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Accounting Fundamentals and Volatility in the Euronext 100 index

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Abstract

To determine whether accounting fundamentals can provide relevant information to clarify firm value, this study examines the value relevance of accounting fundamentals in the Euronext 100 index—specifically, whether applying an accounting fundamental strategy to select stocks yields significant, positive excess market buy-and-hold returns after one and two years of portfolio formation. By integrating valuation theory and accounting research, this study introduces a set of accounting fundamental signals (F-score and L-score) that reflect information that can influence security prices, but not necessarily in a timely manner. Annual financial and market data from Euronext 100 index stocks between 2000 and 2014 reveal, after controlling for earnings, book-to-market ratio, and firm size, that the fundamental strategy provides value-relevant information to investors. The relationship between the accounting fundamental signals (i.e., F-score and L-score) and buy-and-hold market future (one- and two-year) returns is significant and positive. That is, portfolios formed on the basis of high scores on the signals achieve a 13% average market excess annual return between 2000 and 2014. In addition to addressing the practical problem of mispriced stocks, this study contributes to scarce accounting research in European capital markets by detailing the “post-earnings” drift phenomenon in a Euronext 100 index.

Because under the period of analysis the Euronext 100 index showed strong volatility, further this study also explored asymmetric effects which are fundamental to stock market volatility. Considering their relevance, this study therefore examines the conditional volatility of returns to the Euronext 100, with a particular focus on the asymmetric properties of this market. The analysis entails an estimate of the symmetric *GARCH* and asymmetric *EGARCH* and *T-GARCH* models, using a data set of daily closing prices from the index that spans from December 3, 2000, to December 18, 2015. The findings show that conditional variance is an asymmetric function of past residuals, offering strong evidence of asymmetries in the returns of the Euronext 100.

Keywords

Accounting fundamentals, Earnings, Portfolio formation, Asymmetry, EGARCH, T-GARCH.

Resumo

Para avaliar se a informação financeira (*accounting fundamentals* – rácios financeiros) permite determinar o valor da empresa, este estudo analisa a relevância dos rácios financeiros no índice Euronext 100. Especificamente, esta investigação examina se utilizando rácios financeiros é possível a seleção de ações para formar carteiras que gerem rendibilidades positivas segundo uma estratégia *buy-and hold* a um e a dois anos. Assim, integrando a teoria do valor (*valuation theory*) e análise fundamental, este estudo introduz um conjunto de rácios (*F-score e L-score)* que refletem informação que pode influenciar os preços, mas não necessariamente de forma imediata *(lack of timeliess)*. Utilizando informação contabilística e informação de mercado das empresas cotadas no índice Euronext 100 para o período 2000-2014, os resultados mostraram que após se controlar o efeito do rácio dos resultados por ação (*EPS*), o rácio do valor contabilístico sobre o valor de mercado da empresa (*BMR*) e a dimensão da empresa (logaritmo do total do ativo), o coeficiente do F-score mostra que um incremento de uma unidade deste *score* está associado a um aumento das rendibilidades de 2.9% a 3.1%. O efeito do L-score é mais modesto, cerca de 1.8%. Adicionalmente as carteiras constituídas com os rácios que reportam valores mais elevados *i.e.. high scores* para o F-score, segundo uma estratégia *buy-and-hold* a um ano apresentam uma rendibilidade média de 13% quando comparada a rendibilidade do índice no período em análise. Atendendo ao fenómeno do "*mispricing*" das ações, este trabalho contribuí para a escassez de literatura no Mercado Europeu, dando enfoque ao *"post-earnings drift phenomenon"*.

Dado que durante o período em análise se verificou uma forte volatilidade no índice Euronext 100, que coincidiu com a crise financeira de 2008/2009 e com a crise da dívida soberana europeia, e de forma a documentar a reação atípica do mercado durante este período, o presente trabalho tem também como objetivo fornecer um contributo para a análise do comportamento da volatilidade dos mercados financeiros, a qual assume especial relevo em resultado da complexidade e incerteza que atualmente caracteriza os mercados à escala global. Mais concretamente, o que se compara nesta tese são os resultados da abordagem tradicional assente no desvio-padrão e em modelos econométricos como o *GARCH*, *EGARCH* e *T-GARCH*. Para tal, recorre-se a uma amostra constituída pelas rendibilidades do índice bolsista Euronext 100 no período compreendido entre 3 de Dezembro de 2000 e 18 de Dezembro de 2015. Os resultados mostram que a variância condicional é uma função assimétrica de resíduos do passado, havendo uma forte evidência de assimetrias nas rendibilidades do Euronext 100.

Palavras-chave

Rácios contabilísticos, Rendimentos, Carteira de investimento, Assimetria, EGARCH, T-GARCH.

Resumo Alargado

A utilização da análise fundamental tem provado ter sucesso nos mercados desenvolvidos (e.g., Ball and Brown 1968; Kothari 2001; Richardson *et al*. 2010). Porém a evidência empírica tem mostrado uma subavaliavação/sobreavaliação ainda que temporária dos preço das ações, comparativamente ao seu valor intrínseco, fenómeno conhecido na literatura por "*earnings announcement drift*" (Abarbanell and Bushee 1998; Piotroski 2000, 2005), sugerindo assim, a necessidade de analisar a aplicabilidade da análise fundamental, mais concretamente rácios contabilísticos, que fornecem informação relevante aos investidores num mercado importante, como o europeu, nomeadamente o índice Euronext 100. Neste contexto, este estudo tem por objetivo analisar a relevância da análise fundamental na determinação do valor das empresas.

De acordo com a teoria do valor (*valuation theory*), ao longo do tempo os lucros convertem-se em *cash-flows* para os investidores, credores e para a empresa, constituindo estes o principal determinante do valor da empresa, que será refletido no preço das ações. Por sua vez, a análise fundamental através de um conjunto de rácios permite ao investidor analisar de forma detalhada a informação constante nas demonstrações financeiras, de forma a avaliar a eficiência e eficácia da empresa em gerar resultados e o seu potencial de crescimento no futuro (Dosamantes 2013). Assim, com base nos sinais dos rácios (*accounting fundamentals*) propostos por Piotroski (2000) e Lev e Thiagarajan (1993) são utilizados dois scores: o F-score e o L-score respetivamente, para a formação de carteira seguindo uma estratégia *buy-and-hold* a um e a dois anos. Estes *scores* apresentam um grande potencial por terem em conta fatores que se relacionam com os preços futuros das ações (Kim e Lee 2014; Piotrsoki 2005; Amor-Tapia e Tascón 2016). Assim, numa primeira fase, e recorrendo a diferentes modelos econométricos, este estudo evidência a relevância destes *accounting signals,* i.e. F-score e L-Score, na previsão de rendibilidades supranormais, controlando-se variáveis como os resultados por ação (*EPS*), o rácio do valor contabilístico sobre o valor de mercado da empresa (*BMR*) e a sua dimensão (e.g., Dosamantes 2013). Os resultados mostram que um incremento de uma unidade do F-score está associado a um aumento das rendibilidades supranormais de 2.9% a 3.1%. O efeito do L-score é mais modesto, cerca de 1.8%. Com efeito, o F-score evidencia uma relação estatisticamente significativa em todos os modelos; O L-score apenas se revela estatisticamente significativo no modelo de efeitos fixos. Numa segunda fase, constroem-se carteira com base no F-score e no L-score segundo uma estratégia *buy-and-hold* (e.g., Kim e Lee 2014). Os resultados são mais uma vez consistentes com referência ao F-score, que permite rendibilidades supranormais a um ano de 13%, quanto comparado com a rendibilidade do índice no período de 2000 a 2014. As rendibilidades proporcionadas pelo L-score apenas são estatisticamente significativas a dois anos.

Adicionalmente e atendendo que atual contexto de instabilidade nos mercados financeiros à escala global, é relevante a análise do comportamento da volatilidade dos mercados financeiros. Desde o trabalho precursor de Markowitz (1959) que esta é uma variável pertinente, em especial nos processos de tomada de decisão que envolvem variáveis de natureza financeira. Vários autores desenvolveram modelos para tentar descrever as características principais da volatilidade dos ativos financeiros, extensivamente documentadas na literatura e na metodologia. É neste contexto que surge o modelo *ARCH(q)*, proposto por Engle (1982), que tenta modelar a heterocedasticidade condicionada evidenciada pelas rendibilidades dos ativos financeiros. Bollerslev (1986) e Taylor (1986) desenvolveram de forma independente uma extensão deste modelo, vulgarmente designada por *GARCH(p,q)*, cujas principais vantagens residiam, por um lado, no fato de ser mais parcimoniosa do que a anterior e, por outro, na admissão de que a variância condicionada era função não só do quadrado dos resíduos passados mas também dos seus próprios valores históricos. Dada a aceitação que este modelo alcançou, foram propostas numerosas variantes no sentido de contemplar os mais diversos fenómenos associados ao comportamento da volatilidade.

Considerando essas extensões, este trabalho procura examinar a dependência temporal das rendibilidade do índice Euronext 100, para determinar se as rendibilidade apresentam um comportamento assimétrico e, em caso afirmativo, qual o modelo que descreve essa assimetria melhor. Esta questão é relevante dada as respostas distintas aos choques positivos e negativos nos mercados. Dessa forma, aplicaram-se e compararam-se as formulações de heteroscedasticidade condicional assimétricas mais utilizados: *EGARCH, GJR / TGARCH*, e as especificações *GARCH* padrão. Estudos prévios favorecem modelos *EGARCH* (e.g., Cao e Tsay 1992; Loudon *et al.* 2000), enquanto que outros afirmam a superioridade de especificações *GJR-GARCH/TGARCH* (e.g., Brailsford e Faff 1996; Hou 2013; Taylor 2004; Yeh e Lee 2000); algumas investigações ainda indicam que *EGARCH* não supera um *GARCH* padrão para a previsão de volatilidade (e.g., Doidge e Wei 1998; Ederington e Guan 2010). Para complementar e alargar esta literatura, este trabalho tem como objetivo fornecer novas evidências empíricas sobre esta matéria, através de uma análise empírica repartida por três etapas, realizadas durante um período marcado por grande volatilidade do mercado 2000 a 2015. Primeiro, estimamos um modelo auto-regressivo *AR* (*p*) para cada série de rendibilidades, para remover qualquer correlação dos dados. Em segundo lugar, para validar esta especificação, testamos a correlação nos resíduos. Em terceiro lugar, estimamos os modelos, utilizando *GARCH (1,1), EGARCH (1,1,1)* e *TGARCH (1,1,1)* respetivamente. Os resultados mostram que a variância condicional é uma função assimétrica de resíduos do passado, havendo uma forte evidência de assimetrias nas rendibilidades do índice Euronext 100.

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List of Abbreviations

σ	Standard deviation
A	Total of Assets
ADF	Augmented Dicker-Fuller
AIC	Akaike Information Criteria
AR	Auto Regressive
ARCH	Autoregressive Conditional Heteroskedasticity
AT	Asset Turnover
BG	Breusch-Godfrey
BM	Book Market
BMR	Book-to-Market Ratio
BV	Book Value
BVE	Book Value of Equity
CAPEX	Capital Expenditures
CAPM	Capital Asset Pricing Model
CDS	Credit Default Swap
CFA	Chartered Financial Analyst
CFR	Cash Flow from Operations
COGS	Cost of Goods Sold
CR	Current Ratio
DCC	Dynamic Conditional Correlation
DPS	Dividends Per Share
DY	Dividend Yield
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EM	Earnings Margin
EMH	Efficiency Market Hypothesis
EPS	Earnings Per Share
ET	Equity Turnover
FA	Fundamental Analysis
FIFO	First In, First Out
G	Growth
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GJR-GARCH/ TGARCH	Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity

GDP	Gross Domestic Product
GGP	Growth in Gross Profit
GM	Gross Margin
GP	Gross Profit
IT	Inventory Turnover
J-B	Jarque-Bera
K-S	Kolmogorov-Smirnova
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LIFO	Last In, First Out
LR	Leverage Ratio
LTD	Long Term Debt
MC	Market Capitalization
MVE	Market Value of the company
NAV	Net Asset Value
NFO	Net Financial Obligations
NI	Net Income
NIBD	Net Income Before Interest, Taxes and Depreciation
NM	Net Margin
NOA	Net Operating Assets
OJ	Ohlson and Juettner-Nauroth
OLS	Ordinary Least Square
P/E	Price to Earnings
P/B	Price to Book Value
PCF	Price to Cash Flow
PEAD	Post Earnings Announcement Drift
PIIGS	Portugal, Italy, Ireland, Greece and Spain
PS	Per Share
PTE	PreTax Earnings
QMLE	Quasi-Maximum Likelihood Estimation
ROA	Return On Assets
ROE	Return On Equity
RT	Accounts Receivables Turnover
S-W	Shapiro-Wilk
SGAE	Selling, General and Administrative Expenses
SIC	Schwarz Information Criteria
UK	United Kingdom
US	United States
VIF	Variance Inflation Factor
XFIN	External Financing

1. Introduction

The use of fundamental analysis (FA) has been shown to be successful in developed markets (e.g., Ball and Brown 1968; Kothari 2001; Richardson *et al*. 2010). Yet growing evidence of temporary market mispricing (also known as earnings announcement drift or accounting anomalies; Abarbanell and Bushee 1998; Piotroski 2000, 2005) in such markets suggests the need to examine whether the application of accounting fundamental signals can provide relevant value to investors in an important European markets, namely, the Euronext 100 index. This study accordingly seeks to demonstrate the potential use of accounting fundamental signals to investors in this developed market. According to valuation theory, over time accounting earnings convert into free cash flows that move to investors, creditors, and the firm. These are the main components for estimating the intrinsic value of the firm, as reflected in the stock price. In accounting fundamental analysis, observers examine detailed accounting data from financial statements to improve their understanding of how efficiently and effectively a firm can generate earnings over time, as well as its potential to grow and convert the earnings into free cash flows (Dosamantes 2013).

Generally, a FA entails examining companies' economic and financial reports (e.g., profit & loss accounts, balance sheets), including both quantitative and qualitative information, to determine its value. Although typically used to evaluate the real value of traded stocks, this method can be carried out by analysts, brokers, and savvy investors (Bentes and Navas 2013). In conducting an FA, investors can use one or both of the following approaches:

i) Top-down: The analyst investigates international and national economic indicators, such as gross domestic product growth rates, energy prices, inflation, and interest rates. The search for the best asset trickles down to the analysis of total sales, price levels, and foreign competition in a particular sector to identify the best company in the sector.

ii) Bottom-up: The analyst starts the search within a specific sector, irrespective of its industry or region.

With the FA, the analyst seeks to predict the company's future performance, with the recognition that the market price of an asset tends to move toward its intrinsic value. If the intrinsic value of an asset is higher than its market value, it may be time to buy; otherwise, investors should sell.

This study may help such investors use accounting data to construct hedge portfolios in which they can identify possible abnormal returns, which would increase their expected utility. In turn, they might achieve an optimal balance between expected returns and market and country risk. Piotroski (2000) and Lev and Thiagarajan (1993) introduce two key scores: the F-score and the L-score. They should relate positively to one- and two-year future stock returns, such that higher scores increase the likelihood of future market excess returns. To address the possibility of alternative explanations for these scores, including the potential that they instead measure factors that relate consistently to future returns (Kim and Lee 2014; Piotrsoki 2005; Amor-Tapia and Tascón 2016), this study relies on econometric models to show how the scores add value relevance beyond 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 shows that simple, equally weighted portfolios constructed with high F-score stocks yield consistently positive returns. The L-score instead is significant only two years in the future. These results are robust, as confirmed by combine a pooled ordinary least squares (OLS) approach with a fixed effect model.

During the reporting period there was a strong volatility (2008-2009) which coincides with the financial crisis of 2008/2009 and also with the European sovereign debt crisis. In this context, and in order to better understand the atypical behavior of the market during this period, this thesis also aims to provide a contribute to the analysis of the volatile behavior of financial markets. This assumes special importance as a result of the complexity and uncertainty which currently characterizes the markets.

Bellalah *et al*. (2016) empirically test the contagion and the transmission mechanism of shocks in volatility between the peripheral Eurozone countries. They employ the sovereign CDS (Credit Default Swap) spreads and the asymmetric model of dynamic conditional correlation *GARCH DCC* in order to investigate the effects of positive and negative shocks over the long term with a focus in the systemic nature of the crisis in Europe. Results show that changes in the index of sovereign CDS have an extremely noteworthy impact on changes in European stock indexes, especially in the case of Germany, France and the PIIGS (Portugal, Italy, Ireland, Greece and Spain) countries.

Pericoli and Sbracia (2003) defined contagion as the expanding the likelihood of a crisis in a country with the coming of a crisis in another country. This definition expresses that the “infection” may happen amid financial turbulence when there is an increase in the volatility of asset prices and stretches out from one market to another market. For Marais (2003), a concurrent increment in volatility in different markets could arise as a result of ordinary association between these markets or structural changes affecting international markets links. According to Forbes and Rigobon (2002), contagion occurs when cross-border co-movements in asset prices cannot be explained by fundamentals. In this context, contagion can be regarded as critical increment joins between financial markets due to a specific shock to a country or group of countries (Bellalah *et al*. 2016).

In addition to this, it is important for investors to assess the degree of market volatility and how their asymmetric effects have an impact on the value of the shares of a particular company. Thus, the asymmetries in volatility are a topic of particular relevance to our study.

Asymmetries have an important role for characterizing price movements, as manifested in the negative correlations that can arise between stock returns and volatility. Large negative shocks tend to be associated with a greater increase in volatility than large positive shocks (Ederington and Guan 2010), a phenomenon for which gasoline markets offer a paradigmatic case: Increasing oil prices trigger jumps in gasoline prices, but oil price decreases of the same amount invoke smaller dips in gasoline prices. Similarly, in financial markets, the impact of bad news (negative shocks) traditionally is greater than the impact of good news (positive shocks), as initially documented by Black (1976) in stock market returns (see also Christie 1982; Engle and Ng 1991; Pagan and Schwert 1990; Sentana 1992). Asymmetries also arise in sophisticated frameworks, such as those derived from Chinese stock markets (Hou 2013; Yeh and Lee 2000), FTSE 100 spot and futures markets (Tao and Green 2012), Jakarta's Stock Exchange Index IND (Leeves 2007), several European and U.S. stock indices (Ferreira *et al*. 2007), and the S&P 100 (Liu and Hung 2010) and S&P 500 (Awarti and Corradi 2005). According to an analysis of asymmetric influences of days of the week across five indices (Charles 2010), calendar effects are especially interesting when incorporated in models with good volatility forecasts (Bentes *et al*. 2013).

The asymmetric impacts of good and bad news might be explained by leverage theory, which asserts that decreased value for a firm's stock causes that firm's debt-to-equity ratio (in market value terms) to rise (Black 1976 and Christie 1982). That is, a company's financial risk causes greater volatility in its stock returns. Alternatively, volatility feedback (or risk premium) theory postulates that return oscillations due to good news create expectations of greater volatility, which increases the required rate of return and thereby lowers prices (Campbell and Hentschel 1992). The increased expected volatility caused by substantial bad news also raises the required rate of returns and lowers stock prices, thus magnifying the negative impact of bad news.

A popular framework also accounts for the temporal dependencies of stock market volatility, using conditional heteroskedasticity models (e.g., autoregressive or *ARCH*, generalized autoregressive or *GARCH*), which assume that markets are predictable (Bollerslev 1986). That is, in the original formulation (Engle 1982), current volatility is a function of prior squared residuals, but according to Bollerslev (1986), it also depends on the lagged values of the variance. Although the first generation of *ARCH* models enforce a symmetric response of volatility to positive and negative shocks and can accommodate volatility clustering—namely, big shocks are followed by big shocks, and small shocks are followed by small shocks—they cannot capture asymmetric velocity, because of the assumption that only the magnitude of the shock, not the sign, affects price oscillations. In addition, the estimated coefficients often violate the parameter constraints, and these constraints may restrict the dynamics of the conditional variance process, which limits the application of both models. To account for asymmetric effects, more flexible specifications allow for different impacts of positive and negative shocks on volatility, such as the exponential *GARCH* (*EGARCH*, Nelson 1991), which relies on the non-negativity of conditional variance and constrains it to a logarithmic function to capture asymmetric effects, *GJR-GARCH* (Glosten *et al*. 1993) or threshold *GARCH* (*TGARCH*, Zakoian 1994), which include extra terms for negative lagged residuals (Bentes *et al*. 2013).

Considering these extensions, this chapter seeks to examine the temporal dependence of the returns to the Euronext 100, a representative European market, to determine if index returns volatility is asymmetric and, if so, which model describes this asymmetry best. This question is highly relevant because of the likely distinct responses to positive and negative shocks in markets. Accordingly, we apply and compare the most widely used asymmetric conditional heteroskedasticity formulations: *EGARCH, GJR/TGARCH*, and standard *GARCH* specifications. In prior empirical research, some studies favor *EGARCH* models (e.g., Cao and Tsay 1992; Loudon *et al*. 2000), whereas others assert the superiority of *GJR-GARCH/TGARCH* specifications (e.g., Brailsford and Faff 1996; Hou 2013; Taylor 2004; Yeh and Lee 2000); some investigations even indicate that *EGARCH* does not outperform a standard *GARCH* for forecasting volatility (e.g., Doidge and Wei 1998; Ederington and Guan 2010). To complement and extend this literature, we provide new insights with a three-step empirical analysis, undertaken during a period marked by massive market volatility. First, we estimate an autoregressive model *AR(p)* for each return series, to remove any serial correlation from the data. Second, to validate this specification, we test for serial correlation in the residuals. Third, we estimate the models, using *GARCH (1,1), EGARCH (1,1,1),* and *TGARCH (1,1,1)* specifications.

The next section presents the theoretical background for this study, followed by a literature review of empirical studies. Section 4 presents the research design; Section 5 offers the results of volatility, following the results of fundamental analysis in Section 6. Section 7 concludes by presenting the main conclusions, the contributions and limitations of the studies.

2. Theoretical Background

Most research on accounting FA in capital markets uses archival data and econometric models based on multiple regression models, sometimes complemented with time-series analysis for forecasting. The main theoretical background is valuation theory, the efficient market hypothesis (EMH) and followed by volatility.

