Can Fundamental Analysis Provide Relevant Information for Understanding the Underlying Value of a Company?

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Abstract

This chapter investigates the relevance of fundamental analysis (FA) for companies listed on the Euronext 100 index. Can FA provide relevant information that increases understanding of the underlying value of a company? This study leverages an FA strategy to select shares in a portfolio that can systematically yield significant, positive excess market buy-and-hold returns, 1 and 2 years after the portfolio formation. Using annual financial data available from 2000 to 2016, this analysis calculates three scores applied to construct the portfolios: the L-score, F-score, and PEIS. These insights inform investors' potential uses of fundamental signals (scores) to obtain abnormal returns. The results show that portfolios formed with high versus low scores earn 1- and 2-year abnormal returns between 2000 and 2016. This chapter contributes to scarce accounting research in European capital markets by furthering understanding of the possibility of mispriced securities.

Keywords: capital markets, markets efficiency, accounting fundamentals, scores, abnormal returns

1. Introduction

In an efficient market, prices incorporate available information in a timely manner [1–6]. According to valuation theory, over time accounting earnings get converted into free cash flows to investors, creditors, and the firm, which provide the main input for estimating the intrinsic value of the firm, as reflected in stock prices [5–7]. If information is not incorporated into the stock returns in a timely manner though, an anomaly arises, and arbitrage opportunities may emerge. In this sense, a market anomaly is a pattern of stock returns that appear to contradict traditional asset pricing models [8]. Although stock returns may be affected by multiple pieces of information, financial statements are the primary source, in that they summarize firm performance. In turn, a fundamental analysis (FA) undertakes an examination of detailed accounting data contained in financial statements to clarify how efficiently and effectively a firm generates earnings over time, as well as its potential to grow and convert these earnings into free cash flows [5]. One means to summarize the information contained in financial statements is to build measures or scores that integrate a set of signals (j) drawn from the accounting information (i.e., positive/negative news) about the firms (i) in the present year (t), or

$$Score_{it} = \sum\nolimits_{1}^{j} Signal_j \tag{1}$$

This chapter investigates whether investors can exploit documented abnormal returns to fundamental signals, as reflected in financial statement information. To do so, we revisit previously documented anomalies, including the L-score [1], which summarizes 12 signals from financial statements; the F-score [2], which is constructed on the basis of nine signals from financial statements; and the predicted earnings increase score (PEIS) [3], composed of six signals (positive, negative, or no news) that reflect a firm's quintile position on six accounting ratios. Therefore, we examine whether anomalies based on fundamental scores exist several years after the anomaly has been identified and thereby whether portfolios formed on the basis of such strategies can systematically yield significant, positive returns in the 1 and 2 years following portfolio formation.

The results we obtain from companies listed on the Euronext 100 index during 2000–2016 reveal that Piotroski's F-score and Lev and Thiagarajan's L-score effectively catch market anomalies, such that they allow for abnormal returns. In contrast, Wahlen-Wieland's PEIS does not provide a good source to identify market anomalies during our sample period.

With these findings, we make several important contributions. First, we provide evidence of the persistence of fundamental signals, which informs the debate about the information impounded in prices. Second, we show that two anomalies, Piotroski's and Lev and Thiagarajan's, enable investors to construct hedge portfolios that earn 1- and 2-year buy-and-hold abnormal returns. These findings in turn suggest that markets may not be semi-strong efficient; alternatively, the scores could capture some underlying risk. To establish these contributions, in Section 2 we review extant literature. Then Section 3 describes the research design, which tests whether the predictive ability of various fundamental signals documented in previous literature can be exploited in European markets, as we report in Section 4. Finally, we conclude in Section 5.

2. Literature review

Efficient markets have two characteristic features [8]: Investors have essentially complete knowledge of the fundamental structure of their economy (i.e., information), and they are rational information processors who make optimal decisions (i.e., rationality). If either of these two assumptions fails to hold, abnormal stock returns may arise. Employing FA, we examine whether abnormal stock returns can be obtained, years after the anomaly has been discovered.

