# The Relevance of Using Accounting Fundamentals in the Euronext 100 Index

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## Abstract

To determine whether accounting fundamentals provide relevant information about firm value, this study examines if applying an accounting fundamental strategy to select stocks yields positive excess buy-and-hold returns several years later. By integrating valuation theory and accounting research, annual financial and market data from Euronext 100 index stocks between 2000-2014 reveal, after controlling for earnings, book-to-market ratio, and firm size, that a fundamental strategy provides value-relevant information to investors. The relationship between accounting fundamental signals and buy-and-hold market future returns is significant and positive, such that portfolios formed on the basis of high scores achieve a 15% average market excess annual return.

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## 1. Introduction

In a fundamental analysis (FA), the assessor examines companies' economic and financial reports (e.g., profit & loss accounts, balance sheets), including both quantitative and qualitative information. For such analyses, there is a set of financial variables (fundamentals) that analysts generally find useful in their stock valuation. With this study, we examine this usefulness by estimating the incremental value relevance of each variable over earnings (e.g., Dechow *et al.,* 2010; Lev and Thiagarajan, 1993; Piotroski, 2000, 2005; Piotroski and So, 2012). In addition to this general examination of the role of fundamentals for firm valuation, we consider the specific importance of growth and earnings response coefficients.

Using the evidence, we thus establish, if investors can use accounting data more effectively, to construct hedge portfolios in which they can identify possible abnormal returns, which increases their expected utility. In turn, they might achieve an optimal balance between expected returns and market and country risk. In particular, we consider Piotroski's (2000) and Lev and Thiagarajan's (1993) F-score and L-score, which should relate positively to one- and two-year future stock returns; higher scores increase the likelihood of future market excess returns. To address potential alternative explanations for these scores, including the notion that they might measure factors that relate consistently to future returns (Amor-Tapia and Tascón 2016; Kim and Lee, 2014; Piotroski, 2005), we apply econometric models that reveal how the scores add value relevance beyond extant factors, such as the book-to-market ratio, firm size, and earnings per share (Dosamantes, 2013; Ohlson, 1995, 2009).

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

The next section presents a review of literature and pertinent empirical studies. Then we outline the methods we used to construct the fundamental scores, followed by a description of the research design. Following the results and discussion, the last section concludes.

## 2. Literature review

A firm's stock price theoretically reflects both supply and demand sides of the market, so it usually is regarded as investors' views of corporate valuation. If the capital market is efficient in reflecting all available information, nothing can outperform it in assessing a firm's value. However, information collection is costly, so some actors might value the firm better than the market (e.g. Laih *et al.*, 2015). Khan (1986) finds that, following the release of large trader position information, a futures market offers only semi-strong efficiency. In European indexes, Borges (2010) reports results in line with the weak efficiency market hypothesis (EMH) between January 1993 and December 2007, concluding that daily and weekly returns are not normally distributed but instead are negatively skewed and leptokurtic, and they display conditional heteroscedasticity. With mixed evidence across nations, Borges rejects the EMH for daily data from Portugal and Greece, due to the first-order positive autocorrelation in the returns, but also provides empirical evidence that these two countries approached Martingale behaviour after 2003. The French and U.K. data also reject the EMH, but in these cases, it was due to the presence of mean reversions in weekly data.

Furthermore, the EMH does not hold consistently in less developed markets (e.g., Aggarwal and Gupta, 2009; Richardson *et al.,* 2010; Sloan, 1996; Xie, 2001). The more developed a capital market, the closer it comes to market efficiency, according to most researchers. Therefore, in developed markets, prices likely incorporate all available information efficiently into stock prices. Yet a lack of market efficiency might arise when investors do not incorporate all the information disclosed in financial statements; as Abarbanell and Bushee (1997, 1998) indicate, even sophisticated analysts systematically underestimate accounting signals in their earnings forecasts, so stock prices often are temporarily underestimated.

An FA aims to determine the value of firms' securities through a careful examination of key drivers, such as earnings, risk, growth, or competitive position (Lev and Thiagarajan, 1993). It relies on financial reports, which provide fundamental data for calculating financial ratios. Each ratio then provides an evaluation of different aspects of the firm's financial performance. Penman (2009) defines FA as the analysis of information that focuses on valuation; Kothari (2001) calls it a powerful means to identify mispriced stocks relative to their intrinsic value. Richardson et al. (2010) also highlight the research overlap between FA and accounting anomalies, noting that FA research tends to focus on forecasting earnings, stock returns, or the firm's cost of capital. In addition, FA evaluates firms' investment worthiness by looking at their businesses at basic financial levels (Thomsett, 1998), focusing on sales, earnings, growth potential, assets, debt, management, products, and competition. This strategy also might involve analyses of market behaviour that encapsulate underlying supply and demand factors (Beneish *et* *al.,* 2015; Doyle *et al.,* 2003; Piotroski, 2000). The goal is to gain a better ability to predict future security price movements, then apply the improved predictions to the design of equity portfolios (Edirisinghe and Zhang, 2007).

Considerable research in U.S. markets offers strong empirical evidence of the value relevance of FA for explaining future market returns (e.g., Abarbanell and Bushee, 1998; Bagella *et al.,* 2005; Drake *et al.,* 2011; Hirshleifer *et al.,* 2008; Lev *et al.,* 2010; Lev and Thiagarajan, 1993; Piotroski, 2000; Richardson *et al.,* 2010). Research in European markets is comparatively scarce, though 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 with a sample of high-tech stocks to determine if strong and weak versions receive support from U.S. and European stock market data. The strong significance of the DCF variable shows that evaluating fundamentals is crucial for determining observed values, though the relevance of additional variables also implies that something is missing from traditional DCF evaluations. Bagella *et al.* (2005) also highlight some differences between U.S. and European markets, with descriptive evidence that U.S. stocks are riskier, have higher expected rates of growth, and distribute fewer dividends. Moreover, they attract more coverage from analysts, and their growth estimates exhibit lower standard deviations. Empirical evidence also reveals that the relationship between DCF fundamentals and observed earnings per share (E/P) is significantly lower for European stocks, whereas the risk premium used to evaluate stocks is significantly higher for much of the sample period.