2.1. Value investing

Valuation is the process of estimating what something is worth. The value of an asset or liability commonly is referred to as its market value, fair value, or intrinsic value. Financial statements prepared in accordance with generally accepted accounting principles report assets based on their historic costs rather than their current market values. Value investing analyses started with the publication of *Security Analysis* by Graham and Dodd in 1934 (Greenwald *et al*. 2004). These authors detail investment techniques that promise success, regardless of market cycles. Graham, who also published *The Intelligent Investor* in 1949, often is credited as the creator of the equity analyst profession and was one of the founders of the Chartered Financial Analyst function. In addition to his academic contributions, Graham also mentored Warren Buffett, who opted for diversified portfolios and focused on quantitative aspects such as the price-to-earnings ratio (*P*/*E*) and price-to-book ratio (*P*/*B*) early in his career. Yet over time, and under the influence of another Berkshire Hathaway partner, Buffett also started noting qualitative aspects (e.g., competitive advantages, sustainability), thus expanding the original investment strategy proposed by Graham (Holloway *et al*. 2013).

The value investing strategy offered by Graham and Dodd is based on three key characteristics of financial markets:

1) The prices of financial stocks are subject to significant, “capricious” movements. The market shows up every day to buy or sell any financial asset.

2) Fundamental economic values are relatively stable and can be measured with reasonable accuracy by a diligent, disciplined investor. The intrinsic value of a security is one thing; the current price at which it is trading is something else. Although the intrinsic value and market prices may be identical on any given day, they often diverge.

3) A strategy of buying stocks only when their market prices are significantly below the calculated intrinsic value will produce superior returns in the long run. Graham referred to

the gap between value and price as “the margin of safety”; ideally, the gap should amount to about half, but not less than one-third, of the fundamental value. He sought to buy a dollar for 50 cents; the eventual gain would be large and, more important, secure.

Starting with these assumptions, the central process of value investing is simple: A value investor estimates the fundamental value of a financial security and compares that value to the current price that the market is offering. If price is lower than the value by a sufficient margin of safety, the value investor buys the security. That is,

1) Select stocks for valuation.

2) Estimate their fundamental values.

3) Calculate the appropriate margin of safety required for each security.

4) Decide how much of each security to buy, then construct a portfolio and choose a certain level of desired diversification.

5) Decide when to sell stocks.

To estimate value, value investors also rely on a three-phase process:

1) Search to locate potentially rich areas where value investments may locate.

2) Take a valuation approach that is powerful and flexible enough to recognize value in different guises, while still protecting the investor from deluded expectations.

3) Construct an investment portfolio that reduces risk and provides a check on individual security selections.

For Greenwald *et al*. (2004), value investing is an intellectual discipline, but the qualities essential for success in this task may be less mental than temperamental. In particular, a value investor must be aware of the limits of his or her personal competence and be able to distinguish genuine understanding from general competence. Most value investors are specialists in particular industries or certain circumstances, such as bankruptcy workouts. Not every stock that looks like a bargain is worth more than its price. A value investor must be able to identify the difference between an underpriced asset and a cheap price. Even the most experienced investor performs best when operating within his or her circle of competence. Furthermore, value investing demands patience, to wait for the market to offer a bargain, and then, after stocks are purchase, wait for the rest of the market to come around.

Valuation theory defines that the value of the firm is the present value of the future free cash flows that the firm can generate. To estimate these cash flows, it is necessary to estimate future earnings. To estimate future earnings, the analyst needs to examine present and past financial statements, which form the basis for calculating earnings. The assumption is that earnings, sooner or later, transform into free cash flow to investors, in the form of dividends (Dosamantes 2013; Piotroski 2000; Bartov and Kim 2004). Still, value investors have been improving the technique, and several other elements were included in the criteria for selection of assets (Holloway *et al*. 2013).

2.2. Efficient market hypothesis (EMH)

An investment strategy that solely seeks to "beat the market" is doomed to failure; in an efficient stock market, stock prices incorporate and reflect all relevant information. According to the EMH, stocks always trade at their fair value on stock exchanges, so investors cannot purchase undervalued or sell overvalued stocks. It thus should be impossible to outperform the overall market, regardless of expert stock selection or market timing, and the only way an investor might obtain higher returns would be to purchase riskier investments. Ultimately, the EMH suggests that developed capital markets incorporate all available public and private information about the present and past operational performance of the firm into its stock price.

The EMH also is closely linked to the random-walk model and Martingale model. The random character of stocks market prices was first modeled by Jules Regnault, a French broker, in 1863 and then by Louis Bachelier, a French mathematician, in his 1900 PhD thesis, The Theory of Speculation (Kirman, 1992). His work was largely ignored until the 1950s; however, in the early 1930s, several works corroborated his thesis. In particular, Working (1934), Cowles and Jones (1937), and Kendall and Hill (1953) proved for U.S. stock prices and related financial series followed a random walk model. Then the EMH emerged as a prominent theory in the mid-1960s. Paul Samuelson began circulating Bachelier's work among economists. In 1964, Bachelier's dissertation was collected with the resulting empirical studies in an anthology. In 1965, Eugene Fama published his dissertation, arguing for the random walk hypothesis, and Samuelson published a proof of a version of the EMH. Fama (1970) also reviewed both the theory and the evidence for the EMH.

Based on utility-maximizing agents, the EMH requires agents to accept the rational expectations that, on average, the population is correct (even if one person is not), and when new, relevant information appears, they should update their expectations. Agents do not have to be rational though; the EMH acknowledges that when faced with new information, some investors overreact and others underreact. Therefore, the EMH assumes that investors' reactions are random and follow a normal distribution pattern, so that the net effect on market prices cannot be exploited reliably to make an abnormal profit, especially with transaction costs (e.g., commissions, spreads). Thus, each person can be “wrong” about the market, but the market as a whole is always “right” (Fama 1998).

Furthermore, the EMH appears in three main versions. In the weak version, prices of traded assets already reflect all publicly available information. In the semi-strong form, prices reflect all publicly available information and change instantly to reflect new public information. The strong form of the EMH also claims that prices instantly reflect even hidden or "insider" information. Another view of the EMH indicates that the stock market is “micro efficient” but not “macro inefficient” (Samuelson 1947), such that the EMH may be better suited for individual stocks than for an aggregate stock market. Research based on regression and scatter diagrams supports this view too (e.g., Jung and Shiller 2005). No one can consistently achieve returns in excess of average market returns on a risk-adjusted basis, given the information available at the time the investment is made. Timmermann and Granger (2004) argue that stable forecasting patterns thus are unlikely to persist for long periods of time and will self-destruct when discovered by many investors. For example, Grossman and Stiglitz (1980) observe that security prices first need to be efficient, which requires capital market participants to trade actively with useful information that drives the security prices toward their "true" level. In this sense, the capital market is adaptive in its efficiency: What was once mispriced becomes correctly priced.

A firm's stock price theoretically reflects both supply and demand sides of the market, usually regarded as investors' views of corporate valuation. If the capital market is efficient in reflecting all available information, nobody can outperform it in assessing a firm's value. However, information collection is costly, so some groups of people may value the firm better than the market (Laih *et al*. 2015). Khan (1986) finds that, following the release of large trader position information, a futures market reports semi-strong efficiency. In European indexes, Borges (2010) reports results in line with the weak EMH between January 1993 and December 2007, thereby concluding that daily and weekly returns are not normally distributed, because they are negatively skewed, are leptokurtic, and display conditional heteroscedasticity. With mixed evidence across nations, Borges rejects the EMH when considering daily data from Portugal and Greece, due to the first-order positive autocorrelation in the returns, yet also provides empirical tests that show that these two countries approached Martingale behavior after 2003. The French and U.K. data also reject EMH, but in these cases due to the presence of mean reversion in weekly data. The tests for Germany and Spain do not reject of EMH, and the latter market was the most efficient.

With a different approach, Himmelmann *et al*. (2012) examine underreactions and overreactions in the EuroStoxx 50 Index according to the abnormal returns of those stocks in subsequent price increases and decreases. Large price increases and decreases tend to be followed by average market returns, in support of the EMH. In an examination of the fundamental determinants of stock prices in India, Srinivasan (2012) uses annual time-series data for six key sectors during 2006–2011 and concludes that the market is largely efficient.

Yet the EMH does not consistently hold in less developed markets, compared with more developed markets (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 forecast, so stock prices often are temporarily underestimated.

Some research spurred by a lack of support for the EMH relies on accounting FA in capital markets, which leverages information in current and historical financial statements, together with industry and macroeconomic information, to estimate a firm's intrinsic value (Kothari 2001). In addition, FA may work better in emerging or less developed markets; Dosamantes (2013) argues that valuation theory and FA are more valuable and relevant for identifying temporary mispriced stocks than the EMH. Accordingly, FA might produce better results in less efficient markets than in developed markets.

These questions about the validity of the EMH are relevant for investment strategies, and thus for academicians, investors, and regulatory authorities. In particular, EMH is widely accepted as a theory that predicts market movements, but de Sousa and Howden (2015) find that some other, constant impacts clearly challenge the EMH (e.g., January impact; Rozeff and Kinny 1976; Reinganum 1983). Academicians thus seek to understand the behavior of stock prices and standard risk-return models, such as the capital asset pricing model (CAPM), which depends on the hypotheses of normality or random walk behavior of returns. Jegadeesh (1990) offers proof of consistency in individual stock returns, but perhaps the most well-known inconsistency is the size impact. In the long run, equities of smaller companies persistently generate higher returns than those of larger companies (Keim 1983; Fama and French 1993). The preferred solution suggests that beta is not the best proxy for risk and that size can add some predictability to returns. If the problem is a lack of independent variables in the CAPM, a three-factor asset-pricing model might offer an appropriate benchmark for measuring anomalies (Fama and French 1993). Such multi-factor models can improve predictive power and do not contest the EMH but instead define "predictability" according to the factors being studied. Prices still follow a random walk.

For investors, trading strategies have to be designed to account for whether future returns can be predicted according to their past behavior or not, as in the case of the weak form

EMH. If a stock market is not efficient, the pricing mechanism also cannot ensure the efficient allocation of capital in an economy, which would have negative effects for the overall economy, such that regulatory authorities may need to undertake reforms (Borges 2010).

Two factors thus motivate the current study. First, different studies reveal contradictory evidence regarding the EMH for the same countries and same time periods, suggesting the need for replications. Second, market efficiency seemingly develops over time, so constant updates to previous studies are necessary, using more recent data and emerging, powerful techniques, such as those based on joint variance ratio tests. Most research on FA in capital markets instead uses valuation theory and EMH as its main theoretical perspectives (Dosamantes 2013).

2.3. Volatility

The volatility of financial markets is particularly relevant in the modern era, considering its effects on the daily lives of companies and individuals. According to Bollerslev *et al.* (1992: 46): "Volatility is a key variable which permeates most financial instruments and plays a central role in many areas of finance." Since Markowitz (1959) introduced the concept, it has remained a relevant variable, especially in decision-making processes involving financial variables. Such decision making becomes especially evident in times of crisis, such as the 2008 global financial crisis (e.g., Soros 2009). Furthermore, instability is increasing in financial markets may be due to several causes. For example, people experience high levels of risk and uncertainty, and markets are increasingly complex, filled with sophisticated products that have emerged from the derivatives market. Added to these developments, globalization trends extend the range of possible fluctuations of prices in a given market to more financial markets, according to their degree of integration. Therefore, it becomes necessary to analyze and model the volatility of returns on financial assets traded in the stock markets, to give investors the tools they need to make appropriate decisions. The role of information is particularly important in this process, in that it provides decision makers essential knowledge about market behavior (Bentes 2011).

Recognizing the importance of these arguments, several authors have developed models to try to describe the main characteristics of the volatility of financial assets, extensively documented in the literature and methodology. It is in this context that the *ARCH* (*q*) model appears and it is proposed by Engle (1982), which attempts to model the conditional heteroskedasticity evidenced by the returns of financial assets. It is worth to refer that the author mentioned above would, along with Clive Granger to be awarded the Nobel Prize in Economics in 2003 for his work at the time was pioneering. Roughly speaking, this model assumes the existence of time-dependent behavior of volatility, considered to the effect that the conditional variance is not constant. It was particularly useful in modeling the so-called volatility clustering and fat tails and the empirical distribution of the returns of financial assets.

Bollerslev (1986) and Taylor (1986) developed independently an extension of the *ARCH* model, commonly known as *GARCH* (*p*,*q*). Their main advantages reside, on the one hand, in the fact that it is more parsimonious than the previous one and, secondly, the admission that the conditional variance function was not only the square of past residuals but also its own historical values. Given the acceptance that this model has achieved, numerous variants have been proposed in order to contemplate the various phenomena associated with to behavior of volatility, some of them might be seen in more detail in section 4.

3. Literature Review: Empirical Studies

3.1. Fundamental analysis (FA)

When investors seek to determine which stocks to buy/sell at which price, they might conduct a fundamental analysis or a technical analysis. The former postulates that stock markets misprice an asset in the short run but not in the long run, when the "correct" price will emerge. Because there is a long-term equilibrium for every stock price, investors can earn profits by trading the mispriced asset in the short term and then waiting for the market to recognize its "mistake" and re-price. The latter instead assumes that all information already is reflected in the stock price, so trends will benefit the investor, and sentiment changes can predict trend changes. Investors' emotional responses to price movements thus lead to recognizable price chart patterns. Price predictions based on a technical analysis are extrapolations from historical price patterns. Investors also might combine these two approaches; for example, many fundamental investors use technical analyses to determine their entry and exit points, and some technical investors use FA to restrict their portfolios to "good and financially healthy companies" (Menezes 2010). The choice of which approach to apply also depends on the investor's belief in different paradigms regarding the functioning of the stock market.

The FA relies on financial reports, which provide fundamental data for calculating financial ratios. Each ratio provides an evaluation of different aspects of a firm's financial performance (Silva 2009). Penman (2009) defines FA as the analysis of information that focuses on valuation and Kothari (2001) considers its use a powerful means to identify mispriced stocks relative to their intrinsic value. Richardson *et al*. (2010) highlight the research overlap between FA and accounting anomalies and note that recent FA research tends to focus on forecasting earnings, stock returns, or the firm's cost of capital. In addition, FA evaluates firms' investment worthiness by looking at their business at a basic financial level (Thomsett 1998), such as its sales, earnings, growth potential, assets, debt, management, products, and competition. This strategy also might entail analyzing market behavior that encapsulates underlying supply and demand factors (Doyle *et al*. 2003; Piotroski 2000). The goal is to gain a better ability to predict future security price movements, then apply those improved predictions to the design of equity portfolios (Edirisinghe and Zhang 2007).

According to Bentes and Navas (2013), FA is mainly used by shareholders, including Warren Buffett, perhaps the most famous investor in the world, who repeatedly carries out this strategy and acts contrary to many commonly used Wall Street investment strategies. By exploiting bear markets and down stocks, he became the second richest person in the world, according to *Forbes*. The success of this strategy stems from five of its benefits:

1) It allows investors to identify companies with durable or long-term competitive advantages.

2) It is easy to implement.

3) It is a structured, consistent process, performed on the basis of the available financial reports.

4) It can select potential stocks to acquire and thus facilitate the creation of an investment portfolio.

5) It can estimate the intrinsic value of the stocks. Stock markets are not perfectly efficient, so there is always an opportunity to find undervalued stocks (Matos 2009a, b).

Investors also can use FA with different portfolio management styles (Bentes and Navas 2013). For example, buy-and-hold investors believe that identifying good businesses allows them to hold assets that will grow with the company. Using the FA, they can find “good” companies, lower their risk, and mitigate the chance of failure. Managers also might use the FA to identify companies with high future growth rates or to evaluate “good” and “bad” companies, with the assumption that “bad” companies' stock prices will move up and down more than those of “good” companies. The increasing stock price volatility then would create profit opportunities. Using the economic cycle, managers also can determine the “right” time to buy or to sell. Furthermore, the FA allows investors to make their own assessment of the company’s value and ignore the market in the short run. For value investors, the FA helps them restrict their attention to undervalued companies.

Noting these benefits, various studies investigate FA, as summarized in Table 3.1. Overall, empirical literature indicates that accounting fundamental signals successfully predict future earnings and future stock returns. The fundamental signals also have the potential to identify temporary abnormal returns, especially right after earnings are announced and in some cases up to a year after the announcement or disclosure (Dosamantes 2013).

Table 3.1 - 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, Beta and accounting fundamentals	US	An average 12-month cumulative size-adjusted abnormal return of 13.2% is earned according to a fundamental strategy based on Lev and Thiajaran. A significant portion of the abnormal returns is generated around subsequent earnings announcements.
Aggarwal and Gupta (2009)	Follows Piotroski (2000)	Future returns	Accounting fundamentals, *BM* ratio, size, accruals	India	The Piotroski strategy can separate winners from losers for two-year returns after portfolio formation. It generates 98.6% annual return for portfolios with high F-scores and 31.3% annual return for portfolios with low F-scores.
Al-Shubiri (2011)	Valuation theory and fundamental analysis	Share prices	Accounting fundamentals	Jordan (banks)	Positive significant relationship between market price of stock and net asset value per share (*NAV*), *EPS* and dividend percentage.
Amidu and Abor (2006)	Valuation theory and fundamental analysis	Stock returns and earnings	Dividends	Ghana	A key relationship between dividend and earning might directly influence that movement of share prices.
Bagella *et al*. (2005)	Fundamental analysis	Stock price	*P/E* and *CAPM*	US & Europe	An unique model that joins *P/E* and *CAPM* in a single formula.
Dehuan and Jin (2008)	Valuation theory and fundamental analysis	Stock returns	Accounting fundamentals	China	*ROE*, *EPS*, profit margin, *ROA*, changes in sales, and total asset turnover.
Dosamantes (2013)	Valuation theory, fundamental analysis and market under-reaction of high BM ratio firms	Future returns, earnings response coefficient and future earnings growth	Accounting fundamentals, *BM* ratio, size, accruals	Mexico	Mean return earned by a high book-to-market investor can be increased through selection of financially strong high *BM* firms.
Drake *et al*. (2011)	Analysts tend to recommend stocks with high growth, high accruals, and low book-to-market ratios, despite these variables having a negative association with future returns	Stock returns	11 independent variables from accounting fundamentals	US	Short interest is significantly associated in the expected direction with all 11 variables examined. There are abnormal returns from a zero-investment strategy that shorts firms with highly favorable analyst recommendations but high short interest and buys firms with highly unfavorable analyst recommendations but low short interest.
Elleuch and Trabelsi (2009)	Valuation theory: Firm's fundamental or intrinsic value is	Future returns	Accounting fundamentals and	Tunisia	Fundamental accounting signals can be used to discriminate from an overall sample generated over a

	correctly determined by information reflected in financial statements. Sometimes, stock prices do not reflect all information in a timely manner or correctly, so they deviate from fundamental values		accruals		15-month holding period, with negative returns of –11.6%, a winner portfolio generating positive return of 1.9% from a loser one generating negative return of –22.9% over the same holding period.
Holloway *et al*. (2013)	Valuation theory and fundamental analysis	Future returns	Accounting fundamentals and size	Brazil	11 accounting ratios plus 3 sizes: *DY*, σ *EPS*, *GGP*, *Debt*/ *A*, *ROA*, *ROE*, *GM*, *EBITDA* margin, *NM*, *SGAE*/*GP*, Depreciation/*GP*, *A*, Dummy for participation in Bovespa Index, Dummy for financial sector.
Karathanassis and Philippas (1988)	Valuation theory: Fundamental analysis	Share prices	Accounting fundamentals	Greece (banks)	Dividends, retained earnings and size has showed a significant positive influence on share prices.
Lev and Thiagarajan (1993)	Valuation theory and fundamental analysis	Earnings response coefficient and future earnings growth	12 accounting signals, earnings per share	US	More than earnings, the 12 fundamental signals proposed add approximately 70%, on average to the explanatory power of earnings with respect to excess returns.
Lev *et al*. (2010)	Valuation theory: When there is quality in financial information, and it is not compromised, it should be reflected by the prediction of enterprise cash flows and earnings	Future cash flows and future earnings	Accounting fundamentals	US	Accounting estimates beyond those in working capital items (excluding inventory) do not improve the prediction of cash flows. Estimates improve the prediction of the next year's earnings, though not of subsequent years' earnings.
Midani (1991)	Fundamental analysis	Share prices	Accounting fundamentals	Kuwait (industrial services & food)	In a sample of 19 Kuwaiti companies, *EPS* is a determinant of share prices.
Nisa (2011)	Valuation theory: Fundamental analysis and micro economy	Share prices	Share prices and economics data	Pakistan	*P*/*E* Ratio, Net Profit after Tax, Inflation, *DPS*, *GDP* and Annual Turnover as stock price determinant.
Piotroski (2000)	Valuation theory and market under-reaction of high BM ratio firms: Markets do not incorporate historical financial information into prices in a timely manner	Future returns	Accounting fundamentals, BM ratio, size, accruals	US	Mean return earned by a high book-to-market investor can be increased by at least 7.5% annually through selection of financially strong high *BM* firms.
Richardson *et al*. (2010)	Literature review on accounting anomalies and fundamental analysis	Future earnings and future stock returns	Accounting information	Mainly US	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 and less liquid firms with high risk.
Shen and Lin (2010)	Valuation theory: Fundamental analysis	Stock returns	Accounting fundamentals, *EPS* and a vector of the corporate governance	Taiwan market	Corporate governance affects the impact of the relationship between fundamental signals and stock returns. The study employs an endogenous switching model, which combines the response equation and governance index equation simultaneously.
Somoye *et al*. (2009)	Fundamental analysis	Share prices	Dividends per share and *EPS*	Nigeria	Dividend per share and earnings per share as determinants of share prices.
Sunde and Sanderson (2009)	Fundamental analysis, macro and micro economy	Share prices	Accounting fundamentals, economy data	Zimbabwe	Corporate earnings, management, lawsuits, mergers and takeovers, market liquidity and stability, availability of substitutes, Government policy, macroeconomic fundamentals, investor sentiments, technical influences and analyst reports as factors influencing share prices.
Tsoukalas and Sil (1999)	Dividends	Future returns	Dividends ratios	United Kingdom	Based on dividend/price ratio and dividend growth on the share prices. The dividend/price ratio predicts real stock returns for the UK stock market, and there was a strong relationship between real stock returns and dividend yields.
Walkshäusl (2015)	Valuation theory and market underreaction of high *BM* ratio firms.	Future returns, earnings response coefficient and future earnings growth	Accounting fundamentals, *BM* ratio, size, accruals	Europe	As in the US, European value-growth returns strongly depend on the valuation signals contained in the firm's equity financing activities. The high returns of value firms are due to value purchasers; the low returns of growth firms are due to growth issuers.

