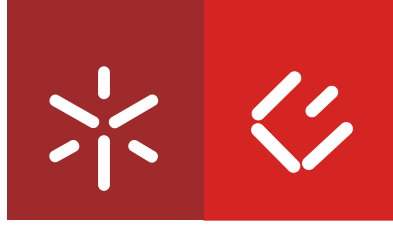


**Universidade do Minho**  
Escola de Economia e Gestão

Laura Cristina Bonjardim Coelho

**Investor sentiment and the cross-section of  
stock returns in the French stock market**



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Dissertação de Mestrado  
Mestrado em Finanças

Trabalho efetuado sob a orientação da  
**Professora Doutora Cristiana Cerqueira Leal**

## Declaração

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## Abstract

This dissertation studies the impact of investor sentiment on aggregated stock returns and a cross-section of market returns, in the French financial market.

Investor sentiment is captured using two distinct measures: a direct measure – the Consumer Confidence Index (CCI) – and an indirect measure – the orthogonalized Investor Sentiment Index (ISI<sup>⊥</sup>). Following the work of Baker and Wurgler (2006) and Baker et al. (2012), the Investor Sentiment Index corresponds to the first principal component of six underlying proxies: market turnover, number and average first-day returns on IPOs, the share of equity issues, dividend premium and volatility premium. The Consumer Confidence Index represents a survey that directly asks investors about their expectations regarding the French stock market.

The analysis of the aggregated market returns suggests that the CCI is the most adequate index to capture investor sentiment, revealing a negative impact on all time horizons studied. The ISI<sup>⊥</sup>, on the other hand, does not reveal a significant impact on the three shorter time horizons. The study of the cross-section market returns takes into consideration several firms' characteristics. In this context, results suggest that ISI<sup>⊥</sup> is the most suitable index.

The study of the cross-section market returns indicates that small, high volatility, unprofitable, non-dividend-paying, less tangible, extreme growth and distressed stocks tend to earn subsequent higher (lower) returns after periods of low (high) sentiment. Results also show that changes in investor sentiment have a higher impact on these type of stock returns. Furthermore, this dissertation suggests that, overall and for both indexes, the observed patterns of the behaviour of investor sentiment do not reflect compensation for classical systematic risks.

**Keywords:** investor sentiment; direct and indirect measures of sentiment; sentiment on aggregated market returns; sentiment on cross-section market returns.

## Resumo

Este estudo investiga o impacto do sentimento do investidor nas rendibilidades agregadas e a nível transversal no retorno das ações no mercado acionista francês.

O sentimento é medido de duas formas distintas: utilizando uma medida direta – o Índice de Confiança do Consumidor (CCI) – e uma medida indireta – o Índice do Sentimento do Investidor ortogonalizado (ISI<sup>⊥</sup>). Seguindo o trabalho de Baker e Wurgler (2006) e Baker et al. (2012), o Índice do Sentimento do Investidor é construído através do principal componente comum de seis *proxies* de sentimento: o volume de transação, a quota de emissão de capital próprio face a todas as emissões, o número e o retorno no primeiro dia em ofertas públicas iniciais, o prémio de dividendos e o prémio de volatilidade. O Índice de Confiança do investidor considera um questionário a investidores em relação às suas expectativas sobre o mercado financeiro francês.

A análise das rendabilidades agregadas sugere que o CCI é o índice mais adequado, revelando um impacto negativo em todos os horizontes temporais estudados. O ISI<sup>⊥</sup>, por sua vez, não revela um impacto significativo nos três horizontes temporais mais curtos. O estudo das rendibilidades a nível transversal tem em consideração uma série de características de empresas. Neste contexto, os resultados sugerem que o ISI<sup>⊥</sup> é o índice mais indicado.

A análise a nível transversal indica que em períodos de baixos (altos) valores dos *proxies* do sentimento do investidor, o posterior retorno é elevado (baixo) em pequenas ações, altamente voláteis, não rentáveis, ações que não pagam dividendos, que apresentam grandes oportunidades de crescimento ou ações que experienciam dificuldades financeiras graves. Os resultados evidenciam também que uma mudança do sentimento do investidor tem um impacto superior nestes tipos de ações. Verifica-se ainda que, de um modo geral e para os dois índices, os padrões de comportamento do sentimento do investidor verificados não refletem uma compensação do risco sistemático clássico.

**Palavras-chave:** sentimento do investidor; medidas diretas e indiretas; sentimento em rendibilidades agregadas; sentimento a nível transversal; risco sistemático.

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# 1. Introduction

This dissertation explores an important topic of the behavioural finance theory. Understanding whether the prevailing investor sentiment affects future stocks returns is vital to perceive which mechanisms play a major role in financial markets. In this study, sentiment is defined as the emotional investor's belief about future market returns that are not supported by the existing stock information.

The classical finance theory premise suggests that the financial market is built by rational investors, meaning that all available information is correctly interpreted and that this information is reflected in the securities' prices (Fama, 1970). This assumption does not take into account that the investor sentiment can play an influence in the investor's financial decisions. However, the financial market history is full of events that seem to defy this rational view of stock markets. Due to this fact, the behavioural finance theory has emerged and is gaining more relevance (Baker and Wurgler, 2007). Under the behavioural finance assumptions, the financial market is not always rational, allowing prices to diverge from their fundamental values, because they are constructed by the actions of normal investors, which are sentiment-driven in their financial decisions. Additionally, the actions of these normal investors cannot be exploited by rational investors due to arbitrage constraints (Shleifer and Vishny, 1997).

This dissertation aims to study whether sentiment influences future stock returns and determine which stocks are, eventually, more influenced by investor sentiment. Baker and Wurgler (2006) support the idea that exists a group of stocks that, given their characteristics, are usually harder to value and more difficult to arbitrage, making them more susceptible to sentiment waves. The authors find that small, young, high volatility, unprofitable, non-paying, extreme growth and distressed stocks are extremely affected by shifts in sentiment

The main literature regarding this topic of behavioural finance is focused on the U.S. stock market alone (Baker and Wurgler (2006, 2007); Kaniel et al. (2004); Brown and Cliff (2004, 2005)). Others authors investigate the effect of investor sentiment in several international countries in order to understand this effect in a global manner (Bathia and Bredin (2013); Baker et al. (2012)). Generally, the investor sentiment has not been studied in many countries, in an individual way. In order to overcome this gap in the literature and to contribute towards a better understanding

of the real effect of investor sentiment in a European context, this dissertation conducts a research specifically on the French market, taking into consideration its own idiosyncratic characteristics.

The period under analysis starts at January 01, 1993 and ends at December 31, 2013. A 20 year investigation period allows the inference of some important sentiment patterns in the French financial market. The data is always presented on a monthly basis. This is true for firm-level characteristics, sentiment measures used as proxies and macroeconomic variables employed to control for macroeconomic effects.

To capture the investor sentiment in the French stock market, two sentiment proxies are used: a direct measure – the Consumer Confidence Index (CCI) - and an indirect measure – the Investor Sentiment Index (ISI $\perp$ ). Based on Baker and Wurgler (2006) and Baker et al. (2012), the ISI is a composite sentiment index that tries to capture the effect of investor sentiment in future stock returns, through the common variation of six underlying sentiment measures: share turnover, number and average first-day returns on IPOs, equity share in new issues, dividend premium and volatility premium. In order to control the effect of macroeconomic conditions on stock returns, six raw sentiment proxies are regressed with six macroeconomic variables: industrial production index (IPI), consumer price index (CPI), French gross domestic production (GDP), inflation rate, policy interest rate and employment growth. Thus, originating an orthogonalized Investor Sentiment Index (ISI $\perp$ ).

Despite not existing any definitive or uncontroversial measure of investor sentiment (Baker and Wurgler, 2006), the choice of the measures used as sentiment proxies is crucial to the quality of the results. In this sense, a comparison is made between the results obtained by ISI $\perp$  and CCI. Given the fact that these two indexes are constructed based on two different sources of information (ISI $\perp$  relates to market variables and CCI is a survey that directly asks investors about their expectations concerning financial markets), it is relevant to understand if their results show similar patterns.

This dissertation has two major objectives. The first is to assess the impact of investor sentiment (measured by ISI $\perp$  and CCI) in the aggregated stock market returns for four distinct time horizons: 1, 6, 12 and 24 months. With this, one intends to investigate the existence of a general influence of investor sentiment that causes a global deviation of market prices from their fundamental values. The confirmation of this proves investor sentiment to be a relevant factor in the introduction of significant risk in the equilibrium of market prices.

The second objective is to examine the impact of investor sentiment in different types of stocks, taking into consideration specific firms' characteristics, namely size, total risk, profitability, dividend policy, asset tangibility and growth opportunities and/or distress. This effect is studied through a cross-section of market returns using three approaches: the sorts analysis, the predictive regressions for long-short portfolios analysis and the systematic risk analysis.

The sorts analysis is conducted for a time horizon of 12 months. It starts by dividing the sample in ten equally weighted portfolios (Baker and Wurgler (2006) suggest that large firms are less affected by sentiment, and hence value weighting tends to obscure the relevant patterns), according to the firms' characteristics enunciated above and the level of sentiment (measured by ISI<sup>L</sup> and CCI) prevailing at the end of each year. Then, it is calculated the average monthly return obtained in each decile and in each category in periods of positive and negative sentiment.

The regressions for long-short portfolios and the systematic risk analysis are both conducted for four distinct time horizons: 1, 6, 12 and 24 months. In the regressions approach, the portfolios are long on stocks with high characteristic values and short on stocks with low values. The study of the systematic risk is included to analyse the impact of investor sentiment in the cross-section of stock returns in a more rigours manner. This analysis involves the regression of long-short portfolios returns dependent on the market risk premium and the market risk premium interacted with investor sentiment (measured ISI<sup>L</sup> by and CCI). The long-short portfolios are constructed as enunciated in the predictive regressions for long-short portfolios analysis.

The results obtained in the study of the aggregated market suggest that CCI is the most adequate index in this context. Using this index, investor sentiment reveals a significant negative impact on the aggregated stock returns for all the time horizons under investigation.

Contrariwise, the results obtained in the study of the cross-section market returns show ISI<sup>L</sup> to be the most suitable index for this context. Using ISI<sup>L</sup>, both the sorts and the predictive regressions for long-short portfolio analysis arrive to the same conclusions. Results support that small, high volatility, unprofitable, non-dividend-paying, less tangible, extreme growth and distressed stocks tend to earn subsequent higher (lower) returns after periods of low (high) sentiment. Results also show that changes in investor sentiment have a higher impact on these type of stock returns, which can be explained by the fact that these firms are harder to value and more difficult to arbitrage. These findings are in line with Baker and Wurgler (2006) for the U.S. stock market and with Baker et al. (2012) for six major financial markets (including the French

market). As for the systematic risk analysis, the main conclusion obtained is that, in general, the patterns indicated for both sentiment indexes,  $ISI^L$  and CCI, do not reflect a compensation for classical systematic risk.

This dissertation is organized in 6 chapters. The next chapter presents the literature review divided into different subsections to allow for a better understanding of important topics related with behavioural finance and, particularly, with investor sentiment. The literature review starts by enunciating the generic differences advocated by classical and behavioural finance theories and describing the limits of arbitrage that market participants may be subjected to. Then, it is presented the definition of investor sentiment and the different measures used to capture its impact (direct and indirect measures and investor sentiment indexes). The most relevant empirical findings in the field of investor sentiment are also described. Chapter 3 describes the construction of the two sentiment measures, the characteristics portfolios and presents the macroeconomic variables used to control for macroeconomic conditions. Chapter 4 describes the methodology implemented to construct the two sentiment measures and to study the impact of investor sentiment in the aggregated stock market and in the cross-section. Chapter 5 presents the results and their interpretations. Chapter 6 describes the main conclusions achieved and enunciates some suggestions for further investigation.

## 2. Literature review

### 2.1. Classical finance vs. Behavioural finance

Shiller (2006) divided the financial theory into two distinct paradigms: the neoclassical finance theory, starting around 1960s, which formulates the well-known capital asset pricing model (CAPM) and the efficient market hypothesis; and the behavioural finance, beginning in the 1980s, which tries to include the prospect theory (Kahneman and Tversky, 1979) and other psychological effects to understand financial markets.

Statman (2005) presents the four blocks that built the classical finance theory: (i) financial markets are constituted by rational investors; (ii) these investors participate in an efficient market; (iii) rational investors create their portfolios according to the rules of mean-variance portfolio theory; (iv) the stocks expected returns are depending on risk factors alone.

Traditional finance argues that investors are rational and, therefore, securities must trade at their fundamental values. The fundamental value represents the discounted sum of all future cash flows. The premise that market participants are rational means that all available information is correctly interpreted and that all information is fully incorporated in the security prices (Fama, 1970). The Efficient Market Hypothesis also emphasizes that even if some sentiment-driven investors do exist, their activities will be neutralized by the action of rational investors, taking advantage of arbitrage opportunities (Shleifer, 2000).

However, the history of financial markets is full of events that seems to defy the foundations of traditional finance. In fact, Baker and Wurgler (2007) present an inventory of bubbles and crashes, such as: the Black Monday Crash (October 1987), the Great Crash (1929), Tronics Boom (early 1960s), Go-Go Years (late 1960s), the Nifty Fifty Bubble (early 1970s) and the Dot.com Bubble (1990s). These events occur due to an extreme level or change in stock prices that cannot be explained only by the available information about the financial markets. This contradicts one of the principal ground of the traditional finance theory.

The difficulty to explain these patterns led to the emergence of the behavioural finance theory. Shefrin (2001) says that behavioural finance is the study of how psychology affects financial decision-making process on financial markets.

The two basic assumptions of behavioural finance are that (i) investors' decision-making process is influenced by sentiment (De Long et al., 1990); (ii) exploiting arbitrage opportunities are both costly and risky, Shleifer and Vishny (1997).

One of the main differences that separate traditional finance and behavioural finance is the way how investors are perceived. On the one hand, traditional finance suggests that financial markets participants are rational. On the other hand, behavioural finance believes that instead of rational, investors are in fact normal. Statman (2005) suggests that normal investors are influenced by psychological biases and emotions and that this type of investors construct their portfolios not only influenced by expected returns and risk factors. In fact, normal investors include other factors on their decision making process.