A firm's stock price theoretically reflects both supply and demand sides of the market, such that it indicates investors' views of the corporate valuation. If the capital market is efficient in reflecting all available information, nothing outperforms its assessments of a firm's value. However, information collection is costly, so some groups of people may value the firm better than the market does [9]. According to [10], following the release of large traders' position information, a futures market reports semi-strong efficiency. Studying European indexes, [11] reports results in line with a weak efficiency market hypothesis (EMH) for the period between January 1993 and December 2007 and reaches the conclusion that daily and weekly returns are not normally distributed, because they are negatively skewed, are leptokurtic, and display conditional heteroscedasticity. Noting the mixed evidence across nations, [11] also rejects the EMH for daily data from Portugal and Greece, due to the first-order positive autocorrelation in the returns, but reports empirical tests that show that these two countries approach Martingale behavior after 2003. The French and U.K. data also reject EMH, but in these cases, it is due to the presence of mean reversion in the weekly data.

A FA seeks to translate information contained in financial statements into estimates of values to distinguish "winners" (undervalued firms) from "losers" (overvalued firms). One approach is to obtain the firm's intrinsic value and systematic errors in market expectations [12]. Another method trades on signals of financial performance. The abnormal returns generated by these signals could be due to the market's inability to comprehend a particular piece of information or to gaps in the rational decision-making process [2, 13].

Prior literature provides various examples of individual signals, such as accruals and post-earnings announcement drift, as well as composite signals built on various pieces of information, such as the F-score [2], PEIS [3], and L-score [1]. These latter, composite signals aggregate information contained in an array of performance measures or screens from financial statements and form portfolios on the basis of firms' overall signals. Previous research indicates that these investment strategies earn abnormal buy-and-hold returns [9–11]. For example, [2] builds an F-score based on nine individual binary signals derived from accounting data (profitability, financial leverage/liquidity, and operating efficiency). Strong (high F-score) value firms (with low book-to-market ratios) experience enhanced future performance and stock returns, compared with weak (low F-score) value firms, suggesting that the market does not impound financial statement information into prices in a timely manner. Many authors use this score to capture signals, such as [14, 15] in the U.S. market, [4] in European markets, and [5, 16] in emerging markets.

In proposing the L-score, [1] investigate a set of financial variables (fundamentals) that analysts claim are useful for security valuation, then examine these claims by estimating the incremental value relevance of the variables over earnings. Their findings support the incremental value relevance of most fundamentals; in the 1980s, fundamentals added approximately 70% to the explanatory power of earnings with respect to excess returns, on average. This U.S.-based score also is applicable to emerging markets [5, 16].

From [3], we obtain the predicted earnings increase score (PEIS), which seeks to determine whether financial statement information can be exploited to identify firms that are more likely to achieve future earnings increases. The findings demonstrate that high-score stocks are more likely to enjoy greater future earnings and abnormal returns, and a hedge portfolio traded on these signals exceeds consensus recommendations of analysts.

3. Research design

3.1. Fundamental scores: F-score, L-score, and PEIS

The F-score is based on 9 fundamental signals defined by [2]; the L-score is based on 12 fundamental signals suggested by [1], and the PEIS relies on 6 fundamental signals [3]. The composite F-score conveys information about annual improvements in firm profitability, financial leverage, and inventory turnover. It ranges from 0 (low) to 9 (high), reflecting nine discrete accounting fundamental measures at time t (see Appendix 1). The F-score equals the sum of F1 through F9, and higher scores imply potential abnormal positive returns and future growth. It also is robust to different levels of financial health, future firm financial performance, asset growth, and future market value [8]. It has proven useful for differentiating winners from losers among groups of firms with varied historical profitability levels [13], as well as in emerging markets such as India [16] and Mexico [5].

The L-score uses annual data to obtain fundamental signals that measure 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, labor force productivity, inventory methods, and audit qualifications. These 12 fundamental signals relate consistently to contemporary and future returns [17, 18]. Due to data restrictions though, the current study computes the L-score using only nine fundamental signals for each firm (see Appendix 2).

Finally, the PEIS determines whether financial statement information can be exploited to identify firms with more likely future earnings increases. The signals measure percentage changes in the net operating assets, gross margins, sales and administrative expenses, asset turnover, and accruals [3]. These six fundamental signals range from −1 to 1 (including 0), depending on the quintile of the sample. The small number of observations available in the low and high original PEIS (see **Table 5**) could bias the results, so we adapt this original score to ensure that each signal ranges from 0 to 1 (similar to the F- and L-scores). In turn, we refer to this measure as PEIS2, which ranges from 1 to 6 (sum of the 6 metrics). For the current study, we compute both PEIS versions (see Appendixes 3 and 4).