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

In particular, considerable research in U.S. markets offers strong empirical evidence of the value relevance of FA for explaining future market returns (e.g., Lev and Thiagarajan 1993; Abarbanell and Bushee 1998; Piotroski 2000; Bagella *et al*. 2005; Lev *et al*. 2010; Richardson *et al*. 2010; Drake *et al*. 2011). Research in European markets is comparatively scarce, though some notable exceptions offer insights. For example, Bagella *et al*. (2005) predict that a large group of investors follows a fundamental approach to stock picking, so they build discounted cash flow models that 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. Their empirical results show that fundamental earning price ratios explain significant cross-sectional variation in the observed *P/E* ratios, and other variables are only partially, weakly relevant. Their results also indicate significant differences between the European and U.S. markets, such that the relationship between observed and fundamental *P/E* ratios is much weaker in Europe.

Walkshäusl (2015) extends a U.S. study by Bali *et al*. (2010) to European stock markets. The European value growth returns are similarly strongly dependent 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, with Piotroski and So's (2012) market expectation errors approach, these authors conclude that the observed value growth returns can be attributed to mispricing.

Oberlechner (2001) conducts a survey regarding the perceived importance of technical analysis and FA among foreign exchange traders and financial journalists in Frankfurt, London, Vienna, and Zurich. Most of the traders use both forecasting approaches; the shorter the forecasting horizon, the more important they consider a technical analysis. Financial journalists put more emphasis on FA than the traders. Furthermore, the importance of technical analysis appears to have increased over the previous decade. This study identifies four distinct clusters of traders, with unique forecasting styles, who vary in the overall importance they attach to fundamental versus technical analysis across different trading locations.

Furthermore, firms with low market-to-book ratios (*BM*) generate systematically lower future stock returns, and Dechow *et al*. (2010) document how short-sellers position themselves in the stock of such firms, then cover their positions as the ratios revert to the mean. Short-sellers refine their trading strategies to minimize transaction costs and maximize investment returns. This evidence is consistent with the idea that short-sellers deploy information about ratios to take positions in stocks with lower than expected future returns.

Fama and French (2006), assert that it is possible to isolate determinants of expected returns by varying one of three components while holding the other two fixed: price-to-book value, expected asset growth, or expected future earnings. This comparative static approach is limited, in that it fails to capture the intended interactions of a well-articulated accounting system. For example, growth can affect both reported earnings and book values. As Penman (2009) notes, biased accounting systems that fail to recognize assets (e.g., advertising, research and development) produce lower current book values and higher future accounting rates of return. Thus, growth affects *P*/*B* and expectations of future profitability simultaneously.

Prior to 2000, a flurry of research used accounting variables and ratios to predict future returns (e.g., Ou and Penman 1989; Lev and Thiagarajan 1993; Abarbanell and Bushee 1997). In general, these studies explicitly or implicitly predicted that if the market does not efficiently price expected earnings and financial statements information, better forecasts of earnings predict future returns. For example, Ou and Penman (1989) report that a trading strategy based on a large set of financial ratios generates significant size-adjusted returns, and Abarbanell and Bushee (1998) note that a trading strategy based on the fundamental signals purportedly used by analysts produce significant returns. Piotroski (2000) applies a trading strategy based on fundamental signals to firms with high *BM* ratios and documents annual market-adjusted returns of 23%. Mohanram (2005) reports high returns from a FA-based trading strategy applied to growth firms. But as critics noted, many correlated variables were included in these predictive regressions for future earnings or future returns, leading to concerns of sample identification for the predictive variables. Although a general approach of using accounting information to forecast future earnings is sound, the selection of explanatory variables needs to be guided by theory. Yet sophisticated information users, including financial analysts, seemingly fail to incorporate these fundamental signals into their earnings forecasts.

Xue and Zhang (2011) maintain that stock markets underreact to information contained in publicly available financial statements, which may result from investors' behavioral biases, such as over-confidence or limited attention spans (e.g., DeBondt and Thaler 1995; Daniel *et al*. 1998; Hirshleifer 2008). Alternatively, perhaps fundamental signals capture an unknown component of the systematic risk that is rightly incorporated into stock prices. According to Li *et al*. (2011), several enormously influential factors are relevant for analyzing firms' equity returns, including firm-specific characteristics that define causal relationships, co-occurrences, and other phenomena.

More recent FA studies seek a more a credible alternative hypothesis, such as in studies that address subsets of stocks in which mispricing is expected to be greatest. Piotroski (2000) focuses on neglected *P*/*B* and applies standard financial statement analyses, thereby uncovering some surprisingly strong predictive power for future returns. Beneish *et al*. (2015)

apply a two-stage financial statement analysis approach, relying first on market-based signals to identify likely extreme performers, then applying fundamental signals to differentiate between winners and losers among this group of extreme performers. Baker and Wurgler (2006) use a variety of measures of investor sentiment, such as stock turnover, closed-end fund discount, and first day of an initial public offering returns, to show that stocks that are difficult to arbitrage exhibit large reversals in the months following periods of high aggregate investor sentiment. According to Zhang (2006), stocks with greater information uncertainty exhibit stronger statistical evidence of mispricing in terms of return predictability, based on cross-sectional regressions with an ex ante *BM* ranking. Nagel (2005) also shows that mispricing is greatest for stocks with low institutional ownership, suggesting that institutional ownership is a proxy for the extent to which short-selling imposes constraints and that short-selling is cheaper for institutional investors. Finally, recent FA research that links accounting attributes to future returns has started to focus on stocks with substantial frictions that might support an anomalous relation (e.g., Richardson *et al*. 2010).

Despite the advantages of FA, even in ideal conditions, it suggests not a specific price but a range of prices. Table 3.2 provides a brief overview of the most commonly used ratios in FA. Table 3.3 reports the preferred methods used in FA in the United States.

Table 3.2 - Commonly used FA ratios.

Prices	Per Share	Profitability	Liquidity and Solvability	Efficiency	Market
Price-to-earnings ratio	Earnings per share	Return on assets	Current ratio	Accounts receivables turnover	Free float
Dividend yield	Cash flow per share	Return on equity	Leverage ratio	Inventory turnover	Index trading
Price to cash flow	Book value per share	Return on investment	Long-term debt	Equity turnover	Frequency index
Price to book value	-	-	-	Earnings margin	Market capitalization
-	-	-	-	Growth in earnings per share	-

Source: Adapted from Matos (2009b).

Table 3.3 - Preferred methods of analysis in U.S.

	Company analysis	Sector analysis	Market analysis
Preferred method	*P/E*	*P/E*	Monetary and fiscal
Alternative method	Set of ratios	Economic cycle	*P/E*

Source: Adapted from Matos (2009b).
Notes: *P/E* – Price to earnings

3.2. Post-earnings announcement drift (PEAD)

A major accounting-based market anomaly is the post-earnings announcement drift (PEAD) (Bernard and Thomas 1990). In financial economics and accounting research, the PEAD refers to the tendency for a stock's cumulative abnormal returns to drift in the direction of an earnings surprise for several weeks (or months), following an earnings announcement (Richardson *et al*. 2010). Once a firm's current earnings become known, the information should be quickly assimilated by investors and incorporated into the efficient market price. However, this is not exactly what happens (Dharmesh and Nakul 1995). For firms that report good news in quarterly earnings, their abnormal security returns tend to drift upward for at least 60 days following their earnings announcement. Firms that report bad news in earnings tend to have their abnormal security returns drift downward for a similar period (Bernard and Thomas 1990).

This phenomenon was initially examined by of Ray Ball and Brown in their research "An empirical evaluation of accounting income numbers" published in the Journal of Accounting Research, Autumn 1968, pp. 159-178. This phenome is one of major earning anomaly supports counterarguments against the EMH, and the robust evidence for the PEAD has prompted substantial consideration.

Several hypotheses seek to explain this phenomenon. A widely accepted explanation refers to investors' underreaction to earnings announcements. In Bernard and Thomas's (1990) a comprehensive summary of PEAD research, they suggest that PEAD patterns feature two main components. First, a positive autocorrelation of seasonal differences (i.e., seasonal random walk forecast errors, or the difference between actual and forecasted returns) is strongest for adjacent quarters and positive for the first three lagged quarters. Second, a negative autocorrelation of seasonal differences occurs four quarters apart. The underreaction generates anomalous returns, because prices do not reflect all of the information contained in current earnings changes. Recent literature also considers underreaction to other corporate information and the relation to momentum in stock returns (Richardson *et al*. 2010).

A general "drift" problem relates to whether an under- or overreaction to relevant events is more likely. As Kothari (2001, pp 191) states "currently the null of market efficiency is rejected regardless of whether positive or negative abnormal returns (i.e., under or overreaction) are observed." In further drift research, Bartov *et al*. (2000) find that institutional ownership, as a proxy for investor sophistication, has a negative association with the magnitude of the abnormal returns after earnings announcements, which suggests that trading by unsophisticated investors, who do not realize the implications of current earnings and stock returns, generates the drift. Battalio and Mendenhall (2005) also find that investors executing small trades respond to less sophisticated signals that do not fully integrate the implications of current earnings changes for future earnings, consistent with the notion that small investors cause the PEAD. Shivakumar (2006) concurs that small traders underreact to earnings surprises relative to larger traders and thus drive the PEAD phenomenon. In contrast, Hirshleifer (2008) argue that the returns to the PEAD strategy cannot be explained by the trading activity of individual investors. This research stream also leaves open the question about why larger, more informed, traders do not exploit the underrations of less informed traders.

Existing studies also suffer some limitations in terms of the proxies used to capture investor sophistication, such as trade size and institutional ownership. As various institutional investors increasingly rely on algorithmic trading, trade sizes have become increasingly small (Elkins/McSherry LLC 2009), so it is difficult to attribute small trades solely to less sophisticated individuals. This change in the market microstructure and the trading behavior of large institutions also has implications for empirical measures that use trade sizes as key input (Easley and O'Hara 1987).

In a similar vein, some recent drift research explores the potential influence of limited attention and other investor cognitive biases. Della Vigna and Pollet (2009) assume that investors are more distracted at the end of the week and find that earnings announcements that occur on Fridays produce more drift than those that occur on other weekdays. Liang (2003) finds that investors' overconfidence about their private information and the reliability of earnings results in an underreaction to current earnings innovations and a slow revision of their forecasts, which in turn produces PEAD. According to Hirshleifer *et al*. (2008), drift in response to earnings surprises is greater in settings with more related companies at the same time, consistent with the limited ability of investors to process large amounts of information (Richardson *et al*. 2010). In addition, Chordia and Shivakumar (2005) suggest that the illusion of inflation can create observed drift after earnings surprises, because investors do not incorporate the effect of inflation in their forecasts. Specifically, these authors find that the sensitivity of earnings growth to inflation monotonically increases across earnings surprise portfolios; controlling for the predictive ability of inflation reduces the predictive ability of earnings surprises for future returns. This explanation is a novel extension of the drift literature but could hold for other earnings-based anomalies.

In contrast, little in-depth analysis of transaction costs appears in recent FA studies, primarily due to the lack of high-quality trade data that would enable researchers to quantify transaction costs. Instead, studies tend to identify measures expected to correlate with actual trading costs, such as market capitalization, analyst following, or trade volumes. They then seek to document cross-sectional variation according to these trading cost proxies, using the strength of the anomalous relation, or they use trade and quote data to estimate relative and effective spreads, even though these measures tend to overstate actual transaction costs expected by institutional investors (Stoll 1993). All studies that incorporate transaction costs attempt to assess whether the anomalous returns are within the bounds of market frictions. Furthermore, Ng *et al*. (2008) find that transaction costs, measured by relative and effective spreads, explain a large portion of drift returns. Mendenhall (2004) finds cross-sectional variation in PEAD based on arbitrage risk, consistent with an underreaction explanation, which is challenging for investors to exploit due to the idiosyncratic risks involved. According to Reed (2015), firms with large short-sale constraints exhibit a lower portion of long-term reactions to earnings announcements that occur on subsequent earnings dates, consistent with the idea that capital market frictions support a drift to earnings-related news.

Of the market frictions explored in the context of PEAD anomalies, Kimbrough (2005) and Levi (2008) find that supplementing earnings releases with additional disclosures leads to less underreaction to earnings surprises. Ke and Ramalingegowda (2005) show that transient institutional investors generate large returns from trading on the PEAD, and their trading increases the speed with which prices enter earnings information. These investors trade less in companies with higher transaction costs, which could explain why PEAD persists.

3.3. Accounting anomalies

This section links the various streams of research into accounting anomalies with FA research, to determine whether the relation between a given accounting attribute and future earnings or stock returns might be unique and add incremental value, beyond previously documented attributes. This discussion focuses mostly on accrual anomalies (Richardson *et al*. 2010). Several studies address whether an accrual anomaly is distinct from other accounting anomalies, and most evidence affirms that it is. For example, Collins and Hribar (2000) show that the accrual anomaly is distinct from PEAD; Barth and Hutton (2004) reveal that the predictive ability of accruals for future returns is not subordinated within the predictive ability of analysts' forecast revisions; and Cheng and Thomas (2006) document how the accrual anomaly differs from the value-glamour anomaly. Desai *et al*. (2004) also posit that the value of the firm and accrual anomalies are related overreactions to past accounting data. In the case of the value-glamour anomaly for example, investors extrapolate past growth in sales and earnings; subsequently, usually at the moment of future earnings announcements, they realize that such growth is not sustainable, because growth rates mean revert. For the accrual anomaly though, investors extrapolate past accruals into the future and are surprised when subsequently announced earnings are lower or higher, due to reversals in the accruals. Thus, both anomalies relate to errors in expectations about future earnings, and some proxies for the value-glamour and accrual anomalies are closely linked, such as sales growth. Yet despite these links, at least empirically, they additive in their ability to forecast future stock returns (Desai *et al*. 2004).

Richardson *et al*. (2010) note various studies that investigate the association between a firm's corporate asset investment and disinvestment decisions and future stock returns. These findings largely suggest that corporate events associated with the expansion of a firm's scale and assets—such as acquisitions (Asquith 1983; Agrawal *et al*. 1992; Loughran and Vijh 1997; Rau and Vermaelen 1998), public equity offerings (Ibbotson 1975; Loughran and Ritter 1995), public debt offerings (Spiess and Affleck-Graves 1999), or bank loans (Billet *et al*. 2006)—are followed by periods of abnormally low, long-term stock returns. Corporate events associated with decreases in firm scale or asset contraction, such as spinoffs (Cusatis *et al*. 1993; McConnell and Ovtchinnikov 2004), stock repurchases (Lakonishok and Vermaelen 1990; Ikenberry *et al*. 1995), debt prepayments (Affleck-Graves and Miller 2003), and other payouts (Michaely *et al*. 1995), instead tend to be followed by periods of abnormally high, long-term stock returns.

Other research also documents a negative relation among various forms of corporate investment and future stock returns. For example, increased accruals, capital investments, sales growth, and external financing all tend to relate negatively to subsequent stock returns (e.g., Fairfield *et al*. 2003; Titman *et al*. 2004; Hirshleifer *et al*. 2004). To study whether firm growth is fairly priced in the cross-section, some researchers introduce and fine-tune various measures of growth (Richardson *et al*. 2006; Anderson and Garcia-Feijoo 2006; Cooper *et al*. 2008), then studies attempt to clarify the underlying sources of firm-level growth effects. The refined measures of firm growth are motivated by the observation that prior studies on the effects of growth on returns use components of a firm's total investment or financing activities and ignore the larger picture of the potential total asset growth effects of comprehensive firm investment and disinvestment.

Cooper *et al*. (2008) use a general measure of firm asset growth that accompanies the year-on-year percentage change in total assets, using a panel of U.S. firms' stock returns. They document a negative correlation between firm asset growth and subsequent firm abnormal returns. Asset growth remains significant for explaining future stock returns and other growth measures, such as sales growth (Lakonishok *et al*. 1994), growth in capital investment (Titman *et al*. 2004), accruals (Sloan 1996), and a cumulative accrual measure of net operating assets (Hirshleifer *et al*. 2004). Cooper *et al*. (2008) thus suggest examining changes in net operating assets (ΔNOA). A change in total assets (TA) combines the changes in operating assets (ΔOA) and in financial assets (ΔFA), so $\Delta TA = \Delta OA + \Delta FA$. The ΔNOA equals ΔOA less changes in operating liabilities (ΔOL), so $\Delta NOA = \Delta OA - \Delta OL$. In turn, $\Delta TA = \Delta NOA + \Delta OL + \Delta FA$. Therefore, Cooper *et al*. (2008) ignore offsetting relations between operating assets and operating liabilities (Richardson *et al*. 2005), though they might be important for improving the forecasting ability of accruals. They include changes in financial assets in their empirical analysis.

In an attempt to address prior gaps, Dechow *et al*. (2010) links accrual anomaly literature to the various investing and financing anomalies, according to the balance sheet. The theoretical rationales for the observed relation between these attributes and future stock returns differ, but they remain closely related. From a forecasting perspective, the question then is whether they are additive for forecasting future earnings and returns. For example, *ΔNOA* = *ΔNFO* (net financial obligations) + *ΔB* can be extended by the recognition that changes in the book value (*ΔB*) must result from net equity issuance, *ΔEQUITY*, and income. With some algebraic manipulation, Dechow shows that *ΔNOA* = *ΔXFIN* - *ΔFA* + income, where external financing (*ΔXFIN*) equals *ΔDEBT* + *ΔEQUITY*. In turn, Dechow shows that the association between a broad measure of accruals (*ΔNOA*) and future stock returns is stronger than the relation between a measure of external financing (*ΔXFIN* or its constituents, *ΔDEBT* and *ΔEQUITY*). Specifically, the accrual measure (*ΔNOA*) is more effective for explaining the cross-section of returns than a net financing measure (*ΔXFIN*). After first sorting according to the accrual measure, the financing measure cannot capture any return variation. It thus appears that the use of external financing proceeds (*ΔNOA*) predicts future returns, rather than the raising or distribution of financing (*ΔXFIN*), as suggested in other studies (e.g., Richardson *et al*. 2010; Dechow *et al*. 2008; Ritter 2003). Although Dechow *et al*. (2008) suggest the importance of a broad-based measure of accruals to forecast future earnings and returns, due to the associated discretion embedded in accruals, alternative explanations for this robust empirical relation also exist, including "that accruals measure changes in invested capital and that changes in invested capital are associated with diminishing marginal returns to new investment (and related overinvestment). Note that these alternative interpretations are not mutually exclusive and probably coexist" (p. 564).

In summary, accrual anomaly literature has evolved to make clear the explicit links with other anomalies, such as those related to financing and investing. Dechow *et al*. (2010) even suggests that the accrual anomaly subsumes these related anomalies. Overall, investors appear to have difficulty interpreting the performance of firms for which net operating assets change substantially.

3.4. Fundamental analysis anomalies

As Kothari (2006) notes, the residual income model (Ohlson 2009) had a sizable impact on valuation approaches and applications of FA. For example, relative to the discounted dividend model, the residual income model offers a conceptual framework that relates the market value of the company (MVE) to its past and future financial information, including current and future expected net income; the book value of equity (BVE), and dividends (Ohlson 1995). However, the applicability and utility of any valuation model depends on the plausibility of the assumptions underlying it, such as the persistence of abnormal earnings and the quality and availability of data required by the model, such as earnings forecasts. Recent advances refine the valuation models and also apply them. For example, Ohlson and Juettner-Nauroth (2005) (OJ) propose a model that focuses on abnormal earnings growth with no clean surplus accounting, as is generally required by previous models (Ohlson 1995; Feltham and Ohlson 1995). Unlike the traditional residual income model, this OJ model specifies earnings per stock, instead of book value per stock, as the fundamental forecasting benchmark, which is far easier to implement in practice.

This proliferation of valuation models also has spawned a growing debate about the superiority, applicability, accuracy, bias, and empirical properties of various models (e.g., Penman 2009; Richardson *et al*. 2010). Various benchmarking studies conclude that different implementations and distinct assumptions across valuation models lead to their differential abilities to predict future returns. For example, by analyzing many situations, Ohlson (2009) concludes that the truncation errors of terminal streams are smaller and less frequent in the OJ model than in a traditional residual income model that relies on book equity as the performance benchmark. Therefore, a finite-term OJ model likely will outperform a finite-term residual income model. Capitalized earnings under the OJ model also capture the *MVE* better than the *BVE* in a conservative accounting setting. The OJ model also offers superior ability to forecast future returns; in a comparison of this ability across different valuation measures, Ali *et al*. (2008) find that the incremental contribution of the OJ model is significant in regressions of future returns on the value-to-price and *BM* ratios. Overall then, the OJ model appears to offer good ability to predict future abnormal returns.

Based on valuation theory, FA aims to find important signals that should be related to future earnings and future stock prices changes. The PEAD effect is important to enhance the power of earnings variation which will reflect on the price stocks, for good and for bad (e.g., Bernard and Thomas 1990).

According to the literature, accounting FA has the potential to predict future earnings and future returns at least in a one-year horizon (e.g., Abarbanell and Bushee 1997; Elleuch and Trabelsi 2009; Piotroski 2000). In this study two fundamental scores were generated for the Euronext 100 firms: F-Score (Piotroski 2000) and L-Score (Lev and Thiagarajan 1993). Next section (4) presents the description of the accounting signals used to construct the scores, and then the construction of the scores.

3.5. Volatility

According to González (2016), portfolio managers also exhibit growing interest in the contagion effects of financial markets, which require cautious investment decisions. They need clear insights into the relationships among those aspects of the stock markets that promote volatilities, including whether positive and negative events have similar effects, in which case the absence of asymmetry should influence portfolio management decisions. Aboura and Wagner (2016) assert, according to finance literature, that asymmetric volatility exists in equity markets, such that returns and volatility relate negatively, and this relation is especially pronounced for negative returns. Asymmetric equity market volatility is a key characteristic of market volatility dynamics and price risk, with asset pricing implications, that also has critical roles for risk prediction, hedging, and option pricing. Finally, asymmetric volatility implies negatively skewed return distributions, so it might help explain some of the probability of large losses.

Chevallier and Ielpo (2014) note three main characteristics of financial returns: leverage (volatility asymmetry), conditional fat-tails (standardized conditional return is more fat-tailed than the Gaussian), and conditional skewness (standardized return is not symmetric). For stock returns, skewness is typically negative, so the probability of a large negative return is greater than that of a large positive return, even after controlling or adjusting for the recent level of volatility.

