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Value investing: a new SCORE model

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Abstract

Purpose – We propose a new SCORE model, inspired by Piotroski's (2000) well-known F-SCORE. But here we examine past, present, and future earnings forecasts in this binary model, which is also made up of nine signals.

Theoretical framework – This research investigates whether a basic accounting-based fundamental analysis method can affect the distribution of returns earned by an investor when applied to a board portfolio of higher growth stocks with high fundamentals (book value).

Design/methodology/approach – At the end of the fiscal year, we determine the market value of the equity and the BM of the Euronext 100 companies. After forming the BM, we keep the organizations with the highest BM and enough financial statement data to calculate the various performance indicators. The analysis covers the years from 2000 to 2020, a period of 21 years.

Findings – We demonstrate that by selecting businesses with strong fundamentals, a high SCORE investor's yearly mean return can be boosted by at least 30%.

Practical & social implications of research – Concerning the study's weaknesses, one of them is the high SCORE of the model providing limited data, which may skew the conclusions.

Originality/value – This study illustrates how, when applied to a board portfolio of high book-to-market firms with growth potential, a simple accounting-based fundamental strategy can alter the distribution of returns earned by an investor.

Keywords: Capital markets, market efficiency, fundamental analysis, European markets, growth stocks.

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1 Introduction

The efficient market hypothesis (EMH) states that markets incorporate information into stock prices (Fama, 1998; Malkiel, 1987, 2003, 2005). The more information that is incorporated into stock prices and the faster that information is reflected in price fluctuations, the more efficient the market is. While most studies support some level of market efficiency, researchers have discovered some market anomalies that reveal patterns of trading strategies that earned higher ex-post returns than would be expected in efficient markets (Geyfman et al., 2016; Navas & Bentes, 2021).

This research investigates whether a basic accounting-based fundamental analysis method can affect the distribution of returns earned by an investor when applied to a board portfolio of higher growth stocks with high fundamentals (book value). We focus only on high market capitalization stocks, so we do not examine small caps. Extensive research shows the returns of a higher growth stock investment strategy in terms of earnings per share (EPS) and sales growth (e.g., Stallings, 2017; Yeh & Hsu, 2014). We look for companies with a high book-to-market ratio (BM) in addition to high EPS growth in the past and future. Research papers on high BM strategies include those of Cordeiro and Machado (2013), Fama and French (1992), Geyfman et al. (2016), and Piotroski (2000). The strategy's success depends on the high performance of a few firms. In this study, we do not engage in any short selling.

Recent studies on the impact of earnings forecasts have attempted to differentiate between value and growth firms (e.g., high and low book-to-market equity (BE/ME) stocks). Growth stocks, as assessed by the BE/ME ratio, have an asymmetrically strong negative response to negative earnings surprises, according to Skinner and Sloan (2002). Jegadeesh et al. (2004) also believe that financial analysts promote growth stocks to attract institutional investors, who often invest more heavily in growth companies. Individual investors' interest in value stocks peaked, according to La Porta et al. (1997), due to forecast revisions as a result of these firms' better-than-expected earnings reports (Jong & Apilado, 2009).

The purpose of this article is to illustrate that by applying a basic screen based on previous financial performance, investors can build a stronger value portfolio. We show that the average return of a high BM and higher growth company can be significantly increased. Between 2000 and 2020, an investment strategy that buys and holds for one and two years generates an annual return of roughly 37%. The returns from this strategy have shown to be consistent over time and when compared to different investment strategies.

We propose a new SCORE model, inspired by Piotroski's (2000) well-known F-SCORE. But here we examine past, present, and future earnings forecasts in this binary model, which is also made up of nine signals. At the same time, we believe that this model is not only simple to design (allowing investors to use stock screeners, for example), but also contributes to the value investing theory, by targeting companies with strong balance sheets (high BM). Many academics have investigated other binary models, such as L-SCORE (Lev & Thiagarajan, 1993), PEIS (Wahlen & Wieland, 2011), and the Mohanram G-SCORE (Mohanram, 2005).

The main difference between our new SCORE and other scores is that existing scores are based solely on past events (past and present returns and metrics), but we propose (as noted in the previous paragraph) to include future earnings estimates in our binary model. This data is updated every quarter when a firm reports its quarterly results, and investors can also rely on it.

The next section reviews the literature on value investing and fundamental analysis (FA). Section 3 discusses the research strategy, while section 4 discusses the empirical findings. Section 5presents several robustness tests. Section 6 concludes the paper.

2 Literature review and motivation

Value investing, as described by Benjamin Graham and David Dodd, is based on three important features of financial markets. First, the prices of financial securities fluctuate significantly and arbitrarily. Every day, the market sets the price of securities at any given time, and it seems to buy or sell any financial asset. It is prone to a wide range of unpredictable "mood" swings that influence the price at which it is prepared to do business. Second, despite market price fluctuations, many financial assets have underlying or fundamental economic values that are reasonably constant and can be evaluated with reasonable accuracy by an attentive and disciplined investor. In other words, the intrinsic value of the asset is one thing; the current price at which it is traded is quite another (Hanauer et al., 2022). Though value and price may be the same on any given day, they often differ.

And third, a technique of purchasing assets only when their market prices are much lower than their projected intrinsic value would yield higher long-term returns. Benjamin Graham refers to this gap between value and price as "the margin of safety"; ideally, the gap should be around half of fundamental value and no less than one-third of fundamental value (Greenwald et al., 2001).

Mutual fund managers have created, tested, and refined their investment theories over time. One of these ideologies is value investing, which combines FA with well-known concepts such as price-to-book ratio (P/B), margin of safety, competitive advantage, dividend yield, and price-to-earnings ratio (P/E). Several research papers, including those by Piotroski (2000), Beukes (2011), and Sareewiwatthana (2011), have examined the success of this investment strategy, which screens firms based on certain financial measures, as a proxy for value investing. Typically, these techniques outperform the market average while posing less risk (Holloway et al., 2013; Linnenluecke et al., 2017).

Some studies argue that the quality of earnings (as a result of solid fundamentals) may reflect higher returns rather than the reverse, i.e., returns are not directly related to earnings, but earnings are related to good fundamentals. According to Penman (1992) and Abarbanell and Bushee (1998), the core objective of FA should be to project accounting earnings rather than explaining security returns (Bradbury et al., 2021). The authors investigated the relationships between basic signals and future earnings changes, allowing them to directly assess the validity of the economic intuition that underpins the original signal formulation. Lev and Thiagarajan (1993) use a different, less direct method that is based on an assessment of the relationships between basic signals and contemporaneous returns.

2.1 The efficient market hypothesis (EMH)

The efficient market hypothesis (EMH) is a widely accepted theory in financial economics that suggests that stock prices reflect all available information in the market, and it is therefore impossible to consistently beat the market by trading based on publicly available information. However, there are several factors that can cause markets to deviate from this ideal, leading to under/over-reactions to information and an inability to fully incorporate all available information (Fama, 1998, 1970; Timmermann & Granger, 2004).