The literature about this topic has other terminologies to define financial market participants. Shiller (2003) separates the market participants into two broad categories: smart money and ordinary investors. He argues that smart money participants could not always drive market prices to their fundamental values. The effects of these two types of market participants draw the attention of many researchers. De Long et al. (1990) stated that smart money investor's activity can intensify the effects of bias investors in the market, rather than make prices go back to their fundamental values. The authors suggest that smart money investors try to anticipate an increase in prices created by the activity of ordinary investors by buying them first. In their study, they also pointed out that rational investors might not always want to offset all of the effects of irrational investors because they are rationally concerned about the risk generated by the irrational investors. Barberis and Shleifer (2003) share the same view about this topic. Goetzmann and Massa (1999) provided empirical evidence that supports the existence of two types of market participants. The authors called them feedback traders and smart money investors.

Despite the abundant terms that define financial market participants, all of them try to separate the financial market into two groups. One that is influenced by psychological factors and sentiment and other that is constituted by professional or institutional traders that construct their portfolios based only in the risk associated and the expected returns of their overall portfolios performance. This dissertation choose to apply the terms rational and normal investors.

## 2.2. Limits of arbitrage

Theoretically, arbitrage is perceived as a riskless activity that allows investors to take advantage of stock mispricing in different markets. By buying and selling the same asset in different markets, with different prices, investors can profit the difference. These investors are called arbitrageurs and their activity is key to understand the securities markets. In fact, the actions of arbitrageurs bring prices to their fundamental values, thus guaranteeing market efficiency (Sharpe and Alexander, 1990).

Shleifer and Vishny (1997) present a remarkable study about this topic that goes against the traditional view of markets' activity. The authors contest the two main assumption about arbitrageurs' activity. They demonstrate that rational investors cannot fully exploit arbitrage opportunities and they also reject the idea that arbitrage is a riskless and costless activity.

Many scholars have evaluated the risks and costs that are associated with arbitrage, and linked it with different types of stocks (Wurgler and Zhuravskaya, 2002; D'Avolio, 2002; Jones and Lamont (2002)). Even if investors can perceive arbitrage opportunities, they may be constrained to act due to capital restrictions. In fact, arbitrageurs may be unwilling to take an opposite position in a situation where, in theory, they can gain the most, i.e., when the mispricing they have bet against gets even worse (Shleifer and Vishny, 1997).

Young, small, unprofitable, extreme growth or distressed stocks have shorter trading history, and are more difficult and uncertain to compare with other stocks (Baker and Wurgler, 2006). This makes their valuation highly subjective. The stock market can take a long time to realise these stocks' true value, and thus, arbitrageurs may face the risk that their positions can be left open for a superior period that they intend to invest, if other investors are hesitant to trade. The risks and costs associated with these types of stocks can, therefore, influence arbitrageurs' actions, leading prices away from their fundamental values for a long period, making markets inefficient.

## 2.3. Investor sentiment

### 2.3.1. Definition of investor sentiment

The main literature has defined investor sentiment in a various ways. Baker and Wurgler (2006) define sentiment as the propensity to speculate or as investor's optimism or pessimism about financial markets. In 2007, the same authors defined investor sentiment as the belief about future cash flows and investment risks that is not explained by the available information. Chang et al. (2009) suggest that investor sentiment corresponds to the investor's opinion about future cash flows and investment risks, influenced by emotion. Brown and Cliff (2004) consider that sentiment embodies the expectations of market players in relation to a norm: a bullish (bearish) investor presumes returns to be above (below) average.

This dissertation understands investor sentiment as the emotional investor' belief about future market returns, that are not supported by the existing stock information.

### *2.3.2. Proxies for investor sentiment*

Investor sentiment is not straightforward to measure (Baker and Wurgler, 2007). Therefore, in order to test the effect of investor sentiment, it is necessary to find some imperfect measures and used them as proxies for investor sentiment. The existing literature presents several proxies, but none of them is considered as being definitive and uncontroversial measures. However, there are a set of variables that are most exploited by the scholars in this area.

The proxies for investor sentiment can be divided into two different groups: direct measures and indirect measures, depending on how investor sentiment is captured. Next, it is presented these two types of measures and it is described some of the most accepted proxies in the prevailing literature, in each category.

The sentiment proxies can be studied individually or they can be used to construct a sentiment index that captures the joint influence of several proxies on stock returns. In this chapter, it is also presented a number of research that study the effect of investor sentiment in the stock market, using sentiment indexes that combine information relatively to several proxies of investor sentiment.



### *2.3.2.1. Direct measures*

The direct measures capture the investor sentiment by directly asking investors about their expectations about current and future economic environment and stock market conditions. Baker and Wurgler (2007) believe that by asking investors about their optimism or pessimism about the market, it is possible to understand how they formulate their financial decisions.

Consumer confidence surveys are the most explored direct measure in the literature, used to study the impact of sentiment in financial markets (Finter et al. 2011). This measure presents some advantages, such as: data availability (for long horizons periods and for several international countries) and data comparability (because is a measure available for several countries and with similar approaches, allows the comparison of the results obtained in an international level – Schmeling, 2009).

In the case of European countries, the consumer confidence index that is more explored by researchers is the **Consumer Confidence Indicator (CCI)**, published on a monthly basis, by the Directorate General for Economic and Financial Affairs (DG ECFIN). Currently, the CCI is conducted to nearly 40,000 consumers from 29 countries in the European Union, using a questionnaire with 15 questions. The questions introduced in this survey can fall into two different categories (Jonsson and Lindén, 2009): micro-oriented questions (e.g. the financial situation of the household and the intention of the respondent to save money) and macro-oriented (e.g. the general economic situation in the country and unemployment).

Lemmon and Portniaguina (2006), Schmeling (2009), Brathia and Bredin (2012), Fisher and Statman (2003), conducted important studies about investor sentiment, using CCI as a proxy for investor sentiment.

Lemmon and Portniaguina (2006) concluded that over the last two decades, the returns on small stocks and future macroeconomic activity can be explain by consumer confidence surveys.

Brathia and Bredin (2012) inspected the relationship between investor sentiment and the G7 stock markets, and showed that investor sentiment (measured through CCI) exhibits a negative relationship with future sock returns. In fact, their results are in line with the prevailing existing literature: periods of high (low) sentiment are followed by low (high) stock returns.

### *2.3.2.2. Indirect measures*

Another way to capture investor sentiment is through the study of market variables. In this approach, the investor sentiment is inferred from market statistics, like price movements and trading patterns.

Beer and Zouaoui (2012) pointed out some advantages of using indirect measures. The authors suggest that these measures are easier to construct, because they correspond to simple market data that is widely available for different countries. Investor's decisions can be observed in real time and show the power of market participants and their bull or bearish' behaviour towards the market.

The **volatility premium** is an indirect measure that is used to capture investor sentiment. This variable identifies investor demand between high and low periods of volatility (Corredor et al. 2013). The motivation for this variable is related with the limits of arbitrage and the valuation difficulty. High volatile stocks are the ones that can experience extreme fluctuations in their valuation. Therefore, noise traders can defend extreme values for this type of stocks, according to their current optimism or pessimism towards the market. Volatile stocks are also the ones that are riskier and costlier to arbitrage (Baker and Wurgler, 2012). Corredor et al. (2013) suggest that volatility premium is expected to be directly related with investor sentiment.

This variable is analogous to the **dividend premium**, applied in the work presented by Baker and Wurgler (2004, 2006), and is a measure of investor demand between dividend-paying and non-paying stocks. Paying firms are usually associated with larger, more profitable firms with weaker growth opportunities (Baker and Wurgler, 2006). The dividend premium is seen as a proxy for the relative investor demand for stocks with these characteristics. Dividend premium and volatility premium are highly inversely related.

The **market turnover**, or liquidity, is consider a proxy for investor sentiment. In fact, in a market with short-selling constraints, high liquidity is associated with the actions of normal investors that are optimistic about the market. This means that high liquidity can be seen as a symptom of overvaluation (Baker and Stein, 2004). Trading volume is associated with differences of opinion and therefore associated with valuation levels (Scheinkman and Xiong, 2003). In fact, Jones (2002) exposes that high levels of liquidity are linked with low future market returns. Summarizing, the

literature suggests that market turnover is inversely related with sentiment: periods of high (low) sentiment lead to low (high) future stock returns.

The outstanding returns earned in the first day of Initial Public Offerings (IPO) have been a phenomenon that is hard to explain without considering investor sentiment (Baker and Wurgler, 2007). Ritter (1998) indicate that high **first-day returns on IPOs** is in fact a well-known pattern related with the procedure of going public. The author also suggests that on IPOs market, it is possible to distinguish three patterns: short-run underpricing, long-run underperformance, and cycles in volume and the level of underpricing. The last pattern, also known as “Hot Issue” market, suggest that first-day returns and **volume of IPOs** are extremely cyclical. In fact, high first-day returns follow periods of high volume on IPOs. This pattern is difficult to explain under rational explanations. These reasons combined indicate that IPOs market is viewed as sensitive to sentiment (Baker and Wurgler, 2006). High first-day returns are considered a signal of investor enthusiasm and, on the contrary, low first-day returns are seen as an indication of market timing (Stigler, 1964 and Ritter, 1991). Baker and Wurgler (2012) pointed out that the theoretical reason to use the volume of IPOs is easier to understand: insiders and long-run shareholders are prone to go public in periods when valuations are greatest, which is likely in periods when sentiment is highest.

In addition to the two proxies mentioned, the existing literature presents another variable that measures the financing activity in order to capture sentiment. The **equity issues over total equity and debt issues** represents the proportion of equity issues in the total issues (equity or debt). It is believe that the choice between financing through equity or debt is related with cost of capital concerns. In fact, Baker and Wurgler (2000) reveal that periods when equity is preferred over debt as a financing source are followed by periods of low stock market returns. The authors could not find an explanation for this situation under the Efficient Market Hypothesis, so the predictive power of equity share indicates inefficiency and reveals that firms time the market when issuing new securities.

The **closed-end fund discount** (CEFD) is a measure that has been widely accepted in the literature as a proxy for investor sentiment. A closed-end fund differs from an open-end fund because the first issues a fixed number amount of shares and to redeem them the investor has to sell their shares directly to others investors, instead of trade them with the fund itself. The closed-

end fund discounts represent the average difference between the net asset value (NAV) and their market prices (Baker and Wurgler 2006, 2007).

Lee et al. (1991) study the so called closed-end fund puzzle, and point out that the closed-end funds are usually sell at a discount of 10 to 20 percent. In their work, the authors tested the theory that proposes that changes in individual investors sentiment concerning with closed-end fund and other securities are the reason for the fluctuations of prices and discounts on closed-end funds. Higher discounts are associated with periods when investors are pessimistic about stock market and, inversely, discounts tend to decrease in periods when investors are optimistic about the marker. The authors conclude that closed-end fund discount is in fact a measure of investor sentiment, and add that investor sentiment may affect the prices of stocks just as the prices of closed-end funds.

Other scholars study the closed-end fund discount as a measure of investor sentiment. Zweig (1973) argues that the closed-end fund market is dominated by non-professionals traders and that the CEFD reflects their expectations. A smaller discount is associated with a bullish investors' behaviour and as the discount increases, it means that investors are getting pessimistic about future returns, as a compensation for the buyers (Baker and Wurgler, 2007). The prevailing understanding about the closed-end fund discount is that CEFD may be used as a sentiment proxy and it is inversely related to the sentiment factor (De Long et al (1990), Neal and Wheatley (1998) and Lee et al (1991)).

In contrast to these studies, Qiu and Welch (2004) analyse the closed-end fund discount as a measure of investor sentiment, and concluded that CEFD does not appear to be a suitable proxy of investor sentiment, when using UBS/Gallup Investor sentiment survey data.

Baker and Wurgler (2007) indicate that individual investors are expected to be more influenced by sentiment than professional or institutional investors. Greenwood and Nagel (2009) used age as a proxy for managers' investment experiences, and conclude that younger and unexperienced investors tend to buy more overvalued assets during bubble periods than their older and more experienced colleagues. Other authors also based their work in **retail investor trades**. Barber et al. (2009), on their work on stock trading behaviour of individual investors, concluded that: individual investors underperform comparatively to a benchmark; exhibit the disposition effect (sell winners too soon and hold losers for too long); are extremely affected by past returns in their

portfolio construction; tend to repeat past behaviours that they relate with pleasure and avoid past behaviours that generated pain; and tend to hold undiversified stock portfolios.

The choice between “safe” securities and “risky” securities has been another measure of sentiment. This can be viewed studying the **mutual fund flows**, in order to understand how mutual fund investors allocate their portfolios across fund categories (Baker and Wurgler, 2007). Frazzini and Lamot (2008) use mutual fund flows as a measure of individual investor sentiment of different stocks and show that high periods of sentiment lead to low future stock returns. The authors found that funds that hold a particular stock that experienced strong inflows, the future return of that stock is relatively poor. Brown et al. (2003) found evidence that equity fund flows are inversely related with bearish investor behaviour.

The **put-call ratio** is also been used as a proxy of investor sentiment (Finter et al. 2011) and represent the ratio of the number of put option over all options (put or call) transacted on the market (Bathia and Bredin, 2012). Finter et al. (2011) propose that the put-call ratio can be seen as a market barometer. In fact, a high (low) put-call ratio is a symptom of investor’s pessimism (optimism) about the market.

Baker and Wurgler (2007) point out that **insider trading** can be seen as a way to capture investor sentiment. It is easy to understand that corporate managers are the ones that are in the best position to assess their company value. In this sense, looking at executives’ personal portfolio can reveal their opinions about stock valuation. Therefore, the actions of this particular type of investor can contain a systematic sentiment component.

#### *2.3.2.3. Investor sentiment indexes*

As mentioned earlier, none of the investor sentiment proxies is considered definitive and uncontroversial. For this reason, the existing literature presents several research that study the joint effect of several proxies, instead of conduct a study based only on one measure, to capture investor sentiment. Researchers construct they own sentiment indexes, in order to overcome some of the limitations identified in the studies that only consider one investor sentiment variable.

The four above studies are examples of research that apply several proxies on their methodology.

