remain the same, though the L-score variable becomes positive and statistically significant at the 5% level.However, the impact is lower than that of the F-score: A one-unit increase is associated with an increase in the subsequent annual return of only about 1.8%, whereas the impactof the F-score invokes a 3.1% increase.

5.2 Buy-and-hold returns for an investment strategy based on F- and L-scores

This is done for each year. Calculations are made to determine the one- and two-year subsequent raw returns as well as the market excess firm returns for each of the nine F-score groupings. The returns over a longer time span (2000–2014) are constantly compounded. The returns for the last year are computed using the period beginning in April of year t and ending in March of year t + 1, and each score is based on year t. (Table 6). The 24-month returns begin in April at time t+1 and end in March at time t+2, with the relevant score corresponding to year t. (Table 7). In order to anticipate future returns, portfolios of similar weight have been used. [insert table 6]

These results were found in the returns over a period of 12 months after the establishment of the portfolio. The value of 25.48 percent assigned to the F7 score is the greatest possible

outcome. Table 6 — panel A shows that the difference in the average return between the portfolios of companies with high F-scores and those with low F-scores is positive and statistically significant at the 1 percent level, with a value of 23.03 percent. This finding provides further evidence that the F-score has a strong capacity for explanatory power. The average of the market excess firm returns over a period of one year for the portfolio with a high F-score is 13.83 percent (Table 6 – panel B), and the average of the returns over a period of two years yields a similar value of 13.82 percent (Table 7 – panel B). Therefore, it would seem that the FA method is effective in predicting returns one and two years in the future.
[insert table 7]

According to Dosamantes (2013), a value of 21 percent was found for the Mexican market between the years 1991 and 2011. Kim and Lee (2014) found that the average raw return for one year over the period 1975–2007 was roughly 31%. Amor-Tapia and Tascón (2016) found that when the F-score was applied to a few different European companies, the results provided a value that was larger than 29 percent during the time period between 1989 and 2011. Based on these data, it seems that the F-score is effective for companies that were listed in the Euronext 100 over the period of 2000–2014, but not as well as in previous research. This outcome might be attributed to the global financial crisis that occurred between 2008 and 2009 as well as the sovereign debt difficulties in Europe (e.g., Oberholzer and Venter 2015; Erdogdu 2016; Kim et al. 2016). Since there is a positive and substantial connection between the F-score and returns, as shown by the Student t-value, it is possible to utilise the F-score to differentiate between growth stocks and value companies, in comparison to equities that have minimal ability to deliver positive anomalous returns.

Tables 8 and 9 provide the findings that were obtained by doing parallel studies on the L-score. [insert table 8]

As was to be anticipated, the raw returns and market excess firm returns increased with an implied trend, if not regularity, as the L-score increased after portfolio construction for both 12-month and 24-month returns that were observed after creation of the portfolio. In general, the L-score predicts the level of future profits more accurately than any other factor. Although it is not statistically significant, the difference in the average return between the portfolios of high and low L-score businesses is 7.51 percent (9.45 percent) for buy-and-hold 12-month (24-month) returns (Table 8 – panel A and B). When the analysis is conducted using the average of returns over the course of two years, the average return difference between portfolios with high and low L-scores is 9.86 percent (9.69 percent) for raw returns (market excess returns). This difference is statistically significant at the 1 percent level (Table 9).[insert table 9]

It is reasonable to anticipate a premium for high-average portfolios; hence, a simulated investing strategy might choose portfolios with high F-score values (i.e., 7, 8, or 9). The outcomes of a buy-and-hold investment strategy are shown in panel A of Table 10 for both 12-month and 24-month returns. The new high F-score indicates an improvement; the excess market returns for a buy-and-hold strategy for 12-month returns increases from 13.83 percent to 17.57 percent. The rise in the returns over the last 24 months went from 13.82 percent to 14.72 percent, and both of these increases are statistically significant at the 1 percent level. Based on these findings, it seems that an FA technique is more effective for projecting returns one year in advance when dealing with high average portfolios. [insert table 10]

In addition, the duplicated analyses for portfolios with high L-scores (i.e., values of 6, 7, and 8) for buy-and-hold returns over 12 months and 24 months were carried out (refer to table 10 – panel B). When compared to the average yearly returns for buy-and-hold strategies of 19.58 percent and 14.42 percent, respectively, the buy-and-hold returns for the timeframe are around 18.54 percent for one year and 15.08 percent for two years. When compared to the returns obtained using the market index for the same time, which are 15.69 percent for one year and 14.29 percent for two years, respectively, the previous returns were 19.26 percent and 14.47 percent. In terms of the L-score, only the buy-and-hold strategy with a two-year time horizon has statistical significance at the 1 percent level.

