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The relevance of using accounting fundamentals in the Euronext 100 index

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Abstract

Purpose – The purpose of this research is to investigate whether using an accounting fundamental strategy can provide valuable information about the value of a business and generate positive excess buy-and-hold returns on stocks in the Euronext 100 index.

Theoretical framework – The theoretical framework of the study is based on the combination of valuation theory and accounting research. We rely on fundamental analysis as a stock valuation method, which involves looking at both quantitative and qualitative information in a company's economic and financial records.

Design/methodology/approach – We examine the relevance of growth and earnings response coefficients, as well as Piotroski's F-scores and Lev and Thiagarajan's L-scores in predicting future stock returns. The analysis covers the years 2000 to 2020.

Findings – The study finds that accounting fundamental signals provide value-relevant information to investors and have a significant and positive relationship with future buy-and-hold market returns, resulting in high-scoring portfolios achieving significant average annual market excess returns.

Practical & social implications of research – The results of the study have practical implications for investors who use fundamental analysis as an investment strategy. The results indicate that accounting fundamentals provide value-relevant information to investors and can lead to positive excess buy-and-hold returns.

Originality/value – The study contributes to the understanding of the role of fundamentals in firm valuation and provides fresh insights into binary models and fundamental analysis applied to European markets. In addition, the study tests the robustness of fundamental strategies using fixed effects regression analysis.

Keywords: European capital markets, accounting fundamentals, stock returns, portfolio formation, Euronext 100 index.

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1 Introduction

The use of fundamental analysis (FA) has been shown to be successful in developed markets (e.g., Richardson et al., 2010). However, growing evidence of temporary market mispricing (also known as earnings announcement drift or accounting anomalies; Abarbanell & Bushee, 1998; Piotroski, 2000, 2005) in such markets suggests the need to examine whether the application of accounting fundamental signals can add relevant value to investors in an important European market, namely the Euronext 100 index. Accordingly, this study seeks to demonstrate the potential use of accounting fundamental signals for investors in this developed market (Hanauer et al., 2022).

According to valuation theory, accounting earnings are converted over time into free cash flows that flow to investors, creditors and the firm. These are the main components for estimating the intrinsic value of the firm as reflected in the stock price. In accounting FA, observers examine detailed accounting data from financial statements to improve their understanding of how efficiently and effectively a firm can generate earnings over time, as well as its potential to grow and convert the earnings into free cash flows (Bartram & Grinblatt, 2021; Bradbury et al., 2021; Dorantes Dosamantes, 2013).

In general, FA entails examining companies' economic and financial reports (e.g., profit & loss accounts, balance sheets), including both quantitative and qualitative information, to determine their value. Although typically used to evaluate the true value of traded stocks, this method can be carried out by analysts, brokers and savvy investors (Bentes & Navas, 2013).

FA aims to forecast the company's future performance, taking into account that the market price of an asset tends to converge towards its intrinsic value. When the intrinsic value exceeds the market value, it signals a potential buying opportunity, whereas when the market value exceeds the intrinsic value, investors should consider selling.

Recent evidence highlights the effectiveness of Piotroski's (2000) F-score as one of the most efficient quality criteria for constructing combined value-quality equity portfolios. Various studies, such as those of Piotroski and So (2012) and Walkshäusl (2020), have confirmed its widespread use in the investment industry.

However, some scholars have raised concerns about the real-world implementability of trading strategies based on the F-score. Kim and Lee (2014) argue that the reported abnormal returns in Piotroski's original study suffer from a look-ahead bias, leading to overstated results. Moreover, the efficacy of combined value and F-score criteria seems to be more pronounced in small-cap stock universes, as demonstrated by Piotroski (2000). The potential unavailability of short-selling and the higher transaction costs of shorting further hinder the practical application of such strategies, especially for larger investors. These investors often face short-selling barriers and may struggle to achieve the same returns observed in small-cap stock universes, where the performance of these strategies is significantly superior (Pätäri et al., 2022).

In summary, while Piotroski's F-score has demonstrated its efficiency in building combined value-quality portfolios, its real-world implementation may present challenges, particularly for larger investors operating in larger-cap stock universes.

Investors are constantly seeking effective and reliable methods to make informed investment decisions and optimize returns. The financial markets are dynamic and subject to various uncertainties that make accurate predictions difficult. The problem we aim to address is the need for a robust and practical investment strategy that can identify companies with strong future financial performance and the potential to outperform the market. By addressing this need, investors can allocate their resources more effectively, reduce investment risks, and achieve higher returns.

In addition to the basic analysis of the role of fundamentals in firm valuation, this study also examines the significance of growth and earnings response coefficients. Specifically, the study focuses on Piotroski's (2000) and Lev and Thiagarajan's (1993) F- and L-scores, which are believed to have a positive relationship with future stock returns (e.g., Kim & Lee, 2014). Higher scores indicate a greater possibility of future market excess returns.

To address potential alternative explanations for the scores, such as their relationship with consistent future returns, econometric models are used to show how the F- and L-scores add value relevance beyond existing factors such as book-to-market ratio, firm size and earnings per share.

The primary objective of this study is to provide fresh insights into binary models and fundamental analysis as applied to European markets, as the existing literature on this form of company valuation is relatively scarce. By testing accounting screenings on Euronext 100 companies, this research aims to examine whether these strategies can be applied to larger firms, thereby contributing to the literature on portfolio construction based on financial performance indicators.

One significant contribution of the present study is its application of these models in a European context, specifically among companies listed on the Euronext 100 index, which represents businesses from France, the Netherlands, Belgium, Portugal and Luxembourg. Remarkably, these two binary models, the F-score and the L-score, have never been tested within the context of these countries, thus addressing a notable gap in the existing literature. In particular, the L-score is significantly underrepresented in the literature compared to the more popular F-score. Importantly, our findings demonstrate the statistical significance of both models, with positive coefficients observed for both the F-score and the L-score among companies listed on the Euronext 100. We argue that our simultaneous application of both binary models (rather than just one) enhances the robustness of our empirical study.

Another important contribution of this study is the robustness testing of the strategies using fixed effects regression analysis. This approach allows for potential differences across firms and over time, particularly during periods that include significant crises, such as the technology bubble of 2000-2002, the subprime crisis of 2008, and the pandemic of 2020, along with subsequent market recoveries.

Moreover, this research aims to demonstrate how fundamental screenings based on previous financial performance can help investors build stronger value portfolios. If successful, this distinction between future "winners" and "losers" can significantly impact the distribution of a value investor's profits.

The empirical results indicate significant value relevance for various financial indicators. In Model 1, the earnings per share (EPS) variable is relevant to investors and statistically significant at the 1% level. The inclusion of the book-to-market ratio (BMR) and firm size variables in Model 2 increases the statistical relevance of the entire model (Adjusted R_2). The BMR and size variables are statistically significant, with the size variable being negatively related to 12-month firm returns three months after the fiscal year end, consistent with findings in the existing literature.

In Models 3-5, the study provides 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 at the 1% level in Models 3 and 5, while the L-score is statistically significant at the 1% level in either Model 4 or 5. In particular, Model 5confirms the additional explanatory power of the F-score after controlling for all other variables.

The research employs a robustness check using panel data linear estimators (random effects and fixed effects models) to estimate Model 6, controlling for individual heterogeneity. The results of Model 6 are consistent with those of Model 5 after controlling for individual heterogeneity, indicating the robustness of the findings.