Walkshäusl (2015) replicates the U.S. study by Bali *et al.*, (2010) in European stock markets. Matching the original study, the European value growth returns depend strongly on the valuation signals contained in a firm's equity financing activities. The high returns of value firms come from value purchasers; the low returns of growth firms are due to growth issuers. Among value issuers and growth purchasers, no value premium exists. The large return difference between value purchasers and growth issuers cannot be explained by common risk factors. However, when Piotroski and So (2012) apply a market expectation errors approach, they conclude that the observed value growth returns can be attributed to mispricing. Table 1 summarizes the range of relevant FA studies.

[insert table 1]

## 3. Fundamental scores: F-score and L-score

The F-score is based on 9 fundamental signals defined by Piotroski (2000); the L-score is based on 12 fundamental signals suggested by Lev and Thiagarajan (1993). The composite F-score conveys information about annual improvements in firm profitability, financial leverage, and inventory turnover. High F-scores imply potential abnormal positive returns and future growth. Although originally developed for firms with high book-to-market ratios (BMR), the F-score is robust to different levels of financial health, future firm financial performance, asset growth, and future market value (e.g., Fama and French, 2006). It has proven useful for differentiating 'winners' from 'losers' among groups of firms with varied historical profitability levels (Piotroski, 2005), as well as in emerging markets such as India (Aggarwal and Gupta, 2009) and Mexico (Dosamantes, 2013). The F-score ranges from 0 (low signal) to 9 (high signal), reflecting the nine discrete accounting fundamental measures at time t (as defined in Appendix 1). The F-score thus equals the sum of F1 through F9.

The L-score uses annual data to measure the fundamental signals proposed by Lev and Thiagarajan (1993). These signals 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, labour force productivity, inventory methods, and audit qualifications. The 12 fundamental signals relate consistently to contemporary and future returns (e.g., Abarbanell and Bushee, 1998; Swanson *et al.*, Rees, and Juarez-Valdes, 2003). Due to data restrictions though, the current study computes the L-score according to nine fundamental signals for each firm (see Appendix 2).

## 4. Research design

### *4.1 Econometric models*

As a benchmark model, the following regression tests the earnings effect on firm returns, with and without the *BMR* and *firm size* as control variables (e.g., Campbell and Shiller, 1988; Dosamantes, 2013; Midani, 1991; Ohlson, 1995):

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

where $R_{it}$ represents the 12-month excess firm returns over the market index for firm *i* at year t, computed three months after the end of the fiscal year, which is December for all firms in the Euronext 100 index. The financial 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:

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

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 and Tascón, 2016; Dosamantes, 2013; Nawazish, 2008; Piotroski, 2000):

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

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

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

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

In these regressions, *BMR* represents the book-to-market ratio, and *SIZE* is the size of the firm measured by the logarithm of the total assets of the firm. The construction of the *F-score* and *L-score* are as detailed in the previous section. If the fundamental signals are value relevant, the coefficient $\beta_4$ in Equations 4 and 5 should be positive and statistically significant. In Equation 6, in addition to $\beta_4$ and $\beta_5$, the coefficients $\beta_1$ and $\beta_2$ should be positive and statistically significant, and $\beta_3$ should be negative and statistically significant.

For example, according to Piotroski (2000), an 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 ratio of this momentum.

According to Caglayan et al. (2018), the book-to-market effect, the average return difference between high book-to-market and low book-to-market ratio securities, has been one of the most investigated topics in the asset pricing literature. Fama and French (1992, 1995) provide risk-based justifications, they attribute this phenomenon to the naive investors' overreaction. Daniel et al. (1998), for example, show investors' overconfidence, biased self-attribution and the tendency of investors to view events as representative to be 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 as a means to understand the 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.

### *4.2 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 2014. Daily and annual data for the market index inform the computation of the market returns. Table 2 provides sample descriptions by stock exchange (Panel A), industry (Panel B), and year (Panel C). French firms represent 66% of the firms listed in the Euronext 100; they are distributed uniformly by industry, and the number of firms listed increases from 2000 (71 firms) to 2014 (95 firms).

[insert table 2]

The Euronext 100 is the 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.

The descriptive statistics for the variables in Table 3 show that the mean annual return is 14.43%; the average annual returns are small relative to the standard deviation, which indicates high volatility in the returns in the period under analysis. The average *EPS* is 2.3213; the *BMR* is below the unit average, such that on average, the stocks listed in Euronext 100 were overvalued during the period of analysis. The average *firm size* is 7.2445, and the average *F*- and *L-scores* are 5.3450 and 3.9070, respectively.

[insert table 3]

Table 4 contains the correlation matrix and collinearity statistics. The *F-score* correlates significantly with all the model variables: returns, *EPS*, *BMR*, *size* (log A), and the *L-score*. The correlations among the independent variables do not produce a multicollinearity problem though, because the variance inflation factor fluctuates between

1.1 and 1.2 (Gujarati, 2004). Regarding the variable returns, *BMR* and *size* show negative correlations. The correlation of *EPS* is marginal, at the 10% level, and that with the *L-score* is not even statistically significant; for the *F-score,* it is statistically significant at the 1% level. This negative correlation of *BMR* contrasts with findings in capital market literature (e.g., Piotroski, 2000). For *size*, the negative correlation could arise because small firms often provide higher expected returns as a liquidity premium (Fama and French, 1992, 1995).