3.2. Data collection and the Euronext 100 stock market

Market-adjusted prices and financial data were collected annually from the Datastream database for all active firms in the Euronext 100 stock market between 2000 and 2016. Daily and annual data for the market index inform the computation of the market returns. The financial

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statements from year t are available at the end of March t + 1. The returns also include dividends paid plus stock splits and reverse stock splits; taxation is not included, so the results are gross values. The annual returns thus can be computed as:

$$\mathrm{R_t} = \frac{P_t}{P_{t-1}} - 1. \tag{2}$$

The Euronext 100 is a blue-chip index of Euronext N.V., spanning about 80% of the major companies on the exchange. Unlike most indexes, it includes companies from various countries within Europe, comprising the largest and most liquid stocks traded on four stock exchanges: Amsterdam, Brussels, Lisbon, and Paris. Each stock must trade more than 20% of its issued shares.

French firms represent 66% of the firms listed in the Euronext 100, Dutch companies account for 20%, and Belgian and Portuguese companies represent 9 and 5%, respectively, as detailed in **Table 1**, **Panel A**. The firms that comprise the Euronext 100 index are distributed uniformly by industry (not reported for brevity, but available on request), and the number of firms listed increased from 72 firms in 2000 to 96 firms in 2015 (**Table 1**, **Panel B**).

Panel A. Firms in the Euronext 100 by stock exchange

Stock exchange	Number of firms listed, 2000–2015	%
Amsterdam	19	20
Brussels	9	9
Lisbon	5	5
Paris	63	66
Total/total/average	96	100

Panel B. Number of firms by year

Year	Number of firms
2000	72
2001	76
2002	76
2003	76
2004	77
2005	79
2006	82
2007	85
2008	86
2009	88
2010	93
2011	94

Panel B. Number of firms by year	
Year	**Number of firms**
2012	96
2013	96
2014	96
2015	96
Source: Euronext 100 index.	

Table 1. Sample description.

4. Empirical results

4.1. Descriptive analysis

To determine whether the measures provide complementary or substitutive information, we perform a correlation analysis. **Table 2** contains the Pearson correlations among the four individual fundamental signals.

In general, the correlations across the four scores are low, indicating that the scores probably capture different aspects of firm performance. The most strongly correlated scores are the F-score and PEIS2, at 0.477, a value that is statistically significant at the 1% level. To test further whether the documented scores, which are useful for constructing successful U.S. strategies (e.g., [13, 14, 19]), also can be successful in Europe, we construct portfolios based on the four scores.

4.2. Buy-and-hold returns for an investment strategy

To construct portfolios based on the four focal scores, we group each observation according to its corresponding signal, by year. Then, we compute, for each score, 1- and 2-year subsequent raw returns and excess market returns, such that the multiperiod (2000–2016) returns are continuously compounded. The 12-month returns are calculated from April of year t to March of year t + 1, and the respective score refers to year t. The 24-month returns run from April in

	F-SCORE	L-SCORE	PEIS	PEIS2
F-SCORE	1			
L-SCORE	0.118**	1		
PEIS	0.219**	0.005	1	
PEIS2	0.477**	0.070*	0.091**	1

Notes: **, and * indicate statistical significance at the 5 and 10% levels (two-tailed), respectively.

Table 2. Analysis of score correlations.

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t + 1 to March in t + 2, and the respective score is for year t. The estimate of future returns uses equally weighted portfolios. We also compute a hedge strategy that takes a long position in firms with high scores and short position in those with low scores, on a yearly basis. Thus, we form two groups, high (H) and low (L), and calculate the difference between them, as well as presenting the t-statistics.