To assess the effectiveness of the F- and L-scores as investment strategies, the study analyses buy-and-hold returns for each year based on the F- and L-scores. The results show that both raw and market excess returns increase with higher F- and L-scores, with a positive average return difference between high and low scoring firms. Notably, the F-score exhibits an average one-year raw return of around 16%, while the L-score has a similar effect on returns. These findings suggest that the FA method effectively forecasts returns at least one year ahead for companies listed on the Euronext 100 between 2000 and 2020.

In conclusion, this study contributes to the existing literature on FA and binary models in European markets. By exploring the value relevance of various financial indicators, including the F- and L-scores, the research provides valuable insights for investors seeking to build strong value portfolios. In addition, robustness testing using fixed effects regression analysis adds credibility to the findings. Overall, this research highlights the importance of considering fundamental factors when valuing firms and making investment decisions.

The next section contains an overview of the theoretical background, while section 3 presents the literature review. The procedures for constructing the fundamental scores are then described in section 4, followed by a description of the research strategy in section 5. Section 6 discusses the results and the last section concludes the study.

2 Theoretical background

Value investing is an investment strategy based on the belief that the market may sometimes undervalue certain assets, such as stocks or companies, creating opportunities for long-term gains. Value investors seek to identify assets that are trading at prices below their intrinsic value, indicating that they are potentially "undervalued". In this approach, investors analyse various fundamental factors of the asset, such as financial ratios, earnings, book value and dividend yield, among others, to assess its true value (Monge et al., 2023; Navas & Bentes, 2023).

The strategy was popularized by Benjamin Graham and David Dodd in their seminal book "Security Analysis" published in 1934. The key principle is to purchase these undervalued assets with the expectation that their market value will eventually rise to reflect their true value and provide profitable returns. Value investors often focus on stocks of stable, established companies with sound financials, steady cash flows and strong market positions.

Graham, who wrote "The Intelligent Investor" in 1949, is often regarded as the pioneer of the equity analyst profession and was a key figure in establishing the Chartered Financial Analyst function. In addition to his academic contributions, Graham served as a mentor to Warren Buffett, who early in his career focused on quantitative aspects such as price-to-earnings (P/E) and price-to-book (P/B) ratios while building diversified portfolios. Over time, influenced by another partner at Berkshire Hathaway, Buffett began to consider qualitative aspects, including competitive advantages and sustainability, thereby expanding upon Graham's original investment strategy (Holloway et al., 2013).

Overall, value investing requires a patient and disciplined approach, as it may take time for the market to recognize the true value of the assets and for investments to yield significant returns (Monge et al., 2023; Navas & Bentes, 2023).

The value investing strategy proposed by Graham et al. (2003) is based on three main characteristics of financial markets. Firstly, the prices of financial stocks are subject to significant and unpredictable fluctuations as the market continuously trades these assets. Secondly, fundamental economic values are relatively stable and can be accurately measured by diligent investors. The intrinsic value of a security is different from its current market price, often leading to divergences between the two. Lastly, a successful approach involves buying stocks when their market prices fall significantly below their calculated intrinsic value, creating a "margin of safety". Graham aimed to purchase stocks at a discount, seeking to obtain a dollar's worth for 50 cents, thereby ensuring potentially substantial and secure gains in the long run.

FA is a method of evaluating the intrinsic value of an asset or business by examining its financial and economic factors, such as earnings, revenues, assets, liabilities, growth potential, competitive advantage, etc. FA can be applied to different types of assets such as stocks, bonds, commodities, currencies, etc. (Graham et al., 2003; Holloway et al., 2013).

Most accounting fundamental analysis research in capital markets has relied on archival data and econometric models based on multiple regression models with time-series analysis for forecasting. Accounting signals, often based on percentage changes from one period to the next, are the key independent variables in these models. Current earnings and current returns, future earnings and future returns, and analysts' return forecasts are the main dependent variables in these models (e.g., Dechow et al., 2010, Dorantes Dosamantes, 2013; Navas & Bentes, 2023). Valuation theory and the market efficiency hypothesis are the two basic theoretical perspectives in this literature.

According to valuation theory, a firm's worth is the present value of the future free cash flows it is expected to generate. Future earnings must be estimated to estimate these cash flows. To forecast future earnings, one needs to study current and previous financial statements, which serve as the building blocks for calculating earnings (Abarbanell & Bushee, 1997, 1998; Bentes & Navas, 2013; Graham et al., 2003; Holloway et al., 2013; Navas et al., 2018; Piotroski, 2000). It is assumed that sooner or later earnings will be transformed into free cash flow for investors in the form of dividends (e.g., Beukes, 2011; Laih et al., 2015; Oppenheimer, 1984; Sareewiwatthana, 2011).

According to the efficient market theory, developed capital markets incorporate all available public and private information about a company's current and historical operational performance into its stock price (Fama, 1998). The more established a capital market is, the closer it is to market efficiency (e.g., Richardson et al., 2010; Sloan, 1996; Xie, 2001). The main theoretical viewpoints in most fundamental analysis research in capital markets have been valuation theory and the efficient market hypothesis (e.g., Bhargava, 2014; Dorantes Dosamantes, 2013; Piotroski, 2000).

FA assesses the investment desirability of a firm by examining its finances at the most fundamental level (Thomsett, 1998), focusing on sales, profits, growth potential, assets, debt, management, products and competition. This analysis may also include market behaviour evaluations that include underlying supply and demand issues (Beneish et al., 2015; Doyle et al., 2003; Piotroski, 2000). The goal is to improve the ability to predict future asset price movements, and then apply these improved predictions to equity portfolio design (Edirisinghe & Zhang, 2007; Pätäri et al., 2022).

3 Literature review

The value significance of FA in explaining future market returns has been demonstrated by extensive research in U.S. markets (e.g., Abarbanell & Bushee, 1998; Bagella et al., 2005; Drake et al., 2011; Hirshleifer et al., 2008; Lev et al., 2010; Lev & Thiagarajan, 1993; Piotroski, 2000; Richardson et al., 2010). There is also a lot of FA research in emerging markets (Dorantes Dosamantes, 2013; Holloway et al., 2013) and the Asia-Pacific region (see Benson et al., 2014, 2015; Linnenluecke et al., 2017a, 2017b). Research in European markets is comparatively scarce, although some notable exceptions offer insights (see Table 1). For example, Bagella et al. (2005) predict that many investors follow an FA approach to stock picking, so they build discounted cash flow (DCF) models, which they test on a sample of high-tech stocks to determine whether strong and weak versions are supported by U.S. and European stock market data.

Table 1
Relevant FA literature

Paper	Theoretical Perspective	Dependent Variable(s)	Independent Variable(s)	Country/ Market	Main Findings
Abarbanell and Bushee (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 changes in earnings and accounting fundamentals	U.S.	Annual return of 13.2% using a fundamental strategy based on L-scores. Most of the returns are generated by 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 returns for portfolios with high F-scores and 31.3% annual returns for portfolios with low F-scores.
Al-Shubiri (2011)	Valuation theory and fundamental analysis	Share prices	Accounting fundamentals	Jordan (banks)	Using multiple regression analysis, the author finds highly positive, significant relationships between the market price of the stock and net asset value per share and the market price of the stock divided by the percentage of gross domestic product, as well as a negative, significant relationship between inflation and the lending interest rate.
Amira and Hafssa (2021)	Debt and beta relationship	Beta (Y1)	Debt (X1) and earnings growth rate (X2)	Morocco	The more indebted a company is (X1), the higher its beta (Y1) would be. The higher the earnings growth rate (X2), the higher the beta (Y1) would be. The panel shows total heterogeneity for the relationship between Y1 and X1, and an individual effect model for the relationship between Y1 and X2.
Amor-Tapia and Tascón (2016)	Valuation theory	Future returns	FSCORE, FSCORE2, GSCORE, PEIS	U.S. & Europe	In four European markets, a hedge strategy that goes long in strong firms (high fundamentals) and short in weak firms (low fundamentals) does not reward investors with one-year ahead buy-and-hold abnormal returns in two measures, Xue and Zhang (2011)'s FSCORE2 and Wahlen and Wieland's PEIS.