[insert table 4]

## 5. Results

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

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

[insert table 5]

In Model 1, the *EPS* variable is relevant to investors and statistically significant at the 10% level. Adding the *BMR* and *size* variables in Model 2 causes *EPS* to lose its statistical significance though. The *BMR* and *size* variables are statistically significant at the 1% level; they relate negatively to 12-month firm returns in the period three months after the end of the fiscal year. We predicted that size should relate negatively to returns, but we did not expect *BMR* to reveal such a link. A possible explanation might be that this variable applies better to companies with low book values, such as small companies, so the *BMR* acts something like a size ratio (see also Dosamantes, 2013).

With Models 3 - 5, we find 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; the *L-score* is not statically significant in either Models 4 or 5. Model 5 affirms the additional explanatory power of the *F-score*, after controlling for all other variables. The coefficient of the *F-score* indicates that a one-unit increase in this metric is associated with an increase in subsequent annual returns of about 2.9%, keeping 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 8%. Investors prefer to buy shares from smaller firms, likely because small companies generate higher returns as a premium related to their low liquidity. In theory, the returns of so-called small caps outperform those of larger companies (e.g., Dosamantes, 2013; Holloway *et al*., 2013; Piotroski, 2000).

Because OLS cannot control for individual heterogeneity (Bevan and Danbolt, 2004), we use a robustness check to estimate Model 6 using panel data linear estimators - that is, a random effects and fixed effects model. The Hausman (1978) test considers the null hypothesis that there is no correlation between individual heterogeneity and the independent variables. By rejecting the null hypothesis, this study reveals that individual heterogeneity is correlated with the independent variables; therefore, the fixed effects method can estimate Model 6. After controlling for individual heterogeneity, the results of Model 6 remain the same as those from Model 5, except that the *L-score* variable becomes positive and statistically significant at the 5% level. However, this impact is lower than that of the *F-score*: A one-unit increase is associated with an increase in subsequent annual returns of only about 1.8%, whereas the impact of the F-score invokes a 2.9% increase.

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

Noting 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 one- and two-year subsequent raw returns and market excess firm returns. Multiperiod (2000–2014) 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 (Table 6). The 24-month returns run from April at t + 1 to March at t + 2, and the respective score is for year t (Table 6). The estimate of future returns uses equally weighted portfolios.

[insert table 6]

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 presents the best result, with a value of 23.92%. The average return difference between portfolios of firms with high versus low *F-scores* is positive, showing a value of 23.80% (Table 6, Panel A)[2], also the all model is statistically significant at the 1% level. This result confirms the explanatory power of the *F-score*. The average of the one-year market excess firm returns for the high *F-score* portfolio is 13.33% (Table 6, Panel A), and the average of two-year excess-returns offers a similar value of 13.82% (Table 6, Panel A). Thus the FA strategy appears efficient for predicting returns one and two years ahead.

These results match prior literature. For example, the high score raw returns for one-year buy-and-hold investors are approximately 18%, and Piotroski (2000) reports 31% for a different period (i.e., 1975–1995) in the U.S. market. For the Mexican market during 1991–2011, Dosamantes (2013) identifies a value of 21%. Kim and Lee (2014) obtain a raw one-year return of approximately 31% for 1975–2007. An application of the *F-score* to several European firms by Amor-Tapia and Tascón (2016) produced a value greater

[2] To overcome the potential risk of survivorship issues, due the small number of observations for the low F-score relative to the high F-score, we require each firm to have at least three years of historical data (see also Piotroski, 2000).

than 29% for the period between 1989 and 2011. These findings suggest that the *F-score* works well for firms listed in Euronext 100 during 2000–2014, though not as well as in some other studies. This result might stem from the international financial crisis of 2008 - 2009 and the sovereign debt crises in Europe (e.g., Erdogdu, 2016; Kim *et al.*, 2016; Oberholzer and Venter, 2015). The Student t-value shows a positive and significant correlation between the *F-score* and returns, so it is possible to use the *F-score* to discriminate between growth stocks and value stocks, relative to those with little potential to provide positive abnormal returns.

The results of parallel analyses for the *L-score* appear in Table 6 Panel B. As expected, for both 12 - and 24 -month returns after the portfolio formation, the raw returns and market excess firm returns increase as the *L-score* increases, with an implicit tendency, if not total regularity. In general, the higher the *L-score*, the higher the future returns. The average return difference between the portfolios of high versus low *L-score* firms is 7.51% (9.45%) for buy-and-hold 12-month (24-month) returns, though it is not statically significant (Table 6, Panel B). When the analysis is based on the average of two-year returns, the average return difference between the portfolios of high versus low *L-scores* is 9.86% (9.69%) for raw returns (market excess returns). The model is statistically significant at the 1% level for a strategy of buy-and-hold for 2 years.

**New scores**

A premium is expected for high-average portfolios, so a simulate investment strategy might select portfolios with high F-score values (i.e., 7, 8, or 9). Table 6.12 and Table 6.13 report the results of a buy-and-hold strategy for 12-month and 24-month returns, respectively. The new high F-score shows an improvement; the excess market return for a buy-and-hold strategy for 12-month returns grows from 13.33% to 16.17%. For the 24-

month returns, there is a decrease from 13.82% to 12.56%. These results suggest that when for high average portfolios, an FA strategy is more efficient for predicting returns one year ahead.