Table 3 contains the buy-and-hold returns for 1 and 2 years. In the 12-month returns observed after the portfolio formation, both raw returns and market excess firm returns increase as the F-score increases, though not consistently. The F7 score indicates the highest result, with a value of 23.29% (18.20%) for raw returns (excess market returns) on the 1-year buy-and-hold strategy, whereas the F9 score offers a high value of 24.46% (16.27%) for raw returns (excess market returns) for the 2-year strategy. The average return difference between portfolios of firms with high versus low F-scores is positive and the model shows to be statistically significant at the 1% level in all metrics (raw returns and excess return, for 1 and 2-year-buy-and-hold), which confirms the explanatory power of the F-score. That is, it is possible to use the F-score to discriminate growth stocks from value stocks, relative to those with little potential to provide positive abnormal returns. For example, if an investor implements a hedge fund

	One-year			**Two-year**		
F-score	**N**	**Mean raw returns**	**Mean excess market returns**	**N**	**Mean raw returns**	**Mean excess market returns**
0	2	11.77%	−25.93%	2	−63.42%	−52.95%
1	10	−2.38%	6.61%	9	−14.03%	0.11%
2	33	−11.71%	−8.36%	29	−19.93%	−12.57%
3	135	0.08%	2.44%	132	−2.83%	1.69%
4	225	8.93%	7.92%	216	3.18%	5.15%
5	267	10.30%	9.43%	253	4.73%	5.52%
6	289	15.07%	11.35%	270	11.30%	8.77%
7	232	23.29%	18.20%	222	19.81%	13.89%
8	133	23.10%	17.47%	123	21.39%	13.15%
9	41	14.85%	10.96%	40	24.46%	16.27%
Low F-score [0 + 1 + 2]	45	−8.59%	−5.81%	40	−20.77%	−11.73%
High F-score [8 + 9]	174	21.16%	15.93%	163	22.14%	13.92%
High-Low		29.75%	21.74%		42.91%	25.65%
t-Stat		5.64***	4.68***		11.11***	7.21***
Total	1367	13.04%	10.71%	1296	9.06%	7.70%

Notes: The 12-month returns begin 3 months after the end of the fiscal year, which is December for all firms. We compute geometric means of the returns. The 24-month returns also begin 3 months after the end of the fiscal year, which is December for all firms. We compute annualized means of the returns.
***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

Table 3. Buy-and-hold returns by F-score.

strategy, shorting the low score companies and taking long positions in high score companies, it would achieve profitability of 29.75% (42.91%) with a 1-year (2-year) buy-and-hold strategy. These results outperform a strategy that uses the market index for the same period, obtaining the investor 21.74% (25.65%) greater raw returns (excess market returns) with the 1-year (2-year) buy-and-hold strategy. Thus, an FA strategy appears more efficient for predicting returns, 1 and 2 years in the future.

These results align with prior literature. For example, the high score raw returns for a 1-year buy-and-hold strategy are approximately 21.16%, similar to the 31% reported in [2] for a different period (i.e., 1975–1995) in the U.S. market. For the Mexican market during 1991–2011, [5] identifies a value of 21%. Then [14] obtain a raw 1-year return of approximately 31% for 1975–2007. An application of the F-score to several European firms produced a value greater than 29% for the period between 1989 and 2011 [4]. These findings suggest that the F-score works well for firms listed in Euronext 100 during 2000–2016, though not as well as it has in some other studies. This result might stem from the international financial crisis of 2008–2009 and the sovereign debt crises in Europe [20, 21]).

The results of L-score appear in **Table 4**.

	One-year			**Two-years**		
L-score	**N**	**Mean raw returns**	**Mean excess market returns**	**N**	**Mean raw returns**	**Mean excess market returns**
0	5	−41.93%	−9.75%	5	−20.63%	−0.74%
1	45	−2.75%	2.46%	42	4.14%	5.51%
2	153	9.82%	9.20%	144	7.17%	6.11%
3	274	14.18%	13.14%	255	9.76%	6.96%
4	356	10.14%	7.95%	334	8.14%	6.27%
5	323	12.16%	9.99%	312	8.86%	8.39%
6	164	17.97%	11.53%	157	11.31%	9.47%
7	44	50.01%	35.09%	44	19.38%	19.19%
8	3	28.41%	26.40%	3	11.69%	17.37%
Low L-score [0 + 1 + 2]	203	5.76%	7.24%	191	5.78%	5.80%
High L-score [7 + 8]	47	48.63%	34.53%	47	18.89%	19.08%
High-Low		42.88%	27.29%		13.11%	13.27%
t-stat		4.03***	2.27**		2.22**	2.66***
Total	1367	13.04%	10.71%	1296	9.06%	7.70%

Notes: The 12-month returns begin 3 months after the end of the fiscal year, which is December for all firms. We compute geometric means of the returns. The 24-month returns also begin 3 months after the end of the fiscal year, which is December for all firms. We compute annualized means of the returns.
***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

Table 4. Buy-and-hold returns by L-score.