In power markets, supply or demand shocks, such as those due to unexpected outages or transmission constraints, cannot be compensated for in the short run, which can lead to sudden jumps, or spikes, in prices, especially if reserve capacity is limited (Erdogdu 2016). Volatility is central to an understanding of the dynamics of markets, in particular with regard to their financial aspects, with massive implications for the economy as a whole. The issue is widely debated, starting with Shiller (1981a, b); LeRoy and Porter (1981) demonstrate that volatility in stock markets is too high to be explained simply by the arrival of new information about firms' fundamental value. Schwert (1989) concludes that only a small percentage of market fluctuations can be explained by traditional models of current value; Grossman and Shiller (1981) instead stress that the new information content contained in previous models has not ever been clearly defined, nor has its real impact on stock prices.

Daly (2008) highlights several main reasons to study financial market volatility. First, when there are large fluctuations in prices in short time intervals (e.g., a day or less), investors cannot accept solely economic explanations, so market confidence likely erodes, with consequences for liquidity. For companies, volatility thus may determine the likelihood of bankruptcy: With a more volatile capital structure, the threat of firm bankruptcy increases. Second, the bid–ask spread set by market makers tends to increase with greater volatility, because it implies an increased risk. Third, the same effect holds for premiums associated with risk hedging transactions, which are especially attractive in periods of market turbulence. Fourth, to risk-averse investors, increased volatility has substantially negative effects, in terms of investment and consumption, as well as other variables such as firm life cycles (see Schwert 1989). Fifth, continuous increases in volatility may prompt regulators or financial institutions to adopt specific policies to encourage enterprises to invest more capital in treasury funds, which is clearly contrary to the efficient allocation of resources.

Considering these issues, it becomes imperative to define the concept of volatility. Many authors use the term to designate the degree of oscillation of a particular variable over time (Daly 2008; Hsu and Murray 2007; Vilder and Visser 2007), such that greater variation means greater volatility. However, despite being closely related in financial terms to ascents and descents in the market, most studies focus exclusively on the latter and their negative impacts (e.g., the increase in related publications after the stock market crash of 1989; Barclay *et al*. 1990; Engle and Susmel 1993; Ferson and Harvey 1991; Koutmos 1996; Koutmos and Booth 1995; Rahman and Yung 1994; Roll 1992). The notion of volatility also traditionally has been associated with the concepts of risk and uncertainty and thus the trade-off of risk and returns—a pillar of modern finance theory that underpins the capital asset pricing model, arbitrage pricing model, portfolio theory, and valuation models of options (Black and Scholes 1973).

Yet the terms are not interchangeable. Knight (1921) explains that risk implies a lack of certain knowledge about the outcome of any decision taken, despite knowledge of the distribution of probability. Uncertainty instead means the probability of each occurrence of possible events is completely unknown. Granger (2005) illustrates the problem: In a given portfolio, a certain asset is facing a negative large shock. Thus the portfolio manager confronts a risk, because of the increasing probability of selling the asset at a lower price than it was purchased. However, if the shock is positive, this possibility becomes uncertainty. Although both shocks increase variance, only one is considered undesirable, so it offers the basis for the distinction between the two concepts (Bentes 2011).

Much of the noise in transactions likely stems from irrational investors, so Hwang and Satchell (2000) propose a renewed view of volatility, defined as the result of a combination of transient volatility caused by noise and permanent volatility that stems from the arrival of random information into the market. This predicted role of information for volatility is not recent, having been reported by Ross (1989), who defines it as a result of the flow of information among various players.

However, a problem arises because volatility is not a directly observable variable. Zare *et al*. (2013) assert that stock market volatility has a negative effect on the recovery of the real economy; a determinant of stock market volatility is central bank policies. The time-varying risk premium or volatility feedback effect (see Campbell and Hentschel 1992; Wu *et al*. 2015) implies that volatility clustering can explain the phenomenon. For Gospodinov and Jamali (2012), higher (lower) stock prices and thus higher (lower) stock returns prompt lower security exchange instability, as suggested by the influence impact or “leverage effect,” which alludes to the unbalanced connection between securities exchange returns and instability.

For Vo *et al*. (2015), the intertemporal relationship between risk and returns is an important finance concept, subject to active research. Empirically, volatility appears asymmetric, so negative shocks to returns are associated more with upward movements of conditional volatility than are positive shocks of the same size. Large shocks, whether positive or negative, result in high instability, which tends to be trailed by high unpredictability (Vo *et al*. 2015). If unpredictability gets valued in the returns, an expected increment in instability raises the required return on the stock, causing the price to drop immediately. Substantial bad news thus not only decreases the price but also increases future volatility, which pushes the price down further, amplifying the impact of bad news. Substantial good news instead raises the price, as well as future volatility. The increased volatility exerts a negative impact on price, which dampens the impact of the good news. As a result, asymmetry occurs.

Asymmetry also can be described as a negative correlation between return and volatility innovations, such that the estimation of the relationship measures the level of asymmetry. Volatility models that represent this property usually depict the arrival progression better and give more precise gauges of instability, which is imperative information for subordinate valuation and risk management. Finally, time series of financial asset returns often exhibit volatility clustering, such that large changes in prices tend to cluster together, resulting in persistence in the amplitudes of the price changes. Using various methods to quantify and model this phenomenon, several economic mechanisms have been proposed to explain the origin of volatility clustering, in terms of market participants’ behavior or news arrival processes (Cont 2007).

Then, the most known definitions of statistical measures of volatility, historical volatility σ:

$$\hat{\sigma} = \sqrt{\frac{\sum_{t=1}^{T}(r_t - \bar{R})^2}{T-1}} \tag{1}$$

where $\hat{\sigma}$ represents the standard deviation of the returns r_t of a sample with T observations, and $\bar{R}$ is the arithmetic mean defined as $\bar{R} = \sum r_t / T$. The returns r_t associated with period t for any asset are determined by the logarithmic (ln) difference of the prices. The simplicity of its calculation is the main advantage of this measure.

However, Brooks (2002) calls for caution when there is a single, abnormally high observation, for which the standard deviation will present an artificially high value, indicating high volatility even though the market actually is relatively quiet. Moosa and Bollen (2002) also criticize this measure, because both temporarily distant returns and the latest returns have equal weight in the value of the standard deviation, which may not be a realistic assumption. Because σ depends on the scale used, it is possible to use the variation coefficient CV instead, obtained by:

$$CV = \frac{\hat{\sigma}}{\bar{\bar{R}}} x100 = \frac{1}{\bar{\bar{R}}} \sqrt{\frac{\sum_{t=1}^{T} (r_t - \bar{R})^2}{T-1}} x100 \tag{2}$$

According to Dajcman *et al*. (2012), international stock market linkages are of great importance for the financial decisions of international investors. Gel and Chen (2012) also assert that measuring volatility is key for assessing risk and uncertainty in financial markets. Solnik (1993) and Harvey (1993) discuss portfolio allocation implications when market volatility is predictable.

Bollerslev *et al*. (1992) find that stock market volatility in the U.S. market affects the average cost of capital, allocation efficiency, and the overall health of the economy. Errunza and Hogan (1998) conclude that it is possible to form alternative portfolios with better forecasts of future portfolio variance. Shiller (1994) calls for macroeconomic, subordinate securities to improve individual capacities to swap risks that cannot be supported in financial markets. The extent to which current equity-related financial derivatives are inadequate to offer this support largely depends on the degree to which equity markets track macroeconomic indicators.

Studies of the statistical properties of financial time series reveal several stylized facts that appear to span various markets, instruments, and periods, including:

1. Excess volatility, such that it is difficult to justify the observed level of variability in asset returns by variations in fundamental economic variables. In particular, large (negative or positive) returns cannot always be explained by the arrival of new information on the market (Cutler 1989).

2. Heavy tails, as occur when an (unconditional) distribution of returns displays a heavy tail with positive excess kurtosis.

3. Volatility clustering, as noted by Mandelbrot in his research “The Variation of Certain Speculative Prices” (Mandelbrot 1963, pp. 418), who explains that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes". A quantitative manifestation of this fact is that, while returns

themselves are uncorrelated, absolute returns $|r_t|$ or their squares display a positive, significant and slowly decaying autocorrelation function: corr($|r_t|$, $|r_{t+\tau}|$) > 0 for τ ranging from a few minutes to several weeks.

4. Volume/volatility correlation, which occurs because trading volume is positively correlated with market volatility. Moreover, trading volume and volatility show the same type of “long memory” behavior (Lobato 2000).

The phenomenon of volatility clustering has been particularly intriguing for researchers, strongly affecting the development of stochastic models in finance; both *GARCH* and stochastic volatility models primarily seek to model this phenomenon. It also has inspired debate about whether long-range dependence appears in volatility. In econometrics, *ARCH* models serve to characterize and model observed time series (Engle, 1982), leading to the use of *GARCH* models in financial forecasting and derivatives pricing. The *ARCH* (Engle 1982) and *GARCH* (Bollerslev 1986) models aim to describe the phenomenon of volatility clustering more accurately, as well as related effects such as kurtosis, according to the idea that volatility depends on prior realizations of the asset process and related volatility processes.

The *EGARCH* (exponential *GARCH*) extension, as introduced by Nelson (1991), also is popular. In this model, log-volatility is expressed as a linear combination of its past values and the past values of the positive and negative elements of the innovations. The formulation is successful because it allows for asymmetries in volatility (so-called leverage effect: Negative shocks tend to have more impact on volatility than positive shocks of the same magnitude) but does not impose any positivity restrictions on the volatility coefficients.

4. Research Design

4.1. Accounting signals

4.1.1. Book-to-Market Ratio (BMR)

The book-to-market ratio (*BMR*) reveals the value of a company by dividing its book value (*BV*) by its market capitalization (*MC*). If the ratio is greater than 1, the stock is undervalued; if it is less than 1, the stock is overvalued. The *BV* denotes the portion of the company held by the shareholders—that is, the company's total tangible assets less its total liabilities. Owners of common stocks in a firm use the *BV* to determine the level of safety associated with each individual stock after all debts are paid. If the company decides to dissolve, the *BV* indicates the value remaining for common shareholders after all assets have been liquidated and all debtors paid. In simple terms, it equals the amount of money a holder of a common stock receives if a company were to liquidate. The ratio predicts positive F- and L-scores (Dosamantes 2013). In addition, long-term growth in *BV* can provide a rough measure of long-term growth in the intrinsic value of a business and thereby identify companies with durable competitive advantages. A company with a durable competitive advantage shows *BV* that is growing over time (Bali *et al*. 2014). The *BMR* ratio appears in Ohlson's (1995) model.

4.1.2. Capital expenditures (CAPEX)

The capital expenditures (*CAPEX*) refer to money spent to acquire or improve the capital goods owned by a company, or the amount of investments in equipment. An expense is a capital expenditure when the resulting asset is a newly purchased capital asset or an investment that improves the useful life of an existing capital asset. In this case, the expense needs to be capitalized, such that the company spreads the (fixed) cost over the useful life of the asset. If the expense maintains the asset at its current condition though, the cost is deducted fully in the year of the expenditure. The amount of *CAPEX* a company has depends substantially on its industry; the most capital-intensive industries exhibit high *CAPEX* levels, such as oil exploration, telecom, manufacturing, and utilities. This ratio informs the L-score (L3 group) (Lev and Thiagarajan 1993).

4.1.3. Cash flow from operations (CFR)

Cash flow from operations (*CFR*) is an accounting item that indicates the money a company earns from its ongoing, regular business activities. The *CFR* is reported on the cash flow statement in a company's quarterly and annual reports. It does not include long-term capital or investment costs, but it integrates earnings before interest and taxes plus depreciation minus taxes. It also includes changes in working capital (current assets minus current liabilities), such as increases or decreases in inventory, short-term debt, accounts receivable, or accounts payable. Income that a company receives from investment activities is reported separately, because it is not from business operations.

Comparing *CFR* with earnings before interest, taxes, depreciation, and amortization (*EBITDA*) can offer insights into how a company finances its short-term capital. Investors examine a company's *CFR* separately from two other components of cash flow, namely, investing and financing activities, to determine the source of the firm's money. Positive cash flow should result from operating activities; if it results instead from the company selling off its assets or issuing new stocks or bonds, then the one-time gains cannot provide a good indicator of financial health. Investors also examine a company's balance sheet and income statement to get a fuller picture of its performance. Cash flow from operating activities similarly excludes dividends paid to stockholders and money spent to purchase long-term capital, because these are one-time or extraordinary expenses. This ratio informs the F-score (F2 group) (Piotroski 2000).

4.1.4. Current ratio (CR)

The current ratio (*CR*) is a liquidity ratio that measures a company's ability to pay its short- and long-term obligations. The *CR* includes the total current assets of a company (liquid and illiquid) relative to that company's total current liabilities. It thus gives an idea of the company's ability to pay back its liabilities (debt and accounts payable) using its assets (cash, marketable shares, inventory, and accounts receivable). Thus, *CR* can give a rough measure of the company's financial health: A higher *CR* means the company is more capable of paying its obligations, because it enjoys a larger proportion of asset value relative to liability value. This ratio is used in F6 group, which belongs to the F-score (Piotroski 2000).

4.1.5. Debt-to-total assets ratio

The ratio of the total debt over total assets is a leverage ratio that defines the total amount of debt relative to assets. It enables comparisons of leverage across different companies. A higher ratio implies a higher degree of leverage and thus financial risk. Companies with larger debt, compared with their assets, produce negative expectations of expected returns (Holloway *et al*. 2013). This ratio is used to calculate the F5 group of the F-score (Piotroski 2000).

4.1.6. Earnings per share (EPS)

The earnings per share (*EPS*) ratio is one of the most commonly used inputs for FA. However, *EPS* ignores the level of equity required to generate the corresponding earnings (net income). For example, if two different companies report the same *EPS*, the most efficient one is the firm that requires less capital to attain that *EPS*. Investors also need to be aware of accounting manipulation effects, which can affect earnings value. It is important to rely on more than a single, specific ratio and instead combine multiple ratios together (Bentes and Navas 2013; Dosamantes 2013). This ratio appears in Ohlson's (1995) model.

4.1.7. Gross margin (GM)

Companies with high margins, regardless of sector, tend to have sustainable competitive advantages; otherwise, other firms would enter the market, and its margins would fall. The gross margin (*GM*) is a measure of the company's total sales revenue minus its cost of goods sold, divided by the total sales revenue, expressed as a percentage. It represents the percentage of total sales revenue that the company retains after incurring the direct costs associated with producing the goods and services that it sells. A higher *GM* implies that the company retains more of each monetary unit of sales to service its other costs and obligations. This variable should relate positively to both scores (Holloway *et al*. 2013). It belongs to the F8 group of Piotroski (2000) and the L4 group of Lev and Thiagarajan (1993).

4.1.8. Return on operating assets (ROA)

Return on operating assets (*ROA*) indicates how profitable the company is relative to its total assets. The *ROA*, measured by the ratio of earnings over total assets, indicates how efficient a company is in using its assets to generate earnings (Holloway *et al*. 2013). It serves to calculate the F1 group of Piotroski's (2000) F- score.

4.1.9. Sales to assets (AT) ratio

The ratio of sales and/or revenues to assets it is also known as asset turnover (*AT*), which offers an indicator of the efficiency with which a company deploys its assets to generate revenues. Generally speaking, the higher the *AT* ratio, the better the company is performing, in that it is generating more revenue per unit of money or assets. Yet this ratio can vary widely across industries, so *AT* comparisons are meaningful only across different companies in the same sector. This ratio is used to compute the F9 group of F-score from Piotroski (2000).

4.1.10. Sales to employee ratio

This ratio measures the value of sales made by the average number of employees. Comparing this ratio within different companies, it indicates the employee turnover ratio. Higher values indicate greater productivity by employees. It is used to calculate the L8 group of Lev and Thiagarajan's (1993) L-score.

4.1.11. Selling, general and administrative expenses (SGAE)

The lower the selling, general, and administrative expenses (*SGAE*), the more attractive the company is, because the cost of its overhead does not burden the company. As reported on the income statement, the *SGAE* is the sum of all direct and indirect selling expenses and all general and administrative expenses of a company. Direct selling expenses can be linked directly to the sale of a specific unit, such as credit, warranty, or advertising expenses. Indirect selling expenses instead cannot be linked directly to the sale of a specific unit, but they are proportionally allocated to all units sold during a certain period, such as telephone, interest, and postal charges. General and administrative expenses include salaries of non-sales personnel, rent, heat, and lights. This variable is used to compute L5 group in Lev and Thiagarajan (1993).

Table 4.1 summarizes the accounting signals, and their expected signs, used to compute both the F- and L-scores.

Table 4.1 - Expected sign of accounting signals

Explanatory Variables	Expected Sign	References
BMR	+	Dosamantes (2013)
CAPEX	+	Lev and Thiagarajan (1993)
CFR	NS	Piotroski (2000)
CR	+	Piotroski (2000)
Debt / Total Assets	-	Holloway *et al.* (2013)
EPS	+	Dosamantes (2013)
GM	+	Holloway *et al.* (2013)
ROA	+	Holloway *et al.* (2013)
AT	+	Piotroski (2000)
Sales to Employee	+	Lev and Thiagarajan (1993)
SGAE	-	Lev and Thiagarajan (1993)

Notes: *BMR* – Book-to-Market ratio; *CAPEX* – Capital expenditures; *CFR* – Cash flow from operations; *CR* – Current ratio; *EPS* – Earnings per share; *GM* – Gross margin; *ROA* – Return on assets; *AT* – Assets turnover; *SGAE* – Selling, general and administrative expenses.

4.2. Construction of the 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 proposed 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 *BMR*, the F-score also is robust to different levels of financial health, future firm financial performance (Piotroski 2000), asset growth, and future market value (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 can range from 0 (low signal) to 9 (high signal). That is, Piotroski (2000) considers nine discrete accounting fundamental measures at time t, as defined in Table 4.2. The F-score equals the sum of F1 through F9.

Table 4.2 - The 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	$\Delta\ Equity>0$	then F7=1; 0 otherwise
8	$\Delta\left[\frac{GM_t}{A_{t-1}}\right]>0$	then F8=1; 0 otherwise
9	$\Delta\left[\frac{Sales_t}{A_{t-1}}\right]>0$	then F9=1; 0 otherwise

Notes: $ROA_{(t)}$ = Return on assets at time t; $ROA_{(t)} = \frac{NBID_t}{A_{t-1}}$; *NIBD* = net income before interest, taxes and depreciation; $NIBD_{(t)} = Sales_{(t)} - COGS_{(t)} - SGAE_{(t)}$; *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; $CFR_{(t)} = EBIT + depreciation - taxes$; *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, also equal to $\frac{Current\ Assets}{Current\ Labilities}$; *Δ Equity* = change in common share outstanding (if the firm issued equity at t, this variable will be greater than zero); $\Delta\left[\frac{GM_t}{A_{t-1}}\right] = \frac{GM_t}{A_{t-1}} - \frac{GM_{t-1}}{A_{t-2}}$; GM = gross margin; *and* $GM_{(t)} = Sales_{(t)} - COGS_{(t)}$

The L-score is constructed from the fundamental signals proposed by Lev and Thiagarajan (1993), using annual data. As Table 4.3 shows, these signals measure percentage changes in inventories, accounts receivables, gross margins, selling expenses, capital expenditure, gross margin, sales and administrative expenses, provision for doubtful receivable, effective tax rates, order backlog, labor force productivity, inventory method, and audit qualifications. The 12 fundamental signals relate consistently to contemporary and future returns (Abarbanell and Bushee 1998; Swanson *et al*. 2003).

Table 4.3 - The original L-Score of Lev and Thiagarajan (1993)

	L-Score Accounting Signals	Definition:
1.	Inventory	Δ Inventory – Δ Sales
2.	Accounts Receivable	Δ Accounts Receivable – Δ Sales
3-4.	Capital Expenditure	Δ Industry Capital Expenditures or R&D – Δ Firm Capital Expenditures (R&D)
5.	Gross Margin	Δ Sales – Δ Gross Margin
6.	Sales and Administrative Expenses	Δ Sales & Administrative Expenses – Δ Sales
7.	Provision for Doubtful Receivables	Δ Gross Receivables – Δ Doubtful Receivables
8.	Effective Tax	$PTEt \times (T_{t-1} - T_t)$ PTE_t = pretax earnings at t, deflated by beginning price T= effective tax rate
9.	Order Backlog	Δ Sales – Δ Order Backlog
10.	Labor Force	$\dfrac{\frac{Sales_{t-1}}{No\ of\ Employees_{t-1}} - \frac{Sales_t}{No\ of\ Employees_t}}{\frac{Sales_{t-1}}{No\ of\ Employees_{t-1}}}$
11.	LIFO Earnings	0 for LIFO; 1 for FIFO LIFO=Last Incomes First Outcomes FIFO= First Incomes First Outcomes
12.	Audit Qualification	1 for Qualified; 0 for Unqualified based on audit opinion

The inventory signal is positive when changes in sales from one period to the next are greater than the changes in inventory. An inventory of finished goods that grows faster than sales might indicate low asset turnover or difficulty complying with sales and inventory cost objectives. If the changes in accounts receivables are greater than the changes in sales, the firm might have difficulty collecting cash, which could affect its daily operations. However, changes in sales that are greater than changes in accounts receivable indicate operational efficiency. If changes in the capital expenditures of the firm are greater than changes in the capital expenditures of the industry, it offers a positive signal. If the changes in gross margin are greater than the changes in sales, the firm’s net profit is growing faster than sales, indicating cost efficiency. If changes in sales and administrative expenses are greater than changes in sales, the firm might experience productivity problems. A declining effective tax rate might indicate that earnings will not persist at current levels, which would affect future performance. As an example, consider how the inventory signal can be computed:

Inventory Change $_{i,t} = \frac{[Inventory_{i,t} - E(Inventory_{i,t})]}{E(Inventory_{i,t})} - \frac{[Sales_{i,t} - E(Sales_{i,t})]}{E(Sales_{i,t})}$;

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

E (Inventory $_{i,t}$) $= \frac{Inventory_{i,t-1} + Inventory_{i,t-2}}{2}$; and

E (Sales $_{i,t}$) $= \frac{Sales_{i,t-1} + Sales_{i,t-2}}{2}$, 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*.

Due to data restrictions, the current study computes the L-score according to nine fundamental signals for each firm. Swanson *et al.* (2003) similarly used five accounting signals in less developed markets to examine the relevance of these fundamentals. Table 4.4 specifies the accounting signals used. Table 4.5 summarizes the differences between the original and the adapted L-score. Similar to Lev and Thiagarajan (1993), this study employs annual data.