The replicated analyses for portfolios with high *L-scores* for buy-and-hold 12- and 24-month returns are in Table 6, Panel B. The average annual buy-and-hold returns for the period are about 18.54% for one year and 15.08% for two years, versus 19.58% and 14.42%, respectively. The returns using the market index for the same period are 15.69% for one year and 14.29% for two years, versus 19.26% and 14.47%.

These findings suggest that researchers should examine more sophisticated investment strategies based on FA, including applications of portfolio theory to minimize risk and maximize expected returns.

### 5.3 Robustness tests

Because the *F-score* performs differently in different periods, such as in response to the international financial crisis of 2008–2009 and the sovereign debt crises in Europe (e.g., Kim *et al.*, 2016), we conduct a robustness test in which we split the period of analysis into two periods: pre-crisis (2000–2007) and post-crisis (2008–2014). Appendixes 3 and 4 detail the results, but briefly, we note that in the pre-crisis period, the portfolios for one-year buy-and-hold returns are similar to the results for the full sample. The average returns on portfolios of firms with high versus low *F-scores* are positive and the model is statistically significant at the 1% level before crisis (except for excess return on a two year buy and hold, where it is only statistically significant at 10%) and after crisis only for two years buy and hold.

Before crisis, the average return difference between portfolios with high versus low *L-scores* is -2.59% (6.86%) for buy-and-hold 12-month raw (market-adjusted) returns, though it is not statistically significant. For two-year buy-and-hold strategies, the average returns for portfolios lose statistical significance too. After crisis, *L-score* starts to gain statistical significance, becoming 1% significant for a two buy and hold strategy. For one year buy and hold strategy the model is statistically significance at 1% too what regards to raw returns, but it is only significant at 10% regarding to excess returns. Overall, L-score is more significant after crisis. For example, the average return difference between the raw returns of portfolios of high versus low *L-scores* increases from 9.86% (full period) to 18.61% (post-crisis period), and the model is more statistically significant.

For the new high *F- scores*, the raw returns increase from 32.73% to 37.69%, and the market-adjusted returns increase from 17.72% to 22.66% before crisis – one-year B&H and for two-year B&H we can assist to a raw return improvement but a decrease in the excess return. After crisis, the new score has shown an improvement only in the raw return for a year B&H strategy.

Furthermore, to control for other potential sources of cross-sectional variation in returns, such as momentum (e.g., Chan *et al.,* 1996) or other known returns (Sloan, 1996), in Appendix 5 we provide the results of separate analyses of the value relevance of accounting signals in the pre-crisis (Panel A) and post-crisis (Panel B) periods. Despite the increase in the adjusted R-square value for all specifications (Models 1–6) in the post-crisis period, both *EPS* and *size* lose their statistical significance except in model 6 where we apply fixed effects. Models 3 and 5 confirm the additional explanatory power of the *F-score* after controlling for other variables; the *L-score* is not statistically significant except in Model 6. In general, for the pre-crisis period, the findings remain unchanged, relative to those for the full period.

## 6. Conclusions

This work provides an overview of FA, stressing its importance for investors looking forward 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 pertinent lines of investigation in capital markets accounting research, in this study we focus on value-relevant fundamentals, conditioned 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, based on financial statement analyses, which investors can use to construct portfolios that enable them to earn abnormal returns. This apparent anomaly initially was documented in U.S. markets.

By 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 2.6% - 2.9% across models. The impact of the *L-score* is much lower and only statistically significant in one of the proposed models (Model 6), such that a one-unit increase in this metric is associated with subsequent annual returns that increase only about 1.8%.

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 abnormal returns in portfolios with high scores. By selecting firms with high scores (i.e., *F-score* of 8 or 9), investors can expect raw returns of approximately 18%. In addition, an investment strategy that buys these expected winners and shorts expected losers (i.e., *F-*

*scores* of 0–2) could have generated a 24% annual return between 2000 and 2014 (see also Piotroski, 2000). Portfolios based on high *L-scores* for 12- and 24-month returns also would produce increased raw returns and market excess firm returns. Although a higher *L-score* generally implies higher future returns, the results of this study reveal significant results only for a strategy based on the average of two-year returns. That is, a fundamental strategy is effective for predicting returns one year ahead; with the *L-score* though, it is only statistically significant for a 24-month buy-and-hold strategy, with lower values for the expected returns.

Noting the evidence that accounting fundamental signals can provide important insights to investors choosing their resource allocations, research in European markets should explore this approach further, consider potential alternative explanations for the value relevance of fundamentals, and investigate whether other strategies might predict periods of financial stress. Furthermore, for this study we ensured that all data were available at the time the 'backtest' was run, so there were no survivorship issues, and the observations were based on information that would be available to all investors before they make investment decisions.