Baker and Wurgler (2006, 2007) studied the U.S. financial market and constructed a composite sentiment index that is based in the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE turnover, the number and average first-day returns on IPOs, the equity share in new issues and the dividend premium.

Baker et al. (2012) construct investor sentiment indices for six major stock market, such as, Canada, France, Germany, Japan, the U.K. and the U.S. The authors choose to investigate investor sentiment through the study of four sentiment measures: volatility premium, the total volume of IPOs and their first-day returns and market turnover.

Corredor et al. (2013) studied the French, German, Spanish and U.K. markets using three sentiment proxies: a direct measure such as, the Consumer Confidence Index, and two indirect measures, market turnover and volatility premium.

## 2.4. Empirical findings

In this section, it is presented some of the most relevant findings about investor sentiment and its effects in the financial markets. The studies presented constitute important sources of inspiration to this dissertation, according to the methodology implemented, the sentiment proxies applied and the markets under investigation.

**Baker and Wurgler (2006)** study how investor sentiment affects the cross-section of stock returns. The authors conduct this study for the period between 1962 through 2001, by collecting firm's characteristics, on a monthly basis, and sentiment proxies, measured annually.

Firm's characteristics are divided in groups: returns, size and age, profitability, dividend policy, asset tangibility and growth opportunities and/or distress. This division are made in order to understand which stocks are more influenced by sentiment. It was formed a composite index of sentiment that is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues and the dividend premium.

The sentiment index is constructed by applying PCA, in order to capture the first principal component common among the six proxies. The relative timing of the variables is also considered,

giving the fact that some variables may take longer to reveal the same sentiment than others. In order to distinguish between a common sentiment component and a common business cycle, the raw sentiment proxies are regressed with some macroeconomic conditions (growth in industrial production index, growth in consumer durables, nondurables, and service, and a dummy variable for NBER recessions).

The main conclusion that arises from this study is that the cross-section of future stock returns is conditional on beginning-of-period proxies for sentiment. Periods of high sentiment are followed by relatively low subsequent returns for young, small, unprofitable, non-dividend-paying, high volatility, extreme growth, and distressed stocks. These types of stocks are considered to be attractive to optimistic investors and speculators and, on the contrary, unattractive to arbitrageurs. The authors also suggest that several firms' characteristics show strong conditional patterns with future stock returns, after controlling for investor sentiment.

**Baker et al. (2012)** conduct a study to explore the effect of global and local components of investor sentiment on six major stock markets: Canada, France, Germany, Japan, United Kingdom and the United States, for a period starting in 1980 and ending in 2005. The authors construct a total sentiment index for each of the countries under investigation, by applying PCA analysis in order to obtain a first principal component common among the four measures used as proxies for investor sentiment. These variables are the volatility premium, the market turnover and the volume and first-day returns on IPOs. Then, the authors formed a global sentiment index that incorporates the first principal component of the six total indices.

The authors conclude that the evidence suggests that investor sentiment affects the time series of the analysed markets returns, and also support the idea that investor sentiment influences the cross-section of international stock markets. Specially, the results predict that the future market returns of high volatility, small, distressed or growth stocks are inversely related with both, total or global, sentiments.

**Corredor et al. (2013)** analysed the investor sentiment in four important European markets: France, Germany, United Kingdom and Spain. The authors construct a sentiment index for each the above mentioned countries, using three proxies of investor sentiment, such as: volatility premium, market turnover and the consumer confidence index. The period under analysis start in 1990 and ends in 2007.

The stock characteristics considered were the book-to-market ratio, size (measured as the stock market capitalization), volatility (measured as the last twelve months' standard deviation) and the dividend per share ratio. Each of the above firm's characteristics is used to construct long-short portfolios. The impact of sentiment is then tested through regression analysis, for different time horizons (6, 12 and 24 months).

The study concludes that investor sentiment strongly affects future returns of firms that are hard to value and difficult to arbitrage, when the selected markets are analysed separately. Despite this conclusion, the results differ across the countries evaluated, making clear that the results are influenced by the choice of the measures used to construct the sentiment index.

The authors also report another important finding in this research. There is evidence that factors, such as cultural or institutional differences, have to be taken into account when studying the sentiment effects.

**Schmeling (2009)** examined if consumer confidence, used as a proxy for investor sentiment, affects expected stock returns, in 18 industrialized countries (including the French market). On average, the study concludes that sentiment is a significant predictor of expected returns. The author also shows that this effect has much more impact for short and medium term horizons (one to six months). This effect is diminished for 12 to 24 months horizons.

Despite the general conclusion that sentiment affects future stock returns, the magnitude of this effect varies across countries (in some countries, sentiment does not exhibit predictive power for future stock returns). For this reason, Schmeling (2009) explores some possible factors that strengthen the relation between sentiment and stock returns. He found that the impact of sentiment on future stock returns is higher for countries that are culturally more influenced by the actions of herd-like investment behaviour and in countries with less efficient regulatory law or less market integrity.



### 3. Data

This dissertation studies the effect of investor sentiment in the French market. The study of the French market is attractive for several reasons. First, most of the main studies in this area of behavioural finance are focused on the U.S. market. Hence, by focusing on a European country this study contributes to the current literature, allowing for a more global understanding of this topic and providing results to compare and contrast to the American context. Secondly, due to limited time and resources, by focusing on a single country a more extensive and careful study could be performed. Data availability had to be taken into consideration, thus implying the selection of a major European financial market. The French market meets such criteria and is a country that has yet to be solely analysed.

The main literature in this field only explores the effect of investor sentiment in the French market when studying this effect in a global context and incorporating other countries in the study. Bathia and Bredin (2013) examined the relationship between investor sentiment and G7 stock market returns. Baker et al. (2012) explore the effect of global and local components of investor sentiment on major markets, as Canada, France, Germany, Japan and the United Kingdom.

In this sense, this dissertation aims to overcome this gap in the literature by conducting a research specifically on the French market, considering its own idiosyncratic characteristics.

The data period under investigation begins on January 01, 1993 and ends on December 31, 2013, combining a total of 252 months. The data is treated on a monthly basis and incorporates all French stocks present in the Euronext Paris stock exchange.

#### 3.1. Sentiment Proxies

Up until now, the existing literature in the area of investor sentiment and its explanatory power of stock returns has not found any final and uncontroversial measures to capture investor sentiment. In fact, there exists a large body of proxies that seem to be adequate in explaining future stock returns. It is important to notice that the sentiment proxies' adequacy is depending on the market that is under study, i.e., different proxies may be accurate in studying markets with different characteristics (Corredor et al. 2013).

Sentiment proxies can be segmented in two different categories. There are explicit measures, resulting by directly asking investors what their expectations are about the market, as in investor surveys, and indirect measures. These measures attempt to capture the effect of investor sentiment in future stock returns by studying patterns in market variables.

This dissertation tries to analyse the effect of investor sentiment using two different indexes of investor sentiment – one direct measure and one indirect measure. Following Baker and Wurgler (2006) and Baker et al. (2012), a sentiment index is formed using indirect measures of investor sentiment. These proxies include: share turnover (TURN), number of IPOs (NIPO) and its average first-day returns (RIPO), the share of equity issues (S), dividend premium ( $P^{D-ND}$ ) and volatility premium (PVOL). As a direct measure it is considered the effect of Consumer Confidence Index for the French market.

This section presents each of the proxies used, the data necessary and the methodology followed to construct them. In the appendices section, table 1 exhibits all the variables that are necessary to collect for the construction of the sentiment proxies.

Market turnover (TURN) is the natural log of total turnover, i.e., total euro volume traded (VO) during a month over the total market capitalization (WC08001) of the previous month. The monthly market turnover (TURN) is defined as mentioned in equation (1):

$$TURN_t = \ln(\textit{turnover by volume}_t / \textit{Market Capitalization}_{t-1}) \quad (1)$$

Share turnover can simply be viewed as market liquidity. Baker and Stein (2004) point out that share turnover can be used as a proxy for investor sentiment. In a market with short-sales constraints, opening and closing a position is desirable, so sentiment-driven players are prone to trade, thus adding liquidity to the market. The authors suggest that investors tend to trade more when they are optimistic rather than when they are betting that the stock price will fall. In this sense, Scheinkman and Xiong (2003) stated that trade volume suggests differences of opinion among the market players. Share turnover and stocks returns are believed to be inversely related (Jones, 2002).

The number of IPOs (*NIPO*) over a given month and the average first-day return of these IPOs (*RIPO*) is a measure of investor's enthusiasm towards the market. Outstanding first-day returns on IPOs, or underpricing, are associated with the investor's level of optimism or pessimism. Market players are interested in timing the equity market for periods when valuations are great,

which presumably occurs in times when investor sentiment is high (Baker, et al., 2012). Baker and Wurgler (2006) propose that IPO volume is directly related with sentiment. Stigler (1964), Ritter (1991) and Loughran et al. (1994) have also debated which factors are behind the volume and the return of IPOs.

NIPO represents the number of IPOs in each month and is extracted at SDC. Equation (2) presents the computation of this proxy, following the methodology implemented by Baker and Wurgler (2006):

$$NIPO_t = \sum \text{Number of IPOs}_t \quad (2)$$

RIPO follows the methodology presented by Baker, et al. (2012), and is calculated as shown in equation (3):

$$RIPO_t = \frac{\text{First trading price}_t - \text{Offer Price}_t}{\text{Offer Price}_t} \quad (3)$$

The equity-share of new issues (S) represents the percentage of gross equity in total capitalization after the issuing, using data from SDC. Baker and Wurgler (2000) show that high values of equity share are followed by low market returns. When sentiment is high, equity is favoured despite debt, in order to reduce the cost of capital. Equation (4) presents the calculation of this proxy:

$$S_t = \frac{\text{Common Equity}_t}{\text{Total Capitalization}_t} \quad (4)$$

The dividend premium,  $P^{D-ND}$ , is calculated as presented by Baker and Wurgler (2006), using raw data from Datastream. Firms are grouped as payers firms and nonpayers firms, taking into account the dividends per share of each firm. The dividend premium is the natural log of the difference of the average market to book ratio of payers and the average market to book ratio of nonpayers. Equation (5) presents the proxy computation:

$$P^{D-ND} = \ln(\overline{MTBV}_{Nonpayer} - \overline{MTBV}_{Nonpayer}) \quad (5)$$

Baker and Wurgler (2004) defend that the dividend premium can be used as a proxy for the relative demand for dividend paying stocks and suggest that the dividend premium is inversely related with sentiment. The explanation lies with the fact that firms are more predisposed to pay

dividends when they are at a premium rather than when they are at a discount (Fama and French, 2001).

The volatility premium represents the natural log of the ratio of the value-weighted average market to book ratio of high volatility stocks to that of low stocks. To do so, it is calculated the monthly stock returns and their variance. Then, the data is divided into deciles and it is computed the average market to book ratio of the top three deciles of the variance and the bottom three deciles. Equation (6) shows the construction of this proxy:

$$PVOL_t = \ln \frac{\overline{MTBV}_{\uparrow 3deciles}}{\overline{MTBV}_{\downarrow 3deciles}} \quad (6)$$

The premise that investor sentiment affects stocks in a different way according to their characteristics justifies the adoption of this proxy. Particularly, younger, small, unprofitable, non-dividend paying, high volatility, extreme growth and distressed stocks tend to have low subsequent returns when sentiment is high (Baker and Wurgler, 2006). These types of stocks are considered the hardest to value and the most difficult to arbitrage. Therefore, it makes sense that high volatile stocks are prone to be more affected by noise traders, because they can defend extreme valuations according to their beliefs about the market. Baker et al. (2012) suggest that high volatile stocks tend to be less attractive to arbitrageurs due to the high transaction costs associated and the higher risk related with these types of stocks.

The Consumer Confidence Index (CCI), from the Directorate General for Economic and Financial Affairs (DG ECFIN), is employed in order to introduce an explicit measure of investor sentiment. For the French market, this measure is based on the answers of 3300 participants asked about their past and future financial private situation, past and future economic situation and about private consumer behaviour. For this reason, this index is considered to point out the level of consumers' enthusiasm towards the economic state, portrayed by their saving and spending actions.

The CCI has been explored by the main literature. In fact, Schemling (2009) presents a paper studying the effect of investor sentiment in future returns in 18 industrialized countries. This research reports that CCI presents a significant explanatory power of expected returns, on average across the examined countries. The author shows that in periods of high (low) sentiment, future stock returns are likely to be lower (higher) on aggregate stock market returns. This evidence is

also seen for returns of value, growth and small stocks and for different predicting periods of analysis. In 2006, Lemmon and Portniaguina conduct an important study on this field, using consumer confidence as a degree of investor optimism. The authors conclude that consumer confidence, used to capture the effect of investor sentiment, can in fact predict the returns of small stocks and stocks with low institutional ownership, during the last 25 years. This research makes a link between their results and those obtained using noise-trader sentiment models.

### **3.2. Firm-level Data**

To study how investor sentiment affects stock returns in the cross-section, a number of specific stock characteristics has to be gathered so as to assess the impact of investor sentiment on them.

The firm-level data is collected from Datastream. The sample includes all common stocks of companies listed on the Euronext Paris (dead or alive). To collect the data several filters are applied: category (Equities), exchange (Euronext.liffe Paris), market (France) and type (Equity). This search yielded a total of 2139 firms. However, it is necessary to remove from the sample all companies that are included in the database after 2013 (end of period under analysis) and those that do not present sufficient available data to calculate the variables necessary to construct the portfolios. Thus, this research examines a final set of 2013 companies.

Following Baker and Wurgler (2006) and Baker et al. (2012), the data is selected to study a specific group of firm-level characteristics, namely: size, profitability, dividend policy, asset tangibility and growth opportunities and/or distress.

In the appendices section, Table 2 presents all variables that are collected in order to construct the firm-level characteristics portfolios and to compute the stock market returns. For each variable, it is presented the source and the code in the database. The data is collected on the first day of each month and is computed on a monthly basis. Table 3 displays the summary statistics (mean, standard deviation, minimum and maximum) obtained for the stock market returns and for each portfolio. Table 3 also presents the means obtained for the stock market returns and for each portfolio for two periods: from 01 January, 1993 through 31 December, 2003 and from 01 January, 2004 through 31 December, 2013.