One major factor is the role of human behavior and emotions in financial decision-making. Behavioral finance studies have shown that investors often exhibit biases and heuristics that lead to irrational decision-making, such as overconfidence, loss aversion, and herding behavior (see, for example, Barberis & Thaler, 2003; Bondt & Thaler, 1985). These biases can lead to market inefficiencies and contribute to under/over-reactions to new information.

Another factor that can contribute to market inefficiencies is the presence of institutional investors and market frictions. Institutional investors, such as mutual funds and pension funds, often have large amounts of assets under management and can have a significant impact on stock prices (see, for example, Greenwood & Thesmar, 2011). In addition, market frictions such as transaction costs and liquidity constraints can prevent all available information from being fully incorporated into stock prices (see, for example, Amihud & Mendelson, 1986).

Overall, while the efficient market hypothesis is a useful theoretical framework for understanding financial markets, there are several factors that can cause deviations from market efficiency in practice. Researchers in finance and economics continue to study these factors and their implications for market behavior and investment strategies.

2.2 High book-to-market and growth of earnings per share strategy

Fundamental strength metrics have been shown to be predictive of future returns in both the accounting and financial literature (e.g., Bradbury et al., 2021; Kumsta & Vivian, 2020; Ng & Shen, 2020; Pätäri et al., 2022; Piotroski, 2000). Dechow et al. (2010) indicate that systematic inaccuracies in market expectations about long-term earnings growth can partially explain the success of contrarian investment techniques and the book-to-market effect. Companies with high book-to-market ratios provide a unique opportunity to test the capacity of simple fundamental analysis heuristics to distinguish between them (Caglayan et al., 2018; Pätäri et al., 2022; Piotroski, 2000).

Ball et al. (2020), Papadamou et al. (2017), and Piotroski (2000) argued that high BM value enterprises employ accounting indicators of financial soundness to distinguish really distressed firms from out-of-favor but financially strong firms. This is consistent with research that suggests that, although the return on growth or glamour companies is mostly driven by momentum (Asness, 1997), the evaluation of value stocks should be based on firm fundamentals as reflected in financial statements. Investing using momentum factors in conjunction with fundamental variables has proven to be profitable (Guerard Jr. et al., 2012). According to Piotroski (2000), financial reports are likely to provide the greatest and most important information that can be used to estimate the future performance of high BM organizations (Greyfman et al., 2019; Linnenluecke et al., 2017).

With regards to momentum, Leivo and Pätäri (2011) state that while momentum investing has been shown to perform best in the short term (Hanauer et al., 2022), value investing has been shown to perform better over longer holding periods. For example, the annualized returns of value portfolios constructed using P/E ratios increase as the holding period exceeds the most commonly used investment horizon of 12 months (Leivo & Pätäri, 2011; Basu, 1977).

2.3 Financial performance signals used to differentiate high BM and GEPS firms

The average high-BM company is in financial trouble (e.g., Fama & French, 1992 and Fama, 1998). Low margins, profitability, cash flows, and liquidity, as well as rising and/or excessive levels of financial leverage, are all linked to this distress (Piotroski, 2000).

Most investors rely heavily on non-financial information when valuing growth stocks, which is often based on long-term estimates of sales and the resulting cash flows (Piotroski, 2000). Earnings information is used by investors in stock valuation decisions because earnings news is correlated with stock market features that emerge when investors change their stock valuations (Stallings, 2017). According to Jong and Apilado (2009), forecasts and EPS have a cointegrating relationship for all companies in the value and growth stock groups, meaning that forecasts and EPS data have a long-run equilibrium relationship.

Stallings (2017) investigates the role of financial statement comparability in stock price sensitivity to firm earnings news, and the findings suggest that the information content of earnings is higher for firms with higher comparability, implying that comparability continues to be useful to investors in stock valuation decisions (Linnenluecke et al., 2017). According to Starlings' research, comparability improves utility by increasing the response to good earnings shocks. This effect is particularly evident for earnings announcements from small businesses, firms with high volatility, growth/value firms, and firms with low return on assets, implying that comparability is more informative for more speculative stocks.

Caglayan et al. (2018) compare the characteristics of growth stocks bought by hedge funds with those of growth stocks heavily bought by non-hedge funds and find some minor differences in characteristics such as book-to-market ratio, size, price, demand, idiosyncratic volatility, illiquidity, intangible returns, and standardized earnings surprises. Controlling for these stock features in Fama and MacBeth's (1973) multivariate regressions does not diminish the predictive power of hedge fund trading (demand) over the cross-sectional variance of future stock returns (Hanauer et al., 2022).

We chose nine key indicators to assess the financial health of companies: profitability, financial leverage/liquidity, operating efficiency, and growth (sales and EPS). As summary performance data, the signals employed are easy to interpret, implement, and understand. Depending on the signal's implications for future prices and profitability, we classify each company's signal realization as "good" or "poor."

If a signal's realization is good, the indicator variable for the signal is equal to one (zero if bad). The sum of the nine binary signals is used to calculate the aggregate signal measure, the SCORE. The aggregate signal is used to assess the overall quality or strength of a company's financial position, and the strength of the aggregate signal is ultimately used to make a purchasing decision.

With respect to the financial growth signals EPS and sales, the PEIS Score authors, Wahlen and Wieland (2011), investigate whether investors can use financial statement information to identify companies with a higher likelihood of future earnings growth, and whether the stocks of those companies generate one-year abnormal returns that outperform those generated by following analysts' consensus recommendations. The method converts financial statement data into a "predicted earnings growth score," which measures the likelihood of one-year earnings growth. The authors find that stocks with high scores are substantially more likely to have future earnings increases than stocks with low scores in the sample of consensus recommendations.

Wieland (2011) finds that in 28.9% of firm-year observations, consensus analyst forecasts incorrectly indicate an increase in one-year-ahead earnings, and that correct (incorrect) businesses achieve 14.8% (25.7%) abnormal returns over the next year, on average. See also Amira and Hafssa (2021), Bradbury et al. (2021), and Caglayan et al. (2018). We use estimated growth of EPS for the next 5 years: GEPS 5y (FW) > 10%, estimated growth of EPS for next year: GEPS (FW) > 10%, past GEPS 5y > 10% and past sales 5y > 10%.

With regards to return on equity (ROE), according to Bourguignon and Jong (2003), Brush (2007), Gallagher et al. (2022), and Lameira et al. (2013), high-growth stocks, which typically have higher ROE, have higher returns than low-growth stocks (lower ROE). Stocks with both high value and strong growth characteristics generate higher returns than stocks with only one of these attributes (Garcia et al., 2018; Yeh & Hsu, 2014; Yen et al., 2004). Gallagher et al. (2022) also used this approach to identify global equity fund exposures to six stock and three currency determinants, as well as how these exposures relate to performance, and they discovered that strong momentum and high ROE provide a statistically significant positive alpha. We use current ROE > 10%.