Table 4.4 - Adaptation of Lev and Thiagarajan's (1993) accounting signals

	L- Score Accounting Signal	Definition
1.	Inventory	Δ Inventory - Δ Sales
2.	Accounts Receivable vs. Sales	Δ Accounts Receivable – Δ Sales
3.	Capital Expenditure	Δ Firm Capital Expenditures
4.	Gross Margin	Δ Sales – Δ Gross Margin
5.	Sales and Administrative Expenses	Δ Sales & Administrative Expenses – Δ Sales
6.	Accounts Receivable	Δ Accounts Receivable
7.	Effective Tax	$PTE_t \times (T_{t-1} - T_t)$ PTE_t = pretax earnings at t, deflated by beginning price T= effective tax rate
8.	Labor 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

Table 4.5 - Differences from the original and the adapted L-scores of Lev and Thiagarajan (1993)

	L-Score Accounting Signal	Observations
3.	Capital Expenditure	Using only the variation of the firm, excluding the sector in order to facilitate calculation
6.	Provision for Doubtful Receivables	Using only the variation of the Accounts Receivable (Net) because only very few firms of the sample present values on Doubtful Receivables, which would turn the signal to 0, unfairly.
9.	Order Backlog	No info about Order Backlog, substituted by the variance of the Sales.
11.	LIFO Earnings	Eliminated: no info about inventory costing method but is presumed LIFO (score 1 for every company)
12.	Audit Qualification	Eliminated: all companies from Euronext 100 present an 1 value (Qualified)

4.3. Fundamental analysis: econometric models

As a benchmark model, the following regression is proposed to test the earnings effect on firm returns, with and without the book-to-market ratio and firm size as control variables (e.g., Campbell and Shiller 1988; Midani 1991; Ohlson 1995; Dosamontes 2013):

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

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 are calculated by including dividends paid plus stock splits and reverse stock splits; taxation is not included, so the results are presented as gross values. The annual returns thus can be computed as:

$$R_t = \frac{P_t}{P_{t-1}} - 1 \tag{3}$$

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 test the value relevance of the fundamental signals (e.g., Piotroski 2000; Nawazish 2008; Dosamantes 2013):

$$R_{it} = \alpha + \beta_1 \times EPS_{it} + \beta_2 \text{ x } BMR_{it} + \beta_3 \times SIZE_{it} + \varepsilon_{it}. \text{ (Model 2)}$$

$$R_{it} = \alpha + \beta_1 \times EPS_{it} + \beta_2 \text{ x } BMR_{it} + \beta_3 \times SIZE_{it} + \beta_4 \times Fscore_{it} + \varepsilon_{it}. \text{ (Model 3)}$$

$$R_{it} = \alpha + \beta_1 \times EPS_{it} + \beta_2 \text{ x } BMR_{it} + \beta_3 \times SIZE_{it} + \beta 4 \times Lscore_{it} + \varepsilon_{it}. \text{ (Model 4)}$$

$$R_{it} = \alpha + \beta_1 \times EPS_{it} + \beta_2 \text{ x } BMR_{it} + \beta_3 \times SIZE_{it} + \beta_4 \times Fscore_{it} + \beta_5 \times Lscore_{it} + \varepsilon_{it}. \text{ (Model 5)}$$

In these equations, *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 were as detailed in the section 4.2.

If the fundamental signals are value relevant, the coefficient β_4 in Models 3 and 4 should be positive and statistically significant. In Model 5, in addition to β_4 and β_5, the coefficients β_1 and β_2 should be positive and statistically significant, and β_3 should be negative and statistically significant.

For example, according to Piotroski (2000), an underreaction to historical information and financial events—the ultimate mechanism underlying the success of the F-score—is the primary mechanism underlying momentum strategies (Chan *et al.* 1996), which can predict future stock returns. In our study, *BMR* is the ratio of the momentum. As such, it is important to demonstrate that a financial statement analysis methodology can identify financial trends, above and beyond the effects of other, previously documented effects.

In a second step, to examine the potential use of fundamental signals to understand the future returns, firm-year observations are classified according F-score and L-score to one-year and two-year raw returns and market-excess firm returns.

4.4. GARCH Model

Let y_t , the return series of a given stock in the regression model, be

$$y_t = x_t'\xi + \varepsilon_t, \dots t = 1, \dots, T, \tag{4}$$

where x_t is a $kx1$ vector of independent variables, and ξ denotes a $kx1$ vector of regression parameters. The ARCH model characterizes the distribution of the stochastic error ε_t conditional on the realized values of a set of variables $\{y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}, \dots\}$. The *ARCH* process is defined in terms of the distribution of the errors of a dynamic linear regression; Engle's (1982) contribution then was to set the conditional variance of errors as a function of the lagged errors, such that

$$\sigma_t^2 = \sigma(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, t, \xi, b), \text{ and} \tag{5}$$

$$\varepsilon_t = \sigma_t^2 Z_t, \tag{6}$$

where $Z_t i.i.d.$ with $E(Z_t) = 0$ and $E(Z_t^2) = 1$. In the *ARCH* framework, the error series is serially uncorrelated with a zero mean, but the conditional variance of ε_t is σ_t^2, which may vary over time. Engle (1982) then defines an ARCH (*p*) process as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2, \tag{7}$$

where ω and α are non-negative to keep the conditional variance non-negative. The conditional variance expression accounts for volatility clustering. As in the *ARCH* model, the variance of the current error is an increasing function of the magnitude of the lagged errors, irrespective of their sign. Thus, large errors of either sign tend to be followed by a large error of either sign, for example, thus capturing positive serial correlation in ε_t^2, or volatility clustering (Daly 2008).

Bollerslev (1986) generalized the ARCH model, producing the *GARCH* (*p*,*q*) specification given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \tag{8}$$

where $\omega > 0, \alpha_1, \dots, \alpha_p \geq 0, and\ \beta_1, \dots, \beta_q \geq 0$ to ensure non-negativity of σ_t^2. In this model, conditional current volatility depends on not only the lagged squared residuals but also the past squared values of the variance itself. Because it is an infinite order *ARCH* process, *GARCH* can parsimoniously represent a higher-order *ARCH* process. The most common *GARCH* specification in applied research is *GARCH (1,1),* where the effect of a shock in volatility declines geometrically over time. The necessary and sufficient condition for the existence of the second moment of ε_t^2, under normality of ε_t^2, is $\alpha + \beta < 1$; that for the fourth moment is $(\alpha + \beta)^2 + 2\alpha < 1$.

This class of models is suitable to deal with symmetric volatility, such that the impact of good and bad news are identical. However, this impact may differ in the presence of good and bad news. Over time, various authors (Awarti and Corradi 2005; Black 1976; Christie 1982; Engle and Ng 1991; Leeves 2007; Liu and Hung 2010; Pagan and Schwert 1990; Sentana 1992) have shown that negative surprises increase volatility more than positive surprises do. This class of models also exhibits several drawbacks, such that the estimated coefficients often violate the parameter constraints, the constraints excessively limit the dynamics of σ_t^2, and persistence remains difficult to capture using only this approach.

4.5. EGARCH Model

To overcome the symmetry limitations of previous models, Nelson (1991) introduced the *EGARCH* model, which constrains conditional variance to be non-negative by assuming the logarithm of σ_t^2 is a function of:

$$log\sigma_t^2 = \omega + \beta log\sigma_{t-1}^2 + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}^2} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2}, \tag{9}$$

where the coefficient γ captures the leverage effect of shocks on volatility and must be negative to produce evidence of asymmetry. In this model, positive and negative innovations of equal size do not generate the same volatility. This formulation has several advantages compared with the pure GARCH specification. First, the log σ_t^2 is modeled even if parameters are negative, so conditional variance will be positive, and there is no need to impose non-negativity constraints on the model parameters. Second, it allows variance to respond more quickly to decreases, compared with increases, in a particular market (Bentes *et al*. 2013).

4.6. TGARCH Model

As an alternative that can analyze the asymmetric property of data, as derived by Glosten *et al*. (1993) and Zakoian (1994), the formulation of *TGARCH* is given by:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}, \tag{10}$$

where $\omega > 0, (\alpha + \gamma) \geq \alpha \geq 0, \beta \geq 0, (\alpha + 0.5\gamma + \beta) < 1$ (second moment), $(\beta^2 + 2\alpha\beta + 3\alpha^2 + \beta\gamma + 3\alpha\gamma + 1.5\gamma^2) < 1$ (forth moment), and I_{t-1} is an indicator function, such as $I_{t-1} = \begin{cases} 1 & \varepsilon_{t-1} < 0 \\ 0 & otherwise \end{cases}$.

This variable distinguishes between positive and negative shocks, so the asymmetric effects are captured by γ. Because I_{t-1} is 0 for positive shocks (ε_t^2) but 1 for negative ones, the conditional variance σ_t^2 is greater in the latter case, supporting a detection of asymmetry. In this model, positive news $(\gamma > 0)$ exerts an impact of α; negative news $(\gamma < 0)$ has an impact of $\alpha + \gamma$. The major advantage of this model compared with the *EGARCH* specification is that the effects on the volatility of positive innovations, relative to negative ones, do not remain fixed over time (Rabemananjara and Zakoian 1993).

4.7. Information Criteria: SIC, AIC and the Logarithm of the Likelihood Function

After the estimated models *GARCH (1,1)*, *EGARCH (1,1,1)* and *TGARCH (1,1,1)* we proceed by determining the most adequate model to the described data. For this purpose, it is resorted to a set of measures for comparing the goodness of fit of each model, using for this purpose the information criteria *SIC*, *AIC* and the maximum value of the logarithm of the likelihood function (log -likelihood).

The criterion defined by Schwarz (1978) is:

$$SIC = ln(\hat{\sigma}^2)+\frac{k}{T}lnT, \tag{11}$$

where $\hat{\sigma}^2$ denotes the residual variance, or the sum of the squares of the residuals divided by the number of degrees of freedom (k/T), where k is the total number of estimated parameters, and T is the sample size.

The criterion developed by Akaike (1974) is:

$$AIC = ln(\hat{\sigma}^2)+\frac{2k}{T}, \tag{12}$$

which offers the main disadvantage that the estimator is not asymptotically consistent, unlike the SIC criterion, so it tends to be more parsimonious in choosing the optimal number of lags.

The logarithm of the likelihood function assumes the following formulation:

$$L_{GED} = \sum_{t=1}^{T}\left[log\left(\frac{\upsilon}{\lambda_\upsilon}\right) - 0,5\left|\frac{z_t}{\lambda_\upsilon}\right|^{\upsilon} - (1+\upsilon^{-1})\log(2) - log\Gamma\left(\frac{1}{\upsilon}\right) - 0,5\log(\sigma_t^2)\right], \tag{13}$$

where $0 < \upsilon < \infty$ and

$$\lambda_\upsilon = \sqrt{\frac{\Gamma(\frac{1}{\upsilon})2^{(-\frac{2}{\upsilon})}}{\Gamma(\frac{3}{\upsilon})}}. \tag{14}$$

5. Volatility: Results

5.1. Preliminary Data Analysis

To investigate the asymmetric properties of stock market volatility, we collected data from the Euronext 100, which covers representative stocks in the European economy, to assess whether asymmetry is common to this market irrespective of its specific nature. The data came from Datastream, a database that features variation in the daily closing prices, for the period from December 3, 2000, to December 18, 2015, for a total of 4166 observations. Figure 5.1 depicts the time series evolution of the index.

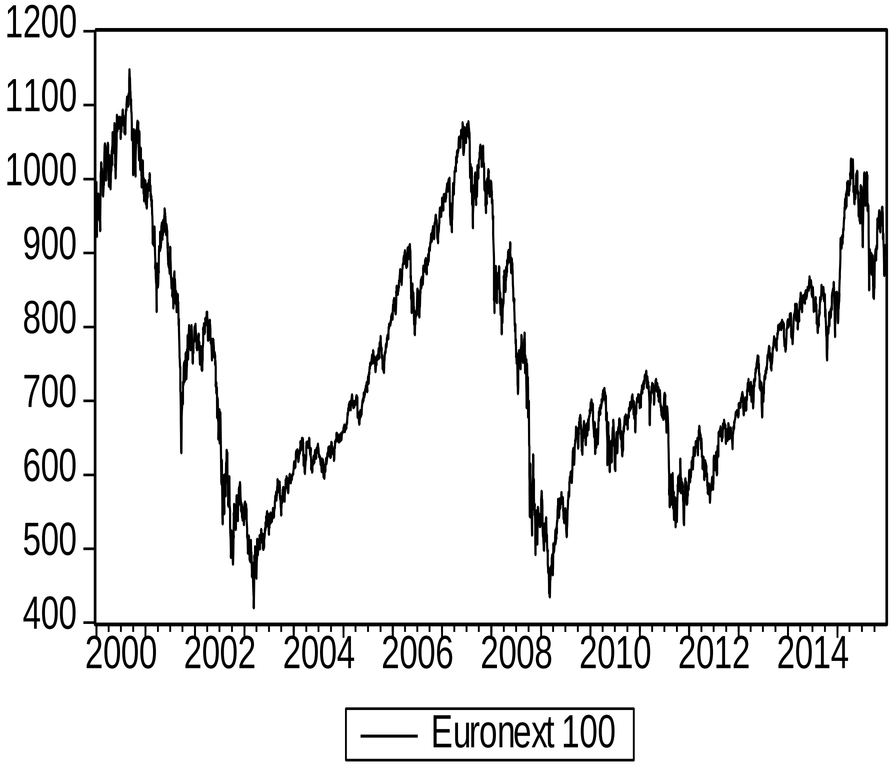

Figure 5.1 - Daily closing prices of the Euronext 100.

We rely on daily returns, computed as the log-difference in the daily stock index, as given by

$$R_t = lnP_t - lnP_{t-1}, \tag{15}$$

where P_t and P_{t-1} are Euronext 100 prices at moments t and $t-1$, respectively. Figure 5.2 reports the fluctuations of the daily returns, illustrating the synchronized behavior of the returns compared with prices (Figure 5.1). Here, the spikes are much more evident. It also offers a clear picture of the volatility clusters. In this work, we focus on returns, not original prices, because the returns are stationary, which is an assumption of *GARCH*-type models.

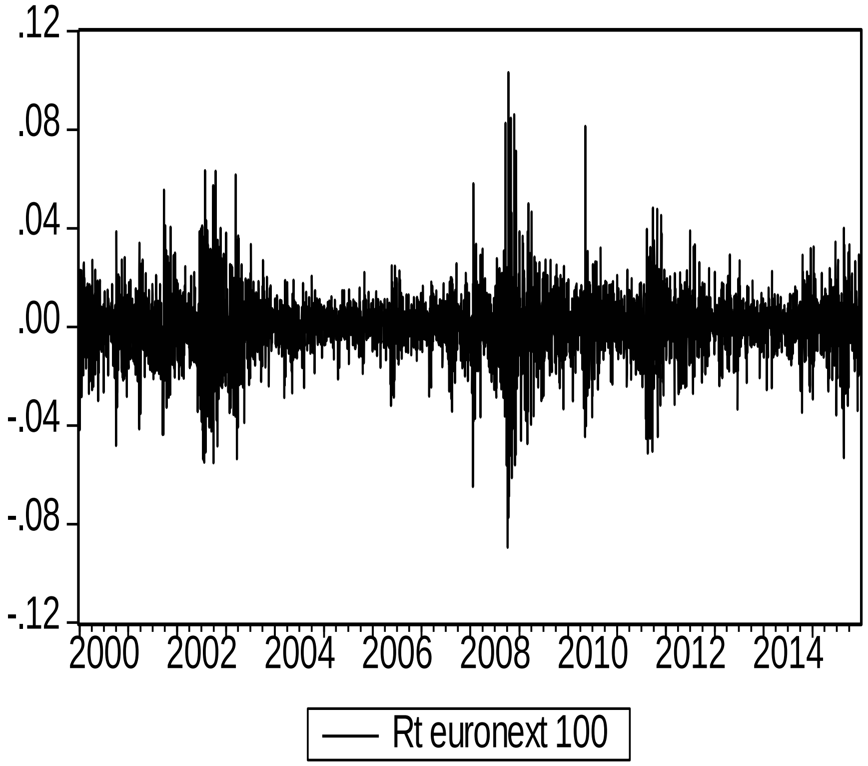

Figure 5.2 - Daily returns of the Euronext 100.

The clusters are quite evident: high volatility checks in 2002, following a low volatility cluster, and then a high volatility cluster around 2008 followed by another low volatility cluster. In 2011 we find another high volatility cluster, following the low volatility, and then again a high volatility cluster in 2012 followed by a period of low volatility returns that is followed by higher volatility between 2014 and 2015. If we compare this chart (Figure 5.2) with the original prices (Figure 5.1), we can determine that the high volatility peaks in returns correspond to peaks in prices, whereas low volatility corresponds to low prices. As expected, these two graphs are synchronized. It is also easy to compare these graphics with crises and periods of expansion; the subprime crisis of 2008 clearly appears as a high volatility cluster, and the subsequent recovery is reflected in a lower cluster. Table 5.1 contains a preliminary analysis of these daily return data for the whole sample period.

Table 5.1 - Preliminary analysis of the daily returns of Euronext 100.

Mean	0.0000
Standard Deviation	0.0135
Kurtosis	8.2077
Skewness	-0.0090
J-B	4706.57**

Notes: J-B: Jarque-Bera (1987) test.
** Significant at 1%.

The statistics indicate a zero mean, which is not surprising because we deal with returns, not closing prices. Furthermore, the average daily returns are very small compared with the standard deviation. Series also display weak negative asymmetry and strong positive kurtosis, implying a heavier tailed distribution than Gaussian, such that we can reject unconditional normality. The Jarque-Bera (1987) test reflects the null hypothesis of normality, which also can be verified in the histogram in Figure 5.3 that signals the presence of kurtosis (fat tails).

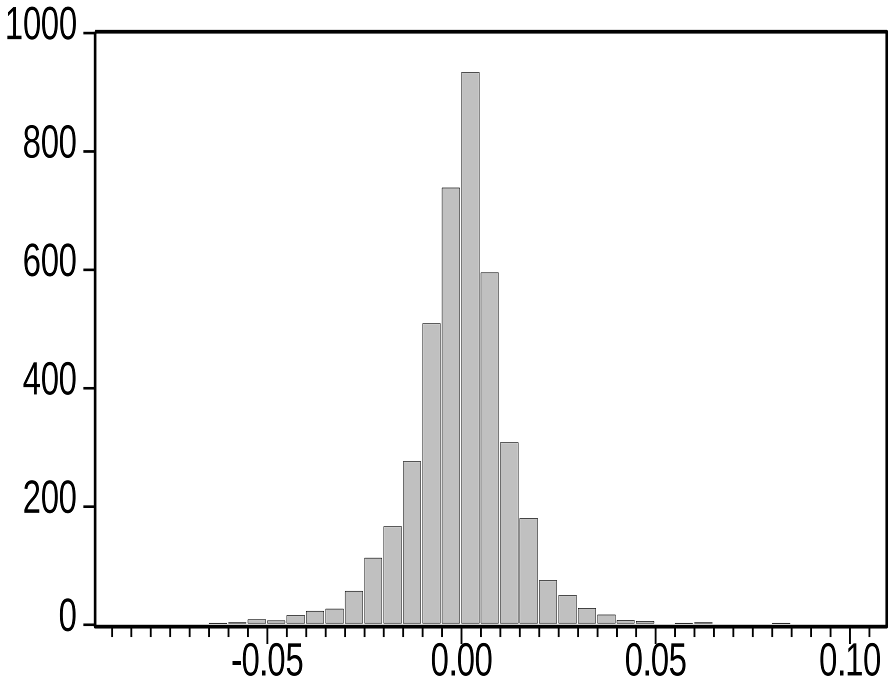

Figure 5.3 - Histogram of daily returns of the Euronext 100.

Before estimating the *ARCH*-type models, we must check for stationarity and the absence of autocorrelation. In addition, because this study is applying heteroskedastic models, we must check for heteroskedasticity (*ARCH-LM* test). We present the results of these checks in Table 5.2.

Table 5.2 - ADF and KPSS unit root tests for the Euronext 100.

Returns	ADF[a, b]	KPSS
EURONEXT 100	-31.4795**	0.065

Notes: MacKinnon *et al.* (1999) critical values: -3.960241 (1%) for constant and -3.410883 (5%) for constant and linear trend. Kwiatkowski *et al.* (1992) critical values: 0.216 (1%) and 0.146 (5%) for constant and linear trend. Exogenous terms are the number of lags in both cases: 0. ADF means Augmented Dicker-Fuller and KPSS is Kwiatkowski, Phillips, Schmidt, and Shin (1992).
** Significant at 1%.

An augmented Dickey–Fuller test (ADF) for unit roots in a time series can deal with a larger and more complicated set of time series models. The ADF testing procedure is the same as that for the Dickey–Fuller test:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \dots + \delta_{\rho-1} \Delta y_{t-\rho+1} + \varepsilon_t, \tag{16}$$

where α is a constant, β is the coefficient on a time trend, and *p* is the lag order of the autoregressive process. Imposing the constraints $\alpha = 0$ and $\beta = 0$ corresponds to modeling a random walk with drift. There are three main versions of the test. By including lags of the order *p*, the ADF formulation allows for higher-order autoregressive processes, so the lag length p must be determined when applying the test. One means to do so is to test down from high orders and examine the t-values of the coefficients. The unit root test then can be conducted under the null hypothesis ($\gamma = 0$) against an alternative hypothesis ($\gamma < 0$). By computing a value for the test statistic

$$DF_\tau = \frac{\hat{\gamma}}{se(\hat{\gamma})}, \tag{17}$$

we can compare it with the critical value for the ADF test. If the test statistic is less than the (larger negative) critical value (because the test is non-symmetrical, there is no need to use the absolute value), the null hypothesis of $\gamma = 0$ is rejected, and no unit root is present. The intuition is that if the series is integrated, the lagged level of the series (y_{t-1}) provides no relevant information in predicting the change in y_t other than that obtained in the lagged changes (Δy_{t-k}). In this case, $\gamma = 0$, the null hypothesis is not rejected but rather is accepted, and the series is non-stationary, such that it has unit roots.

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS; Kwiatkowski *et al.* 1992) test assesses the null hypothesis that an observable time series is stationary around a deterministic trend. The series can be expressed as the sum of the deterministic trend, random walk, and stationary error, and it relies on the Lagrange multiplier test of the hypothesis that the random walk has zero variance. This test is intended to complement unit root tests, such as ADF. The statistics are given by:

$$LM = \frac{\sum_{t=1}^{T} S_t^2}{\hat{\sigma}_u^2}. \tag{18}$$

To confirm our results, we apply the KPSS test, which offers an opposite hypothesis, such that H_0 predicts that the series is stationary. If we do not reject this H_0, it confirms the results of the ADF. Consistent results in both cases indicate stationarity in the returns of Euronext 100. Because we used the return series, not the original prices, we performed unit root tests in levels, equivalent to taking the first differences of the price series. In a Ljung-Box test, H_0

indicates the inexistence of no autocorrelation. However, we still need to verify the autocorrelation and heteroscedasticity. The results are in Figure 5.4.