To calculate the stock market returns it is obtained the Total Return Index (RI) from Datastream (RI already incorporates dividends in its calculation). Despite not being a salient characteristic, Momentum is calculated and presented as a control variable of known mispricing patterns. Momentum (MOM) is defined as the accumulation of 11 monthly returns from 12 to 2 months prior to the given month

The Size portfolio represents the firm's size. Size is measured by the market equity (WC08001) from Datastream. Datastream calculates market equity as the stock's price multiplied by common shares outstanding.

The Total Risk portfolio embodies the risk (systematic or non-systematic) that each firm is subjected to. Total risk is calculated as the standard deviation of monthly returns for 12 months, from January to December each year.

The Profitability portfolio is incorporated to study the impact of investor sentiment in profitable firms and in unprofitable ones. This is reflected using the return on equity ratio ( $E+/BE$ ), which is positive for profitable firms and zero for unprofitable ones. Earnings (E) is calculated as net income before extraordinary items/preferred dividends (WC01551) plus deferred income taxes and investment tax credit on income statements (WC04101), and minus preferred dividend requirements (WC01701). Book equity (BE) is measured as the sum of total shareholders' equity (WC0395) and deferred taxes on balance sheets (WC03263). It is also included a profitability dummy variable ( $E>0$ ), which takes the value of 1 for profitable firms and 0 for unprofitable firms.

The dividend policy portfolio is constructed to distinguish the impact of investor sentiment on dividend-paying firms and on non-dividend-paying firms. To study this impact, it is calculated the dividends to equity ratio ( $D/BE$ ). Dividends (D) are measured as dividends per share (DPS) times the number of shares outstanding (WC05301). Equity is represented by book equity (calculated as mentioned above). In this analysis, it is also included a dividend payer dummy ( $D>0$ ), which is set as 1 for dividend paying firms and 0 for firms that do not pay dividends.

Asset tangibility is a proxy for valuation difficulties (Baker and Wurgler, 2006). Firms that are constituted mainly of intangible assets are considered the ones harder to evaluate, making them more sensitive to investors' concerns about their value (Baker et al., 2012). Firms with more

tangible assets are considered easier to assess their true value. Thus, these firms' value is not dependent on each investor sentiment considerations.

To study the impact of investor sentiment in firms with less tangible assets in opposition to firms with high values of tangible assets it is constructed two portfolios. The PPE/A portfolio, which is based on the ratio of property, plant and equipment (WC02301) over assets (WC02999) and the RD/A portfolio, which is based on the ratio of research and development (WC01201) over assets. A high PPE/A ratio means that a firm is constituted predominantly of tangible assets. On the other hand, a high RD/A ratio means that a firm is constituted mainly of intangible assets.

Following Baker and Wurgler (2006), the impact of investor sentiment on firms with growth opportunities and in distress is studied through the joint analysis of two portfolios: the book to market ratio portfolio (BE/ME) and the external finance ratio portfolio (EF/A). The elements of the book to market ratio are calculated as stated earlier. External finance, represents external financing (WC04500) over total assets. Growth opportunities and distress portfolios are analysed together due to their particular interactions. In fact, low values of book to market ratio may be a signal of growth opportunities and high values may indicate distress. The book to market ratio is also related to a firms' valuation that may vary depending on any source of mispricing or rational expected returns. Likewise, external finance may suggest distress (when EF/A takes low values) or may reflect growth opportunities (when EF/A takes high values). External finance also suggests generic misevaluations because market timing promotes high values of external finance.

**Table 3.**

**Summary Statistics of stock market returns and firm-level characteristics portfolios, 1993-2013**

The table presents the summary statistics (mean, standard deviation, minimum and maximum) for stock market returns and for each firm-level characteristics portfolios constructed. The data is computed on a monthly basis. Stock market returns are computed as monthly changes in the Total Return Index (RI) from Datastream. Momentum (MOM) is defined as the cumulative return for the 11-month period between 12 and 2 months prior to  $t$ . The Size portfolio represents the firm's size. Size is measured by the market equity (ME) from Datastream. The Total Risk portfolio embodies the total risk that each firm is subject. Total risk ( $\sigma$ ) is calculated as the standard deviation of monthly returns for 12 months, from January to December each year. The Profitability portfolio is constructed through the return on equity ratio ( $E+/BE$ ) for firms with positive earnings. Earnings ( $E$ ) is calculated as net income before extraordinary items/preferred dividends (WC01551) plus deferred income taxes and investment tax credit on income statements (WC04101), and minus preferred dividend requirements (WC01701). Book equity (BE) is measured as the sum of total shareholders' equity (WC0395) and deferred taxes on balance sheets (WC03263). A profitability dummy is introduced and is equal to 1 for firms with positive earnings and equals 0 for unprofitable firms. The dividend policy portfolio is constructed through the dividends to equity ratio ( $D/BE$ ). It is incorporated a dividend payer dummy ( $E>0$ ). Dividends ( $D$ ) are measured as dividends per share (DPS) times the number of shares outstanding (WC05301). Equity is represented by book equity. The dividend payer dummy is set 1 to dividend-paying firms and 0 to firms that do not pay dividends. Asset tangibility is measured by the PPE/A ratio portfolio and by the RD/A ratio portfolio. Plant, property and equipment (WC02301) and research and development (WC01201) are scaled by assets (WC02999). The growth opportunities and/or distressed are measured by the BE/ME ratio portfolio and by the EF/A ratio portfolio. The book-to-market ratio (BE/ME) is obtained as the book equity over market equity for the 12 months prior to  $t$ . External finance (EF) represents external financing (WC04500) over total assets.



Variable	Full Sample				Subsample Means		
	Obs.	Mean	Std. Dev.	Min.	Max	1993-2003	2004-2013
<b>Returns</b>							
$R_t(\%)$	296,786	1.16	28.41	-99.92	8,433.33	1.43	0.92
$MOM_{t-1}(\%)$	275,944	12.02	96.44	-301.59	8,412.50	13.46	11.18
<b>Size portfolio</b>							
$ME_{t-1}(\text{€M})$	203,438	2,00	8.24	0.00	148.47	1.67	2.32
<b>Total risk portfolio</b>							
$\sigma_{t-1}(\%)$	507,264	23.15	14.69	11.10	78.98	23.73	22.51
<b>Profitability portfolio</b>							
$E + /BE_{t-1}(\%)$	45,258	0.16	1.23	0.00	75.04	0.13	0.17
$E > 0_{t-1}$	507,276	0.10	0.31	0.00	1.00	0.07	0.14
<b>Dividend policy portfolio</b>							
$D/BE_{t-1}(\%)$	119,967	0.36	0.16	0.00	19.28	0.04	0.04
$D > 0_{t-1}$	307,266	0.51	0.50	0.00	1.00	0.61	0.44
<b>Asset tangibility portfolios</b>							
$PPE/A_{t-1}(\%)$	172,142	45.70	42.60	0.00	785.12	50.45	41.85
$RD/A_{t-1}(\%)$	44,915	6.27	11.82	0.00	174.73	5.18	6.91
<b>Growth opportunities and/or distress portfolios</b>							
$BE/ME_{t-1}$	139,376	1.05	10.05	0.00	913.47	0.88	1.17
$EF/A_{t-1}(\%)$	218,288	5.82	430.51	-42,581.02	31,616.67	7.47	3.97

### 3.3. Macroeconomic variables

Chen et al. (1986) conduct a study to investigate if macroeconomic variables are priced in the stock market. They conclude that stock returns are in fact exposed to systematic economic news and that these variables are priced in the stock market.

In order to control the effect of macroeconomic conditions on stock returns, six macroeconomic variables are collected. The Industrial Production Index (IPI) measures the monthly variation of quantities produced by the French industry. The Consumer Price Index (CPI) measures the experienced cost of living in the French market. The Gross Domestic Production (GDP) represents the health of the French economy. The inflation rate (INFR) in the French market stands for the rising or falling of the goods and services' monthly prices, and consequently represents the purchasing power. The policy interest rate (INTR) reflects the foundations of the French monetary policy. The employment growth (EG) reflects the monthly variation in employment in France.

The macroeconomic variables are used to construct the orthogonalized Investor Sentiment Index (ISI<sup>⊥</sup>) and are employed in the regression analysis, which are conducted for the Consumer Confidence Index (CCI), in the aggregated stock market.

In the appendices section, table 4 presents the source and the code in the database for each macroeconomic variable. The data is obtained for the first day of each month on a monthly basis for the period of the examination of this dissertation (from 01 January, 1993 through 31 December, 2013)

## 4. Methodology

The methodology applied in this dissertation follows mainly the work presented by Baker and Wurgler (2006) and Baker et al. (2012). However, this research introduces some differences comparatively to the works mentioned. In fact, this dissertation measures sentiment through two sentiment indexes, which are constructed based on distinct sources of information. The investor sentiment index is based on market data and the Consumer Confidence Index is a survey that directly asks investors their expectations about the stock market. The inclusion of these two sentiment measures is made in order to investigate potential differences in the impact of sentiment in the aggregated stock market returns and in the cross-section of stock returns, when sentiment is measured by an indirect measure and when sentiment is captured by a direct measure.

### 4.1. Construction of the sentiment indexes

The methodology applied in this dissertation begins with the construction of two sentiment indexes: the Investor Sentiment Index (ISI) and the Consumer Confidence Index (CCI).

CCI involves the standardization of the raw data, as applied by Schemling (2009). The standardization guarantees that the CCI coefficient has a zero mean and a standard deviation of 1. This step aims to increase the similarity of the procedures used in the construction of both indexes.

Following the methodology applied by Baker and Wurgler (2006), the ISI is constructed using a Principal Component Analysis (PCA). The six proxies used as sentiment measures (market turnover, number and average first-day returns on IPOs, the share of equity issues, dividend premium and volatility premium) contain a sentiment component, as well as its own idiosyncratic components, non-sentiment related. The PCA allows isolating the proxies' data, thus creating an index that represents the common sentiment component among the six proxies.

Baker and Wurgler (2006) suggest that some variables take longer to reveal a shift in sentiment than others. More specifically, the authors find that proxies that reflect firm supply decisions ( $TURN$ ,  $RIPO$  and  $P^{D-ND}$ ) are prone to lag behind proxies that represent direct choices by investors ( $S$  and  $NIPO$ ).

To capture the common component in the six proxies and to incorporate the relative timing of each variable, a preliminary index with 12 loadings (the six proxies and their lags) is first constructed. This involves calculating for each proxy, its one-month lagged variable, and applying PCA to create a first-stage index that estimates the principal component of the six raw proxies and their one-month lags.

Then, the correlation between the current and lagged proxies with the first-stage index are calculated and the most correlated variable within each proxy is selected and used to construct the final investor sentiment index (ISI). The PCA is repeated to obtain the first principal component of the 6 selected proxies – rescaling the coefficients so that the index has unit variance.

As for the PCA approach, because it can fail to separate a common sentiment component from a common business cycle component, it is important to ensure that this business cycle component is removed. Therefore, another investor sentiment index (ISI<sup>⊥</sup>) is constructed using orthogonalized proxies for some macroeconomic conditions, to reduce the possibility that these variables are associated with systematic risk. For that reason, the raw variables used as proxies for investor sentiment are regressed with the industrial production index (IPI), inflation rate (INFR), consumer price index (CPI), policy interest rate (INTR), employment growth (EG) and the gross domestic product (GDP). The residuals obtained are cleaner proxies for investor sentiment. The investor sentiment index (ISI<sup>⊥</sup>) of the orthogonalized proxies is constructed following the same procedure as explained before.

## **4.2. The impact of sentiment in future aggregated market returns**

One of the goals of this dissertation is to analyse the impact of sentiment, measured by ISI<sup>⊥</sup> and CCI, in future aggregated market returns. Before the analysis of the predictive power of sentiment in future aggregated market returns, it is important to investigate some aspects that can interfere with the results and lead to misinterpretations.

### *4.2.1. Normality, autocorrelation and heteroscedasticity of returns*

To test the normality of the market returns' distribution, it is performed the *Shapiro-Wilk* normality test (Shapiro and Wilk, 1972). To deal with heteroscedasticity in the residuals series, it is conducted the *Breusch-Pagan and Cook-Weisberg* test for heteroscedasticity (Breusch and

Pagan 1979; Cook & Weisberg 1983). The autocorrelation of the residuals series is tested using the *Breusch-Godfrey* test for serial correlation.

In the presence of heteroscedasticity and autocorrelation, the Newey-West standard errors (Newey and West, 1987) are performed. This method is an extension of the *Huber/White* correction (Huber, 1967; White, 1980), and produces consistent estimates when there is evidence of autocorrelation, additionally to heteroscedasticity.

#### 4.2.2. Regression analysis to test the predictive power of sentiment in the aggregate stock market

The predictive power of the sentiment measures in the stock returns of the aggregate market is tested in four distinct time horizons: 1, 6, 12 and 24 months.

The predictive power of  $ISI^\perp$  is tested using the following model:

$$R_{Xit} = c + dISI^\perp_{t-k} + u_{it}. \quad (7)$$

In equation (7),  $R_{Xit}$  represents the monthly return at time t,  $ISI^\perp_{t-k}$  stands for the  $ISI^\perp$  value at t-k (K expresses the time horizon under test – 1, 6, 12 or 24 months) and  $u_{it}$  expresses the regression's error. The regression is constructed with the Newey-West standard errors, in order to correct for the presence of autocorrelation and heteroscedasticity. In this model it is not included, as explanatory variables, the macroeconomic variables considered in this study, because  $ISI^\perp$  already incorporates the effect of these variables in its construction.

The predictive power of CCI is tested using the following model:

$$R_{Xit} = c + d_1CCI_{t-k} + d_2CPI_{t-k} + d_3CPI_{t-k} + d_4GDP_{t-k} + d_5INFR_{t-k} + d_6INTR_{t-k} + d_7EG_{t-k} + u_{it}. \quad (8)$$

In equation (8),  $R_{Xit}$  corresponds to the monthly return at time t,  $CCI_{t-k}$  represents the CCI value at t-k (k expresses the time horizon under test – 1, 6, 12 or 24 months). In this model it is incorporated the effect of some macroeconomic conditions (see the section Macroeconomic variables, in chapter Data).  $CPI_{t-k}$ ,  $GDP_{t-k}$ ,  $GDP_{t-k}$ ,  $INFR_{t-k}$ ,  $INTR_{t-k}$ ,  $EG_{t-k}$  stand, respectively, for the effect of the industrial production index, the consumer price index, the gross domestic production, the interest rate, the inflation rate, and the employment growth at t-k.  $u_{it}$

represents the regression's error. This model is also constructed with the Newey-West standard errors to correct for the presence of autocorrelation and heteroscedasticity.