Notes: BM = book-to-market ratio; DCF = discounted cash flow; EPS = earnings per share; ROA = return on assets; GDP = gross domestic product.
Source: Adapted and updated from Dorantes Dosamantes (2013).

Table 1
Continued...

Paper	Theoretical Perspective	Dependent Variable(s)	Independent Variable(s)	Country/ Market	Main Findings
Bartram and Grinblatt (2021)	Mispricing and returns	Portfolio returns	Mispricing signal, market capitalization, book/ market, beta, accruals, gross profitability, prior returns	Global (with and without U.S.)	Stocks are sorted into intra-country mispricing quintiles and grouped globally or by geography, country, or economic classification. The most under-priced stocks (Q5) have higher returns than the most overpriced stocks (Q1). The mispricing signal is negatively correlated with market capitalization, book/market, beta, accruals and prior returns.
Bagella et al. (2005)	Fundamental analysis	Stock price	DCF models and E/P	U.S. & Europe	The analysis of the determinants of E/P dispersion for a sample of U.S. high-tech firms shows that fundamental E/P, as estimated by a traditional DCF model, has an almost one-to-one effect on the observed E/P when the model is calibrated by the observed historical risk premium. Fundamental E/P also has superior explanatory power with respect to simpler measures of expected earnings growth. The strong significance of the DCF variable shows that the evaluation of fundamentals is crucial for determining observed values.
Dorantes 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	Mexico	Evidence of the value relevance of accounting fundamental signals. The proposed F- and L-scores provide additional explanatory power for future returns beyond traditional factors such as book-to-market ratios and size factors.
Drake et al. (2011)	Analysts tend to recommend stocks with high growth, high accruals and low BM ratios, despite their negative associations with future returns	Stock returns	11 independent variables from accounting fundamentals	U.S.	Short interest is significantly associated with the expected direction for all 11 variables examined. Abnormal returns from a zero-investment strategy shorts firms with highly favourable analyst recommendations but high interest and buys firms with highly unfavourable analyst recommendations but low interest.
Holloway et al. (2013)	Valuation theory and fundamental analysis	Future returns	Accounting fundamentals and size	Brazil	For a security to be part of a value investing portfolio, managers should account for the standard deviation of earnings per share, ROA, gross margin, company size (total assets) and liquidity (presence in the Bovespa index).
Karathanassis and Philippas (1988)	Valuation theory and fundamental analysis	Share prices	Accounting fundamentals	Greece (banks)	Dividends, retained earnings and size have significant positive influences on share prices.
Lev and Thiagarajan (1993)	Valuation theory and fundamental analysis	Earnings response coefficient and future earnings growth	12 accounting signals, earnings per share	U.S.	On average, the 12 fundamental signals add about 70% 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, but 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 a determinant of share prices.

Notes: BM = book-to-market ratio; DCF = discounted cash flow; EPS = earnings per share; ROA = return on assets; GDP = gross domestic product.
Source: Adapted and updated from Dorantes Dosamantes (2013).

Table 1
Continued...

Paper	Theoretical Perspective	Dependent Variable(s)	Independent Variable(s)	Country/ Market	Main Findings
Navas and Bentes (2023)	Fundamental analysis	One-year and two-year buy-and-hold adjusted returns	SCORE and nine fundamental signals	European markets	High BM companies earn positive market-adjusted returns in the one-year and two-year periods following portfolio construction. The SCORE model outperforms the individual fundamental signals in terms of return and risk-adjusted return. The SCORE model also has a positive and significant correlation with future returns.
Nisa (2011)	Valuation theory and fundamental analysis	Share prices	Share prices and economic data	Pakistan	The previous year's EPS and company size are important factors for determining stock prices in Pakistan. Macroeconomic indicators such as real GDP growth, interest rate and financial development have significant impacts.
Pätäri et al. (2022)	Accrual anomaly	Portfolio returns	Accruals (ACCR) and F-score (FSCORE)	Germany	The low-ACCR portfolio generates the highest net return among 39 comparable portfolios, especially when re-formed every three years. The performance of the low-ACCR portfolio is enhanced by removing microcap firms from the investable universe. The stand-alone FSCORE portfolio has the highest Sharpe ratio and information ratio among the 39 portfolios.
Piotroski (2000)	Valuation theory	Future returns	Accounting fundamentals: BM ratio, size, accruals	U.S.	Mean returns earned by a high BM investor can be increased by at least 7.5% annually by selecting financially strong, high BM firms.
Richardson et al. (2010)	Literature review of accounting anomalies and fundamental analysis	Future earnings and future stock returns	Accounting information	Mainly U.S.	The accounting anomaly and FA literature demonstrates the usefulness of accounting information in forecasting future earnings and stock returns. Anomalous return patterns tend to be concentrated in a subset of small, less liquid firms with high risk.
Shen and Lin (2010)	Valuation theory and fundamental analysis	Stock returns	Accounting fundamentals: EPS and a vector of corporate governance variables	Taiwan	Corporate governance variables affect the relationship between fundamental signals and stock returns. An endogenous switching model combines the response equation and governance index equation.
Tikkanen and Äijö (2018)	Valuation theory	Future returns	Accounting fundamentals: BM ratio, size, accruals	Europe	Replicates Piotroski's (2000) F-Score in European companies.
Tsoukalas and Sil (1999)	Dividends	Future returns	Dividend ratios	United Kingdom	The dividend/price ratio predicts real stock returns for the U.K. stock market, and there is a strong relationship between stock returns and dividend yields.
Walkshäusl (2020, 2019, 2015)	Valuation theory	Future returns, earnings response coefficient and future earnings growth	Accounting. fundamentals: BM ratio, size, accruals	Europe	As in the U.S., European value-growth returns depend on the valuation signals contained in the firm's equity financing activities. The high returns of value firms are due to value buyers; the low returns of growth firms are due to growth issuers.

Notes: BM = book-to-market ratio; DCF = discounted cash flow; EPS = earnings per share; ROA = return on assets; GDP = gross domestic product.
Source: Adapted and updated from Dorantes Dosamantes (2013).

In European stock markets, Walkshäusl (2015) replicates the study of Bali et al. (2010) and both conclude that value growth returns are influenced by accounting signals, especially from equity financing operations. Piotroski and So (2012), on the other hand, conclude that the observed value growth returns are the result of mispricing. Amira and Hafssa (2021) explore the relationship between financial structure and beta on the Casablanca Stock Exchange. They analyse data from 44 companies over the period 2008-2019 and find no direct impact of debt on beta, as well as individual-specific effects between beta and earnings growth, suggesting no generalized relationship.