As expected, for both 1- and 2-year returns observed after portfolio formation, both the raw and the market excess firm returns increase as the L-score increases, with an implicit tendency, if not regularity. In general, the higher the L-score, the higher the future returns. The average return difference between portfolios of high versus low L-score firms is 42.88% (13.11%) for buy-and-hold 1-year (2-year) returns, the model is statically significant at the 1% (5%) level. Similar to the F-score, the FA results seem to outperform the excess market returns calculated on the basis of the Euronext 100 index, for the same period; the average return differences between the portfolios of high versus low L-score firms based on excess market returns are 27.29 and 13.27% for 1-year and 2-year buy-and-hold strategies. These results thus confirm the explanatory power of the L-score.

Table 5 provides the results for an investor that implements a strategy based on PEIS.

Similar to the F-score and L-score, in the 1-year returns observed after portfolio formation, both raw and excess market returns increase with the PEIS—though not consistently. A similar

	One-year			**Two-years**		
PEIS	**N**	**Mean raw returns**	**Mean excess market returns**	**N**	**Mean raw returns**	**Mean excess market returns**
−5	1	24.89%	−16.25%	1	−6.83%	5.01%
−4	7	2.63%	−0.23%	7	23.79%	14.17%
−3	45	5.53%	5.91%	40	11.80%	11.46%
−2	169	11.07%	8.41%	163	8.64%	7.71%
−1	297	9.76%	7.85%	285	7.89%	6.86%
0	349	15.53%	12.85%	327	12.27%	9.88%
1	273	15.07%	12.55%	255	6.04%	5.42%
2	161	14.63%	11.73%	156	10.47%	8.46%
3	51	13.72%	14.83%	49	1.33%	2.69%
4	11	14.00%	10.02%	10	22.17%	15.16%
5	2	13.46%	0.28%	2	−7.08%	5.04%
6	1	−4.37%	−22.61%	1	−6.05%	−19.11%
Low PEIS [−5–4-3]	53	5.51%	4.69%	48	13.22%	11.73%
High PEIS [4 + 5 + 6]	14	12.61%	6.30%	13	15.50%	10.97%
High-Low		7.10%	1.61%		2.28%	−0.76%
t-stat		1.47	1.72*		−0.79	−0.95
Total	1367	13.04%	10.71%	1296	9.06%	7.70%

Notes: The 12-month returns begin 3 months after the end of the fiscal year, which is December for all firms. We compute geometric means of the returns. The 24-month returns also begin 3 months after the end of the fiscal year, which is December for all firms. We compute annualized means of the returns.
***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively

Table 5. Buy-and-hold returns by PEIS.

pattern emerges for the excess market returns. However, the results indicate substantial differences between the raw returns and the excess market returns. The average return difference for portfolios of firms with high versus low PEIS is 7.10% (2.28%) and 1.61% (−0.76%) for raw (excess market) returns with a 1-year and 2-year buy-and-hold strategy. These results could reflect the relatively few observations of both low and high PEIS (e.g., PEIS-5 and 6 reflect only one observation). Thus, we also simulate an investment strategy according to the modified PEIS, or PEIS2 (see Appendix 4). These results appear in **Table 6**.

In the 12-month returns observed after the portfolio formation, both raw returns and market excess returns increase together with the PEIS2, though again not consistently. The P5 score achieves the highest result, with values of 26.88% (21.18%) and 26.60% (16.02%) for raw (excess market) returns over 1 and 2 years. The average return difference between portfolios of firms with high versus low P-scores is positive and the all model is statistically significant at the 1% level for all metrics. If the investor implements a hedge strategy and shorts low score companies while taking long positions in high score companies, it would achieve profitability of 8.21% (30.36%) with a 1-year (2-year) buy-and-hold strategy. This result confirms the greater explanatory power of the PEIS2, compared with the original PEIS. A FA of a 2-year buy-and-hold strategy in turn appears to be more efficient for predicting returns.