### 4.3. The impact of sentiment in the cross section of stock returns

The second goal of this dissertation is to study how investor sentiment affects stock returns in the cross-section. To test the impact of sentiment in a number of specific stock characteristics, it is conducted three tests: sorts analysis, predictive regressions for Long-Short portfolios analysis and systematic risk analysis. The impact of investor sentiment in the cross-section of stock returns follows Baker and Wurgler (2006) and Baker et al. (2012).

#### 4.3.1. Sorts

The sorts' analysis studies the impact of a number of firm characteristics, subordinated to the level of the previous year sentiment, on the stocks returns.

The methodology followed in the sorts analysis starts with the segmentation of the firms in the sample into deciles. This segmentation is done according to the decile rank that a characteristic takes at the beginning of each month and then according to the level (positive or negative) of sentiment (defined by ISI<sup>+</sup> and CCI) at the end of the previous year.

To look for patterns, in each bin, the difference between the stock return in a period of positive sentiment and in a period of negative sentiment is calculated. Decile 10 stands for the highest values obtained in each category, whereas decile 1 represents the lowest ones.

The firm characteristics under study fall into six categories: **size**, measured by market equity; **total risk**, computed as the standard deviation of monthly returns for 12 months; **dividend policy**, through the dividends-to-equity ratio; **profitability**, according to the return on equity; **asset tangibility**, through property, plant and equipment over assets and research and development over assets; and **growth opportunities and/or distress**, measured by the book-to-market ratio and the external finance over assets. These characteristics are more associated with stocks that are difficult to value and arbitrage, thus justifying their inclusion in this study as well as in Baker and Wurgler (2006) and Baker et al. (2012).

### 4.3.2. Predictive Regressions for Long-Short Portfolios

Additionally to the sorts analysis, the impact of investor sentiment in the cross-section of stock returns is analysed through the performance of predictive regressions on equally-weighted portfolios - Baker and Wurgler (2006) suggest that large firms are less affected by sentiment, and hence value weighting tend to obscure the relevant patterns. These portfolios are long on stocks with high characteristic values and short on stocks with low values. The characteristics under study correspond to those analysed previously in the sorts analysis (size, total risk, dividend policy, profitability, asset tangibility, growth opportunities and/or distress). The predictive power of sentiment, measured by  $ISI^\perp$  and  $CCI$ , is studied in four distinct time horizons: 1, 6, 12 or 24 months. The motivation to conduct these regressions is based on the fact that it allows to infer which characteristics have conditional effects and distinguish them from unconditional effects.

Following Baker and Wurgler (2006), for each category (with the exception for the profitability and dividend policy variables), it is calculated the difference between the monthly returns of the top three deciles and the bottom three deciles.

To avoid that a simple “High – Low” analysis can omit some important cross-sectional patterns, the growth and/or distress variables are also divided into portfolios that are based on the medium deciles. Medium corresponds to the four middle deciles.

To study the profitability characteristic, it is calculated the difference between the average monthly returns of profitable firms and unprofitable ones. Similarly, for the dividend policy characteristic, it is calculated the difference between the average monthly returns of dividend-paying firms and non-dividend-paying ones.

To test the predictive power of sentiment in long-short portfolios, it is implemented the following models (for  $ISI^\perp$  and  $CCI$ , respectively):

$$R_{Xit=High,t} - R_{Xit=Low,t} = c + dISI^\perp_{t-k} + u_{it} \quad (9)$$

$$R_{Xit=High,t} - R_{Xit=Low,t} = c + dCCI_{t-k} + u_{it} \quad (10)$$

$R_{Xit=High,t}$  corresponds to the average monthly returns on the top three deciles firms and  $R_{Xit=Low,t}$  stands for the average monthly returns on the three bottom deciles. Therefore, the

dependent variable,  $R_{Xit=High,t} - R_{Xit=Low,t}$ , corresponds to the average monthly return on a long-short portfolio, which is long on stocks on the top three deciles and short on stocks on the bottom three deciles.

As mentioned above, the variables concerning with growth opportunities and/or distress also capture the differences between the top three deciles and the middle four deciles and the differences between the bottom three deciles and the middle four deciles. So, additionally to the models presented above, it is implemented the following regressions (for  $ISI^L$  and  $CCI$ , respectively):

$$R_{Xit=High,t} - R_{Xit=Medium,t} = c + dISI^L_{t-k} + u_{it} \quad (11)$$

$$R_{Xit=Medium,t} - R_{Xit=Low,t} = c + dISI^L_{t-k} + u_{it} \quad (12)$$

$$R_{Xit=High,t} - R_{Xit=Medium,t} = c + dCCI_{t-k} + u_{it} \quad (13)$$

$$R_{Xit=Medium,t} - R_{Xit=Low,t} = c + dCCI_{t-k} + u_{it} \quad (14)$$

In the models (11), (12), (13) and (14),  $R_{Xit=High,t}$  corresponds to the average monthly returns on the top three deciles firms,  $R_{Xit=Low,t}$  stands for the average monthly returns on the bottom three deciles firms and  $R_{Xit=Medium,t}$  represents the average monthly returns of the four middle deciles. The dependent variables,  $R_{Xit=High,t} - R_{Xit=Medium,t}$  corresponds to the average monthly return on a long-short portfolio, which is long on stocks on the top three deciles and short on stocks of the middle four deciles. Similar,  $R_{Xit=Medium,t} - R_{Xit=Low,t}$  corresponds to the average monthly return on a long-short portfolio, which is long on stocks on the middle four deciles and short on stocks on the bottom three deciles.

For the profitability variable, the predictive regression for long-short portfolios is conducted as follows:

$$R_{Xit>0,t} - R_{Xit\leq 0,t} = c + dISI_{t-k} + u_{it} \quad (15)$$

$$R_{Xit>0,t} - R_{Xit\leq 0,t} = c + dCCI_{t-k} + u_{it} \quad (16)$$



In the models (15) and (16),  $R_{Xit>0,t}$  corresponds to the monthly returns of profitable firms, whereas  $R_{Xit\leq 0,t}$  corresponds to the monthly returns of unprofitable firms. The dependent variable,  $R_{Xit>0,t} - R_{Xit\leq 0,t}$ , corresponds to the average monthly return on a long-short portfolio, which is long on profitable firms and short on unprofitable ones.

For the dividend policy variable, the predictive regression for long-short portfolios is conducted as follows:

$$R_{Xit>0,t} - R_{Xit=0,t} = c + dISI_{t-k} + u_{it} \quad (17)$$

$$R_{Xit>0,t} - R_{Xit=0,t} = c + dCCI_{t-k} + u_{it} \quad (18)$$

In the models (17) and (18),  $R_{Xit>0,t}$  stands for the average monthly returns of dividend-paying firms, whereas  $R_{Xit=0,t}$  stands for the average monthly returns of non-dividend-paying firms. The dependent variable,  $R_{Xit>0,t} - R_{Xit=0,t}$ , stands for the average monthly return on a long-short portfolio, which is long on dividend-paying firms and short on non-dividend paying firms.

Following Baker and Wurgler (2006), it is conducted a multivariate regression, in order to distinguish predictability patterns from well-known comovement. In order to do so, it is introduced the Fama and French factors to the previous equations. As an example, equation (9) after the introduction on the Fama and French factors generates a regression of the type:

$$R_{Xit=High,t} - R_{Xit=Low,t} = c + dISI_{t-k} + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + u_{it} \quad (19)$$

RMRF corresponds to the excess difference return between the value-weighted market and the risk-free rate (Fama and French, 1993). This variable is introduced to control for the correlation of the returns in each portfolio constructed by individual stocks and the returns of a portfolio for the market as a whole. The SMB variable represents the difference between the returns of small and big ME portfolios. In order to isolate the existing difference between high and low BE/ME portfolios, it is introduced the HML variable. The variable UMD stands for the difference on returns of high-momentum stocks and low-momentum stocks. Momentum is defined as the accumulation of 11 monthly returns from 12 to 2 months prior to the given month. The Fama and French factors are extracted from the Professor Kenneth French's website, on a monthly basis.

### 4.3.3. Systematic Risk

Baker and Wurgler (2006) suggest that the conditional characteristics effects should not be a compensation for systematic risk. Their results demonstrate that the predictions of the orthogonalized sentiment proxy match the predictions about the cross-sectional stock returns, i.e., the level of sentiment at a giving period explain the future stock return, according to the type of stock that is under analysis. They also evidence that the anecdotal accounts of bubbles and crashes are associated with the sentiment patterns displayed.

Theoretically, the classical finance theory suggests that older, profitable, less volatile, dividend-paying firms should earn superior returns than younger, unprofitable, more volatile, non-paying firms. Baker and Wurgler (2006) suggest that the value of a firm with a long earning history, tangible assets, and stable dividend is less subjective and, therefore, its stock is more likely to be less affected by fluctuations in the propensity to speculate, i.e., more likely to be less affected by investor sentiment. Therefore, younger, unprofitable, more volatile and non-paying firms are considered riskier stocks.

Behavioural finance theory goes against the classical finance theory. In fact, many studies of the impact of investor sentiment in future stock returns conclude that stocks that are harder to arbitrage and more difficult to value tend to earn subsequently higher returns than more stable firms, when sentiment is low. The results obtained in this dissertation, in the sorts analysis and in the predictive regression for Long-Short analysis, also support the idea that small, more volatile, unprofitable, non-dividend, less tangible, growth and distressed stocks tend to be more affected by sentiment. The results also point out that these type of stocks tend to earn subsequent higher returns after a period of low sentiment. The study of the systematic risk is introduced in order to explain this effect in a more rigorous manner.

Systematic risk can be explained in two ways. The first explanation suggests that the systematic risks (beta loadings) of stocks with certain characteristics fluctuate with the sentiment proxies used as sentiment measures (despite the attempt to isolate them from macroeconomic conditions). Specifically, it is predicted returns on the characteristics portfolios for four distinct time horizons (1, 6, 12 and 24 months):

$$R_{Xit=High,t} - R_{Xit=Low,t} = c + dSENTIMENT_{t-k} + \beta(e + fSENTIMENT_{t-k})RMRF_t + u_{it}. \quad (20)$$

In equation (20), *SENTIMENT* presents the impact of the ISI<sup>L</sup> or CCI lagged k periods (1, 6, 12 or 24 months). RMRF stands for the market risk premium. The long-short portfolios are formed based on 8 firm characteristics (X): firm size (ME), total risk ( $\sigma$ ), profitability (E), dividend policy (D), asset tangibility (PPE/A and RD/A) and growth opportunities and/or distress (BE/ME and EF/A). The dependent variable represents the difference between the average monthly returns on the top three deciles and the bottom three deciles in each category. For the profitability and dividend policy characteristics, the dependent variable is the difference between the average monthly returns of profitable and unprofitable firms and dividend-paying and non-paying firms, respectively. For the growth opportunities and distress variables, it is conducted two more regressions, having as the dependent variable the difference between average monthly return on the top three deciles and the middle four deciles and the difference between average monthly return on the middle four deciles and the bottom three deciles.

A second explanation maintains stocks' betas fixed and allows the risk premium to vary with sentiment. This suggests that high and low beta stocks fluctuate in proportion with differences in returns.

## 5. Empirical Results

The following sections present the results obtained and their interpretation and discussion, following the structure presented in Methodology. First, it is described the results obtained from the construction of the two sentiment indexes (ISI $\perp$  and CCI). In order to meet the two main goals of this dissertation, it is presented the results concerning the impact of investor sentiment on the aggregated stock market returns and the predictive power of sentiment in the cross-section of stock returns.

### 5.1 Sentiment measures – ISI $\perp$ and CCI

#### 5.1.1. Construction of ISI $\perp$ and CCI

ISI is constructed considering the first common component of the six raw proxies and their respective timing and results in the following index:

$$ISI_t = 0.1006 * TURN_{t-1} - 0.0439 * S_t + 0.0398 * RIPO_{t-1} - -0.0254 * NIPO_t + 0.7025 * P_{t-1}^{D-ND} + 0.7016 * PVOL_{t-1} \quad (21)$$

The first principal component explains 31.3% of the sample variance, meaning that more than 1/3 of the variance is captured by the first common component among the six proxies. The first principal component in the work of Baker and Wurgler (2006) explained 49% of the sample variance. This result suggests that the index has a significant explanatory power of the sample variance.

The sentiment index reveals distinctive properties. All variables enter the index with their respective timing, like proposed in Baker and Wurgler (2006), meaning that price and investor behaviour precede firm supply variables. However, when looking at the sign of the variables, the results in this study differ from those obtained in Baker and Wurgler (2006) and Baker et al. (2012). In fact, the variables S, NIPO and  $P^{D-ND}$  of this index enter with the opposite signal of those exposed in the works mentioned earlier.

After controlling for some macroeconomic variables, it is obtained an orthogonalized sentiment index (ISI $\perp$ ), expressed by the following equation:

$$\begin{aligned}
ISI_t^\perp = & 0.1007 * TURN_{t-1}^\perp - 0.0443 * S_t^\perp + 0.0398 * RIPO_{t-1}^\perp - 0.0258 * \\
& NIPO_t^\perp + 0.7025 * P_{t-1}^{D-ND^\perp} + 0.7016 * PVOL_{t-1}^\perp
\end{aligned}
\tag{22}$$

Here, the first principal component explains 31.3% of the sample variance, identical to the raw index. Baker and Wurgler (2006) present an orthogonalized index that explains 53% of the sample variance in the U.S. market. Baker et al. (2012) show an orthogonalized index for the French market that explains 40% of the sample variance. The results obtained in this dissertation suggest a significant explanatory power of the sample variance by the first principal component common among the six proxies for investor sentiment, mainly when compared to the results obtained in Baker et al. (2012) for the same market.