In terms of recent research, Bradbury et al. (2021) examine the use and utility of equity accounting. According to descriptive research, the frequency of disclosure of investments in associates is higher than the percentage of earnings. Nevertheless, equity accounting is important in terms of value. For example, Gallagher et al. (2022) use a method to identify the exposures of global equity funds to six equity and three currency factors, as well as how these exposures relate to performance. The six equity factors are value, size, momentum (MOM), investment-to-assets (I/A), return on equity (ROE), and illiquidity (ILLIQ). They find that the average fund is underexposed to all equity factors except for ROE. Bradbury et al. (2021) examine the use of equity accounting for associates in Australian firms. They collect data from the annual reports of the largest 200 firms listed on the ASX in 2015 and 2018 and analyse the frequency and type of disclosures related to associates. They find that there is diversity in the reporting of associates, which may reflect different perspectives on the nature and importance of the associate relationship. They also find that disclosure focuses on balance sheet investment rather than the performance of the associate. They suggest that this implies an equity method investment perspective.

The study by Navas and Bentes (2023) proposes a new SCORE model for value investing, inspired by Piotroski's (2000) F-score. The SCORE model is a binary model consisting of nine signals that examine the past, present and future earnings forecasts of high book-to-market firms with growth potential. The signals are based on profitability, leverage, liquidity, operating efficiency and earnings quality indicators. The study applies the SCORE model to the Euronext 100 companies from 2000 to 2020 and compares the performance of high and low SCORE portfolios. The study finds that the high SCORE portfolio outperforms the low SCORE portfolio by at least 30% in terms of annual mean return, after controlling for size, value and momentum factors. The study also shows that the SCORE model is robust to different market conditions and sub-periods. The study concludes that the SCORE model is a simple and effective tool for fundamental analysis and value investing in European markets.

Pätäri et al. (2022) investigate whether the F-score, a financial statement-based indicator proposed by Piotroski (2000), can add value to anomaly-based portfolios in the German stock market. The study applies the F-score as a supplementary criterion to 12 accounting-based primary criteria, such as book-to-market, earnings-to-price, cash flow-to-price, etc., and forms annually rebalanced long-only portfolios based on different combinations of primary and supplementary criteria. The study also considers the impact of different holding periods (1 year and 3 years) and updating frequencies (annual and 3-year) on portfolio performance. The study finds that the F-score enhances the performance of all 12 primary criteria portfolios in terms of mean return, Sharpe ratio and Jensen's alpha, after controlling for size, value and momentum factors. The study also finds that the F-score boost is stronger for the 1-year holding period than for the 3-year holding period, but it still holds on average for the latter. Moreover, the study finds that the use of a 3-year updating frequency is especially beneficial for the low accrual portfolio supplemented with the high F-score threshold, which generates the best overall performance among all 75 portfolios examined. The study concludes that the F-score is a simple and effective tool for fundamental analysis and value investing in the German stock market.

The study by Bartram and Grinblatt (2021) explores global market inefficiencies by using point-in-time accounting data to estimate the monthly fair values of more than 25,000 stocks from 36 countries. The study constructs a trading strategy based on the deviations from fair value and measures its risk-adjusted returns (alpha) across different regions and markets. The study also controls for size, value and momentum factors and considers the impact of transaction costs on the profitability of the strategy (see also Hanauer et al., 2022). The study finds that the trading strategy generates a significant alpha in most regions, especially in the Asia-Pacific, and that the alpha is higher in emerging markets than in developed markets. The study also finds that the alpha is positively related to the country's trading costs, but still exceeds the institutional trading costs. The study concludes that global equity markets are inefficient, especially in countries with market frictions that deter arbitrageurs (Bartram & Grinblatt, 2021). The study by Hanauer et al. (2022) applies linear regression (LR) and tree-based machine learning (ML) methods to estimate the monthly peer-implied fair values of European stocks based on 21 accounting variables, inspired by Bartram and Grinblatt (2021). The study compares the performance of trading strategies based on deviations from fair value using LR and ML models, and measures their risk-adjusted returns (alpha). The study finds that ML methods, such as random forest and gradient boosting, outperform LR methods in estimating fair value and generating alpha. The study also finds that ML strategies earn a substantially higher alpha than LR strategies (48-66 vs. 11-36 basis points per month for value-weighted portfolios). The study concludes that ML methods can boost agnostic fundamental analysis by allowing for non-linearities and interactions in the data, and that European stock markets exhibit significant non-naive market inefficiencies. These studies have implications for international finance, valuation, asset pricing, market efficiency and FA.

Monge et al. (2023) analysed investment strategies based on value and growth (see also Amira & Hafssa, 2021; Navas & Bentes, 2023) using unit root tests and ARFIMA models. While Monge et al. (2023) focused on investment strategies, Amira and Hafssa (2021) examined the financial risk of companies associated with debt and earnings growth. MSCI Growth showed mean reversion behaviour, while MSCI Value exhibited higher persistence. The neural network model predicted an increase in both types of investments in the second half of 2022, with growth stocks outperforming value stocks.

The breadth of relevant FA studies is summarized in Table 1.

4 Fundamental scores: F-score and L-score

The F-score is based on Piotroski's (2000) 9 fundamental signals, whereas the L-score is based on the 12 fundamental signals recommended by Lev and Thiagarajan (1993). The annual gains in business profitability, financial leverage and inventory turnover are represented by the composite F-score. High F-scores indicate the possibility of abnormally high positive returns and future growth. The F-score is robust to different levels of financial health, future firm financial performance, asset growth and future market value, and was originally established for firms with high book-to-market ratios (BMRs) (e.g., Fama & French, 2006). The F-score is a number that ranges from 0 to 9 and represents the nine discrete accounting fundamental metrics at time t (as defined in Appendix A). As a result, the F-score is equal to the sum of F1 to F9.

The L-score measures the key signals described by Lev and Thiagarajan (1993) using annual data. These indicators track percentage changes in inventories, accounts receivable, gross margins, selling expenses, capital expenditures, gross margins, sales and administrative expenses, provisions for doubtful receivables, effective tax rates, order backlogs, labour productivity, inventory methods and audit qualifications. The 12 fundamental signals have a consistent relationship with current and future returns (e.g., Abarbanell & Bushee, 1998; Swanson et al., 2003). However, due to data limitations, the current study calculates the L-score for each organization using 9 fundamental signals (see Appendix B).

5 Research design

5.1 Econometric models

The following regression, which uses the BMR and company size as control variables, analyses the earnings effect on firm returns as a benchmark model (e.g., Campbell & Shiller, 1988; Dorantes Dosamantes, 2013; Midani, 1991; Nawazish, 2008; Ohlson, 2009, 1995):

$$R_{it} = \alpha + \beta_1 \times EPS_{it} + \varepsilon_{it} \quad (1)$$

where R_{it} represents the 12-month company (i) returns in year (t), calculated three months after the fiscal year end, which is December for all Euronext 100 index companies. At the end of March (t + 1), the financial statements for year (t) are usually published and generally available to the public. Dividends paid, as well as stock splits and reverse stock splits, are included in the price returns; however, taxation is not included in order to facilitate the study, therefore the results are gross values. As a result, annual returns can be calculated as follows, in Equation 2:

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

The variable EPS_{it} indicates the earnings per share deflated by the price at the beginning of year t for firm i.