Lag	AC	PAC	Q-Stat	Prob
1	-0.014	-0.014	0.7812	0.377
2	-0.031	-0.031	4.8536	0.088
3	-0.062	-0.063	20.721	0.000
4	0.037	0.034	26.363	0.000
5	-0.058	-0.062	40.602	0.000
6	-0.026	-0.030	43.445	0.000
7	0.021	0.021	45.305	0.000
8	0.032	0.022	49.639	0.000
9	-0.015	-0.013	50.634	0.000
10	-0.030	-0.028	54.464	0.000
11	0.003	0.000	54.508	0.000
12	0.009	0.005	54.853	0.000
13	0.013	0.015	55.515	0.000
14	-0.000	0.002	55.516	0.000
15	0.008	0.005	55.800	0.000
16	0.033	0.033	60.316	0.000
17	0.020	0.024	61.951	0.000
18	-0.039	-0.033	68.267	0.000
19	-0.029	-0.025	71.677	0.000
20	-0.006	-0.010	71.838	0.000
21	0.011	0.007	72.346	0.000
22	0.018	0.022	73.692	0.000
23	-0.009	-0.012	74.046	0.000
24	0.008	0.003	74.329	0.000
25	0.012	0.012	74.891	0.000
26	0.005	0.009	74.978	0.000
27	-0.035	-0.029	80.206	0.000
28	0.008	0.005	80.481	0.000
29	0.034	0.029	85.348	0.000
30	0.023	0.022	87.638	0.000
31	-0.033	-0.024	92.256	0.000
32	0.033	0.034	96.878	0.000
33	-0.016	-0.019	97.909	0.000
34	-0.045	-0.042	106.31	0.000
35	-0.025	-0.012	108.95	0.000
36	0.031	0.020	112.96	0.000

Figure 5.4 - Correlogram of returns for the Euronext 100.

The null hypothesis of no autocorrelation is rejected; the probability is zero in all cases. Because the values are statistically significant at 5% and 1%, we can conclude that there is autocorrelation. To confirm this result, as detailed in Table 5.3, we also employ the Breusch-Godfrey (BG) test, where H_0 again predicts no autocorrelation.

Table 5.3 - Autocorrelation test BG applied to returns for the Euronext 100.

BG Test	*F* Statistic	χ^2 Statistic
	5.4367**	53.8064**

Notes: For calculating the test values, ten lags were computed.
** Significant at 1%.

Both tests indicate evidence of autocorrelation. One of the assumptions of *ARCH* models is a lack of autocorrelation, so this assumption is not verified. We accordingly must eliminate it. We also test for heteroscedasticity, because *ARCH* models are heteroskedastic, such that we can use them only if the data series exhibit heteroscedasticity. We rely on the *ARCH-LM* test (Engle 1982), in which H_0 predicts no conditional heteroskedasticity, as summarized in Table 5.4.

Table 5.4 - ARCH-LM test for the Euronext 100.

ARCH-LM Test	*F* Statistic	χ^2 Statistic
	103.8812**	832.8034**

Notes: For calculating the test values, ten lags were computed.
** Significant at 1%.

According to this test, the values are statistically significant at 1%, so we reject the null hypothesis (H_0) of no heteroscedasticity. We confirm this result with McLeod and Li's (1983) tests, applied to the squared residuals. In this second test, the values are all statistically significant, so we reject the null hypothesis (H_0). Heteroscedasticity exists, which justifies the use of *ARCH*-type models. Figure 5.5 contains a correlogram of square residuals for the Euronext 100.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.209	0.209	182.20	0.000
		2	0.281	0.249	512.27	0.000
		3	0.265	0.188	804.19	0.000
		4	0.223	0.107	1010.9	0.000
		5	0.331	0.219	1468.4	0.000
		6	0.207	0.055	1647.4	0.000
		7	0.199	0.020	1813.1	0.000
		8	0.193	0.022	1968.5	0.000
		9	0.212	0.066	2156.3	0.000
		10	0.252	0.097	2421.4	0.000
		11	0.217	0.066	2618.0	0.000
		12	0.249	0.097	2876.5	0.000
		13	0.218	0.052	3074.6	0.000
		14	0.136	-0.069	3151.9	0.000
		15	0.198	0.004	3316.6	0.000
		16	0.218	0.067	3514.7	0.000
		17	0.195	0.031	3673.1	0.000
		18	0.212	0.052	3861.4	0.000
		19	0.183	0.043	4001.8	0.000
		20	0.129	-0.056	4071.9	0.000
		21	0.170	-0.021	4193.1	0.000
		22	0.148	-0.023	4285.0	0.000
		23	0.182	0.035	4424.3	0.000
		24	0.099	-0.054	4465.4	0.000
		25	0.135	0.010	4542.3	0.000
		26	0.105	-0.023	4588.6	0.000
		27	0.155	0.039	4689.5	0.000
		28	0.226	0.101	4904.6	0.000
		29	0.091	-0.044	4938.9	0.000
		30	0.181	0.053	5076.8	0.000
		31	0.123	-0.003	5140.8	0.000
		32	0.117	-0.022	5197.9	0.000
		33	0.142	-0.009	5282.1	0.000
		34	0.100	-0.012	5323.8	0.000
		35	0.160	0.049	5431.5	0.000
		36	0.093	-0.010	5467.8	0.000

Figure 5.5 - Correlogram of Square Residuals for the Euronext 100.

5.2. Results

To remove any possible serial correlation in the data, we first estimate an *AR*(*p*) model; the correlogram plots for the return series suggest using *AR*(*5*) for the Euronext 100 returns. To affirm the adequacy of a time-series model to account for the conditional mean, we also ran diagnostic tests, as summarized in Table 5.5.

Table 5.5 - Residual analysis for the fitted *AR*(*p*) model.

	EURONEXT 100
Mean	-3.885E-19
Std. Dev.	0.0135
Skewness	-0.134053
Kurtosis	7.7669
J-B	3951.252**

Notes: J-B represents the statistics of the Jarque and Bera's (1987) normal distribution test.
** Significant at 1%.

The mean and standard deviation are very low. The mean of the residuals is very small compared with the standard deviation. As observed in Table 5.5, the Jarque-Bera test of the *AR*(*p*) residuals indicates non-normality; together with the negative skewness and excess kurtosis, this result reveals a heavier tailed distribution than normal. The histogram in Figure 5.6 corroborates this finding; the residuals do not follow a normal distribution.

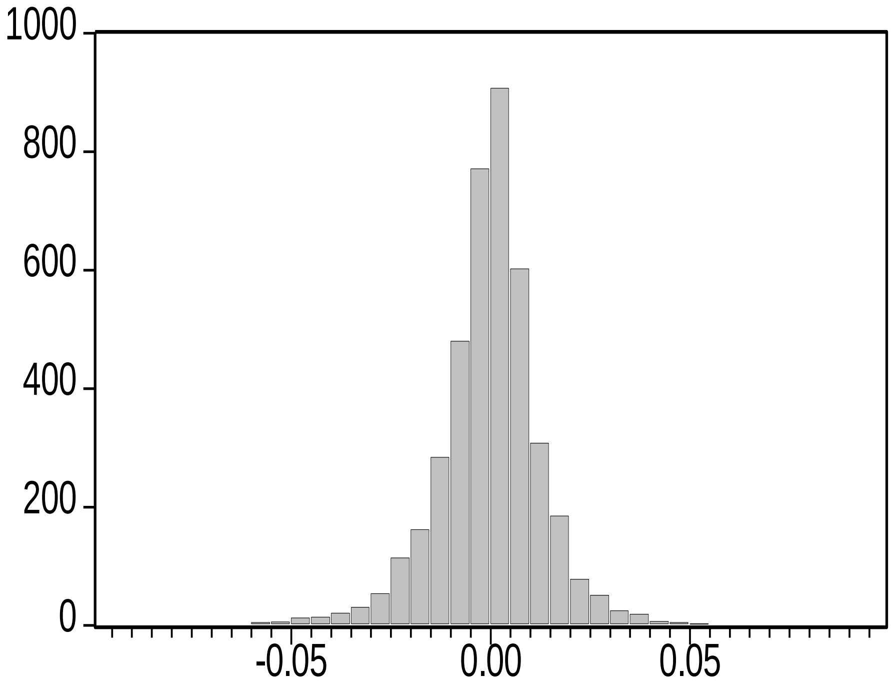

Figure 5.6 - Histogram of the residuals of the model *AR (5*).

To verify if the *AR(5)* model is sufficient to capture serial correlation in the data, we checked whether, after estimating *AR(5*), autocorrelation remains, again using the Box-Ljung and Breusch-Godfrey tests.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0174	0.895
		2	0.002	0.002	0.0389	0.981
		3	0.000	0.000	0.0392	0.998
		4	-0.000	-0.000	0.0395	1.000
		5	-0.000	-0.000	0.0398	1.000
		6	-0.029	-0.029	3.4509	0.750
		7	0.022	0.022	5.3975	0.612
		8	0.024	0.024	7.7606	0.457
		9	-0.013	-0.013	8.4420	0.490
		10	-0.031	-0.031	12.470	0.255
		11	0.004	0.004	12.547	0.324
		12	0.009	0.008	12.866	0.379
		13	0.013	0.014	13.555	0.406
		14	0.002	0.003	13.579	0.482
		15	0.006	0.004	13.733	0.546
		16	0.033	0.031	18.222	0.311
		17	0.019	0.022	19.789	0.285
		18	-0.039	-0.038	26.192	0.095
		19	-0.026	-0.027	28.926	0.067
		20	-0.005	-0.007	29.040	0.087
		21	0.012	0.013	29.651	0.099
		22	0.019	0.022	31.162	0.093
		23	-0.007	-0.007	31.365	0.114
		24	0.009	0.004	31.675	0.135
		25	0.012	0.013	32.305	0.149
		26	0.004	0.009	32.361	0.181
		27	-0.027	-0.026	35.512	0.126
		28	0.005	0.001	35.614	0.153
		29	0.032	0.028	39.861	0.086

Figure 5.7 - Correlogram of the residuals of the *AR (5)* model.

As shown in Figure 5.7, the null hypothesis of non-autocorrelation is not rejected; therefore, the *AR(5)* model captured linear dependence in the mean. The Breusch-Godfrey test provided the same conclusion, so the absence of autocorrelation is not rejected, as Table 5.6 indicates.

Table 5.6 - Autocorrelation test BG applied to the *AR (5)*.

BG Test	*F* Statistic	χ^2 Statistic
	0.3149	0.3147

Notes: For calculating the test values, ten lags were computed.
** Significant at 1%.

Neither the Ljung-Box nor the Breusch-Godfrey statistics are significant (large *p-values*) in any series, so there is no serial correlation on the residual series. That is, the *AR*(p) specification we adopted is satisfactory for capturing linear dependence in the original return series.

Having fitted an *AR*(*p*) model to capture linear dependence in the mean, and noting the evidence of *ARCH* effects in the residual series, we proceed with an estimation of *GARCH*, *EGARCH*, and *T-GARCH* models and seek to capture dependence in the variance values. To estimate the parameters, we used quasi-maximum likelihood estimation (QMLE) with Eviews 7.0 software. Because the original return series exhibits fat tails, we selected a Student-*t* distribution. The model estimates and residual tests for the returns of the Euronext 100 index are in Table 5.7.

Table 5.7 - *ARCH* Model estimates.

	$\hat{\omega}$		$\hat{\alpha}$		$\hat{\beta}$		$\hat{\gamma}$		Student's *t*	
GARCH	1.69E-06	**	0.0966	**	0.8965	**	-		-8.5796	**
	(4.11E-07)		(0.0095)		(0.0094)		-		(1.0880)	
EGARCH	-0.2669	**	0.1087	**	0.98	**	-0.1457	**	11.5361	**
	(0.0251)		(0.0130)		(0.104)		(0.0104)		(1.8672)	
T-GARCH	2.00E-06	**	-0.0212	**	0.9154	**	0.1809	**	11.3605	**
	(2.89E-07)		(0.0077)		(0.0078)		(0.0151)		(1.8193)	

Notes: Values in brackets are standard errors.
** Significant at 1%.

The parameters ω, α, and β in the conditional variance equations are mainly positive and highly significant. The statistical significance of the Student's *t*-distribution means that this distribution is adequate to capture the statistical behavior of the Euronext 100 returns. In the symmetric *AR(5)* model with *GARCH (1,1)*, all the coefficients are positive and statistically significant at 1%, revealing volatility clusters, such that high volatility periods succeed low periods, and so on. Both *AR(5)* models with *EGARCH (1,1,1)* and *GJR-GARCH (1,1,1)* reveal persistent asymmetric effects in volatility; the $\hat{\gamma}$ in the *EGARCH (1,1,1)* model is negative, and it is positive in the *GJR-GARCH (1,1,1)*. The effect of bad news thus is greater than that of good news. To verify if these models capture ARCH effects, we computed an *ARCH-LM* test for residuals and the correlogram of squared residuals, as detailed in Table 5.8.

Table 5.8 - *ARCH-LM* test for the residuals.

ARCH-LM Test	AR(5)-GARCH(1,1)	AR(5)-EGARCH(1,1,1)	AR(5)-GJR-GARCH(1,1,1)
F Statistic	1.1471	0.7225	1.1778
χ^2 Statistic	1.4573	7.2312	11.7753

Notes: For calculating the test values, ten lags were computed.
** Significant at 1%.

The null hypothesis of the absence of heteroscedasticity is not rejected, indicating the absence of this phenomenon. Therefore, all these models capture this phenomenon, justifying the need for models of conditional heteroscedasticity. Figure 5.8 to Figure 5.10 contain the correlogram of residuals square for each model, Table 5.9 the residuals and the histograms of *GARCH*, *EGARCH* and *TGARCH* models are represented in Figure 5.11 to Figure 5.13.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.019	-0.019	1.4605	
		2	0.013	0.012	2.1475	
		3	0.019	0.019	3.6033	0.058
		4	0.008	0.009	3.8809	0.144
		5	0.007	0.007	4.0850	0.252
		6	0.012	0.012	4.7294	0.316
		7	-0.003	-0.003	4.7751	0.444
		8	0.007	0.006	4.9775	0.547
		9	-0.001	-0.001	4.9796	0.662
		10	-0.008	-0.008	5.2253	0.733
		11	0.027	0.027	8.3463	0.500
		12	-0.015	-0.014	9.2697	0.507
		13	0.002	0.001	9.2880	0.595
		14	-0.029	-0.030	12.842	0.381
		15	-0.010	-0.011	13.269	0.427
		16	0.018	0.018	14.570	0.408
		17	-0.012	-0.010	15.155	0.440
		18	-0.032	-0.031	19.323	0.252
		19	-0.013	-0.015	20.045	0.272
		20	-0.004	-0.003	20.123	0.326
		21	-0.000	0.001	20.124	0.387
		22	-0.007	-0.007	20.331	0.437
		23	0.012	0.014	20.933	0.463
		24	-0.016	-0.015	21.959	0.462
		25	-0.013	-0.012	22.703	0.478
		26	-0.012	-0.013	23.350	0.499
		27	0.003	0.002	23.390	0.555
		28	-0.016	-0.015	24.434	0.551
		29	-0.016	-0.015	25.457	0.549
		30	-0.008	-0.007	25.726	0.588
		31	-0.017	-0.017	26.931	0.575
		32	-0.013	-0.015	27.604	0.591
		33	-0.006	-0.006	27.768	0.633
		34	-0.002	-0.001	27.791	0.680
		35	0.003	0.005	27.832	0.722
		36	-0.020	-0.021	29.534	0.686

Figure 5.8 - Correlogram of residuals square for *AR(5)-GARCH(1,1)* model.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.031	-0.031	4.0331	
		2	0.000	-0.001	4.0334	
		3	0.006	0.006	4.2068	0.040
		4	-0.003	-0.003	4.2523	0.119
		5	0.020	0.020	5.9421	0.114
		6	0.004	0.005	5.9941	0.200
		7	-0.002	-0.002	6.0078	0.305
		8	0.006	0.006	6.1774	0.404
		9	-0.014	-0.014	7.0491	0.424
		10	0.006	0.005	7.1984	0.515
		11	0.018	0.019	8.6189	0.473
		12	-0.001	0.000	8.6237	0.568
		13	0.007	0.007	8.8268	0.638
		14	-0.021	-0.020	10.697	0.555
		15	0.004	0.003	10.766	0.630
		16	0.021	0.020	12.575	0.560
		17	0.003	0.004	12.604	0.633
		18	-0.021	-0.021	14.451	0.565
		19	0.003	0.002	14.488	0.632
		20	0.004	0.005	14.562	0.692
		21	0.010	0.010	15.001	0.723
		22	0.017	0.017	16.205	0.704
		23	0.038	0.039	22.226	0.387
		24	0.002	0.004	22.242	0.446
		25	0.003	0.004	22.282	0.503
		26	-0.002	-0.003	22.299	0.561
		27	0.008	0.007	22.592	0.601
		28	0.001	-0.000	22.597	0.656
		29	-0.010	-0.009	22.976	0.686
		30	0.013	0.013	23.683	0.698
		31	-0.019	-0.018	25.138	0.671
		32	0.005	0.003	25.238	0.713
		33	0.005	0.004	25.330	0.753
		34	0.012	0.013	25.983	0.764
		35	0.011	0.012	26.535	0.780
		36	-0.019	-0.018	28.075	0.753

Figure 5.9 - Correlogram of residuals square for *AR(5)-EGARCH(1,1,1)* model.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.043	-0.043	7.8154	
		2	-0.010	-0.012	8.2526	
		3	-0.004	-0.005	8.3135	0.004
		4	-0.007	-0.008	8.5332	0.014
		5	0.019	0.019	10.096	0.018
		6	0.011	0.013	10.603	0.031
		7	-0.007	-0.006	10.814	0.055
		8	0.004	0.004	10.880	0.092
		9	-0.013	-0.012	11.540	0.117
		10	0.003	0.002	11.578	0.171
		11	0.018	0.018	12.984	0.163
		12	-0.009	-0.008	13.355	0.205
		13	0.005	0.005	13.463	0.264
		14	-0.026	-0.025	16.283	0.179
		15	0.000	-0.001	16.284	0.234
		16	0.016	0.014	17.321	0.239
		17	-0.004	-0.003	17.398	0.296
		18	-0.026	-0.026	20.172	0.213
		19	-0.004	-0.006	20.241	0.262
		20	0.002	0.002	20.252	0.319
		21	0.005	0.003	20.351	0.374
		22	0.010	0.010	20.774	0.411
		23	0.026	0.028	23.646	0.311
		24	0.000	0.004	23.646	0.366
		25	-0.005	-0.003	23.745	0.418
		26	-0.014	-0.015	24.585	0.429
		27	0.006	0.004	24.749	0.477
		28	-0.004	-0.005	24.815	0.529
		29	-0.011	-0.012	25.357	0.554
		30	0.005	0.005	25.456	0.603
		31	-0.019	-0.019	27.012	0.571
		32	-0.003	-0.005	27.042	0.621
		33	0.005	0.003	27.135	0.665
		34	0.007	0.007	27.319	0.703
		35	0.008	0.008	27.565	0.734
		36	-0.022	-0.021	29.662	0.680

Figure 5.10 - Correlogram of residuals square for *AR(5)-TGARCH(1,1,1)* model.

Table 5.9 - Residual analysis for the *AR(5)-GARCH* models.

	AR(5)-GARCH(1,1)	AR(5)-EGARCH(1,1,1)	AR(5)-TGARCH(1,1,1)
Mean	-0.0624	0.0199	0.0250
Std. Dev.	0.9973	0.9996	1.0010
Skewness	-0.3344	-0.3268	-0.3300
Kurtosis	4.0446	3.7516	3.7404
J-B	266.68**	171.939**	170.53 **

Notes: J-B represents the statistics of Jarque and Bera's (1987) normal distribution test.
** Significant at 1%.

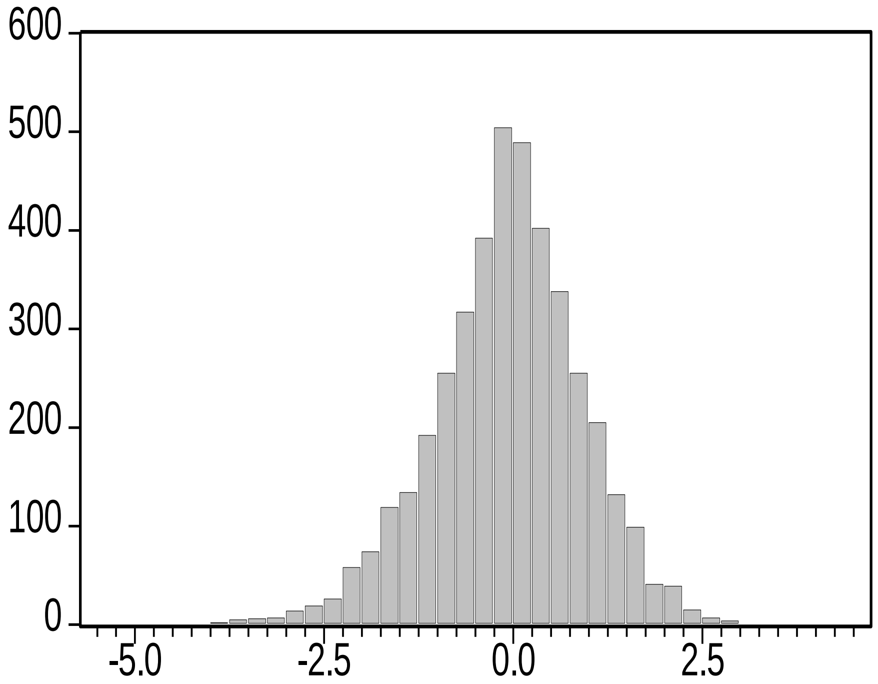

Figure 5.11 - Histogram of the residuals of the *AR(5)-GARCH(1,1)* model.