Based on these results, academics should investigate more complex investing methods based on FA, including an application of portfolio theory, with the goal of reducing risk and increasing projected returns. When taking into consideration the fact that the Euronext 100 index had high levels of volatility over the time period of the research, it is probable that it is feasible to forecast financial crises and recessions.

7. CONCLUSIONS

This article presents an overview of FA and emphasises the significance of the concept for investors who are planning forward for a period of at least one year. In order to discover organisations that have strong financial performance and the ability to confront the future, investors are required to employ both qualitative and quantitative information in accordance with this strategy. Putting up this kind of work is essential to successful investment. This study aims to expand and connect various different lines of enquiry that have been taking place in the field of capital markets accounting research. The domains of value-relevant fundamentals, conditioned returns-fundamentals analysis, and earnings response coefficient are the primary focuses of our attention.

This would be the case if the markets were efficient. The present research investigates the explanatory power of accounting signals for forecasting yearly returns in a different scenario by employing companies that are listed in the Euronext 100 index as its subjects. The findings indicate that the F-score, in addition to the value relevance of EPS, BMR, and firm size, is statistically significant at the 1% level. According to the F-score coefficient, an increase of one unit in this parameter is related with an increase in the following year returns of around 2.9 percent to –3.1 percent across all models. A one-unit rise in this measure is connected with future yearly returns that increase by just around 1.8 percent, indicating that the influence of the L-score is substantially smaller and only statistically significant in one of the suggested models (Model 6).

Investors should be rewarded with one and two year buy-and-hold with abnormal returns in portfolios that have high scores if they use an investing strategy that develops portfolios using the F- and L-scores. When investors choose companies that have high scores (i.e., an F-score of 8 or 9), they may anticipate to get raw returns of roughly 19 percent. In addition, an investment strategy that buys predicted winners and sells short projected losers (i.e., F-scores 0–2) might have provided an annual return of 23% between the years 2000 and 2014, according to the F-scores (see also Piotroski 2000). Increased raw returns and market excess firm returns would be produced by portfolios that are built on high L-scores for 12-month and 24-month returns. In general, a higher L-score is indicative of better future returns; however, the findings of this research demonstrate statistically significant outcomes only for a strategy that is based on the average of returns over a period of two years. That is to say, a basic approach is effective for projecting returns one year into the future. On the other hand, the L-score is only statistically significant for a buy-and-hold strategy that spans 24 months, with lower values for the projected returns.

FA appears to be more suitable for informing long-term investment strategies than a traditional market index investment strategy because it is based on a multitude of accounting reports that cover the most important financial aspects of a company. This is because FA covers the most important financial aspects of a company. Piotroski (2000), Dosamantes (2013), and Amor-Tapia and Táscon (2017) all provide their support to this conclusion as well (2016). However, a further contribution has also been made to the FA and capital market literature by the present research. First, the results about the value relevance of accounting fundamentals give insights into the levels of market efficiency in Europe. These levels may be determined based on the findings. Second, the findings of using a fundamental technique to construct portfolios have consequences for investors that may be put into practise. The semi-strong version of the EMH, in which security prices reflect all information that is publicly accessible, does not get confirmed by these findings in terms of the kind of market efficiency (Fama 1970). It is necessary to do more study in order to determine whether or not the value relevance of accounting basics is an essential indicator of market inefficiency. Particularly, the good fundamentals of certain companies are not represented in the value of their securities by such companies. These findings could provide an explanation for why the semi-strong version of the EMH has not yet been verified. The data used in this research are yearly; however, it is possible that utilising quarterly data might provide findings that are more accurate and could possibly represent the "post-earnings drift" impact. When an investor has a diverse portfolio, regression models also have a good chance of being successful (Piotroski 2000; Kim and Lee 2014).

In addition, this research made sure that all of the data were ready to be used at the time that the "back test" was carried out. As a result, there were no survivorship issues, and the findings were based on information that would be accessible to all investors before they made decisions regarding their investments. However, there are certain restrictions that come with this research. Aside from accounting for the impacts of time, the econometric models do not take into account significant macroeconomic factors. These variables include but are not limited to: inflation rates; economic depressions; regulatory changes in the market. Additional out-of-sample testing may help enhance inferences about the utility of a certain accounting trait, which may be used to estimate either future stock returns or future profits. This variation in key institutional elements or other characteristics should be evaluated, whether it occurs over time or across different organisations. Any change in the results that were seen might also aid reinforce the conclusions that were drawn from the data. Tests evaluating the prediction power of a particular trait might potentially be carried out in a way that is considered more "fair."