The following regressions serve to test the value relevance of the fundamental signals (Amor-Tapia & Tascón, 2016; Dorantes Dosamantes, 2013; Piotroski, 2000):

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

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

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

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

In these regressions, BMR stands for book-to-market ratio, while SIZE stands for company size as defined by the logarithm of total assets. The F-score and L-score are constructed as explained in the previous section. If the fundamental signals are value relevant, the coefficient β_4 in Equations 4 and 5 should be positive and statistically significant. In Equation 6, in addition to β_4 and β_5, the coefficients β_1 and β_2 should be positive and statistically significant, and β_3 should be negative and statistically significant.

For example, according to Piotroski (2000), under-reaction to historical information and financial events (the ultimate mechanism underlying the success of the F-score) is the primary motivation for momentum strategies (Chan et al., 1996), which can predict future stock returns. In our study, BMR is the measure of this momentum.

According to Caglayan et al. (2018), the book-to-market effect, the average return difference between securities with high book-to-market and low book-to-market ratios, has been one of the most studied topics in the asset pricing literature. Fama and French (1992, 1995) provide risk-based justifications, attributing this phenomenon to the overreaction of naive investor. Daniel et al. (1998), for example, identify investor overconfidence, biased self-attribution and the tendency of investors to view events as representative as the source of this overreaction. La Porta et al. (1997) and Brav et al. (2005) find significant evidence of expectations error, supporting the view of overreaction as the basis for the book-to-market premium (Caglayan et al., 2018).

Next, to examine the potential use of fundamental signals to understand future returns, we classify the firm-year observations according to their F- and L-scores, relative to one- and two-year raw returns and market excess firm returns.

5.2 Data collection and the Euronext 100 stock market

The Euronext 100 is Euronext N.V.'s blue-chip index, covering around 80% of the largest companies on the exchange. Unlike other indexes, it contains companies from a variety of European countries, as well as the largest and most liquid stocks trading on four different stock exchanges: Amsterdam, Brussels, Lisbon and Paris. More than 20% of the issued shares of each stock must be traded. We present three research questions for our study:

- Are accounting signals (F-score and L-score) relevant for investors in predicting future firm returns?
- Does the inclusion of accounting signals (F-score and L-score) along with traditional financial variables (EPS, BMR and firm size) enhance the explanatory power of the models in predicting firm returns?
- Do the F-score and L-score exhibit different levels of value relevance in predicting future firm returns?

To answer our research questions, we rely on a number of hypotheses, which we test to check if they are confirmed or not:

H1: Accounting signals (F-score and L-score) have a clear relevance for investors in predicting future firm returns, specifically within the context of Euronext 100 companies.

H1a: The F-score is positively and significantly associated with future firm returns.

H1b: The L-score is positively and significantly associated with future firm returns.

H2: The inclusion of accounting signals (F-score and L-score) along with traditional financial variables (EPS, BMR and firm size) increases the explanatory power of the models in predicting firm returns.

H2a: The models that include accounting signals (F-score and L-score) exhibit higher adjusted R-squared values compared to models without these signals.

H3: There are significant differences in the value relevance of the F-score and L-score in predicting future firm returns.

H3a: The F-score has a stronger positive association with future firm returns compared to the L-score.

H3b: The F-score exhibits higher explanatory power in predicting future firm returns compared to the L-score.

Annual market-adjusted prices and financial data were collected from the Datastream database for all active firms in the Euronext 100 stock market between 2000 and 2020 (See Supplementary Material – Database). Econometric models and statistics were calculated using IBM's EViews and SPSS. Annual data for the market index are used to calculate market returns. Table 2 provides sample descriptions by stock exchange (Panel A) and industry (Panel B). French firms represent 64% of the firms listed in the Euronext 100 and they are evenly distributed by industry.

The descriptive statistics for the variables in Table 3 show that the average annual return is 10%; the average annual returns are small relative to the standard deviation, which indicates high volatility of returns in the period under analysis. The average EPS is 2.58, the BMR is 8.14, also lower than the standard deviation, and the kurtosis of these three metrics is greater than 3, which may mean that we are dealing with a non-normal distribution. The average firm size is 4.56, and the average F- and L-scores are 5.88 and 4.60 respectively and the standard deviation is lower than the mean.

Table 2
Sample - firms listed in the Euronext 100

Panel A: By stock exchange			
Stock Exchange	**Firms listed 2000–2020**	**%**	**Average market capitalization as of 2020 (in M EUR)**
Amsterdam	21	22%	699,492
Brussels	9	9%	18,638
Lisbon	5	5%	10,606
Paris	61	64%	29,475
Total/average	96	100%	152,244
Panel B: By industry			
Industry Classification	Firms listed 2000–2020	%	Average market capitalization as of 2020 (in M EUR)
Aerospace & Defence	4	4%	32,627
Automobiles & Parts	3	3%	12,347
Banks	6	6%	28,684
Beverages	4	4%	53,265
Chemicals	6	6%	17,335
Construction & Materials	3	3%	24,319
Electricity	3	3%	38,968
Electronic & Electrical Equipment	3	3%	20,550
Fixed Line Telecommunications	4	4%	19,063
Food & Drug Retailers	6	6%	11,046
Food Producers	1	1%	38,361
Gas, Water & Multi-utilities	3	3%	12,038
General Financial	4	4%	7,002
General Industrials	2	2%	22,944
General Retailers	1	1%	59,488
Health Care Equipment & Services	1	1%	23,970
Industrial Engineering	3	3%	4,899
Industrial Metals	2	2%	5,346
Industrial Transportation	3	3%	5,947
Life Insurance	4	4%	17,798
Media	5	5%	17,210
Mining	1	1%	1,910
Nonlife Insurance	2	2%	1,879
Oil & Gas Producers	3	3%	126,337
Oil Equipment, Services & Distribution	1	1%	453
Personal Goods	4	4%	2,773,192
Pharmaceuticals & Biotechnology	2	2%	57,916
Software & Computer Services	4	4%	9,246
Support Services	3	3%	7,722
Technology Hardware & Equipment	3	3%	40,182
Travel & Leisure	2	2%	7,718
Total/average	96	100%	152,244

Notes: M EUR = Millions of Euros.

Table 4 contains the correlation matrix and collinearity statistics. Returns are significantly correlated with all metrics except BMR. What regards to the independent variables: EPS is only significantly correlated with F-score and BMR with firm size and with L-score. Firm size is significantly correlated with both ratios and F-score is also significantly correlated with L-score. However, the correlations between the independent variables do not create a multicollinearity problem as the variance inflation factor varies between 1.0 and 1.2 (Gujarati, 2004). Regarding the variable returns, firm size shows negative correlations, as expected according to the literature. The negative correlation could arise because small firms often offer higher expected returns as a liquidity premium (e.g., Fama & French, 1992, 1995).

6 Results

6.1 Explanatory power of accounting signals: F- and L-scores

Table 5 reports the OLS results for the five proposed models from Equations 1 and 3-6, estimated using dummy variables to control for time, industry and country effects.

In Model 1, the EPS variable is relevant to investors and statistically significant at the 1% level. Adding the BMR and size variables in Model 2 increases the statistical relevance of the entire model (Adjusted R^2). The BMR and size variables are statistically significant; the size variable is negatively related to 12-month firm returns in the period three months after the fiscal year end, according to the literature.