We also look at leverage and liquidity. Debt is forced on enterprises whose ability to self-finance their obligations or new investments remains insufficient in an environment where every financial resource is vital to finance the production of wealth and, hence, the increase in the value of the company (Molay, 2010). For certain companies, covering needs with medium- and long-term debt, regardless of the nature of the debt, will put the company in a position of insolvency in the eyes of bondholders, causing its value to fluctuate according to the level of debt chosen, or even according to its exposure to the risk of bankruptcy (Amira & Hafssa, 2021). Debt is also a multidimensional signal, it is the result of a need for financing in the face of expansion potential (Ding et al., 2020), but it can also be seen by others as an indication of financial difficulties (Amira & Hafssa, 2021; Baraccat et al., 2020; Gallagher et al., 2022). We use total debt/total equity: Debt/Eq < 2 and current ratio: CR > 1.

With regards to financial performance signals, we also rely on operating efficiency. Companies with high margins have inspired portfolio managers to maintain a stock in their assets under management, according to Holloway et al. (2013), who have contributed to value investing research. In their study of Warren Buffett's investment strategy, Buffett and Clark (2008) attempted to construct a criterion for identifying companies with competitive advantages. According to the authors, companies with gross profit margins above 40% have a competitive edge. A gross profit margin of 20% or less indicates a fiercely competitive market (Holloway et al., 2013). See also Abarbanell and Bushee (1998) and Piotroski (2000). We use operating margin: OM > 15% and net profit margin: NPM > 10%.

2.3.1 *Composite score*

We define SCORE as the sum of the individual binary signals, as shown in Equation 1:

$$\begin{aligned} SCORE &= S1\ GEPS\ 5y(FW) + S2\ GEPS\ 5y + \\ & S3\ Sales + S4\ ROE + S5\ OM + S6\ Debt/Eq + \\ & S7\ GEPS(FW) + S8\ NPM + S9\ CR \end{aligned} \tag{1}$$

where GEPS 5y (FW) = growth of earnings per share for five years (forward); ROE = return on equity; OM = operating margin; Eq = equity; GEPS (FW) = growth of earnings per share for one year (forward); NPM = net profit margin; and CR = current ratio.

The SCORE varies from 0 to 9, based on the nine underlying signals, with a low (high) SCORE indicating a company with few (mainly) positive signals. We expect the SCORE to be positively related to changes in future company performance and stock returns to the extent that current fundamentals predict future fundamentals. The investment method outlined in this paper, like F-SCORE (Piotroski, 2000) and L-SCORE (Lev & Thiagarajan, 1993), focuses on selecting firms with high SCORE signals rather than acquiring firms based on the relative realization of any given signal. The aggregate of these nine binary signals is used to make an investment decision.

3 Research design

We look at the top 98 companies on the Euronext stock exchange (see Supplementary Material - Euronext 100). These include firms from France, the Netherlands, Belgium, Portugal, and Luxembourg. We research companies in the Euronext 100 index. At the end of the fiscal year, we determine the market value of equity and BM. We examine the financial report every fiscal year. We also determine a company's size by looking at the market capitalization (MC) distribution from the fiscal year. After forming the BM, we keep the organizations with the highest BM and enough financial statement data to calculate the various performance indicators. The analysis covers the years from 2000 to 2020, a period of 21 years.

Company-specific returns are defined as one-year (two-year) buy-and-hold returns obtained from the beginning of the fourth month following the fiscal year end. We chose the fourth month to ensure that investors have access to the relevant annual financial data at the time of portfolio building. Stock splits, reverse splits, and dividends paid are all factored into the adjusted returns. Financial data were retrieved using Datastream, and econometric models and statistics were calculated using EViews.

To investigate the influence of price to earnings (P/E) - Equation 2 - and price to earnings forward (P/E FW) – Equation 3 - on company returns with and without the control variables of firm size, the following regression models are proposed:

$$R_{it} = \alpha + \beta_1 \times PE_{it} + \varepsilon_{it} \tag{2}$$

$$R_{it} = \alpha + \beta_1 \times PE\left(FW\right)_{it} + \varepsilon_{it} \tag{3}$$

where R_{it} represents the 12-month company returns, PE_{it} represents the price to earnings ratio of the current period, and $PE\left(FW\right)_{it}$ denotes the price to earnings ratio ahead of the current period. Rt is defined as

In Equation 4 (Model 3), we test PE(FW) and SIZE:

$$R_{it} = \alpha + \beta_1 \times PE\left(FW\right)_{it} + \beta_2 \times SIZE_{it} + \varepsilon_{it} \tag{4}$$

where $SIZE_{it}$ represents the logarithm of market capitalization of the current period

In Equation 5 (Model 4), we put all variables together, PE(FW), SIZE and the SCORE:

$$R_{it} = \alpha + \beta_1 \times PE\left(FW\right)_{it} + \beta_2 \times SIZE_{it} + \beta_3 \times SCORE_{it} + \varepsilon_{it} \tag{5}$$

Similar to Piotroski (2000), the basic methodology of this study is to create portfolios based on the firm's aggregate score. Low SCORE firms are those with the lowest aggregate signals (SCORE of 0 or 1), and we predict that they will have the worst stock performance in the future. Companies with the highest scores (i.e., SCORE of 8 or 9) have the strongest fundamental signals and are classed as high SCORE companies. Given the strength and consistency of their fundamental signals, we expect these companies to have the strongest subsequent return performance. This study is designed to see if the high SCORE portfolio outperforms other companies.

The first test compares high SCORE company returns to low SCORE company returns, while the second test compares high SCORE companies to the entire portfolio of all high fundamentals companies. Given the controversy surrounding the use of parametric test statistics in the context of long-term returns (e.g., Kothari & Warner, 1997; Barber & Lyon, 1997), the primary findings are validated using the traditional t-statistics approach to test whether SCORE can capture future returns (e.g., Piotroski, 2000).

Price data were collected from the Refinitiv database for all companies in the Euronext 100 index between April of 2000 and March of 2021. Monthly asset data are used to calculate returns. Figure 1 shows the fluctuations in monthly returns and illustrates the synchronized behavior of the returns compared to the prices of the index. Clusters are evident and volatility is present throughout the period. It is also noted that the spikes differ in time, especially in 2001-2002 (tech bubble), 2008-2009 (stock market crash), and 2020 (COVID). Compared to the following figure (Figure 2), the coordinated behavior of returns compared to prices is evident. The spikes are a lot more noticeable. It also gives a good picture of the volatility clusters.

If we take a closer look at the SIZE and BM (SCORE) of the companies by year (Figure 3), we see that SIZE is more stable (shows less variation) than BM. We see only a slight decrease during the crisis periods mentioned in the previous paragraph (2002-2003 and 2008-2009). Regarding BM, a significant decrease is noticeable in the last year of observation, i.e. 2020, during the COVID-19 crisis, which halted the economy. The second significant decrease is noticeable in 2014 and 2015, two years after the subprime crisis in 2012. The best period for BM was between 2004 and 2005, before the stock market crash in 2008.