REFERENCES

1. Abarbanell, J., & Bushee, B. (1997). Fundamental analysis, future earnings, and stock prices. *Journal ofAccounting Research, 35 (1),* pp. 1-24.
2. Abarbanell, J., & Bushee, B. (1998). Abnormal returns to a fundamental analysis strategy. *Accounting Review,73 (1),* pp. 19-45.
3. Aggarwal, N., & Gupta, M. (2009). Do high book-to-market stocks offer returns to fundamental analysis inIndia? *Decision (0304-0941), 36 (2),* pp. 155-175.
4. Amor-Tapia, B., & Tascón, M. (2016). Separating Winners from Losers: Composite Indicators Based on Fundamentals in the European Context. *Journal of Economics and Finance, 66 (1),* pp. 70-94.
5. Bagella, M., Becchetti, L., & Adriani, F. (2005). Observed and ‘‘fundamental’’ price earnings ratios: A comparative analysis of high-tech stock evaluation in the US and in Europe. *Journal of InternationalMoney and Finance 24,* pp. 549-581.
6. Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance61*, pp. 1645-1680.
7. Bali, T., Demirtas, K., & Hovakimian, A. (2010). Corporate financing activities and contrarian investment. *Review of Finance 14*, pp. 543-584.
8. Beneish, M., Lee, C., & Nichols, D. (2015). In short supply: Short-sellers and stock returns. *Journal ofAccounting and Economics*, pp. 33-57.
9. Bentes, S., & Navas, R. (2013). The Fundamental Analysis: An Overview. *International Journal of LatestTrends in Finance and Economic Sciences 3*, pp. 389-393.
10. Bevan, A., & Danbolt, J. (2004). Testing for inconsistencies in estimating of UK capital determinants. *AppliesFinancial Economics, 14,* pp. 55-66.
11. Borges, M. (2010). Efficient market hypothesis in European stock markets. *The European Journal of Finance,*pp. 711-726.
12. Campbell, J., & Shiller, R. (1988). The dividend-price ratio and expectations of future dividends and discountfactors. *Review of Financial Studies, 1(3),* pp. 195–228.
13. Chan, L., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *Journal of Finance 51,* pp. 1681–1713. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and
14. Overreactions. *Journal of Finance 53,* pp. 1839-1885.
15. Debondt, W., & Thaler, R. (1995). Financial Decision-Making in Markets and Firms: A Behavioral Perspective. Em V. M. R.A. Jarrow, *Handbooks in Operations Research & Management Science, Vol. 9: Finance.*

16. Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics, 50*, pp. 344-401.
17. Dosamantes, C. (2013). The Relevance of Using Accounting Fundamentals in the Mexican Stock Market.
18. *Journal of Economics, Finance and Administrative Science, 18*, pp. 2-10.
19. Doyle, J., Lundholm, R., & Soliman, M. (2003). The predictive value of expenses excluded from 'Pro Forma' earnings. *Review of Accounting Studies 8*, pp. 145-174.
20. Drake, M., Rees, L., & Swanson, E. (2011). Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. *The Accounting Review, 86 (1)*, pp. 101-130.
21. Edirisinghe, N., & Zhang, X. (2007). Generalized DEA model of fundamental analysis and its application toportfolio optimization. *Journal of Banking & Finance 31*, pp. 3311-3335.
22. Erdogdu, E. (2016). Asymmetric volatility in European day-ahead power markets: A comparativemicroeconomic analysis. *Energy Economics 56*, pp. 398-409.
23. Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance, 25(2),*pp. 383-417.
24. Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. *Journal ofFinance, 50 (1)*, pp. 131-155.
25. Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of FinancialEconomics 82*, pp. 491-518.
26. Fama, E., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance, 47(2)*, pp. 427-465.
27. Gujarati, D. N. (2004). *Basic Econometrics.* The McGraw−Hill.
28. Hausman, J. (1978). Specification Tests in Econometrics. *Econometrica, 46 (6)*, pp. 1251–1271.
29. Hirshleifer, D., Myers, J., Myers, L., & Teoh, S. (2008). Do individual investors drive post-earningsannouncement drift? *Accounting Review*, pp. 1521-1550.
30. Holloway, P., Rochman, R., & Laes, M. (2013). Factors Influencing Brazilian Value Investing Portfolios. *Journal of Economics, Finance and Administrative Science*, pp. 18-22.
31. Khan, A. (1986). Conformity with Large Speculators: A Test of Efficiency in the Grain Futures Market. *AtlanticEconomic Journal 14*, pp. 51-55.