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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 earnings change and accounting fundamentals | U.S. | An average 12-month, cumulative, size-adjusted, abnormal return of 13.2% can be earned using a fundamental strategy based on L-scores. A significant portion of the abnormal returns is generated around subsequent earnings announcements. |
| Aggarwal and Gupta (2009) | Follows Piotroski (2000) | Future returns | Accounting fundamentals, BM ratio, size, accruals | India | The Piotroski strategy can separate winners from losers for two-year returns after portfolio formation. It generates 98.6% annual 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 stock divided by percentage gross domestic product, as well as a negative, significant relationship of inflation and lending interest rate. |
| 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, evaluated with a traditional DCF model, has almost a one-to-one effect on the observed E/P when the model is calibrated by the observed historical risk premium. The 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. |
| Dosamantes (2013) | Valuation theory, fundamental analysis, and market under-reaction of high BM ratio firms | Future returns, earnings response coefficient, and | Accounting fundamentals, BM ratio, size | Mexico | The evidence of the value relevance of accounting fundamental signals. The proposed F- and L-scores offer extra explanatory power for future returns beyond |

| | | | | | |
|---|---|---|---|---|---|
| | | future earnings growth | | | 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 short firms with highly favourable analyst recommendations but high interest and buys firms with highly unfavourable analyst recommendations but low interest. |
| Elleuch and Trabelsi (2009) | Valuation theory | Future returns | Accounting fundamentals and accruals | Tunisia | Fundamental accounting signals can discriminate an overall sample generated over a 15-month holding period, with negative returns of –11.6%, a winner portfolio generating a positive return of 1.9%, and a loser portfolio generating a negative return of –22.9% in the same holding period. |
| 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 Bovespa index). |
| Karathanassis and Philippas (1988) | Valuation theory: 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 | US. | The 12 fundamental signals add approximately 70% on average to the explanatory power of earnings with respect to excess returns. |
| Lev *et al.* (2010) | Valuation theory | Future cash flows and future earnings | Accounting fundamentals | U.S. | Accounting estimates beyond those in working capital items (excluding inventory) do not improve predictions of cash flows. Estimates improve the prediction of the next year's earnings, though not of subsequent years' earnings. |
| Midani (1991) | Fundamental analysis | Share prices | Accounting fundamentals | Kuwait (industrial services & food) | In a sample of 19 Kuwaiti companies, EPS is a determinant of share prices. |
| Nisa (2011) | Valuation theory and fundamental analysis | Share prices | Share prices and economic data | Pakistan | Previous year's EPS and company size are important factors for determining stock prices in Pakistan. Macroeconomic indicators like real GDP growth, rate |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | of interest, and financial development have significant impacts. |
| Piotroski (2000) | Valuation theory | Future returns | Accounting fundamentals: BM ratio, size, accruals | U.S. | Mean returns earned by a high BM investors can be increased by at least 7.5% annually through a selection of 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. | Accounting anomaly and FA literature demonstrate the usefulness of accounting information in forecasting future earnings and stock returns. Anomalous return patterns are commonly 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 the corporate governance variables | Taiwan | Corporate governance variables affect the relation between fundamental signals and stock returns. An endogenous switching model combines the response equation and governance index equation. |
| 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 (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 purchasers; 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 operating assets; GDP = gross domestic product.

Table 2. Sample description: Firms in the Euronext 100

Panel A. By stock exchange

| Stock Exchange | Firms listed in any period, 1990–2015 | % | Average market capitalization as of 2014 (in EUR) |
|---|---|---|---|
| Amsterdam | 18 | 19% | 31 052 906 |
| Brussels | 9 | 9% | 21 562 959 |
| Lisbon | 5 | 5% | 7 379 336 |
| Paris | 63 | 66% | 29 354 532 |
| Total/total/average | 95 | 100% | 27 675 550 |

Panel B. By year

| Year | Listed firms |
|---|---|
| 2000 | 71 |
| 2001 | 75 |
| 2002 | 75 |
| 2003 | 75 |
| 2004 | 76 |
| 2005 | 78 |
| 2006 | 81 |
| 2007 | 84 |
| 2008 | 85 |
| 2009 | 87 |
| 2010 | 92 |
| 2011 | 93 |
| 2012 | 95 |
| 2013 | 95 |
| 2014 | 95 |

Source: Euronext 100, European Classification System

Table 3. Descriptive statistics

| Variable | Firm-year observations | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| R | 1195 | 0.1443 | 0.1135 | 0.4989 | -0.9287 | 5.1673 |
| EPS | 1224 | 2.3213 | 1.7940 | 6.4518 | -122.10 | 50.4320 |
| BMR | 1159 | 0.7306 | 0.4146 | 1.2844 | -0.3898 | 18.0290 |
| Log A | 1295 | 7.2445 | 7.1535 | 0.7449 | 4.7049 | 9.3163 |
| F-Score | 1330 | 5.3450 | 5 | 1.9448 | 0 | 9 |
| L-Score | 1330 | 3.9070 | 4 | 1.7714 | 0 | 8 |

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

Table 4. Correlation matrix

| | VIF | R | EPS | BMR | Log A | F-Score | L-Score |
|---|---|---|---|---|---|---|---|
| R | | 1 | | | | | |
| EPS | 1.062 | 0.051$^{*}$ | 1 | | | | |
| BMR | 1.171 | -0.173$^{***}$ | -0.174$^{***}$ | 1 | | | |
| Log A | 1.142 | -0.069$^{**}$ | -0.023 | 0.243$^{***}$ | 1 | | |
| F-Score | 1.096 | 0.131$^{***}$ | 0.077$^{***}$ | -0.193$^{***}$ | -0.097$^{***}$ | 1 | |
| L-Score | 1.221 | 0.045 | -0.092$^{***}$ | -0.245$^{***}$ | -0.266$^{***}$ | 0.389$^{***}$ | 1 |

Notes: 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.