This research aims to investigate whether a basic accounting-based fundamental analysis method can influence the distribution of returns earned by an investor. To achieve this goal, we propose the following hypotheses:

H1: Can applying a basic accounting-based fundamental analysis method to a broad portfolio of higher growth stocks with high fundamentals (book value) impact the distribution of returns earned by an investor?

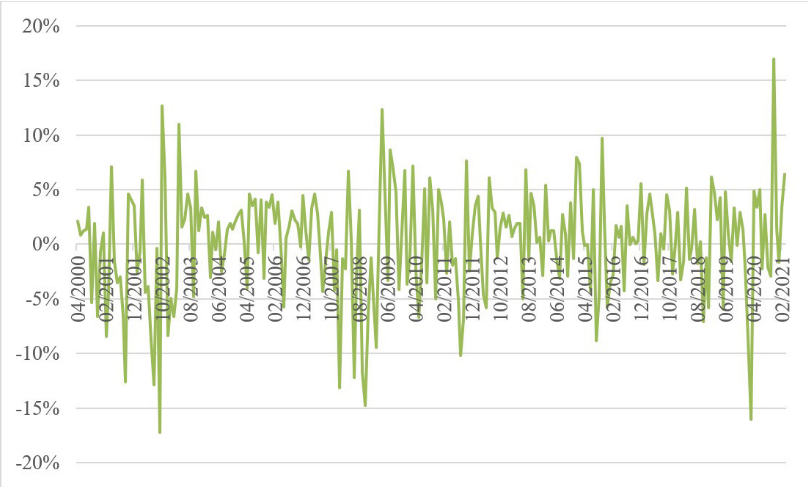

Figure 1. Monthly returns of the Euronext 100 index

Figure 2. Price evolution of the Euronext 100 index (accumulated returns)

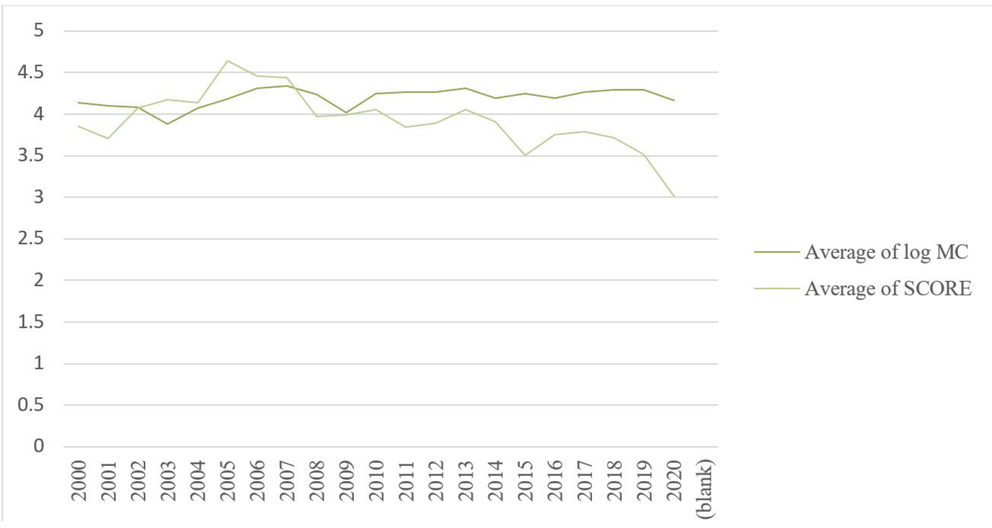

Figure 3. Average of SIZE (log MC) and BM (SCORE) per year

H2: Does investing in companies with high BM and greater growth lead to a significantly higher average return?

H3: Considering that SCORE incorporates future earnings projections, does it offer any advantages over other binary models such as F-SCORE and L-SCORE?

4 Empirical results

4.1 Descriptive statistics

Table 1 shows descriptive statistics for the financial characteristics of high-SCORE enterprises, as well as evidence of portfolio returns.

The average (median) company in the SCORE quantile of all companies has a mean SCORE ratio of 3.93 (4.00), as indicated in panel A. The portfolio of high BM companies consists of low performing enterprises, as shown by Fama and French (1992) and Piotroski (2000); the average (median) sales growth in the last five years of realization is -0.0024 (0.0244) and the predicted EPS growth for the upcoming fiscal year is -0.0566 (0.0372). In terms of high P/Es, negative P/Es were converted to high values (999) in order to choose companies with positive P/Es and avoid distorting the results, because a negative P/E does not imply that the stock is cheap. The median, on the other hand, does not have this problem.

In terms of distribution, the kurtosis is quite high, greater than 3, except for SCORE. The Jarque-Bera test has a statistical significance of 1% (except for SCORE), indicating that all ratios except SCORE do not fit a normal distribution. The negative skew variants of SCORE, GEPS, and Sales have a larger left tail than

Table 1
Statistical description

Panel A: Financial characteristics							
Variable	**Mean**	**Median**	**Standard deviation**	**Skewness**	**Kurtosis**	**J.B. test**	**Proportion with positive sign**
P/E	147.00	17.99	432.3311	7.83	108.44	981364 **	n/a
P/E FW	154.80	17.27	410.1183	6.18	75.16	474324 **	n/a
SIZE	4.20	4.08	0.8006	1.20	3.07	1243 **	n/a
SCORE	3.93	4.00	1.6202	-0.0151	0.0085	0.0806	n/a
GEPS 5y (FW)	0.0170	0.0378	0.2792	-0.6850	5.5225	2647 **	0.25
GEPS 5y	0.0114	0.0310	0.2675	-0.5175	4.4212	1686 **	0.25
Sales	-0.0024	0.0244	0.1830	-2.9511	15.98597	23739 **	0.13
ROE	0.2696	0.2079	0.5250	9.7374	136.18	1547109 **	0.73
OM	0.1816	0.1076	0.4372	7.7909	104.79	917456 **	0.33
Debt/Eq	0.9080	0.5913	1.5324	9.1158	193.41	3085367 **	0.86
GEPS (FW)	-0.0566	0.0372	12.133	-25.536	745.56	45654461 **	0.39
NPM	0.0933	0.0607	0.3541	7.9646	186.96	2878134 **	0.27
CR	1.2796	1.1454	0.6434	3.0927	20.785	38445 **	0.62
Panel B: Buy-and-hold returns from a high score investment strategy							
Returns	**Mean**	**10th percentile**	**25th percentile**	**Median**	**75th percentile**	**90th percentile**	**Percentage positive**
One-year returns							
Raw	0.4104	-0.1377	0.0500	0.1998	0.4796	1.6078	0.8182
Market-adjusted	0.3602	-0.1481	-0.0194	0.1605	0.3857	1.8105	0.6364
Two-year returns							
Raw	0.3734	-0.1321	0.0835	0.2429	0.4981	1.1655	0.8182
Market-adjusted	0.2734	-0.0816	-0.0043	0.1719	0.3038	1.2374	0.6364
Company-Year Observations		1962					