In Models 3–5, we find evidence of the value relevance of the F- and L-scores over and above the value relevance of EPS, BMR and firm size. The F-score is statistically significant at the 1% level in Models 3 and 5; the L-score is also statistically significant at the 1% level in Models 4 and 5. Model 5 confirms the additional explanatory power of the F-score ($\beta=0.033$; $p<0.001$) 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 subsequent annual returns of about 3.3%, holding 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 3.7%. Investors prefer to buy shares of smaller firms, probably because small companies generate higher returns as a premium for their low liquidity. In theory, the returns of so-called small caps outperform those of larger companies (e.g. Dorantes Dosamantes, 2013; Holloway et al., 2013; Piotroski, 2000).

Table 3
Descriptive statistics

Variable	Firm-year observations	Min	Max	Mean	Std. Dev.	Kurtosis
R	1834	-0.91	3.93	0.10	0.42	8.64
EPS	1886	-174.44	208.82	2.58	12.90	136.89
BMR	1786	-0.40	1369.31	8.14	72.83	161.74
Log A	1897	1.86	8.77	4.56	1.01	2.00
F-Score	1937	1	9	5.88	1.61	-0.27
L-Score	1988	1	9	4.60	1.70	-0.33

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 the text.

Table 4
Correlation matrix

	VIF	R	EPS	BMR	Log A	F-Score	L-Score
R		1					
EPS	1.006	.081**	1				
BMR	1.122	.034	.008	1			
Log A	1.168	-.076**	.004	.310**	1		
F-Score	1.064	.130**	.073**	-.001	-.088**	1	
L-Score	1.114	.129**	.004	.047*	-.172**	.258**	1

**Indicate statistically significant at the 1% level; *Indicate statistically significant at the 5% level.

Notes: VIF = variance inflation factor; 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 the text.

We apply a robustness check to estimate Model 6 using panel data linear estimators - that is, a random effects and fixed effects model - because OLS cannot account for individual heterogeneity (Bevan & Danbolt, 2004). The null hypothesis of the Hausman (1978) test is that there is no relationship between individual heterogeneity and the independent variables. This study indicates that individual heterogeneity is related to the independent variables by rejecting the null hypothesis; thus, the fixed effects method can be used to estimate Model 6. The results of Model 6 are identical to those of Model 5 after controlling for individual heterogeneity. However, this impact is smaller than that of the F and L -scores: a one-unit increase is associated with an increase in subsequent annual returns of only about 2.4% and 1.7%, respectively, rather than the earlier Model 5 values of 3.3% and 2.8%. The remaining metrics, size and BMR, are statistically significant at 1% and 5% respectively and gain coefficient weight in Model 6. EPS is still statistically significant at 1%, but has less impact, as occurred with the two scores.

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

Given that the econometric results show positive and significant correlations between F- and L-scores, we examine the buy-and-hold returns for an investment strategy based on F- and L-scores for each year by grouping each observation according to its corresponding scores. For each of the nine F-score groups, we compute the subsequent one- and two-year raw returns and market excess firm returns. Multi-period (2000-2020) returns are continuously compounded. The 12-month returns are calculated from April of year t to March of year t + 1, and the corresponding score refers to year t (Table 6). The 24-month returns run from April of year t + 1 to March of year t + 2 and the respective score is for year t (Table 6). Equally weighted portfolios are used to estimate future returns.

Both raw and market excess returns increase as the F-score increases in the one-year return observed after portfolio construction. Portfolios of firms with high vs. low F-scores have a positive average return difference (25.67%, Table 6, Panel A). The entire model is statistically significant at the 1% level, with a value of 16.44% of raw returns for the high score. This finding supports the explanatory power of the F-score. For the portfolio with the high F-score, the average one-year market excess returns are 11.31% and the average two-year excess returns are 6.68% (Table 6, Panel A). In this case, it is not worth holding the stocks in the portfolio for longer than a year because the information contained in the company may be different two years later. Therefore, the FA method appears to be effective at forecasting returns for at least one year in advance.

Table 5
Value relevance of accounting signals

Variable	Model 1: Earnings Response Coefficient	Model 2: Benchmark	Model 3: Value Relevance of F-score	Model 4: Value Relevance of L-score	Model 5: Value Relevance of Fundamentals - Pooled Effects	Model 6: Value Relevance of Fundamentals - Fixed Effects
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
EPS	0.003***	0.003***	0.002***	0.003***	0.003***	0.003***
t-statistic	*4.88*	*4.95*	*4.41*	*5.06*	*4.57*	*4.19*
BMR		0.001**	0.001**	0.001*	0.001*	0.001**
t-statistic		*2.18*	*2.22*	*1.77*	*1.88*	*2.23*
Size		-0.038***	-0.039***	-0.036***	-0.037***	-0.163***
t-statistic		*-3.32*	*-3.50*	*-3.16*	*-3.35*	*-5.30*
F-score			0.038***		0.033***	0.024***
t-statistic			*7.61*		*6.53*	*6.24*
L-Score				0.032***	0.028***	0.017***
t-statistic				*6.52*	*5.23*	*4.12*
Intercept	0.018	0.126*	-0.077	-0.058	-0.198**	0.510***
t-statistic	*0.29*	*1.69*	*-0.98*	*-0.73*	*-2.45*	*3.55*
Time Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES
N# obs.	1796	1768	1768	1768	1768	1768
Adjusted R^2	0.406	0.419	0.438	0.433	0.446	0.573

***Indicate statistically significant at the 1% level; **Indicate statistically significant at the 5% level; *Indicate statistically significant at the 10% level.
Notes: EPS = earnings per share; BMR = book-to-market ratio. F-score and L-score are as defined in the text.

These findings are consistent with previous research. For example, for one-year buy-and-hold investors, high score raw returns are around 16%, but Piotroski (2000) claims 31% for a different period (i.e., 1975-1995) in the U.S. market. Between 1991 and 2011, Dorantes Dosamantes (2013) puts the value at 21% for the Mexican market. For the period 1975-2007, Kim and Lee (2014) obtain a raw one-year return of around 31%. Amor-Tapia and Tascón (2016) apply the F-score to many European companies and find a value of more than 29% for the period 1989-2011. These data imply that the F-score works effectively for companies listed on the Euronext 100 between 2000 and 2020, but not as well as some other researchers have found. This finding could be attributed to the global financial crisis of 2008-2009, as well as European sovereign debt issues (e.g., Erdogdu, 2016; Kim et al., 2016; Oberholzer & Venter, 2015). The F-score and returns are positively and significantly correlated according to the Student t-value.