$^{***}$, $^{**}$, and $^{*}$ indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

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$^{*}$ | 0.001 | 0.001 | 0.001 | 0.001 | -0.001 |
| *t-statistic* | *1.76* | 0.81 | 0.92 | 0.92 | 0.95 | -0.30 |
| BMR | | -0.040$^{***}$ | -0.035$^{***}$ | -0.039$^{***}$ | -0.035$^{***}$ | -0.067$^{***}$ |
| *t-statistic* | | -3.09 | -3.54 | -3.90 | -3.50 | -4.68 |
| Size | | -0.075$^{***}$ | -0.076$^{***}$ | -0.074$^{***}$ | -0.076$^{***}$ | -0.212$^{***}$ |
| *t-statistic* | | -4.05 | -3.14 | -3.04 | -3.12 | -3.10 |
| F-score | | | 0.026$^{***}$ | | 0.026$^{***}$ | 0.029$^{***}$ |
| *t-statistic* | | | 3.56 | | 3.43 | 3.67 |
| L-Score | | | | 0.007 | 0.002 | 0.018$^{**}$ |
| *t-statistic* | | | | 0.98 | 0.29 | 2.09 |
| Intercept | 0.312$^{***}$ | 0.755$^{***}$ | 0.599$^{***}$ | 0.715$^{***}$ | 0.589$^{***}$ | 1.508$^{***}$ |
| *t-statistic* | *3.81* | 4.02 | 3.12 | 3.72 | 3.03 | 3.00 |
| Time Dummies | YES | YES | YES | YES | YES | YES |
| Industry Dummies | YES | YES | YES | YES | YES | YES |
| N# obs. | 1185 | 1135 | 1135 | 1135 | 1135 | 1135 |
| Adjusted $R^2$ | 0.403 | 0.410 | 0.416 | 0.410 | 0.416 | 0.435 |

Notes: OLS = ordinary least squares; EPS = earnings per share; BMR = book-to-market ratio. F-score and L-score are as defined in the text.
$^{***}$, $^{**}$, and $^{*}$ indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 6. Buy-and-hold 12-month and 24-month returns by F-score and L-score

Panel A.

Buy-and-hold 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 | 6 | 41,48% | 25,22% | 6 | -24,01% | -10,37% |
| 2 | 21 | -19,40% | -11,63% | 15 | -22,45% | -10,48% |
| 3 | 73 | 7,59% | 5,80% | 70 | -1,88% | 3,73% |
| 4 | 205 | 7,73% | 8,50% | 188 | 2,76% | 7,18% |
| 5 | 228 | 11,24% | 11,37% | 206 | 2,22% | 5,26% |
| 6 | 263 | 16,15% | 13,67% | 244 | 11,35% | 10,94% |
| 7 | 217 | 23,92% | 18,55% | 204 | 17,93% | 12,67% |
| 8 | 133 | 18,22% | 13,51% | 120 | 17,99% | 11,91% |
| 9 | 49 | 17,14% | 12,83% | 47 | 19,93% | 13,72% |
| Low F-Score [0+1+2] | 27 | -5,87% | -3,44% | 35 | -22,51% | -9,19% |
| High F-Score [8+9] | 182 | 17,93% | 13,33% | 141 | 21,52% | 13,82% |
| High-Low | | 23,80% | 16,77% | | 44,04% | 23,02% |
| New High F-Score [7+8+9] | 399 | 21,18% | 16,17% | 371 | 18,20% | 12,56% |
| New High-Low | | 27,06% | 19,61% | | 40,71% | 21,75% |
| t-stat | | $3,68^{***}$ | $2,88^{***}$ | | $8,30^{***}$ | $4,57^{***}$ |
| Total | 1195 | 14,43% | 12,31% | 1100 | 8,99% | 8,91% |

Panel B.

Buy-and-hold 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 |
| 0 | 22 | -13,21% | 0,70% | 22 | 2,83% | 7,63% |
| 1 | 80 | 13,05% | 10,91% | 75 | 3,39% | 4,63% |
| 2 | 116 | 16,19% | 10,78% | 107 | 5,73% | 4,29% |
| 3 | 215 | 14,64% | 12,15% | 197 | 9,07% | 8,94% |
| 4 | 277 | 13,68% | 12,41% | 252 | 6,44% | 7,29% |
| 5 | 244 | 13,15% | 11,23% | 225 | 9,77% | 9,14% |
| 6 | 180 | 18,18% | 14,48% | 164 | 15,31% | 14,22% |
| 7 | 54 | 17,96% | 19,53% | 51 | 12,62% | 14,01% |
| 8 | 7 | 32,12% | 17,24% | 7 | 27,49% | 17,86% |
| Low L-Score [0+1+2] | 218 | 12,07% | 9,81% | 204 | 4,56% | 4,78% |
| High L-Score [7+8] | 61 | 19,58% | 19,26% | 58 | 14,42% | 14,47% |
| High-Low | | 7,51% | 9,45% | | 9,86% | 9,69% |
| New High L-Score [6+7+8] | 241 | 18,54% | 15,69% | 222 | 15,08% | 14,29% |
| New High-Low | | 6,47% | 5,88% | | 10,52% | 9,51% |
| t-stat | | 1,54 | 1,55 | | $3,20^{***}$ | $3,42^{***}$ |
| Total | 1195 | 14,43% | 12,31% | 1100 | 8,99% | 8,91% |

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

The 24-month returns begin three months after the end of the fiscal year, which is December for all firms. Annualized means of the returns are computed.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Appendix 1.** *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 | $\Delta\left(\frac{LTD}{\bar{A}}\right)<0$ | 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; $\bar{A}$ = Average of total assets; $\bar{A} = \frac{A_{t-1}+A_t}{2}$; 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 2.** *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 | $PTE_t \times (T_{t-1} - T_t)$<br>$PTE_t$ = pretax earnings at t, deflated by beginning price<br>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 $Change_{i,t} = \frac{[Inventory_{i,t} - E(Inventory_{i,t})]}{E(inventory_{it})} - \frac{[Sales_{i,t} - E\ (sales_{i,t})]}{E\ (Sales_{i,t})}$;

Inventory $Signal_{i,t}$ = 1 if Inventory Change $_{i,t}$ < 0;0 otherwise;

E $(Inventory_{i,t}) = \frac{[Inventory_{i,t-1} - E\ (Inventory_{i,t-2})}{2}$; 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 two-year average of inventory for the corresponding year, which includes the average of inventory for year t – 1 and t – 2; and

E $(Sales_{i,t})$ = 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.