Note: J.B. test = Jarque-Bera test; P/E = price to earnings; P/E (FW) = price to earnings forward; SIZE = log MC (market capitalization); GEPS 5y (FW) = estimated growth of earnings per share 5 years forward; GEPS 5y = growth of earnings per share for last 5 years; ROE = current return on equity; OM = operating margin; Debt/Eq = debt/ equity; GEPS (FW) = estimated growth of earnings per share forward (for next fiscal year); NPM = net profit margin; CR = current ratio. Statistical significance: **p-value<0.01.

the normal distribution, with the values being the most negatively skewed. This suggests that, on average, these measures have more sharply negative values than positive values. Because there are no negative values in the case of SCORE, it can be concluded that most businesses have low score values. The existence of fat tails is demonstrated by the higher kurtosis values detected in all series (except SCORE), with future GEPS being the most leptokurtic. As a result, severe occurrences are increasingly common.

Panel B shows the one-year and two-year buy-and-hold returns of the total portfolio of high BM firms, as well as the percentage of firms in the portfolio with positive raw and market-adjusted returns over the corresponding investment horizons. The high BM companies earn positive market-adjusted returns in the one-year and two-year periods after portfolio construction. This is also supported by Dosamantes (2013), Fama and French (1992), Greyfman et al. (2019), Pätäri et al. (2022), and Piotroski (2000).

4.2 Returns on a FA strategy

The Spearman correlations between the individual fundamental signal indicator variables, the aggregate fundamental signal SCORE, and the one-year and two-year buy-and-hold adjusted returns, are all shown in Table 2.

As expected, SCORE has a significant positive association with one-year and two-year returns (0.166 and 0.248, respectively). For one-year forward adjusted returns, the three greatest individual explanatory factors are P/E FW (-0.392), GEPS FW (0.253), and P/E (-0.184). When compared to the two-year buy-and-hold strategy, however, SCORE jumps to second place, with only P/E FW remaining in first. This suggests that when price matters (particularly forward price metrics), SCORE is likely to outperform a simple strategy alone.

Table 3 shows the results for the basic investment approach. Panel B shows one-year market-adjusted returns. The conclusions and findings are comparable when raw returns (Panel A) and a two-year investment horizon (Panel C) are used.

As shown in Panel B, high-scoring firms outperform low-scoring ones, with mean market-adjusted returns of 0.360 vs. 0.008, respectively. The average return difference over a year is 0.352. A second comparison shows the difference in return between the portfolio of high SCORE firms and the whole portfolio. As shown, high SCORE firms achieve a mean market-adjusted return of 0.360 vs. 0.053 for the entire BM quantile, with a significant difference of 0.307.

The return improvements exceed the average performance of the various portfolios. The investment strategy, as described in the introduction, is intended to alter the overall distribution of returns generated by a high BM investor. Consistent with that goal, the results

Table 2
Correlation analysis between the nine fundamental signals and SCORE

	R	R 2y	log MC	P/E	P/E (FW)	GEPS (FW)	GEPS5y	GEPS5y (FW)	Sales5y	ROE	CR	Debt/ Eq	OM	NPM	SCORE
R	1.000	0.710**	-0.153**	-0.184**	-0.392**	0.253**	0.060*	0.065*	-0.007	0.091**	0.041	-0.031	0.069**	0.065**	0.166**
R 2y	0.710**	1.000	-0.077**	-0.208**	-0.304**	0.182**	0.163**	0.030	0.051*	0.213**	0.062**	-0.068**	0.166**	0.197**	0.248**
log MC	-0.153**	-0.077**	1.000	0.055*	0.133**	-0.058*	0.055*	-0.188**	0.036	0.069**	-0.144**	0.046	0.135**	0.143**	-0.016
P/E	-0.184**	-0.208**	0.055*	1.000	0.573**	0.150**	-0.332**	0.267**	-0.061*	-0.315**	-0.035	0.057*	-0.279**	-0.461**	-0.248**
P/E (FW)	-0.392**	-0.304**	0.133**	0.573**	1.000	-0.512**	-0.111**	0.008	-0.013	-0.169**	-0.010	0.034	-0.143**	-0.189**	-0.288**
GEPS (FW)	0.253**	0.182**	-0.058*	0.150**	-0.512**	1.000	-0.143**	0.313**	-0.011	0.025	-0.035	-0.004	0.001	-0.082**	0.290**
GEPS5y	0.060*	0.163**	0.055*	-0.332**	-0.111**	-0.143**	1.000	-0.185**	0.381**	0.291**	-0.014	-0.050*	0.226**	0.383**	0.400**
GEPS5y (FW)	0.065*	0.030	-0.188**	0.267**	0.008	0.313**	-0.185**	1.000	0.022	-0.012	-0.039	-0.007	0.023	-0.089**	0.303**
Sales5y	-0.007	0.051*	0.036	-0.061*	-0.013	-0.011	0.381**	0.022	1.000	0.202**	-0.010	-0.057*	0.089**	0.086**	0.289**
ROE	0.091**	0.213**	0.069**	-0.315**	-0.169**	0.025	0.291**	-0.012	0.202**	1.000	-0.110**	0.271**	0.465**	0.360**	0.371**
CR	0.041	0.062**	-0.144**	-0.035	-0.010	-0.035	-0.014	-0.039	-0.010	-0.110**	1.000	-0.283**	-0.031	-0.004	0.256**
Debt/Eq	-0.031	-0.068**	0.046	0.057*	0.034	-0.004	-0.050*	-0.007	-0.057*	0.271**	-0.283**	1.000	0.125**	-0.052*	-0.090**
OM	0.069**	0.166**	0.135**	-0.279**	-0.143**	0.001	0.226**	0.023	0.089**	0.465**	-0.031	0.125**	1.000	0.831**	0.566**
NPM	0.065**	0.197**	0.143**	-0.461**	-0.189**	-0.082**	0.383**	-0.089**	0.086**	0.360**	-0.004	-0.052*	0.831**	1.000	0.544**
SCORE	0.166**	0.248**	-0.016	-0.248**	-0.288**	0.290**	0.400**	0.303**	0.289**	0.371**	0.256**	-0.090**	0.566**	0.544**	1.000

Note: R = one-year return; R 2y = two-year return; MC = market capitalization; P/E = price to earnings; P/E (FW) = price to earnings forward; GEPS (FW) = estimated growth of earnings per share forward (for next fiscal year); GEPS 5y = growth earnings per share for last 5 years; GEPS 5y (FW) = estimated growth of earnings per share 5 years forward; ROE = current return on equity; CR = current ratio; Debt/Eq = debt/equity; OM = operating margin; NPM = net profit margin. Statistical significance: **p-value<0.01; *p-value<0.05.