The scores we analyze thus are robust, with high statistical significance and strong returns (including excess market returns). Therefore, researchers should examine more sophisticated investment strategies based on FA, including applications of portfolio theory to minimize risk and maximize

	One-year			**Two-years**		
PEIS2	**N**	**Mean raw returns**	**Mean excess market returns**	**N**	**Mean raw returns**	**Mean excess market returns**
1	159	4.31%	5.38%	155	−7.46%	−1.22%
2	278	10.84%	8.28%	268	3.35%	5.39%
3	326	7.91%	7.75%	307	7.40%	7.43%
4	291	15.58%	13.80%	268	17.90%	13.26%
5	165	26.88%	21.18%	155	26.60%	16.02%
6	72	12.52%	8.35%	67	22.89%	11.28%
Low PEIS [1]	159	4.31%	5.38%	155	−7.46%	−1.22%
High PEIS [7]	72	12.52%	8.35%	67	22.89%	11.28%
High-Low		8.21%	2.97%		30.36%	12.50%
t-stat		3.71***	3.20***		11.67***	6.61***
Total	1291	12.51%	10.69%	1220	10.23%	8.46%

Notes: The 12-month returns begin 3 months after the end of the fiscal year, which is December for all firms. We compute geometric means of the returns. The 24-month returns also begin 3 months after the end of the fiscal year, which is December for all firms. We compute annualized means of the returns.
***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6. Buy-and-hold returns by PEIS2.

expected returns. It may be possible to predict financial crises and recessions, especially considering the strong volatility in the Euronext 100 index during the study period [19, 20].

5. Conclusions

This overview of FA stresses its implications for investors looking forward at least 1 or 2 years. It requires investors to use qualitative and quantitative information to identify companies that achieve strong financial performance and thus can face the future. This effort is a cornerstone of investing. With this study, we seek to extend and link several lines of investigation in capital markets accounting research. We focus on value-relevant fundamentals and conditional returns for the FA response coefficient. In addition, we test whether the L-score, F-score, and PEIS [1–3], originally documented in U.S. markets and based on financial statement analyses, can be used by investors to construct portfolios that enable them to earn abnormal returns in other markets. If markets are efficient, anomalies should tend to disappear once they have been discovered, whether by learning or arbitrage.

Among the firms listed in the Euronext 100 index during 2000–2016, we investigate the explanatory power of accounting signals for predicting annual returns in a different setting. The F-score and PEIS2 are statistically significant at the 1% level for all metrics (raw returns and excess returns, 1- and 2-year buy-and-hold). The impact of the L-score is also positive and statically significant (1–5% level). If they adopt an investment strategy and construct portfolios using F-scores, L-scores, and PEIS2, investors should be rewarded with abnormal returns on their 1- and 2-year buy-and-hold strategies. By selecting firms with high scores, investors can expect raw returns on their 1-year buy-and-hold approach that range between 12 and 48% (F-score 21%, L-score 48%, PEIS2 12%). In addition, an investment strategy that encouraged buying these expected winners and shorting expected losers could have generated 8–42% annual returns between 2000 and 2016 (F-score 30%, L-score 43%, PEIS2 8%). Portfolios composed of high score firms over 2-year returns also would produce increased raw and market excess firm returns. Because FA is based on various accounting reports that cover the most important financial aspects of a firm, it appears more efficient for implementing long-term investing strategies than a traditional market index, as also suggested in prior research [2, 4, 5].

The current study advances FA and capital market literature in several ways. First, the findings pertaining to the value relevance of accounting fundamentals provide insights into market efficiency in Europe. With regard to the type of market efficiency [22], we do not find support for the semi-strong form of the EMH, in which security prices reflect all publicly available information. Further research is needed to determine whether the value relevance of accounting fundamentals is an important signal of market inefficiency. In particular, some firms have high fundamentals that are not reflected in their security prices. These results may explain the lack of verification for the semi-strong form of the EMH [23]. Second, the results of using a fundamental strategy to form portfolios have practical implications for investors. Noting the evidence that accounting fundamental signals can provide important insights to investors as they make decisions about their resource allocations, research in European markets should explore this approach further, to provide alternative explanations for the value relevance of fundamentals, and investigate whether other strategies can predict periods of financial stress.

This study required all data to be available at the time the "back test" was run, so there were no survivorship issues, and the observations are based on information that would be available to all investors before they made investment decisions. It also uses annual data; perhaps results using quarterly data would be more accurate and potentially reflect a "post-earnings drift" effect. Regression models also can work well if an investor is diversified [2, 14].