**Appendix 3.** *Buy-and-hold 12-month and 24-month returns by F-score*

Panel A.
Before crisis (2000 - 2007)

| F-Score | 1 Year B&H | | | 2 Year B&H | | |
|---|---|---|---|---|---|---|
| | N | Mean R | Mean ER | N | Mean R | Mean ER |
| 1 | 4 | -7,07% | -10,89% | 4 | -16,60% | -2,06% |
| 2 | 13 | -14,25% | -1,32% | 8 | -3,63% | 4,25% |
| 3 | 36 | -0,41% | 0,73% | 33 | 5,20% | 6,18% |
| 4 | 112 | 3,88% | 8,08% | 97 | 5,59% | 9,64% |
| 5 | 110 | 4,40% | 9,80% | 89 | 1,22% | 4,52% |
| 6 | 134 | 18,86% | 16,61% | 116 | 16,93% | 13,86% |
| 7 | 130 | 28,76% | 22,70% | 118 | 18,26% | 14,08% |
| 8 | 66 | 18,80% | 14,58% | 54 | 13,28% | 8,49% |
| 9 | 29 | 23,31% | 13,16% | 27 | 22,84% | 13,11% |
| Low F-Score [1+2] | 17 | -12,56% | -3,57% | 12 | -7,95% | 2,15% |
| High F-Score [8+9] | 95 | 20,17% | 14,15% | 81 | 16,47% | 10,03% |
| High-Low | | 32,73% | 17,72% | | 24,42% | 7,88% |
| New High F-Score [7+8+9] | 225 | 25,13% | 19,09% | 199 | 17,53% | 12,43% |
| New High-Low | | 37,69% | 22,66% | | 25,48% | 10,29% |
| t-stat | | $4,55^{***}$ | $2,88^{***}$ | | $3,98^{***}$ | $1,67^{*}$ |
| Total | 634 | 14,00% | 13,36% | 546 | 11,32% | 10,35% |

Panel B.
After crisis (2008 - 2014)

| F-Score | 1 Year B&H | | | 2 Year B&H | | |
|---|---|---|---|---|---|---|
| | N | Mean R | Mean ER | N | Mean R | Mean ER |
| 1 | 2 | 138,59% | 97,45% | 2 | -38,83% | -26,99% |
| 2 | 8 | -27,78% | -28,39% | 7 | -43,96% | -27,31% |
| 3 | 37 | 15,38% | 10,73% | 37 | -8,21% | 1,55% |
| 4 | 93 | 12,36% | 9,00% | 91 | -0,26% | 4,56% |
| 5 | 118 | 17,63% | 12,84% | 117 | 2,98% | 5,82% |
| 6 | 129 | 13,33% | 10,61% | 128 | 6,30% | 8,29% |
| 7 | 87 | 16,68% | 12,35% | 86 | 17,47% | 10,73% |
| 8 | 67 | 17,65% | 12,47% | 66 | 21,83% | 14,70% |
| 9 | 20 | 8,19% | 12,36% | 20 | 15,99% | 14,55% |
| Low F-Score [1+2] | 10 | 5,49% | -3,22% | 9 | -42,82% | -27,24% |
| High F-Score [8+9] | 87 | 15,47% | 12,44% | 86 | 20,47% | 14,67% |
| High-Low | | 9,98% | 15,66% | | 63,29% | 41,91% |
| New High F-Score [7+8+9] | 174 | 16,08% | 12,40% | 172 | 18,97% | 12,70% |
| New High-Low | | 10,58% | 15,61% | | 61,79% | 39,94% |
| t-stat | | 0,20 | 0,80 | | $8,53^{***}$ | $5,73^{***}$ |
| Total | 561 | 14,92% | 11,13% | 554 | 6,69% | 7,50% |

Notes: The 12-month returns begin three months after the end of the fiscal year, which is December for all firms. Geometric means of the returns are computed.
The 24-month returns begin three months after the end of the fiscal year, which is December for all firms. Annualized means of the returns are computed.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Appendix 4.** *Buy-and-hold 12-month and 24-month returns by L-score*

Panel A.
Before crisis (2000 - 2007)

| L-Score | 1 Year B&H | | | 2 Year B&H | | |
|---|---|---|---|---|---|---|
| | N | Mean R | Mean ER | N | Mean R | Mean ER |
| 0 | 10 | -0,62% | 4,59% | 10 | 14,10% | 13,79% |
| 1 | 45 | 4,66% | 5,61% | 40 | 5,56% | 6,39% |
| 2 | 67 | 22,32% | 14,18% | 58 | 12,55% | 7,97% |
| 3 | 99 | 18,30% | 16,08% | 83 | 13,47% | 11,47% |
| 4 | 151 | 13,72% | 13,43% | 126 | 8,15% | 8,83% |
| 5 | 140 | 13,70% | 12,92% | 124 | 12,81% | 11,49% |
| 6 | 94 | 11,23% | 13,96% | 80 | 13,46% | 12,29% |
| 7 | 27 | 10,17% | 16,46% | 24 | 9,80% | 12,45% |
| 8 | 1 | 42,90% | 34,06% | 1 | 42,31% | 21,43% |
| Low L-Score [0+1+2] | 122 | 13,93% | 10,23% | 108 | 10,10% | 7,93% |
| High L-Score [7+8] | 28 | 11,34% | 17,09% | 25 | 11,10% | 12,81% |
| High-Low | | -2,59% | 6,86% | | 1,00% | 4,89% |
| t-stat | | 0,13 | 0,74 | | 0,57 | 1,00 |
| Total | 634 | 14,00% | 13,36% | 546 | 11,32% | 10,35% |