Table 3
Buy-and-hold returns for a value investment strategy based on fundamental signals

	Mean	10%	25%	Median	75%	90%	% Positive	*n*
Panel A: One-Year Raw Returns								
All Firms	0.093	-0.357	-0.139	0.053	0.272	0.512	0.580	1962
SCORE								
0	0.067	-0.533	-0.255	-0.001	0.391	1.048	0.232	56
1	0.044	-0.514	-0.274	0.013	0.302	0.627	0.451	51
2	0.025	-0.449	-0.206	-0.011	0.194	0.516	0.452	241
3	0.048	-0.418	-0.191	0.016	0.211	0.494	0.498	444
4	0.079	-0.321	-0.123	0.062	0.249	0.462	0.594	465
5	0.126	-0.323	-0.090	0.111	0.318	0.492	0.620	382
6	0.177	-0.266	-0.057	0.114	0.336	0.600	0.633	218
7	0.201	-0.308	-0.069	0.182	0.363	0.658	0.687	83
8	0.414	-0.138	0.046	0.174	0.388	1.608	0.765	17
9	0.400	n/a	0.064	0.287	0.791	n/a	1.000	5
Low Score	0.056	-0.524	-0.264	0.006	0.349	0.847	0.336	107
High Score	0.410	-0.138	0.050	0.200	0.480	1.608	0.818	22
High-All	0.317	0.219	0.189	0.147	0.208	1.095	0.238	---
High-Low	0.354	0.386	0.314	0.194	0.131	0.761	0.482	---
Panel B: One-Year Market-Adjusted Returns								
All Firms	0.053	-0.269	-0.131	0.020	0.184	0.375	0.539	1962
SCORE								
0	0.028	-0.432	-0.203	0.054	0.217	0.686	0.411	56
1	-0.014	-0.391	-0.230	-0.035	0.122	0.444	0.373	51
2	-0.029	-0.358	-0.214	-0.045	0.102	0.334	0.402	241
3	0.017	-0.315	-0.173	-0.015	0.150	0.359	0.446	444
4	0.043	-0.244	-0.124	0.007	0.175	0.352	0.499	465
5	0.098	-0.182	-0.068	0.071	0.238	0.375	0.599	382
6	0.118	-0.148	-0.059	0.098	0.208	0.356	0.601	218
7	0.169	-0.202	-0.039	0.119	0.264	0.478	0.627	83
8	0.358	-0.148	-0.009	0.077	0.290	1.810	0.647	17
9	0.368	n/a	-0.053	0.444	0.712	n/a	0.600	5
Low Score	0.008	-0.412	-0.216	0.012	0.172	0.571	0.393	107
High Score	0.360	-0.148	-0.019	0.160	0.386	1.810	0.636	22
High-All	0.307	0.121	0.112	0.140	0.201	1.436	0.097	---
High-Low	0.352	0.264	0.196	0.149	0.214	1.240	0.244	---
Panel C: Two-Year Raw Returns								
All Firms	0.086	-0.217	-0.068	0.070	0.217	0.378	0.626	1879
SCORE								
0	0.001	-0.427	-0.242	0.000	0.146	0.599	0.250	55
1	-0.046	-0.510	-0.161	-0.020	0.132	0.346	0.373	48
2	0.002	-0.279	-0.121	0.000	0.101	0.278	0.456	236
3	0.042	-0.267	-0.105	0.023	0.161	0.352	0.525	421
4	0.086	-0.199	-0.053	0.061	0.204	0.353	0.583	437
5	0.123	-0.166	-0.002	0.105	0.240	0.386	0.675	367
6	0.156	-0.139	-0.002	0.121	0.266	0.459	0.693	213
7	0.255	-0.102	0.004	0.180	0.369	0.578	0.735	80
8	0.354	-0.132	0.067	0.214	0.412	1.165	0.765	17
9	0.440	n/a	0.138	0.340	0.792	n/a	1.000	5
Low Score	-0.021	-0.466	-0.204	-0.009	0.139	0.481	0.307	103
High Score	0.373	-0.132	0.083	0.243	0.498	1.165	0.818	22
High-All	0.287	0.085	0.151	0.173	0.281	0.787	0.192	---
High-Low	0.394	0.333	0.288	0.252	0.359	0.684	0.511	---
Panel D: Two-Year Market-Adjusted Returns								
All Firms	0.052	-0.190	-0.083	0.031	0.148	0.287	0.580	1879
SCORE								
0	-0.003	-0.307	-0.164	-0.009	0.095	0.434	0.393	55
1	-0.078	-0.368	-0.176	-0.057	0.047	0.244	0.255	48
2	-0.029	-0.261	-0.126	-0.018	0.072	0.183	0.415	236
3	0.017	-0.217	-0.110	0.000	0.106	0.237	0.439	421
4	0.045	-0.168	-0.076	0.009	0.119	0.281	0.501	437
5	0.089	-0.139	-0.011	0.066	0.175	0.316	0.657	367
6	0.120	-0.087	0.000	0.078	0.211	0.312	0.697	213
7	0.227	-0.087	-0.001	0.154	0.279	0.464	0.627	80
8	0.269	-0.082	-0.001	0.138	0.219	1.237	0.647	17
9	0.288	n/a	-0.017	0.289	0.593	n/a	0.600	5
Low Score	-0.038	-0.335	-0.169	-0.031	0.073	0.345	0.329	103
High Score	0.273	-0.082	-0.004	0.172	0.304	1.237	0.636	22
High-All	0.222	0.108	0.079	0.141	0.155	0.950	0.056	---
High-Low	0.311	0.254	0.165	0.203	0.231	0.892	0.308	---

in Table 3 show that the 10th, 25th, 50th (median), 75th, and 90th percentile returns of the high SCORE portfolio are much greater than the comparable returns of the two low SCORE portfolios.

To conclude this subsection, we answer the three proposed hypotheses. The first hypothesis is validated since the complete distribution of realized returns shifts to the right, automatically validating H2, which shows that high-score stocks (8-9) have a market excess return of 36% over one year and 27% over two years.

Regarding H3, research (unrelated to the purpose of this paper) conducted by the same authors tested F-SCORE and L-SCORE for the same firms and over the same time period. Additional information is available upon request. Table 4 compares the new SCORE, which includes projected earnings, with the conventional scores (F-SCORE and L-SCORE).

Comparing these binary scores shows that SCORE has two advantages and one disadvantage. Regarding the advantages, the gains are higher for a one-year buy-and-hold strategy, as well as for a two-year buy-and-hold strategy. Specifically, for the two-year buy-and-hold strategy, the traditional scores lose steam, while the new SCORE proves to be more resilient. There are two explanations for this.

First, as mentioned above, SCORE includes two of the nine factors, namely future earnings expectations for the next year and the next five years. This encourages investors to hold their stocks over a longer term, even if the actual results do not meet expectations.