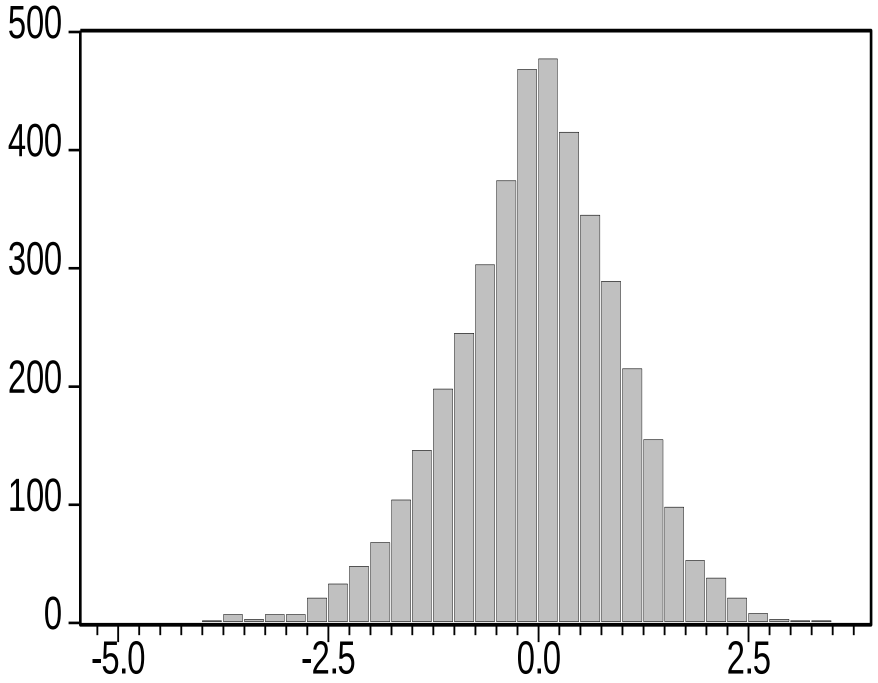

Figure 5.12 - Histogram of the residuals of the *AR(5)-EGARCH(1,1,1)* model.

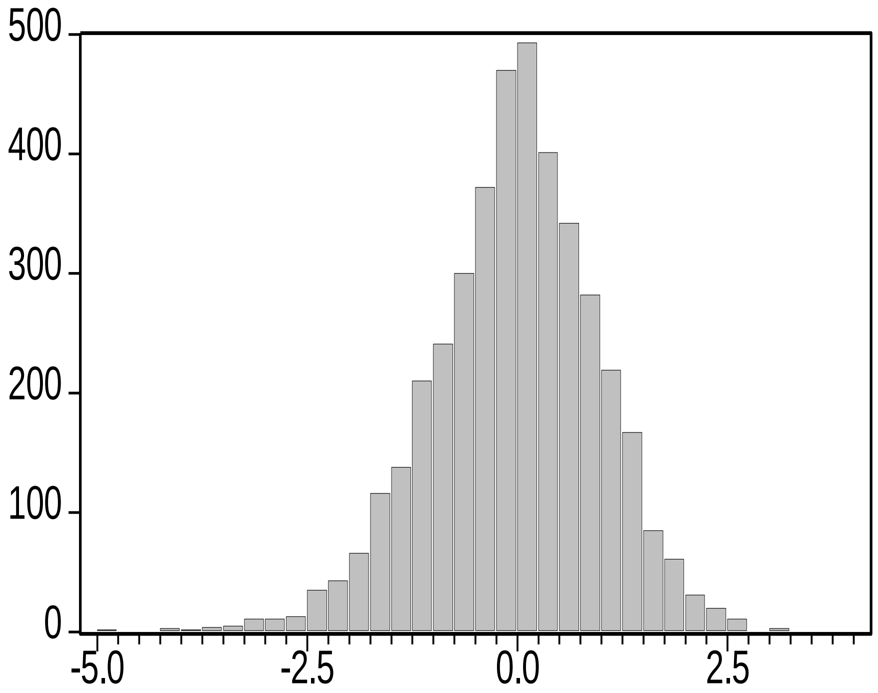

Figure 5.13 - Histogram of the residuals of the *AR(5)-TGARCH(1,1,1)* model.

Regarding the descriptive statistics (see Table 5.9), the means are -6.2% for *GARCH (1,1)*, 1.99% for *EGARCH (1,1,1)*, and 2.5% for *TGARCH (1,1)*, and the standard deviations are consistently high in all models, compared with the mean. The Jarque-Bera (1987) test of the residuals indicates non-normality, which, together with the negative skewness and excess kurtosis, reveals a heavier tailed distribution than the normal distribution. These results are corroborated by the histograms, which clearly reveal that the residuals do not follow a normal distribution.

Next, we determine the most adequate model of the described data, using the SIC, AIC, and maximum value of the logarithm of the likelihood function (log-likelihood). To select the best model, we search for the one that maximizes the value of the logarithm of the likelihood function and minimizes the SIC and AIC criteria. We present the pertinent values in Table 5.10. According to these information criteria, the best model that captures the behavior of the data is *EGARCH*, followed by *TGARCH*, and finally *GARCH*. These results are not surprising; asymmetry exists in the data, and the *GARCH* model assumes symmetrical effects on volatility.

Table 5.10 - Information criteria.

Models	Log-likelihood	SIC	AIC
AR(5)-GARCH(1,1)	12813.8	-6.1465	-6.1571
AR(5)-EGARCH(1,1,1)	12911.06	-6.1912	-6.2034
AR(5)-TGARCH (1,1,1)	12901.32	-6.1865	-6.1987

6. Fundamental Analysis: Results

6.1. Preliminary data analysis

Market-adjusted prices and financial data can be collected annually from Yahoo Finance and the Datastream databases 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 6.1 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).

Table 6.1 - Sample description

Panel A.

Firms in the Euronext 100 by exchange

Exchange	Number of 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.

Firms in the Euronext 100 by industry

Industry Classification	Number of firms listed in any period, 1990–2014	%	Average market capitalization as of 2014 (in EUR)
Aerospace & Defense	4	4%	20 052 593
Automobiles & Parts	3	3%	4 977 051
Banks	6	6%	107 764 379
Beverages	4	4%	43 981 884
Chemicals	6	6%	12 435 688
Construction & Materials	3	3%	18 240 240
Electricity	3	3%	22 562 429
Electronic & Electrical Equipment	3	3%	17 526 019
Fixed Line Telecommunications	3	3%	11 643 943
Food & Drug Retailers	6	6%	10 937 394
Food Producers	1	1%	30 231 450
Gas, Water & Multi-utilities	3	3%	28 521 492
General Financial	4	4%	8 143 448
General Industrials	2	2%	28 110 825
General Retailers	1	1%	106 734 298
Health Care Equipment & Services	1	1%	15 980 741
Industrial Engineering	3	3%	6 491 717
Industrial Metals	2	2%	14 920 841
Industrial Transportation	3	3%	6 651 313
Life Insurance	4	4%	21 077 043
Media	5	5%	10 804 884
Mining	1	1%	5 099 906
Nonlife Insurance	2	2%	7 116 799
Oil & Gas Producers	3	3%	111 194 240
Oil Equipment, Services & Distribution	1	1%	3 496 385
Personal Goods	4	4%	72 674 339
Pharmaceuticals & Biotechnology	2	2%	9 316 301
Software & Computer Services	4	4%	11 227 598
Support Services	3	3%	9 005 573
Technology Hardware & Equipment	3	3%	27 110 749
Travel & Leisure	2	2%	9 916 094
Total/total/average	95	100%	27 675 550

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

The Euronext 100 is the blue chip index of Euronext N.V., spanning about 80% of the major companies on the exchange. Unlike most other 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 index is reviewed quarterly with size and liquidity analyses of the traded stocks. Figure 6.1 shows the one-year return, accumulated returns over 2000–2014, and average annualized returns, revealing that the yearly volatility is high and tendencies are unstable. Moreover, the index shows an annualize return of -1.44% over the 14 years.

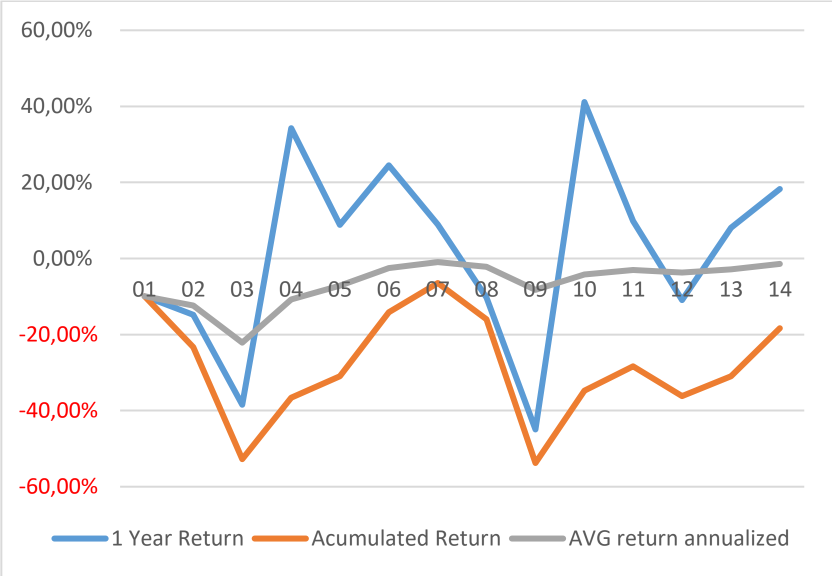

Figure 6.1 - Yearly evolution of the Euronext 100 index.

Table 6.2 reports the pertinent values (reported on Figure 6.1), and Table 6.3 contains the descriptive statistics for the annual returns of the Euronext 100 index for the whole sample period.

Table 6.2 - Annual returns, accumulated returns, and total return annualized of the Euronext 100 index.

	March-00	March-01	March-02	March-03	March-04
Price	1015.66	914.56	779.42	479.67	643.99
1 Year Return		-9.95%	-14.78%	-38.46%	34.26%
Accumulated Return		-9.95%	-23.26%	-52.77%	-36.59%
Total return annualized		-9.95%	-12.40%	-22.12%	-10.77%
	March-05	**March-06**	**March-07**	**March-08**	**March-09**
Price	700.93	872.39	950.13	852.95	469.65
1 Year Return	8.84%	24.46%	8.91%	-10.23%	-44.94%
Accumulated Return	-30.99%	-14.11%	-6.45%	-16.02%	-53.76%
Total return annualized	-7.15%	-2.50%	-0.95%	-2.16%	-8.21%
	March-10	**March-11**	**March-12**	**March-13**	**March-14**
Price	662.86	728.06	648.5	701.13	829.01
1 Year Return	41.14%	9.84%	-10.93%	8.12%	18.24%
Accumulated Return	-34.74%	-28.32%	-36.15%	-30.97%	-18.38%
Total return annualized	-4.18%	-2.98%	-3.67%	-2.81%	-1.44%

Table 6.3 - Descriptive statistics of annual returns of the firms listed on Euronext 100 index for the whole sample period (2000–2014).

Mean	0.1443
Median	0.1135
Standard Deviation	0.4989
Kurtosis	14.3515
Skewness	2.3017
Minimum	-0.9287
Maximum	5.1673
Number of observation	1195

The mean annual return is 14.13%; the average annual returns are small relative to the standard deviation, which indicates high volatility in the returns in the period under analysis. The annual returns series also display a strong positive kurtosis, indicative of a violation of the normal distribution (Table 6.4), according to the Kolmogorov-Smirnova, Shapiro-Wilk, and Jarque-Bera tests.

Table 6.4 - Normality test of the annual return of the firms listed on the Euronext 100 index.

	Kolmogorov-Smirnova			**Shapiro-Wilk**			**Jarque-Bera**		
	Statistic	df	Sig.	Statistic	df	Sig.	gl	Limit	J-B
Annual var	0.103	1195	0***	0.862	1195	0***	1194	1275,50	7471,15***

*** Statistically significant at 1% level.

Non-normality has effects on inference (T and F tests) when samples are small. However, this sample is large, and the F and T tests are asymptotically valid for large samples. Therefore, this study may continue as if there are no constraints.

The descriptive statistics for the independent variables are in Table 6.5, showing that the average *EPS* is 2.3213; the *BMR* is below the unit, indicating that on average, the stocks listed in Euronext 100 were overvalued during the period of analysis; the average firm size is 7.2445; and the average F- and L-scores are 5.3450 and 3.9070, respectively.

Table 6.5 - Descriptive statistics of the independent variables.

Variable	Firm-year observations	Mean	Median	Std.Dev.	Min	Max
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: *EPS* = earnings per share; *BMR* = book-to-market ratio; *Log A* = log of total assets (size). F-score and L-score are as defined in Section 4.2.

Table 6.6 reports the correlation matrix and collinearity statistic. The F-score is significantly correlated with all the model variables: returns, *EPS, BMR*, size (*log A*), and the L-score. The correlations among the independent variables do not produce a multicollinearity problem though, because the variance inflation factor fluctuates between 1.1 to 1.2 (Gujarati 2004). Regarding the variable returns, *BMR*, and size show negative correlations. The correlation of *EPS* is marginal, at the 10% level, and that with the L-score is not even statistically significant; for F-score is statistically significant at 1% level. The negative correlation of *BMR* differs from findings in capital market literature (e.g., Piotroski 2000; Nawazish 2008). For size, the negative correlation could arise because small firms often provide higher expected returns as a liquidity premium (e.g., Fama and French 1992, 1995).

Table 6.6 - Correlation matrix.

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

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

6.2. Explanatory power of accounting signals F-score and L-score

This study uses ordinary least square (OLS) regressions with a pooled cross-sectional method. Table 6.7 reports the pooled OLS results for the five proposed models from Equations (Model 1 – Model 5), which were estimated using time dummy variables, to control for time effects (e.g., macro-economic conditions) and industry dummies.

Table 6.7 - 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	0.002	0.002	-0.001
t-statistic	1.76	0.76	0.75	0.88	0.78	-0.50
BMR		-0.041***	-0.036***	-0.040***	-0.036***	-0.069***
t-statistic		-4.18	-3.64	-4.03	-3.60	-4.77
Size		-0.088***	-0.091***	-0.087***	-0.090***	-0.219***
t-statistic		-3.59	-3.71	-3.55	-3.70	-3.20
F-score			0.029***		0.029***	0.031***
t-statistic			4.00		3.87	4.04
L-Score				0.008	0.002	0.018**
t-statistic				1.03	0.28	2.05
Intercept	0.747***	1.580***	1.481***	1.552***	1.475***	1.347***
t-statistic	13.08	7.13	6.69	6.95	6.62	2.75
N# obs.	1185	1135	1135	1135	1135	1135
Adjusted R^2	0.404	0.418	0.426	0.418	0.425	0.457

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

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

Models 3–5 show evidence of the value relevance of the F- and L-scores. Beyond the value relevance of *EPS, BMR*, and firm size, the F-score is statistically significant at the 1% level in Models 3 and 5; the L-score is not statically significant in either Model 4 or Model 5. Model 5 affirms the additional explanatory power of the F-score after controlling for all other variables. The coefficient of the F-score indicates that a one-unit increase in this metric is associated with an increase in the subsequent annual return of about 2.9%, keeping the size, *BMR, EPS*, and L-score constant. For the size variable, a one-unit decrease is associated with an increase in subsequent annual returns of about 9.0%. Thus, investors prefer to buy shares from smaller firms, likely because small companies generate higher returns, as a premium related to their low liquidity. In theory, the returns of so-called small caps outperform those of larger companies (e.g., Piotroski 2000; Dosamantes 2013; Holloway *et al.* 2013).

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

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

Since the previous econometric results show positive and significant correlations between F-score/L-score, to examine the buy-and-hold returns for an investment strategy based on the F- and L-scores, for each year, each observation is grouped according to its corresponding scores. For each of the 9 F-score groups, one- and two-year subsequent raw returns and market excess firm returns are computed. 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 6.8). The 24-month returns run from April at $t + 1$ to March at $t + 2$, and the respective score is for year t (Table 6.9). The estimate of future returns uses equally weighed portfolios.

Table 6.8 - Buy-and-hold 12-month returns by F-score.

Panel A: Raw returns							
F-score	Mean	N	Min	Max	25%	Median	75%
0	11.77%	2	-59.51%	83.05%	-59.51%	11.77%	83.05%
1	-0.91%	9	-83.79%	194.13%	-64.63%	-12.80%	10.44%
2	-6.50%	28	-92.87%	123.00%	-48.10%	-15.12%	27.39%
3	2.00%	119	-90.27%	157.01%	-25.60%	-0.14%	21.87%
4	9.56%	199	-80.73%	231.54%	-19.72%	6.76%	27.34%
5	12.43%	233	-79.89%	207.09%	-19.13%	8.02%	32.65%
6	17.35%	245	-74.30%	272.02%	-6.34%	13.43%	38.84%
7	25.48%	204	-86.89%	516.73%	-5.30%	17.09%	39.84%
8	20.12%	119	-80.88%	268.64%	-0.16%	16.66%	33.28%
9	14.37%	37	-36.60%	63.91%	-1.69%	18.57%	29.11%
Low F-score [0+1+2]	-4.27%	39	-92.87%	194.13%	-50.42%	-13.64%	27.39%
High F-score [8+9]	18.76%	156	-80.88%	268.64%	-1.11%	17.73%	32.61%
High-Low	23.03%		11.98%	74.51%	49.31%	31.37%	5.21%
t-statistic	4.58***						
Total	14.43%	1195	-92.87%	516.73%	-13.74%	11.50%	33.42%

Panel B: Market excess firm returns							
0	-25.93%	2	-93.76%	41.91%	-93.76%	-25.93%	41.91%
1	11.00%	9	-54.68%	152.99%	-36.98%	7.03%	25.21%
2	-3.39%	28	-70.85%	83.21%	-26.19%	-1.28%	16.63%
3	4.96%	119	-51.81%	122.75%	-12.78%	1.01%	17.06%
4	9.51%	199	-70.78%	197.28%	-9.01%	5.89%	24.42%
5	11.54%	233	-65.11%	188.85%	-8.92%	8.32%	25.68%
6	13.33%	245	-98.76%	281.97%	-6.77%	11.07%	26.70%
7	20.42%	204	-65.31%	492.27%	-6.12%	11.55%	31.75%
8	15.12%	119	-66.96%	234.39%	-4.30%	9.84%	26.35%
9	9.69%	37	-41.44%	55.07%	-6.91%	8.34%	27.97%
Low F-score [0+1+2]	-1.22%	39	-93.76%	152.99%	-29.89%	0.99%	20.38%
High F-score [8+9]	13.83%	156	-66.96%	234.39%	-5.58%	9.47%	27.63%
High-Low	15.05%		26.80%	81.39%	24.32%	8.47%	7.25%
t-statistic	3.46***						
Total	12.31%	1195	-98.76%	492.27%	-8.49%	7.81%	25.93%

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

Table 6.9 - Buy-and-hold 24-month returns by F-score.

Panel A. Raw returns							
F-score	Mean	N	Min	Max	25%	Median	75%
0	-63.42%	2	-80.15%	-46.70%	-80.15%	-63.42%	-46.70%
1	-17.07%	8	-68.17%	18.31%	-46.57%	-6.32%	9.54%
2	-20.98%	25	-78.06%	30.84%	-36.91%	-25.40%	-0.75%
3	-2.65%	112	-72.99%	87.11%	-20.32%	-2.27%	12.26%
4	2.38%	185	-69.65%	143.82%	-15.34%	3.57%	16.57%
5	4.14%	213	-59.99%	140.51%	-14.45%	2.82%	21.63%
6	11.69%	223	-64.51%	186.61%	-5.71%	11.47%	26.38%
7	20.98%	191	-74.75%	312.58%	-0.95%	15.35%	34.24%
8	20.93%	106	-48.57%	105.91%	6.11%	21.29%	36.54%
9	23.32%	35	-27.86%	80.30%	0.68%	26.11%	41.22%
Low F-score [0+1+2]	-22.51%	35	-80.15%	30.84%	-43.93%	-25.40%	0.65%
High F-score [8+9]	21.52%	141	-48.57%	105.91%	5.34%	23.37%	39.33%
High-Low	44.04%		31.57%	75.07%	49.27%	48.77%	38.68%
t-statistic	10.44***						
Total	8.99%	1100	-80.15%	312.58%	-10.75%	8.30%	25.67%

Panel B. Market excess firm returns							
0	-52.95%	2	-71.04%	-34.86%	-71.04%	-52.95%	-34.86%
1	1.07%	8	-38.48%	30.71%	-25.80%	12.61%	21.36%
2	-8.98%	25	-48.65%	27.68%	-23.83%	-10.45%	6.03%
3	3.47%	112	-52.31%	79.12%	-9.62%	3.27%	12.43%
4	6.03%	185	-50.43%	152.92%	-8.19%	5.45%	16.91%
5	6.82%	213	-46.26%	124.12%	-5.47%	6.60%	17.13%
6	10.23%	223	-61.02%	170.19%	-4.77%	10.32%	23.26%
7	15.38%	191	-50.05%	296.19%	-2.22%	10.60%	25.14%
8	13.63%	106	-33.96%	85.02%	-0.19%	10.90%	25.36%
9	14.40%	35	-34.34%	55.79%	2.74%	12.03%	27.12%
Low F-score [0+1+2]	-9.19%	35	-71.04%	30.71%	-27.97%	-10.45%	14.31%
High F-score [8+9]	13.82%	141	-34.34%	85.02%	1.29%	11.18%	25.80%
High-Low	23.02%		36.71%	54.31%	29.26%	21.64%	11.49%
t-statistic	6.21***						
Total	8.91%	1100	-71.04%	296.19%	-5.45%	7.70%	20.47%

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

In the 12-month returns observed after 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 25.48%. The average return difference between portfolios of firms with high versus low F-scores is positive and statistically significant at the 1% level, with a value of 23.03%. 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 13.83%, and the average of two-year returns offers a similar value of 13.82% (Table 6.9). 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 19%, and Piotroski (2000) reports 31% for a different period (i.e., 1975–1995) and 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 than 29% for the period between 1989 and 2011. Tehrani *et al*. (2008) test the model only for 2004 and 2005 in the Iranian market and obtain a high score return of 100%. 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., Oberholzer and Venter 2015; Erdogdu 2016; Kim *et al*. 2016). 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 6.10 and Table 6.11.

Table 6.10 - Buy-and-hold 12-month returns by L-score.