32. Kim, J.-B., Li, L., Lu, L., & Yu, Y. (2016). Financial statement comparability and expected crash risk. *Journalof Accounting and Economics 61(2-3)*, pp. 294-312.
33. Kim, S., & Lee, C. (2014). Implementability of Trading Strategies Based on Accounting Information: Piotroski (2000) Revisited. *European Accounting Review, 23 (4)*, pp. 553–558.
34. Kothari, S. (2001). Capital market research in accounting. *Journal of Accounting and Economics, 31 (1)*, pp.105-231.
35. Laih, Y.-W., Lai, H.-N., & Li, C.-A. (2015). Analyst valuation and corporate value discovery. *InternationalReview of Economics and Finance*, pp. 235–248.
36. Lev, B., & Thiagarajan, S. (1993). Fundamental information analysis. *Journal of Accounting Research, 31 (2)*,pp. 190-215.
37. Lev, B., Li, S., & Sougiannis, T. (2010). The usefulness of accounting estimates for predicting cash flows andearnings. *Review of Accounting Studies, 15 (4)*, pp. 779-807.
38. Li, X., Bao, J., & Hendler, J. (2011). Fundamental Analysis Powered by Semantic Web. *IEEE Symposium on Computational Intelligence for Financial Engineering and Economics*, pp. 1-8.
39. Midani, A. (1991). Determinants of Kuwaiti Stock Prices: An Empirical Investigation of Industrial Services, and Food Company Shares. *Journal of Administrative Sciences and Economics, 98*.
40. Nagel, S. (2005). Short sales, institutional investors, and the cross section of stock returns. *Journal of FinancialEconomics 78*, pp. 277-309.
41. Nawazish, E. (2008). Size and Value Premium in Karachi Stock Exchange. *Cahier DRM – Finance (6)*, pp. 1-39. Oberholzer, N., & Venter, P. (2015). Univariate GARCH models applied to the JSE/FTSE stock indices.
42. *Procedia Economics and Finance 24*, pp. 491-500.
43. Ohlson, J. (1995). Earnings, book-values, and dividends in equity valuation. *Contemporary Accounting Research11*, pp. 661-687.
44. Ohlson, J. (2009). Accounting data and value: the basic results. *Contemporary Accounting Research 26*, pp. 231-259.
45. Penman, S. (2009). In: Financial Statement Analysis and Security Valuation fourth ed McGraw-Hill.
46. Piotroski, J. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research, 38 (3)*, pp. 1-41.

47. Piotroski, J. (2005). Discussion of “Separating winners from losers among low book-to-market stocks usingfinancial statement analysis”. *Review of Accounting Studies, 10 (2/3)*, pp. 171-184.
48. Piotroski, J., & So, E. (2012). Identifying expectation errors in value/glamour strategies: a fundamental analysisapproach. *Review of Financial Studies 25,* pp. 2841-2875.
49. Richardson, S., Tuna, I., & Wysocki, P. (2010). Accounting anomalies and fundamental analysis: A review ofrecent research advances. *Journal of Accounting & Economics, 50 (2-3)*, pp. 410-454.
50. Silva, M. (2009). *Investir e Ganhar mais.* Sintra: Keditora.
51. Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *TheAccounting Review, 71 (3)*, pp. 289-315.
52. Swanson, E., Rees, L., & Juárez-Valdés, L. (2003). The contribution of fundamental analysis after a currencydevaluation. *The Accounting Review, 78 (3)*, pp. 875-902.
53. Tehrani, R., Raei, R., Faizabad, A., & Rahmati, M. (2008). Separating Winners from Losers among Iranian Investment Companies during the Years 2004 to 2005. *International Journal of Economic Perspectives,2 (1)*, pp. 12-23.
54. Thomsett, M. (1998). *Mastering Fundamental Analysis.* USA: Dearborn Financial Publishing, Inc. Walkshäusl, C. (2015). Equity financing activities and European value-growth returns. *Journal of Banking & Finance 57,* pp. 27-40.
55. Xie, H. (2001). The mispricing of abnormal accruals. *The Accounting Review, 76 (3)*, pp. 357-373.
56. Xue, Y., & Zhang, M. (2011). Fundamental Analysis, Institutional Investment, and Limits to Arbitrage. *Journalof Business Finance & Accounting*, pp. 1156-1183.
57. Zhang, X. (2006). Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research23*, pp. 565-590.