Second, the construction of the model is different from traditional models. Rather than comparing the current state of the firm with the past, the new model focuses on the company's present and future prospects. This approach places more emphasis on the company's fundamentals and less on year-to-year fluctuations, which encourages investors to hold their stocks for longer.

However, the disadvantage of SCORE is its low score, which does not capture as much as traditional models. In the short term (one year), it does not allow investors to hedge their portfolios by buying high scores and selling low scores. This effect, however, is reduced when investors hold their stocks for longer periods (two years or more).

There are, however, some concerns about the model that need to be addressed. The number of high-score observations is low, which may introduce some bias, and the model needs to be tested on other indices to understand its behavior in other markets.

5 Other sources of cross-sectional variation in returns

The observed return pattern could be driven by a link between SCORE and another known return pattern, such as momentum, size, or the influence of accounting ratios. These concerns are addressed in this section. First, Table 5 shows the average of the accounting metrics of the portfolios with high and low SCORE firms, and as can be observed, firms with a high SCORE have stronger earnings growth (past and predicted), sales, and higher values of performance measures such as return on equity and margins. Furthermore, the debt ratios seem better in high SCORE firms than in low SCORE firms (lower debt to equity, higher current ratio).

Table 5 shows that the price metrics and size are statistically significant. P/E has a positive sign (which was expected to be negative), but this is rectified by P/E FW. ROE, OM, NPM and past and predicted GEPS also show statistical significance. OM has an opposite sign to what was expected, which is common in some similar research (for gross margin ratio), but which may also be applicable to OM (see Abarbanell & Bushee, 1998; Lev & Thiagarajan, 1993; Piotroski, 2000), and the rationale is that businesses with low margins have more opportunities to improve their margins than firms with already high values of this metric (Graham et al., 2003). The most statistically significant accounting ratio is ROE (*t*-statistic = 5.21), which is followed by the predicted GEPS for the coming year.

Table 4
Comparison between the new SCORE and traditional scores (F-SCORE and L-SCORE)

	1 Year B&H			2 Year B&H		
	SCORE	**F-SCORE**	**L-SCORE**	**SCORE**	**F-SCORE**	**L-SCORE**
Low Score	0.056	-0.092	-0.033	-0.021	-0.010	0.026
High Score	0.411	0.164	0.218	0.374	0.119	0.143
High-Low	0.355	0.257	0.251	0.394	0.129	0.117

Second, in Table 6, Panel A shows the results of a pooled regression; Panel B shows the time-series average of the coefficients from 21 annual regressions, as well as *t*-statistics based on the experimentally obtained time-series distribution of coefficients.

Models 1-4 (Panel A) in Table 6 are detailed in Subchapter 3.3 (equations 2 to 5). The results of the cross-section and period fixed effect regressions are shown in Panel B. Model 1 is a one-year buy-and-hold investment, whereas Model 2 is a two-year buy-and-hold investment.

Table 5
Average of the accounting metrics for the portfolios of high and low score firms

Variable	All firms	High SCORE firms	Low SCORE firms	High-low difference	t-statistic (p-value)
P/E	147.00	16.39	555.47	-539.09	2.22 **
P/E FW	154.80	13.44	444.20	-430.75	-3.33 ***
SIZE	4.200	4.077	4.247	-0.170	-3.62 ***
GEPS 5y (FW)	0.017	0.185	-0.140	0.325	-0.43
GEPS 5y	0.011	0.220	-0.495	0.714	3.28 ***
Sales	-0.002	0.220	-0.495	0.714	-0.49
ROE	0.270	0.361	-0.068	0.429	5.21 ***
OM	0.182	0.299	-0.051	0.351	-3.26 ***
Debt/Eq	0.908	0.486	2.895	-2.409	-0.91
GEPS (FW)	-0.057	0.467	-0.896	1.363	4.02 ***
NPM	0.093	0.195	-0.175	0.369	2.38 **
CR	1.280	1.880	0.990	0.890	1.95 *

Notes: P/E = price to earnings; P/E (FW) = price to earnings forward; SIZE = log MC (market capitalization); GEPS 5y (FW) = estimated growth of earnings per share 5 years forward; GEPS 5y = growth of earnings per share for last 5 years; ROE = current return on equity; OM = operating margin; Debt/Eq = debt/equity; GEPS (FW) = estimated growth of earnings per share forward (for next fiscal year); NPM = net profit margin; CR = current ratio. Statistical significance: ***p-value<0.01; **p-value<0.05; *p-value<0.1.

Table 6
Cross-sectional regression

	Panel A: Coefficients from Pooled Regressions				SCORE	Adj. R^2
	Intercept	P/E	P/E FW	Log(MC)		
(1)	0.062	-0.001*	---	---	---	0.390
	(1.624)	(-1.757)	---	---	---	
(2)	0.090**	---	-0.001***	---	---	0.403
	(2.370)	---	(-6.298)	---	---	
(3)	0.268***	---	-0.001***	-0.044***	---	0.408
	(4.910)	---	(-5.638)	(-4.518)	---	
(4)	0.141**	---	-0.001***	-0.046***	0.032***	0.421
	(2.441)	---	(-4.396)	(-4.781)	(6.228)	

	Panel B: Time-Series Average of Coefficients (2000-20)			
	Intercept	P/E FW	Log(MC)	SCORE
(1)	1.547***	-0.001***	-0.378***	0.039***
	(12.04)	(-7.239)	(-12.48)	(6.093)
(2)	1.111	-0.001***	-0.047**	0.047***
	(1.169)	(-5.986)	(-2.105)	(10.29)

Notes: P/E = price to earnings; P/E (FW) = price to earnings forward; Log MC (market capitalization); Adj. R^2 = adjusted R^2. Statistical significance: ***p-value<0.01; **p-value<0.05; *p-value<0.1.

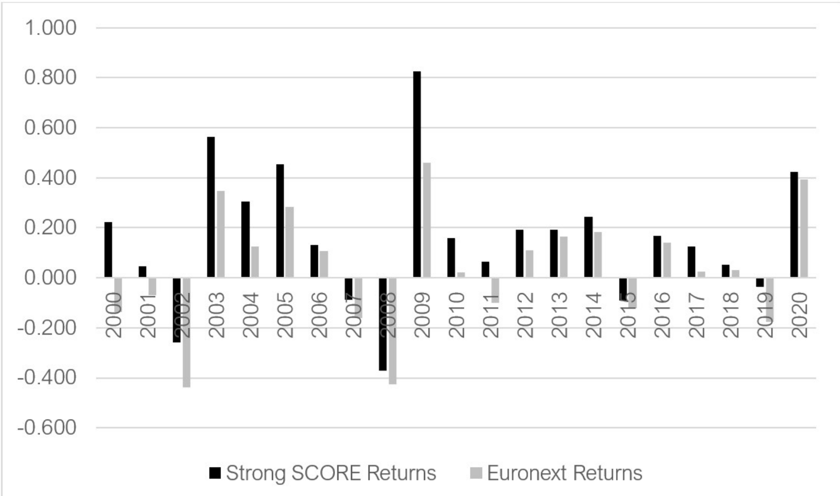

Figure 4. Returns on a strong SCORE (SCORE greater than or equal to 5) based on a calendar year FA, as well as the benchmark return. Returns are accumulated over a one-year period beginning four months (April 1st) after the end of the fiscal year. The *x* axis (vertical) depicts returns, while the *x* axis (horizontal) depicts time (year by year)

According to Panel A, all measures are statistically significant, with P/E at 10% and others at 1%. The signs continue to be consistent with the predictions. We can also observe in Model 4 that SCORE is the most important variable in the equation, since it has the highest *t*-statistic value. Regarding Panel B, we see that all measures remain statistically significant at 1% except for SIZE, which becomes statistically significant at 5% after a longer buy-and-hold period (Model 2), and all sign are consistent with the predictions. The change is caused by SCORE, which becomes more important the longer we hold the stock, when it reaches a *t*-statistic value greater than 10.