Panel B.
After crisis (2008 - 2014)

| L-Score | 1 Year B&H | | | 2 Year B&H | | |
|---|---|---|---|---|---|---|
| | N | Mean R | Mean ER | N | Mean R | Mean ER |
| 0 | 12 | -23,70% | -2,54% | 12 | -6,57% | 2,49% |
| 1 | 35 | 23,83% | 17,74% | 35 | 0,91% | 2,62% |
| 2 | 49 | 7,80% | 6,13% | 49 | -2,35% | -0,06% |
| 3 | 116 | 11,51% | 8,80% | 114 | 5,88% | 7,10% |
| 4 | 126 | 13,64% | 11,19% | 126 | 4,73% | 5,76% |
| 5 | 104 | 12,41% | 8,95% | 101 | 6,03% | 6,25% |
| 6 | 86 | 25,78% | 15,05% | 84 | 17,07% | 16,06% |
| 7 | 27 | 25,75% | 22,59% | 27 | 15,13% | 15,39% |
| 8 | 6 | 30,32% | 14,44% | 6 | 25,02% | 17,27% |
| Low L-Score [0+1+2] | 96 | 9,71% | 9,28% | 96 | -1,68% | 1,24% |
| High L-Score [7+8] | 33 | 26,58% | 21,11% | 33 | 16,93% | 15,73% |
| High-Low | | 16,87% | 11,83% | | 18,61% | 14,49% |
| t-stat | | $2,66^{***}$ | $1,67^{*}$ | | $4,50^{***}$ | $4,63^{***}$ |
| Total | 561 | 14,92% | 11,13% | 554 | 6,69% | 7,50% |

Notes: The 12-month returns begin three months after the end of the fiscal year, which is December for all firms. Geometric means of the returns are computed.
The 24-month returns begin three months after the end of the fiscal year, which is December for all firms. Annualized means of the returns are computed.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Appendix 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. |
| Panel A: Pre-crisis | | | | | | |
| EPS | 0.005 | 0.007* | 0.007* | 0.007* | 0.007* | 0.007 |
| *t-statistic* | 1.51 | 1.76 | 1.87 | 1.79 | 1.86 | 1.33 |
| BMR | | -0.049** | -0.045** | -0.048** | -0.045** | -0.069** |
| *t-statistic* | | -2.43 | -2.23 | -2.38 | -2.22 | -2.18 |
| Size | | -0.100*** | -0.099*** | -0.100*** | -0.099*** | 0.045 |
| *t-statistic* | | -2.62 | -2.59 | -2.61 | -2.59 | 0.38 |
| F-score | | | 0.025** | | 0.025** | 0.039*** |
| *t-statistic* | | | 2.22 | | 2.18 | 3.12 |
| L-Score | | | | 0.005 | 0.001 | 0.015 |
| *t-statistic* | | | | 0.40 | 0.02 | 1.01 |
| Intercept | -0.032 | 0.766* | 0.581* | 0.741** | 0.580* | -0.454 |
| *t-statistic* | -0.28 | 2.63 | 1.92 | 2.49 | 1.90 | -0.521995 |
| Time Dummies | YES | YES | YES | YES | YES | YES |
| Industry Dummies | YES | YES | YES | YES | YES | YES |
| N# obs. | 628 | 597 | 597 | 597 | 597 | 597 |
| Adjusted $R^2$ | 0.384 | 0.386 | 0.348 | 0.342 | 0.347 | 0.362 |
| Panel B: Post-crisis | | | | | | |
| EPS | 0.002 | -0.001 | -0.001 | -0.001 | -0.001 | -0.004* |
| *t-statistic* | 1.08 | -0.64 | -0.65 | -0.50 | -0.59 | -1.73 |
| BMR | | -0.046*** | -0.043*** | -0.045*** | -0.042*** | -0.097*** |
| *t-statistic* | | -4.45 | -4.13 | -4.29 | -4.06*** | -5.43 |
| Size | | -0.044 | -0.046 | -0.043 | -0.046 | -0.559** |
| *t-statistic* | | -1.53 | -1.62 | -1.48 | -1.59 | -2.16 |
| F-score | | | 0.023*** | | 0.022** | 0.021** |

| | | | | | | |
|---|---|---|---|---|---|---|
| *t-statistic* | | | 2.69 | | 2.52 | 2.18 |
| L-Score | | | | 0.008 | 0.003 | 0.020** |
| *t-statistic* | | | | 1.00 | 0.39 | 2.11 |
| Intercept | 0.278*** | 0.589*** | 0.477** | 0.539** | 0.461** | 4.154** |
| *t-statistic* | 2.96 | 2.63 | 2.11 | 2.35 | 2.00 | 2.18 |
| Time Dummies | YES | YES | YES | YES | YES | YES |
| Industry Dummies | YES | YES | YES | YES | YES | YES |
| N# obs. | 557 | 538 | 538 | 538 | 538 | 538 |
| Adjusted $R^2$ | 0.544 | 0.574 | 0.579 | 0.574 | 0.579 | 0.585 |

Notes: OLS = ordinary least squares; 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. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.