Table 5 exhibits the summary statistics (mean, standard deviation, minimum and maximum) obtained for the raw proxies and the orthogonalized proxies and presents the correlations within each of the sentiment components and within ISI and ISI<sup>⊥</sup>. In the appendices section, figure 1 plots the raw and orthogonalized proxies used to construct ISI and ISI<sup>⊥</sup>.

**Table 5.**  
**Investor Sentiment Data, 1993-2013**

Mean, standard deviations and correlations for investor sentiment proxies. The first panel presents raw sentiment proxies. Market turnover (TURN) is the natural log of total turnover, i.e., total euro volume traded (VO) during a month over the total market capitalization (WC08001) of the previous month. The equity-share of new issues (S) represents the percentage of gross equity in total capitalization after the issuing. NIPO represents the number of IPOs in each month. RIPO is the average first-day return on IPOs and is calculated as the difference between the first trading price and the offer price divided by the offer price. The dividend premium ( $P^{D-ND}$ ) is the natural log of the difference of the average market to book ratio of payers and the average market to book ratio of nonpayers. The volatility premium (PVOL) represents the natural log of the ratio of the value-weighted average market to book ratio of high volatility stocks to that of low stocks. In Panel B, the six raw proxies are regressed on some macroeconomic conditions: industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), employment growth (GS) and policy interest rate (INTR). The orthogonalized proxies labelled with a “ $\perp$ ”, are the residuals from these regressions.  $ISI^{\perp}$  is the first principal component of the six orthogonalized proxies.

	Correlations with Sentiment						Correlations with Sentiment Components					
	Mean	SD	Min	Max	ISI	$ISI^{\perp}$	TURN	S	RIPO	NIPO	$P^{D-ND}$	PVOL
<b><math>TURN_{t-1}</math></b>	-7.58	2.49	-20.09	6.41	0.14	0.14	1.00					
<b><math>S_t</math></b>	0.71	0.25	0.07	1	-0.03	-0.03	0.05	1.00				
<b><math>RIPO_{t-1}</math></b>	0.15	0.57	-0.32	7.22	0.03	0.03	0.16	0.07	1.00			
<b><math>NIPO_t</math></b>	1.45	1.55	0	8	-0.01	-0.01	0.05	0.30	-0.12	1.00		
<b><math>P_{t-1}^{D-ND}</math></b>	-2.19	2.72	-9.10	0.90	0.99	0.99	0.03	-0.06	0.05	0.02	1.00	
<b><math>PVOL_{t-1}</math></b>	-0.24	0.53	-1.74	0.02	0.90	0.90	0.03	-0.05	0.04	0.01	0.10	1.00
<b>Panel B: Controlling for Macroeconomic Conditions</b>												
<b><math>TURN_{t-1}^+</math></b>	0.00	2.50	-12.50	13.99	0.14	0.14	1.00					
<b><math>S_t^+</math></b>	0.00	0.25	-0.64	0.30	-0.03	0.03	0.05	1.00				
<b><math>RIPO_{t-1}^+</math></b>	0.00	0.57	-0.47	7.08	0.03	0.03	0.16	0.07	1.00			
<b><math>NIPO_t^+</math></b>	0.00	1.55	-1.50	6.55	-0.01	-0.01	0.05	0.30	-0.12	1.00		
<b><math>P_{t-1}^{D-ND\perp}</math></b>	0.00	2.72	-7.00	3.16	0.99	0.99	0.03	-0.06	0.05	0.01	1.00	
<b><math>PVOL_{t-1}^+</math></b>	0.00	0.53	-1.51	0.30	0.90	0.90	0.02	-0.05	0.04	0.001	0.08	1.00

### 5.1.2. $ISI^{\perp}$ and CCI - Comparison

After the construction of  $ISI^{\perp}$  and the standardization of CCI, it is important to look at each sentiment measure's characteristics. Table 6 presents the summary statistics (mean, standard deviation, minimum and maximum) for each of the two sentiment measures and the correlation between these two sentiment indexes.

**Table 6.**  
**Summary statistics and correlations of the sentiment measures ( $ISI^{\perp}$  and CCI)**

Mean, standard deviation (SD), minimum (Min) and Maximum (Max) and the correlations between the sentiment measures.  $ISI^{\perp}$  is composed by six orthogonalized indirect sentiment proxies: share turnover (TURN), number and average first-day returns (NIPO and RIPO), share of equity issues (S), dividend premium ( $P^D - ND$ ) and volatility premium (PVOL). The orthogonalization is conducted through the regression of six macroeconomic variables with each raw sentiment proxy: industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), policy interest rate (INTR) and employment growth (GS). CCI is the standardized consumer confidence index published by DG ECFIN. All variables are computed on a monthly basis.

	Mean	SD	Min	Max	Correlation	
					ISI	CCI
ISI	-0.0092	1	-2.3058	1.1148	1.00	
CCI	-1.35e-07	1	-2.1540	2.4072	-0.0205	1.00

Due to the standardization of the Consumer Confidence Index (CCI) and the rescaling of the coefficients of the orthogonalized Investor Sentiment Index ( $ISI^{\perp}$ ) the mean of both sentiment indexes is very close to 0 and the standard deviation is 1. Looking at table 6, the correlation between the two sentiment indexes is -0.0205. This suggests that the two indexes are weakly correlated and that the two sentiment measures move in opposite directions. Therefore, the correlation value indicates that  $ISI^{\perp}$  and CCI are two very distinct measures and that they capture different impacts of sentiment on the stock market.

Lemmon and Portniaguina (2006) and Qiu and Welch (2004) provide evidence of a low correlation between direct and indirect measures of sentiment in the U.S. stock market. However, Brown and Cliff (2004) suggest that many commonly cited indirect measures of sentiment are related to direct measures (surveys) of investor sentiment.

The relationship between  $ISI^\perp$  and CCI is demonstrated by figure 2, which plots the evolution of both sentiment measures through the data period under analysis (between January 01, 1993 and December 31, 2013).

**Figure 2.**

**Sentiment indexes evolution through January 01, 1993 and December 31, 2013**

Sentiment indexes evolution through January 01, 1993 and December 31, 2013 in the French market.  $ISI^\perp$  represents the principal common component of six underlying proxies of sentiment: share turnover (TURN), number of IPOs (NIPO), average first-day returns (RIPO), share of equity issues (S), dividend premium ( $P^{D-ND}$ ) and volatility premium (PVOL). The orthogonalization is conducted through the incorporation of six macroeconomic variables with each raw sentiment proxies: industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), policy interest rate (INTR) and employment growth (GS). CCI is the standardized consumer confidence index published by DG ECFIN. All variables are computed on a monthly basis.

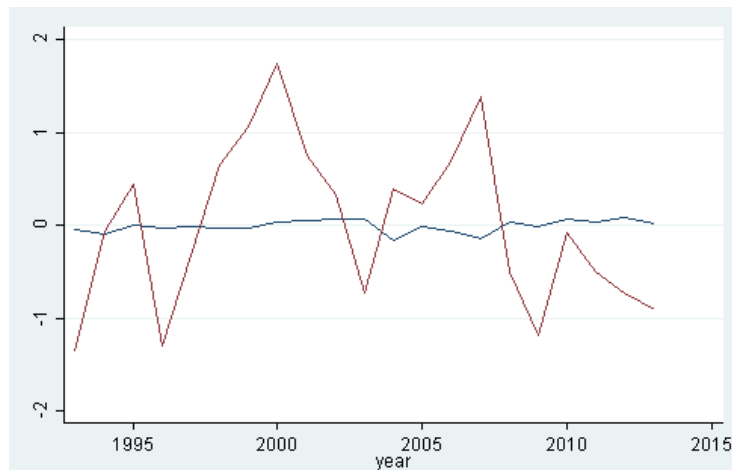


Figure 2 also evidences the difference between the two sentiment measures.  $ISI^\perp$  is a much more stable index. The evolution of CCI seems to be much closer to the economic environment and the financial market trends experienced in the French market. For example, the abrupt fall of CCI in 2009 may be associated with a decrease of the consumers' confidence due to the U.S. financial crisis. Since 2011 the CCI is falling, thus reflecting the European debt crisis.

The most important conclusion that arises from the comparison of the two sentiment indexes is the capacity of CCI (in opposition to the incapacity of the  $ISI^\perp$ ) to capture the French financial market trends. This suggests that CCI is more appropriate than  $ISI^\perp$  to reflect the impact of sentiment in the aggregated stock market.



## 5.2. The impact of sentiment in future market returns

### *5.2.1. Analyses to normality, autocorrelation and heteroscedasticity of returns*

The Shapiro-Wilk normality test (Shapiro and Wilk, 1972) indicates that the market return series do not follow a normal distribution. The Breush-Pagan and Cook-Weisberg test for heteroscedasticity on the residuals series (Breush and Pagan, 1979; Cook and Weisberg, 1983), suggest the presence of heteroscedasticity. The residuals series also indicate the presence of autocorrelation, tested by the Breush-Godfrey test.

To deal with heteroscedasticity and autocorrelation it is implemented the Newey-West standard errors (Newey and West, 1987) in the regressions conducted for the aggregated stock market and in the cross-section.

### *5.2.2. Regression analysis to test the predictive power of sentiment in the aggregate stock market*

The two sentiment measures, ISI<sup>L</sup> and CCI, are analysed according to their predictive power in the aggregated stock market returns, in four distinct time horizons: 1, 6, 12 and 24 months. The results (coefficients and p-values) obtained through the regressions are displayed in table 7.

These results also suggest that the two sentiment indexes move in opposite directions. Looking at CCI, it is possible to infer that this sentiment measure has a negative impact in the aggregated stock market returns. CCI's coefficients for all four distinct time horizons (1, 6, 12 and 24) exhibit statistical significance at a 5% level. Thus, as mentioned earlier (see Chapter 5, ISI and CCI – comparison), the results obtained suggest that CCI is a better measure to test the predictive power of sentiment in the aggregated stock market returns. Looking at the 1 month time horizon, the coefficient for predicting the impact of CCI in the aggregate stock market returns indicates that a one-unit increase in CCI (which equals a one-SD increase, because the indexes are standardized) is associated with a decrease of, approximately, 35% on the aggregate stock market returns. This impact remains stable during the other time horizons under study. In fact, an increase of 1 on the CCI's standard deviation leads to a decrease of 35.47%, 36.76% and 34.84%, respectively, for 6, 12 and 24 time horizon.

Looking at the results obtained when sentiment is measured by ISI, the results suggest that ISI only has a significant positive impact in the aggregated stock market return for a time horizon of 24 months. The results indicate that for a time horizon of 24 months, a one-unit increase in ISI is associated with an increase of 68.70% on the aggregated stock market returns.

**Table 7.**

**Predictive power of the sentiment measures in the aggregate stock market**

Results (coefficients and p-values in brackets) of the regression analysis to test the impact of the orthogonalized sentiment index ( $ISI^\perp$ ) and the consumer confidence index (CCI) in the aggregate stock market returns for different time horizons (1, 6, 12 and 24 months).  $ISI^\perp$  represents the principal common component of six underlying proxies of sentiment: share turnover (TURN), number of IPOs (NIPO), average first-day returns (RIPO), share of equity issues (S), dividend premium ( $P^D-ND$ ) and volatility premium (PVOL), contemporaneous or one-month lagged. The orthogonalization is conducted through the incorporation of six macroeconomic variables: industrial production index, consumer price index, gross domestic production, inflation rate, policy interest rate and employment growth. CCI is the standardized consumer confidence index published by DG ECFIN. All variables are computed on a monthly basis. When sentiment is measured by CCI, the independent variables are the CCI and the six macroeconomic variables. When sentiment is measured by  $ISI^\perp$ , the independent variable is ISI. In both regressions, the explanatory variable is the aggregate stock market returns. The period under analysis starts on January 01, 1993 and ends on December 31, 2013.

	Time Horizon							
	1 month		6 months		12 months		24 months	
	d	p(d)	d	p(d)	d	p(d)	d	p(d)
$ISI^\perp$	0.2977	[0.395]	0.0791	[0.816]	0.0633	[0.832]	0.6870	[0.019]
CCI	-0.3499	[0.018]	-0.3547	[0.018]	-0.3676	[0.015]	-0.3484	[0.018]

Baker et al (2012) and Schmeling (2009) study the impact of investor sentiment on several international countries. In the French market, both studies use the standardized Consumer Confidence Index published by DG ECFIN. Their results are in line with the results obtained in this dissertation, and show that sentiment negatively forecasts aggregate stock market returns in the French market.

Schmeling (2009) also suggests that in the French market, the average coefficient estimate across the forecasting horizons (1, 6, 12 and 24) show a large impact of sentiment on returns. In fact, the average coefficient is -54%.

The main conclusion that arises from the  $ISI^\perp$  results is the incapacity of this measure to predict future stock returns in short horizons periods. This result is in line with Brown and Cliff

(2004). The authors suggest that there is weak evidence that the composite sentiment measures predict future stock returns over short horizons.

### 5.3. The impact of sentiment in the cross section of stock returns

#### 5.3.1. Sorts

The sort's analysis is implemented following the methodology proposed by Baker and Wurgler (2006) for a time horizon of 12 months. Table 8 presents the results of the sorts using  $ISI^{\perp}$  as a sentiment measure. Similarly, table 9 displays the results of the sorts using CCI as a proxy for sentiment. In the appendices section, figures 3 and 4 plot the future returns by  $ISI^{\perp}$  and CCI, respectively, according to the sentiment level and the decile rank in each firm characteristics portfolio.

The sorts analysis is conducted to study the impact of sentiment conditional to the previous year sentiment and the decile rank in several stock characteristics, namely: size, total risk, profitability, dividend policy, asset tangibility and growth opportunities and/or distress. For each category, the results indicate the average monthly stocks return for each decile. Decile 10 stands for the highest values obtained in each category, whereas decile 1 represents the lowest ones.