After controlling for variations in size and price ratios, the coefficients on SCORE show that a one-point increase in the aggregate score is associated with an approximately 3.2% to 3.9% increase in the one-year return obtained and a 4.7% increase in the two-year return.

Finally, Appendix A and Figure 4 demonstrate the long-term robustness of the fundamental analysis. Due to the limited sample numbers in any one year, companies with mostly positive news signals (SCORES of 5 or above) are compared to companies with mostly poor news signals (SCORES of 4 or less) each year. The average market return difference over the 21 years covered by this analysis is positive (0.104). The approach is effective in all years, since the premium (strong SCORE - benchmark return difference) is positive and statistically significant (t-statistic = 3.014) in 21 out of 21 years.

6 Conclusions

This study illustrates how, when applied to a board portfolio of high book-to-market firms with growth potential, a simple accounting-based fundamental strategy can alter the distribution of returns earned by an investor. Although this paper does not support the discovery of the optimal set of financial ratios for evaluating the performance prospects of individual value companies, the results convincingly demonstrate that investors can use relevant historical data to eliminate companies with poor prospects from a generic high BM portfolio. We show that by selecting businesses with strong fundamentals, a high score investor's yearly mean return can be boosted by at least 30%. Furthermore, between 2000 and 2020, an investment strategy that buys projected winners and sells expected losers delivers a 35% yearly return, and the strategy appears to be robust across time and to controls for competing investment strategies.

Superior performance within a portfolio with excellent fundamentals is not contingent on buying firms with cheap share prices. A positive link between the sign of the initial historical information and future firm performance, as well as subsequent annual earnings announcements, indicates that the market initially underreacts to previous information. These findings are corroborated by Piotroski (2000), who claims that one-sixth of the yearly return difference between ex-ante strong and weak corporations is earned during the three four-day periods preceding earnings announcements. Post-earnings-announcement drift (PEAD), proposed by Bernard and Thomas (1989, 1990), is another name for these phenomena.

There are a number of policy implications for monetary authorities, firms, and investors. For monetary authorities, the SCORE model could be used as a tool to help identify companies with strong fundamentals and growth potential that could be targeted for economic stimulus measures. Incorporating SCORE into their analysis could help central banks make more informed decisions about interest rates and other monetary policy tools.

For firms, companies with high SCOREs could use this information to attract more investment by highlighting their strong fundamentals and growth potential, and firms with low SCOREs could use this as a signal to investors that they need to improve their fundamentals and focus more on long-term growth.

As for investors, they could use the SCORE model as a tool to identify companies with strong fundamentals and growth potential, which could lead to higher returns over the long term. The model could also help investors better diversify their portfolios by identifying companies with different growth prospects from those identified by traditional models.

Overall, incorporating the SCORE model into decision-making could help promote more sustainable, long-term growth in the economy by encouraging investors to focus on companies with strong fundamentals and growth potential.

As for the study's weaknesses, one is that the model's high SCORE provides limited data, which could skew conclusions. As a result, section 5 may become more important as the SCORE is expanded (from 8-9 to 5-9), also known as Strong SCORE. This model could also be tried on another data set and the results compared.

Another weakness is that we have only tested a single index so far. As a result, the accuracy of the results depends heavily on the effectiveness of the method used, which is itself subject to a number of limitations that may affect the relevance of the results.

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APPENDIX A. By calendar year, one-year returns and market-adjusted returns for a hedging portfolio with a long position in Strong SCORE companies and a short position in Weak SCORE companies

Year	Strong SCORE Returns	Weak SCORE Returns	Euronext Returns	Strong - Weak Return Difference	Strong - Benchmark Return Difference	Weak - Benchmark Return Difference	Number of Observations
2000	0.223	-0.026	-0.137	0.250	0.360	0.110	83
2001	0.045	-0.092	-0.070	0.137	0.115	-0.022	88
2002	-0.257	-0.386	-0.439	0.129	0.182	0.053	88
2003	0.565	0.432	0.349	0.133	0.216	0.083	90
2004	0.305	0.149	0.124	0.156	0.181	0.024	93
2005	0.455	0.273	0.285	0.182	0.170	-0.012	93
2006	0.132	0.140	0.107	-0.008	0.025	0.033	94
2007	-0.087	-0.145	-0.160	0.058	0.073	0.015	96
2008	-0.370	-0.368	-0.426	-0.001	0.057	0.058	96
2009	0.827	0.620	0.460	0.207	0.367	0.160	96
2010	0.158	0.070	0.021	0.088	0.137	0.050	96
2011	0.066	-0.134	-0.099	0.200	0.165	-0.035	96
2012	0.191	0.082	0.110	0.109	0.081	-0.029	96
2013	0.193	0.201	0.166	-0.008	0.027	0.035	96
2014	0.243	0.079	0.184	0.165	0.059	-0.105	96
2015	-0.090	-0.091	-0.122	0.002	0.032	0.031	95
2016	0.169	0.189	0.141	-0.020	0.028	0.048	94
2017	0.126	0.036	0.026	0.090	0.100	0.010	94
2018	0.052	-0.044	0.030	0.096	0.022	-0.075	94
2019	-0.035	-0.226	-0.177	0.191	0.141	-0.049	94
2020	0.425	0.402	0.393	0.023	0.032	0.010	94
Average	0.160	0.056	0.036	0.104	0.123	0.019	---
(t-Statistic)	---	---	---	---	(3.014)	(1.151)	---

Notes: Strong SCORE = SCORE greater than or equal to 5; Weak SCORE = SCORE less than 5.

Supplementary Material

Supplementary material accompanies this paper.

APPENDIX B. Supplementary Material.

Supplementary data to this article can be found online at: Navas, Raúl Daniel; Bentes, Sónia Ricardo, 2023, "Supplementary data - Value Investing: A New SCORE Model", https://doi.org/10.7910/DVN/1UOITO.

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The authors have no conflict of interest to declare.

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