Panel A. Raw returns							
L-score	Mean	N	Min	Max	25%	Median	75%
0	-13.21%	22	-83.79%	60.89%	-30.02%	-12.51%	6.55%
1	13.05%	80	-90.27%	212.75%	-14.74%	11.49%	28.50%
2	16.19%	116	-92.87%	319.15%	-12.01%	13.98%	36.82%
3	14.64%	215	-67.69%	272.02%	-12.37%	8.79%	33.55%
4	13.68%	277	-80.73%	379.46%	-16.85%	11.47%	33.11%
5	13.15%	244	-86.89%	516.73%	-13.09%	8.14%	29.98%
6	18.18%	180	-78.01%	157.26%	-3.39%	20.97%	39.71%
7	17.96%	54	-64.59%	233.16%	-13.98%	3.16%	43.30%
8	32.12%	7	11.13%	52.01%	25.22%	33.08%	39.08%
Low L-score [0+1+2]	12.07%	218	-92.87%	319.15%	-16.01%	10.78%	31.06%
High L-score 8+9]	19.58%	61	-64.59%	233.16%	-11.59%	11.13%	42.90%
High-Low	7.51%		28.27%	-85.98%	4.42%	0.34%	11.85%
t-statistic	1.54						
Total	14.43%	1195	-92.87%	516.73%	-13.74%	11.50%	33.42%
Panel B. Market excess firm returns							
0	0.70%	22	-38.86%	42.49%	-14.99%	-1.04%	16.03%
1	10.91%	80	-70.85%	171.61%	-9.92%	6.54%	24.66%
2	10.78%	116	-93.76%	329.10%	-9.87%	4.20%	30.44%
3	12.15%	215	-54.68%	281.97%	-9.41%	7.81%	25.78%
4	12.41%	277	-98.76%	370.62%	-10.85%	7.21%	24.63%
5	11.23%	244	-66.96%	492.27%	-7.99%	6.64%	21.97%
6	14.48%	180	-46.26%	117.77%	-2.24%	13.77%	29.82%
7	19.53%	54	-50.00%	243.39%	-8.24%	7.55%	26.07%
8	17.24%	7	-8.06%	43.89%	2.40%	20.58%	29.74%
Low L-score [0+1+2]	9.81%	218	-93.76%	329.10%	-12.27%	4.62%	26.61%
High L-score [8+9]	19.26%	61	-50.00%	243.39%	-7.11%	8.14%	26.07%
High-Low	9.45%		43.76%	-85.71%	5.16%	3.53%	-0.54%
t-statistic	1.55						
Total	12.31%	1195	-98.76%	492.27%	-8.49%	7.81%	25.93%

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

Table 6.11 - Buy-and-hold 24-month returns by L-score.

Panel A. Raw returns							
L-score	Mean	N	Min	Max	25%	Median	75%
0	2.83%	22	62.19%	76.85%	-19.89%	9.01%	30.71%
1	3.39%	75	-72.99%	57.37%	-12.16%	2.05%	27.04%
2	5.73%	107	-80.15%	96.91%	-13.99%	6.28%	24.95%
3	9.07%	197	-61.90%	166.34%	-10.58%	7.94%	25.55%
4	6.44%	252	-69.65%	213.05%	-13.42%	5.24%	20.47%
5	9.77%	225	-74.75%	312.58%	-6.39%	7.24%	23.02%
6	15.31%	164	-64.51%	92.05%	-2.74%	16.89%	32.55%
7	12.62%	51	-50.40%	138.74%	-15.58%	9.18%	32.62%
8	27.49%	7	-0.36%	67.55%	6.88%	17.99%	46.74%
Low L-score [0+1+2]	4.56%	204	-80.15%	96.91%	-15.44%	5.36%	25.98%
High L-score 8+9]	14.42%	58	-50.40%	138.74%	-13.75%	10.32%	33.94%
High-Low	9.86%		29.75%	41.83%	1.69%	4.96%	7.95%
t-statistic	3.20***						
Total	8.99%	1195	-80.15%	312.58%	-10.75%	8.30%	25.67%

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

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

As expected, for both 12- and 24-month returns observed after portfolio formation, the raw returns and market excess firm returns increase as the L-score increases, with an implicit tendency, if not regularity. In general, the higher the L-score, the higher the future returns. The average return difference between 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. 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), statistically significant at the 1% level.

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 13.83% to 17.57%. For the 24-month returns, the increase was from 13.82% to 14.72%, and both increases are statistically significant at 1%. These results suggest that when for high average portfolios, an FA strategy is more efficient for predicting returns one year ahead.

Table 6.12 - Buy-and-hold 12-month returns by F-score (New High Score).

Panel A: Raw returns							
F-score	Mean	N	Min	Max	25%	Median	75%
0	11.77%	2	-59.51%	83.05%	-59.51%	11.77%	83.05%
1	-0.91%	9	-83.79%	194.13%	-64.63%	-12.80%	10.44%
2	-6.50%	28	-92.87%	123.00%	-48.10%	-15.12%	27.39%
3	2.00%	119	-90.27%	157.01%	-25.60%	-0.14%	21.87%
4	9.56%	199	-80.73%	231.54%	-19.72%	6.76%	27.34%
5	12.43%	233	-79.89%	207.09%	-19.13%	8.02%	32.65%
6	17.35%	245	-74.30%	272.02%	-6.34%	13.43%	38.84%
7	25.48%	204	-86.89%	516.73%	-5.30%	17.09%	39.84%
8	20.12%	119	-80.88%	268.64%	-0.16%	16.66%	33.28%
9	14.37%	37	-36.60%	63.91%	-1.69%	18.57%	29.11%
Low F-score [0+1+2]	-4.27%	39	-92.87%	194.13%	-50.42%	-13.64%	27.39%
New High F-score[7+8+9]	22.57%	360	-86.89%	516.73%	-3.94%	17.31%	35.75%
High-Low	26.84%		5.97%	322.60%	46.49%	30.96%	8.36%
t-statistic	4.58***						
Total	14.43%	1195	-92.87%	516.73%	-13.74%	11.50%	33.42%

Panel B: Market excess firm returns							
0	-25.93%	2	-93.76%	41.91%	-93.76%	-25.93%	41.91%
1	11.00%	9	-54.68%	152.99%	-36.98%	7.03%	25.21%
2	-3.39%	28	-70.85%	83.21%	-26.19%	-1.28%	16.63%
3	4.96%	119	-51.81%	122.75%	-12.78%	1.01%	17.06%
4	9.51%	199	-70.78%	197.28%	-9.01%	5.89%	24.42%
5	11.54%	233	-65.11%	188.85%	-8.92%	8.32%	25.68%
6	13.33%	245	-98.76%	281.97%	-6.77%	11.07%	26.70%
7	20.42%	204	-65.31%	492.27%	-6.12%	11.55%	31.75%
8	15.12%	119	-66.96%	234.39%	-4.30%	9.84%	26.35%
9	9.69%	37	-41.44%	55.07%	-6.91%	8.34%	27.97%
Low F-score [0+1+2]	-1.22%	39	-93.76%	152.99%	-29.89%	0.99%	20.38%
New High F-score [7+8+9]	17.57%	360	-66.96%	492.27%	-6.02%	10.88%	29.53%
High-Low	18.79%		26.80%	339.28%	23.87%	9.89%	9.15%
t-statistic	3.46***						
Total	12.31%	1195	-98.76%	492.27%	-8.49%	7.81%	25.93%

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

Table 6.13 - Buy-and-hold 24-month returns by F-score (New High Score).

Panel A. Raw returns							
F-score	Mean	N	Min	Max	25%	Median	75%
0	-63.42%	2	-80.15%	-46.70%	-80.15%	-63.42%	-46.70%
1	-17.07%	8	-68.17%	18.31%	-46.57%	-6.32%	9.54%
2	-20.98%	25	-78.06%	30.84%	-36.91%	-25.40%	-0.75%
3	-2.65%	112	-72.99%	87.11%	-20.32%	-2.27%	12.26%
4	2.38%	185	-69.65%	143.82%	-15.34%	3.57%	16.57%
5	4.14%	213	-59.99%	140.51%	-14.45%	2.82%	21.63%
6	11.69%	223	-64.51%	186.61%	-5.71%	11.47%	26.38%
7	20.98%	191	-74.75%	312.58%	-0.95%	15.35%	34.24%
8	20.93%	106	-48.57%	105.91%	6.11%	21.29%	36.54%
9	23.32%	35	-27.86%	80.30%	0.68%	26.11%	41.22%
Low F-score [0+1+2]	-22.51%	35	-80.15%	30.84%	-43.93%	-25.40%	0.65%
New High F-score [7+8+9]	21.21%	332	-74.75%	312.58%	0.57%	18.74%	35.49%
High-Low	43.72%		5.40%	281.74%	44.50%	44.15%	34.84%
t-statistic	10.44***						
Total	8.99%	0	-80.15%	312.58%	-10.75%	8.30%	25.67%

Panel B. Market excess firm returns							
0	-52.95%	2	-71.04%	-34.86%	-71.04%	-52.95%	-34.86%
1	1.07%	8	-38.48%	30.71%	-25.80%	12.61%	21.36%
2	-8.98%	25	-48.65%	27.68%	-23.83%	-10.45%	6.03%
3	3.47%	112	-52.31%	79.12%	-9.62%	3.27%	12.43%
4	6.03%	185	-50.43%	152.92%	-8.19%	5.45%	16.91%
5	6.82%	213	-46.26%	124.12%	-5.47%	6.60%	17.13%
6	10.23%	223	-61.02%	170.19%	-4.77%	10.32%	23.26%
7	15.38%	191	-50.05%	296.19%	-2.22%	10.60%	25.14%
8	13.63%	106	-33.96%	85.02%	-0.19%	10.90%	25.36%
9	14.40%	35	-34.34%	55.79%	2.74%	12.03%	27.12%
Low F-score [0+1+2]	-9.19%	35	-71.04%	30.71%	-27.97%	-10.45%	14.31%
New High F-score [7+8+9]	14.72%	332	-50.05%	296.19%	-0.21%	10.85%	25.46%
High-Low	23.91%		20.99%	265.47%	27.76%	21.31%	11.15%
t-statistic	6.21***						
Total	8.91%	1100	-71.04%	296.19%	-5.45%	7.70%	20.47%

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

The replicated analyses for portfolios with high L-scores (i.e., values of 6, 7, and 8) for buy-and-hold 12-month and 24-month returns are in Table 6.14 and Table 6.15.

Table 6.14 - Buy-and-hold 12-month returns by L-score (New High Score).

Panel A. Raw returns							
L-score	Mean	N	Min	Max	25%	Median	75%
0	-13.21%	22	-83.79%	60.89%	-30.02%	-12.51%	6.55%
1	13.05%	80	-90.27%	212.75%	-14.74%	11.49%	28.50%
2	16.19%	116	-92.87%	319.15%	-12.01%	13.98%	36.82%
3	14.64%	215	-67.69%	272.02%	-12.37%	8.79%	33.55%
4	13.68%	277	-80.73%	379.46%	-16.85%	11.47%	33.11%
5	13.15%	244	-86.89%	516.73%	-13.09%	8.14%	29.98%
6	18.18%	180	-78.01%	157.26%	-3.39%	20.97%	39.71%
7	17.96%	54	-64.59%	233.16%	-13.98%	3.16%	43.30%
8	32.12%	7	11.13%	52.01%	25.22%	33.08%	39.08%
Low L-score [0+1+2]	12.07%	218	-92.87%	319.15%	-16.01%	10.78%	31.06%
New High L-score [6+7+8]	18.54%	241	-78.01%	233.16%	-6.71%	19.41%	39.75%
High-Low	6.47%		14.85%	-85.98%	9.31%	8.63%	8.69%
t-statistic	1.54						
Total	14.43%	1195	-92.87%	516.73%	-13.74%	11.50%	33.42%

Panel B. Market excess firm returns							
0	0.70%	22	-38.86%	42.49%	-14.99%	-1.04%	16.03%
1	10.91%	80	-70.85%	171.61%	-9.92%	6.54%	24.66%
2	10.78%	116	-93.76%	329.10%	-9.87%	4.20%	30.44%
3	12.15%	215	-54.68%	281.97%	-9.41%	7.81%	25.78%
4	12.41%	277	-98.76%	370.62%	-10.85%	7.21%	24.63%
5	11.23%	244	-66.96%	492.27%	-7.99%	6.64%	21.97%
6	14.48%	180	-46.26%	117.77%	-2.24%	13.77%	29.82%
7	19.53%	54	-50.00%	243.39%	-8.24%	7.55%	26.07%
8	17.24%	7	-8.06%	43.89%	2.40%	20.58%	29.74%
Low L-score [0+1+2]	9.81%	218	-93.76%	329.10%	-12.27%	4.62%	26.61%
New High L-score [6+7+8]	15.69%	241	-50.00%	243.39%	-5.49%	12.90%	29.71%
High-Low	5.88%		43.76%	-85.71%	6.78%	8.28%	3.10%
t-statistic	1.55						
Total	12.31%	1195	-98.76%	492.27%	-8.49%	7.81%	25.93%

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

Table 6.15 - Buy-and-hold 24-month returns by L-score (New High Score).

Panel A. Raw returns							
L-score	Mean	N	Min	Max	25%	Median	75%
0	2.83%	22	-62.19%	76.85%	-19.89%	9.01%	30.71%
1	3.39%	75	-72.99%	57.37%	-12.16%	2.05%	27.04%
2	5.73%	107	-80.15%	96.91%	-13.99%	6.28%	24.95%
3	9.07%	197	-61.90%	166.34%	-10.58%	7.94%	25.55%
4	6.44%	252	-69.65%	213.05%	-13.42%	5.24%	20.47%
5	9.77%	225	-74.75%	312.58%	-6.39%	7.24%	23.02%
6	15.31%	164	-64.51%	92.05%	-2.74%	16.89%	32.55%
7	12.62%	51	-50.40%	138.74%	-15.58%	9.18%	32.62%
8	27.49%	7	-0.36%	67.55%	6.88%	17.99%	46.74%
Low L-score [0+1+2]	4.56%	204	-80.15%	96.91%	-15.44%	5.36%	25.98%
New High L-score [6+7+8]	15.08%	222	-64.51%	138.74%	-4.10%	15.79%	33.75%
High-Low	10.52%		15.64%	41.83%	11.34%	10.44%	7.77%
t-statistic	3.20***						
Total	8.99%	1195	-80.15%	312.58%	-10.75%	8.30%	25.67%

Panel B. Market excess firm returns							
0	7.63%	22	-32.50%	52.34%	-11.70%	10.27%	24.81%
1	4.63%	75	-48.65%	44.30%	-8.62%	7.09%	17.72%
2	4.29%	107	-71.04%	74.93%	-7.24%	5.24%	16.81%
3	8.94%	197	-61.02%	145.45%	-4.03%	8.10%	21.26%
4	7.29%	252	-59.91%	192.17%	-7.23%	4.70%	16.05%
5	9.14%	225	-47.17%	296.19%	-5.96%	6.59%	19.55%
6	14.22%	164	-52.11%	67.55%	2.76%	13.52%	26.57%
7	14.01%	51	-26.16%	120.10%	-2.13%	12.42%	22.35%
8	17.86%	7	1.51%	43.04%	5.24%	21.43%	24.29%
Low L-score [0+1+2]	4.78%	204	-71.04%	74.93%	-8.47%	6.41%	17.79%
New High L-score [6+7+8]	14.29%	222	-52.11%	120.10%	2.30%	13.28%	25.59%
High-Low	9.51%		18.94%	45.17%	10.77%	6.87%	7.80%
t-statistic	3.42***						
Total	8.91%	1195	-71.04%	296.19%	-5.45%	7.70%	20.47%

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

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 (see Table 6.10 and Table 6.11 for the raw returns). 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%, respectively (see Table 6.10 and Table 6.11 for market excess firm returns). For the L-score, only the two-year buy-and-hold strategy is statistically significant at the 1% level (Table 6.15).

These findings suggest that researchers should examine more sophisticated investment strategies based on FA, including an application of portfolio theory to minimize risk and maximize expected returns. It may be possible to predict financial crises and recessions, especially considering that the Euronext 100 index experienced strong volatility in the study period (Figure 6.1).

7. Conclusions

This work provides an overview of FA, stressing its importance for investors looking forward for at least a one-year period. 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.

Piotroski (2000) and Lev and Thiagarajan (1993) offer two scores, the F-score and the L-score, that are based on financial statement analyses and that investors can use to construct portfolios that enable them to earn abnormal returns. This apparent anomaly initially was documented in U.S. markets. Yet if markets are efficient, then anomalies should tend to disappear once they have been discovered, either by learning or arbitrage.

By using firms listed in the Euronext 100 index, the current study examines the explanatory power of accounting signals for predicting annual returns in a different setting. The results show that 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 the subsequent annual returns of about 2.9%-3.1% 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 the F- and L-scores, investors should be rewarded with one- and two-year buy-and-hold with abnormal returns in portfolios with high scores. By selecting firms with high scores (i.e., F-score 8 or 9), investors can expect raw returns of approximately 19%. In addition, an investment strategy that buys these expected winners and shorts expected losers (i.e., F-scores 0–2) could have generated a 23% annual return between 2000 and 2014 (see also Piotroski 2000). Portfolios based on high L-scores for 12-month 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 efficient 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.

Because FA is based on a plethora of accounting reports, covering the most important financial aspects of a firm, it appears that it is more suitable for informing long-term investing strategies than a traditional market index investment strategy. This conclusion is also supported by Piotroski (2000), Dosamantes (2013), and Amor-Tapia and Táscon (2016). But the current study also contributes further to FA and capital market literature. First, the findings about the value relevance of accounting fundamentals provide insights into the levels of market efficiency in Europe. Second, the results using a fundamental strategy to form portfolios have practical implications for investors. Regarding the type of market efficiency (Fama 1970), these results do not confirm the semi-strong form of the EMH, in which security prices reflect all information that is publicly available. Further research is needed to evaluate whether the value relevance of accounting fundamentals is an important signal of market inefficiency. In particular, some firms have high fundamentals that are not reflected in their security prices. These results may explain the lack of verification for the semi-strong form of the EMH. The current study uses annual data; perhaps results using quarterly data would be more accurate and potentially reflect the PEAD effect. Regression models also can work well if an investor is diversified (Piotroski 2000; Kim and Lee 2014).

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

However, this study has a few limitations. The econometric models do not include important macroeconomic variables such as inflation rates, economic depressions, or regulatory changes in the market, beyond controlling for time effects. Further out-of-sample tests could strengthen inferences about the usefulness of a given accounting attribute, to forecast either future earnings or future stock returns. If relevant institutional factors or other characteristics vary over time or across firms, this variation should be tested; any variation in the observed outcomes also might help strengthen the resulting inferences. Tests of the predictive ability of a given attribute also might be conducted in a more “fair” manner (e.g., Richardson *et al*. 2010).

The relative consistency of explanations across anomalous variables requires additional research attention. A striking feature of the current state of accounting anomalies and FA is the failure to exploit knowledge of the accounting system itself to link accounting information to stock prices and returns. Fama and French (2006, 2008) and Penman (2009) recognize this tautology and attempt to combine multiple forecasting variables in a logically consistent manner. Significant opportunity thus exists for accounting researchers to benefit from their knowledge of accounting systems to identify key interrelations among accounting data, then combine this knowledge with empirical asset pricing literature (e.g., Penman and Reggiani 2013).

Ohlson (1995, 2009) and Richardson *et al.* (2003, 2006, 2010) provide relevant frameworks for empirical research that addresses accounting anomalies and FA. Chee *et al.* (2013) have sought to enrich these studies by using linear information dynamics to additively decompose ex post stock returns over a rolling five-year period into fundamental and speculative components. Their framework might be extended to improve measures of expected returns and forecasts of persistence in residual income. Another opportunity for FA literature stems from the sparse uses of macroeconomic information. Incorporating macroeconomic information directly into a forecasting framework offers promise, which is a fruitful area for further research (e.g., Basu *et al.* 2010).

Using information beyond the accounting details contained in financial statements is another option. The primary financial statements provide an articulated view of the firm's ability to generate future earnings and free cash flow. But substantial contextual information also exists, beyond that contained in primary financial statements, which may be highly relevant for forecasting future earnings and returns. Various industry-specific metrics likely are relevant for forecasting future earnings too, such as same-store sales metrics for retailers, load factors for airlines, and capacity utilization for manufacturers. Such metrics are often available in financial reports; other times, they are collected mostly by third-party data providers. Academic research in accounting and finance typically ignores this information or uses it only to condition standard models of earnings persistence (Richardson *et al.*, 2010). Finally, another source of information could come from notes to the financial statements.

Because under the period of analysis the Euronext 100 index showed strong volatility, further this study also explored asymmetric effects which are fundamental to stock market volatility. Estimates of stock market volatility are important for making capital budgeting decisions and formulating optimal portfolios. Volatility clustering is a stylized fact, present in most financial time series, such that volatility offers a fundamental variable for both theoretical and applied work. In particular, financial volatility exhibits asymmetric behavior; bad news in the market have a greater impact than good news of the same magnitude. Considering the importance of this effect, we have applied three models of conditional volatility—symmetric GARCH and asymmetric *EGARCH* and *T-GARCH*—to the daily returns of the Euronext 100 index over 2000-2015. Our main objective is to investigate the extent to which symmetric/asymmetric effects are present in the data.

These data exhibit some notable characteristics. In particular, the prices of this stock index are non-stationary, but the returns, which are the focus of our study, are not. Therefore, we employed unit root tests and determined that the values of the standard deviation imply that volatility is high in this index; we also conducted a combined analysis of the estimators and found that the distributions move away from normalcy, indicating leptokurtic behavior. That is, the kurtosis values are always greater than 3, indicating an excessive concentration of frequencies around the skew and tails of the respective distributions. This indication is confirmed by tests of the skewness and kurtosis coefficient values and the normal distributions proven by the Jarque-Bera tests. The uncertainty in financial asset returns thus is higher than would be expected if it followed a Gaussian distribution.

A preliminary analysis of the results uncovers non-normality, serial correlation, and heteroskedasticity in the return series. We thus fitted an *AR(5)* model to the Euronext 100 return series to capture autocorrelation in the data. A diagnostic analysis of the residuals shows that serial correlation is no longer present; this specification was appropriate to remove the evident autocorrelation in the return series. The *ARCH-LM* test and Ljung-Box statistic of the squared residuals also imply heteroskedasticity. To investigate the asymmetric effects, we estimated *GARCH, EGARCH*, and *T-GARCH* models. The results show that the stock index returns of Euronext 100 exhibit asymmetry. Finally, the diagnostic test of the residuals shows no *ARCH* effects; these models are adequate to account for this data feature.

In the maximum likelihood estimates, the parameters of time-varying correlation, skewness, and fat-tails are all statistically significant, and t-Student density suits the data well and increases the log-likelihood substantially (Wu *et al*. 2015). The information criteria indicate that the best model is *EGARCH*, followed by *TGARCH* and finally *GARCH*. The great advantage of these models is that they can capture the linear dependence of the volatility of the financial assets.

8. References

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