This study also has several limitations. The scores do not include important macroeconomic variables, such as inflation rates, economic depressions, or regulatory changes in the market, beyond controlling for time effects. Additional out-of-sample tests could strengthen inferences about the usefulness of a given accounting attribute, to forecast either future earnings or future stock returns. If relevant institutional factors or other characteristics vary over time or across firms, this variation should be tested; any variation in the observed outcomes also might help strengthen the resulting inferences. Tests of the predictive ability of a given attribute also might be conducted in a more "fair" manner.

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Appendix 1. Original F-Score of Piotroski [2]

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>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.

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Appendix 2. Adaptation of Lev and Thiagarajan's [1] 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	$\frac{\frac{Sales_{t-1}}{No\ of\ Employees_{t-1}} - \frac{Sales_t}{No\ of\ Employees_t}}{\frac{Sales_{t-1}}{No\ of\ Employees_{t-1}}}$
9.	Sales	Δ Sales

Notes: As an example consider how the inventory signal can be computed: Inventory $Change_{i,\ t} = \frac{[Inventory_{i.t} - E(Inventory_{i.t})]}{E(inventory_{it})} - \frac{[Sales_{i.t} - E\ (sales_{i.t})]}{E\ (Sales_{i.t})}$; Inventory $Signal_{i,\ t}$ = 1 if Inventory Change $_{I,\ t}$ < 0, and 0 otherwise; E $(Inventory_{i,\ t}) = \left[\frac{Inventory_{i.t-1} - E\ (Inventory_{i.t-2})}{2}\right.$; and E $(Sales_{i,\ t}) = \frac{[\ Sales_{i.t-1} - E\ (Sales_{i.t-2})]}{2}$; where Inventory $Change_{i,\ t}$ = percentage change in inventory minus percentage change in sales of firm i in year t; Inventory $Signal_{i,\ t}$ = binary signal indicating a positive (1) or negative (0) signal of firm i in year t; E $(Inventory_{i,\ t})$ = last 2-year average of inventory for the corresponding year, which includes the average of inventory for years t – 1 and t – 2; and E $(Sales_{i,\ t})$ = last 2-year average of sales value for the corresponding year, which includes the average of sales for years t – 1 and t – 2. Thus, the L-Score = L1 + L2 + L3 + L4 + L5 + L6 + L7 + L8 + L9.

Appendix 3. Wahlen and Wieland [3] PEIS

P-score	Signal	Quintile scoring
		+1 0 –1
1	RNOA	Bottom Middle Top
2	ΔGM	Top Middle Bottom
3	ΔSGA	Bottom Middle Top
4	ΔAT	Top Middle Bottom
5	ΔNOA	Bottom Middle Top
6	$ACC_{(t)}$	Bottom Middle Top

Notes: RNOA = return on net operating assets, or operating income/[$(NOA_t + NOA_{t-1})$/2]; ΔGM = change in gross margin; ΔSGA = change in sales/selling, general, & administrative expenses; ΔAT = change in asset turnover; ΔNOA = change in net operating assets; and $ACC_{(t)}$ = [operating income – cash flow from operations]/Average NOA. PEIS = P1 + P2 + P3 + P4 + P5 + P6.

Appendix 4. Adaptation of Wahlen and Wieland [3], PEIS2

P -score	Ratio	Condition
1	ΔRNOA>0	then P1 = 1; 0 otherwise
2	ΔGM > 0	then P2 = 1; 0 otherwise
3	ΔSGA>0	then P3 = 1; 0 otherwise
4	ΔAT > 0	then P4 = 1; 0 otherwise
5	ΔNOA>0	then P5 = 1; 0 otherwise
6	$ACC_{(t)} > 0$	then P6 = 1; 0 otherwise

Notes: ΔRNOA = change in return on net operating assets, or operating income/[(NOA_t + NOA_{t-1})/2]; ΔGM = change in gross margin; ΔSGA = change in sales/selling, general, & administrative expenses; ΔAT = change in asset turnover; ΔNOA = change in net operating assets; and $ACC_{(t)}$ = [operating income – cash flow from operations]/average NOA. PEIS2 = P1 + P2 + P3 + P4 + P5 + P6.

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