The size portfolio is constructed by the firms' market equity. Decile 10 represents the average monthly return in large firms, whereas, decile 1 indicates the result obtained for small stocks. When sentiment is positive (negative), using  $ISI^{\perp}$  as a sentiment measure, the results suggest that small stocks earn -2.01% (4.91%) and large stocks earn 1.61% (1.74%). Globally, the results indicate that in periods of high (low) sentiment, small stocks tend to earn subsequent lower (higher) returns. The results also suggest that small stocks are more affected by shifts in sentiment than large stocks. In fact, the difference between the average stock returns in periods of positive and negative sentiment in decile 1 is -6.92% and in decile 10 is -0.13%. When sentiment is measured by CCI, the results also indicate the same pattern. In periods of positive (negative) sentiment, small stocks earn 0.02% (0.94%) and large stocks earn 0.91% (1.35%). The results also suggest that a shift in sentiment has more impact in small stocks rather than in large stocks. Comparing the two sentiment measures, the results show that changes in  $ISI^{\perp}$  have a higher impact in the stocks return than shifts in CCI. In fact, as mentioned above, the difference between

the stock returns in periods in high and low sentiment is -6.92% when sentiment is measured by  $ISI^{\perp}$ , whereas this difference when sentiment is measured by CCI is only -0.92%. Therefore, the results suggest that  $ISI^{\perp}$  has a higher impact in the stocks returns of small firms than CCI. The results obtained in this characteristic are in line with those obtained by Baker and Wurgler (2006) and Baker et al. (2012) and reveal the existence of a size effect of Banz (1981), which indicates that smaller firms have higher risk adjusted returns than larger firms.

The total risk portfolio measures the impact of the total risk (systematic or non-systematic) that each firm is subjected to. Total risk is the standard deviation of monthly returns for 12 months, from January to December each year. Decile 10 stands for high volatility stocks, whereas decile 1 shows the results obtained for more stable stocks. Looking at the impact of  $ISI^{\perp}$ , the results show that when sentiment is positive (negative) extreme volatility stocks earn 2.35% (3.13%). These results indicate that when sentiment is high (low), more volatility stocks tend to earn lower (higher) future stock return. Looking at the impact of CCI, the results point out that when sentiment is high (low), high volatility stocks 0.73% (1.65%). The difference between stock returns in periods of positive and negative sentiment is -0.41% for stable firms, whereas for high volatility stocks is -0.92%. This result means that a shift in sentiment has a higher impact in extreme volatility stocks. These results are in line with the empirical findings presented by Baker and Wurgler (2006) and Baker et al. (2012). The authors suggest that highly volatile stocks tend to be the ones harder to value and more difficult to arbitrage. Therefore, these stocks tend to be more affected by fluctuations in sentiment.

The impact of sentiment and profitability in stock returns is measured by the decile rank that each firm obtains in the return on equity ratio portfolio (E/BE). To capture the main contrasts, it is important to compare the results obtained for profitable firms with those obtained for unprofitable ones. Column  $\leq 0$  indicates the results obtained by unprofitable firms and decile 10 corresponds to high profitable firms. When sentiment is positive (using  $ISI^{\perp}$  as a sentiment proxy), the average stock return in decile 10 (more profitable firms) is 1.04% and in unprofitable firms is 0.61%. When sentiment is negative, firms that are more profitable earn 2.27% and unprofitable ones earn 2.42%. These results indicate that when sentiment is high (low), unprofitable firms tend to earn low (high) future stock returns, which is in line with the findings obtained by Baker and Wurgler (2006). The explanation lies with the fact that unprofitable firms are harder to value and more difficult to arbitrage, thus being more exposed to sentiment fluctuations. When sentiment is

measured through CCI, in positive sentiment periods, the average stock return in decile 10 is 1.44% and 0.54% for unprofitable firms. In negative sentiment periods, the average stock return in decile 10 is 1.23% and 1.14% for unprofitable firms. These results differ from those obtained using  $ISI^{\perp}$  as a proxy, given the fact that unprofitable firms in negative sentiment periods do not earn higher returns than profitable firms. However, the results point out an important aspect. A shift in sentiment affects more unprofitable firms than high profitable ones. Comparing the two sentiment measures, the results obtained by  $ISI^{\perp}$  suggest that this measure has a higher impact in the cross-section stock returns than CCI.

To analyse the impact of sentiment and the dividend policy in stock returns it is divided the sample according to the dividends to equity ratio portfolio (D/BE). To capture the main differences, the sample is also divided into paying and non-paying firms. The values for non-paying firms are under the column  $\leq 0$ . Looking at the results obtained by  $ISI^{\perp}$ , when sentiment is positive, the stocks return of non-paying firms is 0.79%, whereas for firms in decile 10 (firms with a higher dividends to equity ratio) is 1.92%. In contrast, when sentiment is negative, non-paying firms earn 2.76% and high dividend-paying firms earn 2.63%. Globally, the results indicate that in periods of high (low) sentiment, non-dividend-paying stocks earn relatively low (high) subsequent returns. A shift in  $ISI^{\perp}$  has a higher impact in non-dividend-paying firms than in dividend-paying firms. Looking at the results obtained by CCI, when sentiment is positive (negative), the average monthly return of non-dividend-paying firms is 0.66% (1.15%) and for firms in decile 10 is 1.01 (1.23). The results indicate that shifts in CCI have a higher impact in non-dividend-paying firms than in dividend-paying firms. However, when sentiment is measured by CCI, the pattern indicated by  $ISI^{\perp}$  does not occur, so in periods of low sentiment, non-dividend-paying firms do not earn subsequent higher returns than dividend-paying firms. Globally, the results indicate that  $ISI^{\perp}$  has a higher impact in future stock return of non-dividend-paying stocks than CCI.

The impact of asset tangibility and investor sentiment in stocks returns is analysed by two variables: property, plant and equipment over assets (PPE/A) and research and development over assets (RD/A). A high value of PPE/A indicates that a firm is composed mainly by tangible assets, making their valuation less affected by investors' consideration. On the other hand, a high value of RD/A indicates that a firm is composed mainly by intangible assets, making it more difficult to evaluate their true value (Baker and Wurgler, 2006). Looking at the results obtained for the PPE/A ratio portfolio (using  $ISI^{\perp}$  as a sentiment measure), when sentiment is positive, firms in decile 10

(firms with more tangible assets) earn 0.96% whereas firms in decile 1 (firms with more intangible assets) earn -1.28%. In contrast, when sentiment is negative, firms with more tangible assets earn 0.48% and firms with more intangible assets earn 0.53%. Thus, suggesting that when sentiment is high (low) firms with more intangible assets earn relatively low (high) subsequent returns. The difference between the returns obtained in periods of high and low sentiment is higher for firms with more intangible assets than for firms with more tangible assets. This result points out that shifts in  $ISI^{\perp}$  have higher impact in firms with more intangible assets. When sentiment is measured by CCI, this pattern is not verified. Comparing the two sentiment measures, the results obtained by  $ISI^{\perp}$  suggest that this proxy of sentiment has a higher impact in stock returns according to the level of the PPE/A ratio portfolio than CCI.

Looking at RD/A ratio, when sentiment is high (using  $ISI^{\perp}$  as a sentiment proxy), firms in decile 10 (high intangible stocks) present an average stock return of -1.12%, whereas decile 1 (high tangible stocks) earn 2.92%. When sentiment is negative, firms in decile 10 show an average stock return of 2.32% and in decile 1 earn -1.52%. This means that firms with less tangible assets are more influenced by sentiment changes. When sentiment is high (low), less tangible assets firms tend to earn subsequent lower (higher) returns. The results obtained using CCI as a sentiment measure suggest the same pattern mentioned for  $ISI^{\perp}$ . In fact, when sentiment is positive (negative), the stock return of firms in decile 1 is 2.92% (-1.52%), whereas in decile 10 is -1.12% (2.32%). Globally, the results obtained for the two sentiment measures indicate that when sentiment is high (low), firms with less tangible assets earn relatively low (high) subsequent returns. These results are more conclusive about the conditional effect of sentiment than those obtained by Baker and Wurgler (2006).

The impact of sentiment and the effect of growth opportunities and/or distress in stock returns is analysed through the book-to-market equity ratio portfolio (BE/ME) and by external finance ratio portfolio (EF/A). Due to the multidimensional nature of these variables, the effects of growth opportunities and distress are analysed together. In fact, Baker and Wurgler (2006) suggest that high values of BE/ME and low values of EF/A may indicate distress, whereas low values of BE/ME and high values of EF/A may suggest growth opportunities. Thus, suggesting that firms in extreme deciles react more to sentiment than firms in the middle deciles. Looking at the results obtained for BE/ME (when sentiment is measured by  $ISI^{\perp}$ ), in periods when sentiment is positive (negative), firms in decile 1 (extreme growth stocks) earn 0.69% (1.18%), firms in decile 5 earn 2%

(2.55%) and firms in decile 10 (distressed stocks) earn 1.33% (2.07%). The results suggest that firms in the extreme decile are more affected by shifts in  $ISI^{\perp}$  than firms in the middle decile. The results also indicate that when sentiment is negative (positive), extreme growth and distressed stocks earn subsequent higher (lower) returns. The results obtained measuring sentiment by CCI do not reveal the pattern described for  $ISI^{\perp}$ . Once more, the impact of sentiment in stock returns using  $ISI^{\perp}$  as a sentiment proxy is higher than when sentiment is measured by CCI.

Looking at EF/A ratio, using  $ISI^{\perp}$  as a sentiment measure, when sentiment is positive (negative), firms in decile 1 (distressed firms) earn 1.43% (1.42%), firms in decile 5 earn 2,09% (4.83%) and firms in decile 10 (extreme growth stocks) earn -1.68% (14.19%). The results obtained for the EF/A ratio differs a little from those obtained for the BE/ME. The results indicate that only extreme growth stocks earn relatively low (high) subsequent returns when sentiment is positive (negative). The results obtained for the distressed stocks reveal that sentiment does not have an impact on the future stocks returns. The results obtained for CCI do not confirm that extreme growth stocks and distressed stocks earn relatively low (high) subsequent returns in periods of high (low) sentiment. Globally, the results obtained by  $ISI^{\perp}$  in this variable follow the results obtained by Baker and Wurgler (2006) and Baker et al. (2012) for extreme growth stocks but not for distressed stocks.

Summarizing, the results obtained demonstrate that sentiment has a higher impact in the cross-section of stock returns when is measured by  $ISI^{\perp}$  than when is measured by CCI. The results also suggest that when sentiment is measured by  $ISI^{\perp}$ , periods of high (low) sentiment are followed by low (high) stock returns in small stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, less tangible stocks, extreme growth stocks and distressed stocks.

**Table 8.**

***Future Returns by  $ISI^{\perp}$  and Firm Characteristics, 1993-2013***

The table presents the average monthly returns for portfolios according to firm characteristics portfolios and the level of the orthogonalized Investor Sentiment Index ( $ISI^{\perp}$ ). In each month, it is presented 10 equal-weighted portfolios according to several different firm characteristics portfolios, such as: size (ME), total risk ( $\sigma$ ), return on equity for profitable firms (E/BE), dividends-to-equity for dividend payers (D/BE), asset tangibility (measured by PPE/A and RD/A) and growth opportunities and/or distress (measured by BE/ME and EF/A). Within each category, decile 1 stands for the lowest values obtained, whereas the highest values are displayed in decile 10. Then, it is computed the average monthly return of each portfolio in each decile for positive and negative periods of  $ISI^{\perp}$ , and the difference between these two averages.



		Decile											Comparisons		
<i>SENTIMENT</i> <sup>L</sup>		≤0	1	2	3	4	5	6	7	8	9	10	10 - 1	10 - 5	5 - 1
<b>ME</b>	Positive		-2.01	-2.41	1.23	0.09	0.36	1.35	0.74	2.35	1.24	1.61	3.62	1.25	2.37
	Negative		4.91	11.47	0.23	0.79	0.33	1.45	1.93	1.92	1.84	1.74	-3.17	1.41	-4.58
	Difference		-6.92	-13.88	1	-0.7	0.03	-0.1	-1.19	0.43	-0.6	-0.13	6.79	-0.16	6.95
<b>σ</b>	Positive		0.02	2.65	-0.81	0.83	-2.28	1.55	3.14	0.36	0.43	2.35	2.33	4.63	-2.3
	Negative		2.64	1.91	-0.45	1.63	-0.11	7.2	3.99	0.67	1.32	3.13	0.49	3.24	-2.75
	Difference		-2.62	0.74	-0.36	-0.8	-2.17	-5.65	-0.85	-0.31	-0.89	-0.78	1.84	1.39	0.45
<b>E/BE</b>	Positive	0.61	-0.48	1.28	-0.11	0.75	0.87	-0.05	1.93	0.46	1.92	1.04	1.52	0.17	1.35
	Negative	2.42	1.32	1.17	-0.27	0.03	0.67	4.61	13.35	1.78	2.63	2.27	0.95	1.6	-0.65
	Difference	-1.81	-1.8	0.11	0.16	0.72	0.2	-4.66	-11.42	-1.32	-0.71	-1.23	0.57	-1.43	2
<b>D/BE</b>	Positive	0.79	0.60	1.93	-0.05	-0.11	1.41	-0.72	1.25	1.28	0.49	1.92	1.32	0.51	0.81
	Negative	2.76	0.88	13.35	4.61	-0.27	1.5	1.7	-0.48	1.17	1.84	2.63	1.75	1.13	0.62
	Difference	-1.97	-0.28	-11.42	-4.66	0.16	-0.09	-2.42	1.73	0.11	-1.35	-0.71	-0.43	-0.62	0.19
<b>PPE/A</b>	Positive		-1.28	0.91	-1.23	-1.11	2.35	1.29	2.45	-0.17	1.45	0.96	2.24	-1.39	3.63
	Negative		0.53	22.21	-0.99	0.99	4.02	2.82	-0.71	1	0.86	0.48	-0.05	-3.54	3.49
	Difference		-1.81	-21.3	-0.24	-2.1	-1.67	-1.53	3.16	-1.17	0.59	0.48	2.29	2.15	0.14
<b>RD/A</b>	Positive		2.92	6.05	0.23	0.99	-0.83	5.09	-1.39	0.35	2.37	-1.12	-4.04	-0.29	-3.75
	Negative		-1.52	-1.39	-2.82	0.49	1.92	1.73	0.83	8.47	-3.56	2.32	3.84	0.4	3.44
	Difference		4.44	7.44	3.05	0.5	-2.75	3.36	-2.22	-8.12	5.93	-3.44	-7.88	-0.69	-7.19
<b>BE/ME</b>	Positive		0.69	4.19	1.56	2.37	2	-2.91	-1.02	-0.64	1.75	1.33	0.64	-0.67	1.31
	Negative		1.18	34.19	2.18	0.19	2.55	-0.41	0.98	-0.09	-1.82	2.07	0.89	-0.48	1.37
	Difference		-0.49	-30	-0.62	2.18	-0.55	-2.5	-2	-0.55	3.57	-0.74	-0.25	-0.19	-0.06
<b>EF/A</b>	Positive		1.43	0.43	1.51	-0.34	2.09	2.5	0.08	1.21	0.06	-1.68	-3.11	-3.77	0.66
	Negative		1.42	0.45	1.47	0.82	4.83	2.3	1.1	0.12	1.54	14.19	12.77	9.36	3.41
	Difference		0.01	-0.02	0.04	-1.16	-2.74	0.2	-1.02	1.09	-1.48	-15.87	-15.88	-13.13	-2.75