Table 6
Buy-and-hold (B&H) 12-month and 24-month returns by F-score and L-score

Panel A.						
B&H 12 and 24-month returns by F-score						
F-Score	**1 Year B&H**			**2 Year B&H**		
	N	**Mean R**	**Mean ER**	**N**	**Mean R**	**Mean ER**
1	14	-27.51%	-30.09%	13	-1.17%	-6.02%
2	23	-1.75%	-2.37%	20	-0.89%	-0.81%
3	90	-7.89%	-7.22%	86	4.61%	2.78%
4	244	5.58%	1.55%	228	6.42%	3.45%
5	448	6.93%	1.24%	414	7.77%	3.19%
6	394	11.87%	7.40%	367	9.71%	7.00%
7	386	12.03%	10.67%	382	9.10%	7.27%
8	262	15.47%	11.08%	260	11.36%	6.26%
9	76	19.68%	12.10%	75	13.81%	8.08%
Low F-Score [1+2]	37	-9.23%	-10.42%	33	-0.97%	-2.36%
High F-Score [8+9]	338	16.44%	11.31%	335	11.92%	6.68%
High-Low		25.67%	21.73%		12.89%	9.03%
t-stat		5.60	6.71		3.21	3.15
Total	1937	9.52%	5.60%	1845	8.71%	5.30%
Panel B.						
B&H 12 and 24-month returns by L-score						
L-Score	1 Year B&H			2 Year B&H		
	N	Mean R	Mean ER	N	Mean R	Mean ER
1	91	-13.52%	-11.01%	85	-1.71%	0.94%
2	132	-1.08%	-2.16%	127	3.50%	1.57%
3	276	5.90%	2.31%	263	6.57%	3.64%
4	441	9.96%	5.25%	415	9.29%	5.02%
5	456	8.27%	3.08%	436	6.98%	3.60%
6	325	10.50%	8.31%	311	9.96%	7.10%
7	189	21.17%	15.81%	180	15.71%	11.59%
8	66	20.20%	14.25%	63	10.64%	6.08%
9	12	30.40%	37.19%	12	32.71%	25.06%
Low L-Score [1+2]	223	-3.29%	-3.73%	212	2.59%	1.46%
High L-Score [8+9]	78	21.81%	17.87%	75	14.26%	9.20%
High-Low		25.10%	21.61%		11.68%	7.74%
t-stat		5.59	6.35		4.34	4.17
Total	1988	9.52%	5.60%	1892	8.71%	5.30%

Notes: The 12-month returns begin three months after the fiscal year end, which is December for all firms. Geometric means of the returns are calculated. The 24-month returns begin three months after the fiscal year end, which is December for all firms. Annualized means of the returns are calculated. E = raw returns; ER = excess market returns.

The results of the parallel analyses for the L-score are shown in Table 6, Panel B. For 12- and 24-month returns after portfolio formation, returns and market excess increase as the L-score increases, with an implicit tendency, if not absolute regularity. In general, the higher the L-score, the higher the future returns. The average return difference between the portfolios of high and low L-score firms is 25.10% for buy-and-hold 12-month returns, and the entire model is statistically significant at 1% (Table 6, Panel B). The high L-score return is about 21.81% (5.37% higher than the high F-score return).

In response to the three research questions, based on the information provided:

Are the accounting signals (F-score and L-score) relevant for investors in predicting future firm returns? Yes, the accounting signals (F-score and L-score) are relevant for investors in predicting future firm returns. The results of the OLS models show that both the F-score and L-score are statistically significant at the 1% level, indicating their importance in predicting subsequent annual returns.

Does the inclusion of accounting signals (F-score and L-score) along with traditional financial variables (EPS, BMR and firm size) enhance the explanatory power of the models in predicting firm returns? Yes, the inclusion of accounting signals (F-score and L-score) along with traditional financial variables (EPS, BMR and firm size) enhances the explanatory power of the models in predicting firm returns. The adjusted R-squared values for Models 3, 4 and 5 are higher than those for Models 1 and 2, suggesting that the additional inclusion of the F-score and L-score improves the models' ability to explain the variance in future firm returns.

Do the F-score and L-score exhibit different levels of value relevance in predicting future firm returns? Yes, the F-score and L-score exhibit different levels of value relevance in predicting future firm returns. While both signals are statistically significant in different models (F-score in Models 3 and 5, and L-score in Models 4 and 5), further analysis is needed to directly compare their value relevance and determine which signal has a stronger association with future firm returns.

Based on the information provided in the table and the analysis, here are the results for the hypotheses:

H1: The accounting signals (F-score and L-score) show a clear relevance for investors in predicting future firm returns, specifically within the context of Euronext 100 companies.

The results support Hypothesis H1. Both the F-score and L-score show statistical significance at the 1% level in predicting future firm returns. The coefficients for these signals are positive (0.038*** for F-score and 0.032*** for L-score), indicating that an increase in these metrics is associated with higher subsequent annual returns.

H1a: The F-score is positively and significantly associated with future firm returns.

The results support Hypothesis H1a. The F-score coefficient is statistically significant at the 1% level in Models 3 and 5. An increase in the F-score is associated with a higher subsequent annual return of about 3.3%, controlling for size, BMR, EPS and L-score.

H1b: The L-score is positively and significantly associated with future firm returns.

The results support Hypothesis H1b. The L-score coefficient is statistically significant at the 1% level in Models 4 and 5. An increase in the L-score is associated with a higher subsequent annual return.

H2: The inclusion of accounting signals (F-score and L-score) along with traditional financial variables (EPS, BMR and firm size) increases the explanatory power of the models in predicting firm returns.

The results support Hypothesis H2. The adjusted R-squared values for Models 3, 4 and 5 are higher than those for Models 1 and 2. This indicates that the inclusion of accounting signals (F-score and L-score) enhances the ability of the models to explain the variance in future firm returns when combined with traditional financial variables.

H3: There are significant differences in the value relevance of the F-score and L-score in predicting future firm returns.

The results partially support Hypothesis H3. Both the F-score and L-score show statistical significance in predicting future firm returns in different models (F-score in Models 3 and 5, and L-score in Models 4 and 5). However, further analysis is needed to directly compare the value relevance of the two signals.

Overall, the findings indicate that both the F-score and L-score are relevant for investors in predicting future firm returns and that their inclusion in the models improves the explanatory power of the models. However, the precise differences in value relevance between the two signals require further investigation.

7 Conclusions

Our paper provides novel evidence on the value relevance of accounting using a comprehensive sample of firms from the Euronext 100 over 21 years. We extend the literature on the F-score and L-score metrics by showing that they capture different aspects of firm performance and risk, and that they have additional explanatory power for future returns beyond earnings, book-to-market and firm size. We also show that our results are robust to different estimation methods, such as OLS, random effects and fixed effects models. Our paper has important theoretical implications for understanding how investors use accounting information to assess firm value across different markets, geographies and economic classifications. We also contribute to the literature on cross-country differences in accounting quality, investor protection and market efficiency by examining how these factors affect the value relevance of accounting signals. We hope that our paper will stimulate further research on the role of accounting information in global capital markets.

While previous research has explored the value relevance of accounting signals for predicting returns in different markets, there is a specific gap in the literature regarding European markets, particularly those listed on the Euronext 100 index. The existing literature often focuses on other regions, such as the U.S. market, leaving a gap in our knowledge of how fundamental analysis can be applied to European companies. Our study addresses this gap by examining the value relevance of accounting signals, specifically EPS, BMR, firm size, F-score and L-score, for predicting annual returns in the context of European markets.

Our research makes a significant contribution to both researchers and practitioners in several ways: i) Advancing academic understanding: By analysing the value relevance of fundamental accounting signals in European markets, our study extends the theoretical understanding of fundamental analysis and its effectiveness in predicting future returns. This advancement allows academics to gain deeper insights into market dynamics, investor behaviour and the applicability of accounting signals in different market contexts; ii) Empowering investment decision-making: Practitioners, including investors, fund managers and financial analysts, will benefit from our research by gaining evidence-based insights into the construction of effective investment strategies. By incorporating the F-score and L-score into their decision-making processes, practitioners can identify companies with favourable financial performance and growth potential, leading to improved portfolio performance and risk management; iii) Market efficiency and stability: By providing evidence on the value relevance of accounting signals in European markets, our research contributes to market efficiency and stability. A better informed investment community can facilitate the allocation of capital to companies with strong fundamentals, potentially reducing information asymmetry and enhancing overall market efficiency.

This paper provides an overview of FA and emphasises its importance for investors looking ahead at least one year. This approach requires investors to use qualitative and quantitative information to identify companies that have good financial performance and the strength to face the future. This effort is a cornerstone of investing. To extend and link several relevant lines of accounting research in capital markets, in this study we focus on value-relevant fundamentals, conditional return-fundamentals analyses and earnings response coefficients.

In particular, we use Piotroski's (2000) and Lev and Thiagarajan's (1993) F-score and L-score, which are based on financial statement analyses and can be used by investors to construct portfolios that generate positive returns.

Using firms listed in the Euronext 100 index, we examine the explanatory power of accounting signals for predicting annual returns in a different setting. Beyond the value relevance of EPS, BMR and firm size, the F-score is statistically significant at the 1% level. The F-score coefficient indicates that a one-unit increase in this metric is associated with an increase in subsequent annual returns of about 2.4%-3.8% across models. The impact of the L-score is also statistically significant in all proposed models, such that a one-unit increase in this metric is associated with an increase in subsequent annual returns of only about 1.7%-3.2%.

With an investment strategy that constructs portfolios using F- and L-scores, investors should be rewarded with improved one- and two-year buy-and-hold positive returns in portfolios with high scores. By selecting firms with high scores (i.e., an F-score of 8 or 9), investors can expect raw returns of approximately 16%. In addition, an investment strategy that buys these expected winners and shorts expected losers (i.e., F-scores of 0-2) could have generated an annual return of 25% between 2000 and 2020 (see also Piotroski, 2000). Portfolios based on high L-scores for 12- and 24-month returns would also generate higher raw returns and market excess firm returns.

While a higher L-score generally implies higher future returns, the results of this study reveal significant results for a strategy based on the average of one- and two-year returns. That is, a fundamental strategy is effective for predicting returns one year ahead.

Research in European markets should extend the accounting fundamental signals approach to provide important insights for investors deciding how to allocate their resources. It should also investigate whether other strategies can predict periods of financial stress. In addition, we confirmed that all data were available at the time of the "backtesting" to ensure that there were no survivorship issues and that the findings were based on information that would be available to all investors prior to making investment decisions.

In summary, our research addresses a significant problem faced by investors, fills a gap in the literature regarding the value relevance of accounting signals in European markets, and offers valuable insights to both researchers and practitioners. By providing evidence on the effectiveness of fundamental analysis in predicting future returns, our study aims to foster more informed and efficient investment decisions in the dynamic landscape of financial markets.

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APPENDIX A. Original F-score of Piotroski (2000)

F-score	Ratio	Condition
1	$ROA_{(t)}>0$	then F1=1; 0 otherwise
2	$CFR_{(t)}>0$	then F2=1; 0 otherwise
3	$\Delta ROA>0$	then F3=1; 0 otherwise
4	$\frac{CFR_t}{A_{t-1}} > ROA_{(t)}$	then F4=1; 0 otherwise
5	$\Delta\left(\frac{LTD}{\overline{A}}\right)<0$	then F5=1; 0 otherwise
6	$\Delta CR<0$	then F6=1; 0 otherwise
7	Δ Equity offer>0	then F7=1; 0 otherwise
8	$\Delta\left[\frac{GM_t}{A_{t-1}}\right]>0$	then F8=1; 0 otherwise
9	$\Delta\left[\frac{Sales_t}{A_{t-1}}\right]>0$	then F9=1; 0 otherwise

Notes: $ROA_{(t)}$ = Return on assets at time t. or $\frac{NBID_t}{A_{t-1}}$; NIBD = net income before interest. taxes and depreciation. such that $NIBD_{(t)} = Sales_{(t)} - COGS_{(t)} - SGAE_{(t)}$; SGAE = selling. general. and administrative expenses; COGS = cost of goods sold; $A_{(t-1)}$ = total assets at the beginning of the period t; $CFR_{(t)}$ = cash flow from operations at time t. or EBIT + depreciation – taxes; EBIT = earnings before interest and taxes; $\Delta ROA = ROA_{(t)} - ROA_{(t-1)}$; LTD = long-term debt; $\overline{A}$ = Average of total assets; $\overline{A} = \frac{A_{t-1} + A_t}{2}$; CR = current ratio at time t; $CR = \frac{Current\ Assets}{Current\ Labilities}$; Δ Equity = change in common share outstanding (if the firm issued equity at t. this variable will be greater than 0); $\Delta\left[\frac{GM_t}{A_{t-1}}\right] = \frac{GM_t}{A_{t-1}} - \frac{GM_{t-1}}{A_{t-2}}$; GM = gross margin; and $GM_{(t)} = Sales_{(t)} - COGS_{(t)}$. The F-Score = F1+F2+F3+F4+5+F6+F7+F8+F9.

APPENDIX B. Adaptation of Lev and Thiagarajan's (1993) L-score

	L- Score Accounting Signal	Definition
1.	Inventory	Δ Inventory – Δ Sales
2.	Accounts Receivable vs. Sales	Δ Accounts Receivable – Δ Sales
3.	Capital Expenditure	Δ Firm Capital Expenditures
4.	Gross Margin	Δ Sales – Δ Gross Margin
5.	Sales and Administrative Expenses	Δ Sales & Administrative Expenses – Δ Sales
6.	Accounts Receivable	Δ Accounts Receivable
7.	Effective Tax	$PTE_t \times (T_{t-1} - T_t)$ PTE_t = pretax earnings at t. deflated by beginning price T= effective tax rate
8.	Labour Force	$\dfrac{\dfrac{Sales_{t-1}}{No\,of\ Employees_{t-1}} - \dfrac{Sales_t}{No\,of\ Employees_t}}{\dfrac{Sales_{t-1}}{No\,of\ Employees_{t-1}}}$
9.	Sales	Δ Sales

Notes: As an example. consider how the inventory signal can be computed:

Inventory $\text{Change}_{i.\,t} = \dfrac{[Inventory_{i.t} - E(Inventory_{i.t})]}{E(inventory_{it})}$ - $\dfrac{[Sales_{i.t} - E\ (sales_{i.t})]}{E\ (Sales_{i.t})}$;

Inventory $\text{Signal}_{i.\,t}$ = 1 if Inventory Change $_{i.\,t}$ < 0;0 otherwise;

E $(\text{Inventory}_{i.\,t}) = \dfrac{[Inventory_{i.t-1} - E\ (Inventory_{i.t-2})}{2}$; and

E $(\text{Sales}_{i.\,t}) = \dfrac{[Sales_{i.t-1} - E\ (Sales_{i.t-2})]}{2}$.

Where:

Inventory $\text{Change}_{i.\,t}$ = Percentage change in inventory minus percentage change in sales of firm *i* in year t;

Inventory $\text{Signal}_{i.\,t}$ = Binary signal indicating a positive (1) or negative (0) signal of firm *i* in year t;

E $(\text{Inventory}_{i.\,t})$ = Last two-year average of inventory for the corresponding year. which includes the average of inventory for year *t – 1* and *t – 2*; and

E $(\text{Sales}_{i.\,t})$ = Last two-year of sales value for the corresponding year. which includes the average of sales for year *t – 1* and *t – 2*.

Thus. the L-Score = L1+L2+L3+L4+L5+L6+L7+L8+L9.

Supplementary Material

Supplementary material accompanies this paper.
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