**Table 9.**

**Future Returns by CCI and Firm Characteristics, 1993-2013**

The table presents the average monthly returns for portfolios according to firm characteristics portfolios and the level of the Consumer Confidence Index (CCI). In each month, it is presented 10 equal-weighted portfolios according to several different firm characteristics portfolios, such as: size (ME), total risk ( $\sigma$ ), return on equity for profitable firms (E/BE), dividends-to-equity for dividend payers (D/BE), asset tangibility (measured by PPE/A and RD/A) and growth opportunities and/or distress (measured by BE/ME and EF/A). Within each category, decile 1 stands for the lowest values obtained, whereas the highest values are displayed in decile 10. Then, it is computed the average monthly return of each portfolio in each decile for positive and negative periods of CCI, and the difference between these two averages

		Decile										Comparisons			
		≤0	1	2	3	4	5	6	7	8	9	10	10 - 1	10 - 5	5 - 1
<b>ME</b>	Positive		0.02	0.57	-0.78	0.79	0.92	1.5	1.24	1.23	1.93	0.91	0.89	-0.01	0.9
	Negative		0.94	0.62	0.78	1.53	1.36	1.61	1.84	1.71	1.77	1.35	0.41	-0.01	0.42
	Difference		-0.92	-0.05	-1.56	-0.74	-0.44	-0.11	-0.6	-0.48	0.16	-0.44	0.48	0	0.48
<b>σ</b>	Positive		0.19	2.12	0.23	2.16	-0.367	0.4	1.42	0.75	0.75	0.73	0.54	1.097	-0.557
	Negative		0.60	2.08	0.62	1.76	-0.13	0.77	1.99	1.2	1.81	1.65	1.05	1.78	-0.73
	Difference		-0.41	0.04	-0.39	0.4	-0.237	-0.37	-0.57	-0.45	-1.06	-0.92	-0.51	-0.683	0.173
<b>E/BE</b>	Positive	0.54	1.01	1.01	0.84	0.72	-0.74	0.53	0.53	0.47	1.44	1.44	0.43	2.18	-1.75
	Negative	1.14	-1.42	1.25	1.3	0.98	1.03	1	1.33	1.2	1.13	1.23	2.65	0.2	2.45
	Difference	-0.60	2.43	-0.24	-0.46	-0.26	-1.77	-0.47	-0.8	-0.73	0.31	0.21	-2.22	1.98	-4.2
<b>D/BE</b>	Positive	0.66	0.47	-0.74	-0.74	0.53	0.72	0.84	-0.26	1.44	1.01	1.01	0.54	0.29	0.25
	Negative	1.15	1.11	1.03	1.11	1.33	0.98	1.14	1.01	1.13	1.25	1.23	0.12	0.25	-0.13
	Difference	-0.49	-0.64	-1.77	-1.85	-0.8	-0.26	-0.3	-1.27	0.31	-0.24	-0.22	0.42	0.04	0.38
<b>PPE/A</b>	Positive		0.27	1.18	0.05	2.4	1.32	1.49	0.98	0.21	0.13	0.20	-0.07	-1.12	1.05
	Negative		0.90	1.31	1.16	1.05	1.19	1.21	1.56	1.17	1.06	1.03	0.13	-0.16	0.29
	Difference		-0.63	-0.13	-1.11	1.35	0.13	0.28	-0.58	-0.96	-0.93	-0.83	-0.2	-0.96	0.76
<b>RD/A</b>	Positive		-2.54	0.36	0.77	-0.09	1.92	0.84	1.59	1.33	0.05	0.44	2.98	-1.48	4.46
	Negative		1.07	1.11	1.19	0.83	0.84	0.77	0.73	1.04	2.49	1.12	0.05	0.28	-0.23
	Difference		-3.61	-0.75	-0.42	-0.92	1.08	0.07	0.86	0.29	-2.44	-0.68	2.93	-1.76	4.69
<b>BE/ME</b>	Positive		2.17	5.55	1.83	1.57	0.3	-0.43	-0.15	0.91	-0.05	0.45	-1.72	0.15	-1.87
	Negative		1.32	1.53	1.58	0.99	1.48	0.69	1.4	1.08	0.48	0.32	-1	-1.16	0.16
	Difference		0.85	4.02	0.25	0.58	-1.18	-1.12	-1.55	-0.17	-0.53	0.13	-0.72	1.31	-2.03
<b>EF/A</b>	Positive		2.13	0.91	1.16	0.55	0.26	-0.16	0.17	0.09	0.36	3.68	1.55	3.42	-1.87
	Negative		1.46	0.9	1.1	1.08	1.59	1.4	1.15	0.96	1.59	2.98	1.52	1.39	0.13
	Difference		0.67	0.01	0.06	-0.53	-1.33	-1.56	-0.98	-0.87	-1.23	0.70	0.03	2.03	-2

### *5.3.2. Predictive Regressions for Long-Short Portfolios*

The predictive regressions for long-shorts portfolios are constructed according to some characteristics especially sensitive to investor sentiment: size, total risk, dividend policy, profitability, asset tangibility, growth opportunities and/or distress. This study is conducted for four distinct time horizons: 1, 6, 12 and 24 months. The results (coefficients and p-values) are presented in table 10. In the appendices section, Table 11 presents the results obtained for the predictive regressions for long-shorts after controlling for RMRF, SMB, HML and UMD.

The results indicate that both sentiment indexes affect the future stock returns according to the stocks' characteristics under study. However, the results also indicate that the magnitude of this impact varies according to the sentiment index used as proxy of investor sentiment, CCI or  $ISI_{\perp}$ , and according to the time horizon under investigation.

The Size portfolio is constructed based on the firms' market equity. Both sentiment measures exhibit a negative impact in future stock returns (with the exception of the result obtained for  $ISI_{\perp}$  for a time horizon of 6 months). This suggests that when sentiment is high (low), this category of stock earns relatively low (high) subsequent returns. Relatively to the size characteristic, the results indicate that the impact of sentiment (measured by  $ISI_{\perp}$  and CCI) is higher for a time horizon of 12 months. Comparing the two sentiment measures, results suggest that the magnitude of the impact on future stock returns is higher when sentiment is measured by  $ISI_{\perp}$  rather than CCI. For example, in terms of magnitude, the coefficient for predicting SMB indicates that a one-unit increase in  $ISI_{\perp}$  and CCI (which equals a one-SD increase, because the indexes are standardized) is associated, respectively, with a -33% and 8% lower monthly return on the small minus large portfolio, for a time horizon of 24 months. The results obtained in this category are in line with those obtained by Baker and Wurgler (2006) for the U.S. market and with Baker et al. (2012) for a global index of six major stock markets (including France), both for a time horizon of 12 months.

The results obtained for the Total Risk portfolio indicate a negative impact of sentiment (measured by  $ISI_{\perp}$  and CCI) in future stock returns. As indicated by the Size portfolio, the negative sign of the coefficient suggests that when sentiment is high (low), this category of stock earns relatively low (high) subsequent returns. Analysing, in particular, the impact of CCI, the results suggest that the magnitude of this impact is relatively low and stable throughout the four distinct

horizons. The ISI<sup>L</sup>'s results indicate that the magnitude of the sentiment impact on the future stock returns is higher for a time horizon of 24 months. Globally, the results obtained in this category suggest that ISI<sup>L</sup> has a higher impact than CCI on the future stock returns in this characteristic (high volatility stocks). In fact, for example, for a time horizon of 24 months, the results indicate that an one-unit increase in ISI<sup>L</sup> and CCI lead, respectively, to a -57% and -1% lower monthly return in high volatility stocks. The results obtained in this study are in line with those obtained by Baker and Wurgler (2006) and Baker et al (2012).

As mentioned earlier in Methodology, to study the profitability characteristic, regressions are run to predict the difference between profitable portfolios and unprofitable portfolios. The results obtained suggest that sentiment, measured by ISI<sup>L</sup> and CCI, have significant predictive power for these portfolios, and indicate that the coefficient for predicting profitable and unprofitable portfolios is positive (with the exception of the result obtained by CCI for a time horizon of 24 months). This means that when sentiment is high, profitable firms earn subsequent higher returns than unprofitable ones. Comparing the two sentiment indexes, the results, in this characteristic, suggest that ISI<sup>L</sup> has a higher impact than CCI in future stock returns. For example, for a time horizon of 6 months, a one-unit increase in ISI<sup>L</sup> and CCI is associated, respectively, to a 47% and 10% higher monthly return in profitable firms.

To study the dividend policy characteristic, regressions are run to predict the difference between paying portfolios and non-paying portfolios. The results obtained suggest that sentiment, measured by ISI<sup>L</sup> and CCI, has a significant predictive power for these portfolios, and indicate that the coefficient for predicting paying and non-paying portfolios is positive (with the exception of the result obtained by ISI for a time horizon of 1 month). This indicates that when sentiment is high (low), paying firms earn subsequent higher (lower) returns than non-paying firms. The magnitude of the impact of sentiment in future stock returns in this characteristic, measured by ISI<sup>L</sup> is higher than when sentiment is measured by CCI. For example, for a time horizon of 6 months, a one-unit increase in ISI<sup>L</sup> and CCI is associated, respectively, to an 89% and 29% higher monthly return in paying firms.

The results obtained for the Profitability and Dividend policy panel are in line with the results achieved by Baker and Wurgler (2006), which suggest that high (low) sentiment forecast relatively lower (higher) returns on non-paying and unprofitable firms.

Asset tangibility, as a proxy for valuation difficulties, is measured by property, plant and equipment over assets and research and development over assets. As mentioned in the Sorts section, a lower PPE/A ratio and a higher RD/A ratio indicate that a firm has less tangible assets, making that firm harder to value and more difficult to arbitrage and therefore more sensitive to sentiment variations.

Looking at the PPE/A portfolio, the results indicate that sentiment has a significant positive impact (with the exception of the results obtained by ISI $\perp$  for a time horizon of 1 and 12 months) on the future stock returns of high PPE/A ratio. This finding means that when sentiment is high (low), firms with a higher PPE/A ratio earn subsequent higher (lower) returns than lower PPE/A ratio firms. On the other hand, the results obtained for the RD/A portfolio suggest that sentiment has a significant negative impact (with the exception of the results obtained by CCI for a time horizon of 1 month) on the future stock returns of high RD/A ratio. Thus, indicating that when sentiment is high (low), firms with higher RD/A ratio earn subsequent lower (higher) returns than lower RD/A ratio firms.

The results obtained in the tangibility panel indicate that ISI $\perp$  has a higher impact on future stock return than CCI. Globally, the results indicate that when sentiment is high, firms with less tangible assets tend to earn subsequent lower returns. The results obtained by Baker and Wurgler (2006) suggest that sentiment only has marginal predictive power for the tangibility characteristics. This study, however, suggests that sentiment exhibits significant predictive power for these conditional characteristics.

Firms' growth opportunities is based on the BE/ME ratio and on the EF/A ratio. The BE/ME portfolio is constructed long on firms with medium BE/ME ratio and short on low BE/ME ratio and the EF/A portfolio, long on high EF/A ratio and short on medium EF/A ratio. Firms' distress is also based on the BE/ME ratio and on the EF/A ratio. It is calculated the BE/ME portfolio, long on high BE/ME ratio and short on medium BE/ME and also the EF/A portfolio, long on firms with medium EF/A ratio and short on low EF/A ratio. Baker and Wurgler (2006) suggest that growth and distress variables do not have a simple monotonic relationship with sentiment. In fact, the authors suggest that with growth and distress variables, firms with extreme values react more to sentiment than firms in the middle values, suggesting a U-shaped pattern. Therefore, a simple "High – Low" analysis could fail to demonstrate important patterns of the cross-section.

Looking at the growth opportunities portfolios, the results indicate that there exists a significant positive impact on the future stock returns of medium BE/ME ratio firms (with the exception of the results obtained for ISI<sup>⊥</sup> for a time horizon of 12 months and for CCI for a time horizon of 24 months) and a significant negative impact on the future stock returns of high EF/A ratio firms (with the exception of the result obtained for CCI for a time horizon of 6 months). These results mean that when sentiment is high, medium BE/ME ratio firms earn subsequent higher returns than low BE/ME ratio firms. Likewise, when sentiment is high, high EF/A ratio firms earn subsequent lower returns than medium EF/A ratio firms. Globally, the results presented in these portfolios indicate that when sentiment is high, extreme growth stocks earn relatively low subsequent returns.

Looking at the distress portfolios, the results suggest that both sentiment measures exhibit a negative impact on future stock returns of high BE/ME ratio firms (with the exception of the result obtained for ISI<sup>⊥</sup> for a time horizon of 24 months) and a positive impact on medium EF/A ratio firms (with the exception of the result obtained for CCI for a time horizon of 6 months). These results imply that when sentiment is high, high BE/ME ratio firms earn subsequent lower returns than medium BE/ME ratio firms. Similarly, when sentiment is high, medium EF/A ratio firms earn subsequent higher returns than low EF/A ratio firms. Over all, the results displayed in these portfolios point out that when sentiment is high (low), distressed stocks earn relatively low (high) subsequent returns.

The comparison of the results obtained in tables 10 and 11 indicate that the sentiment coefficients' values do not suffer great variation (in sign and in magnitude) after controlling for RMRF, SMB, HML and UMD. This result is in line with the results obtained by Baker and Wurgler (2006).

Globally, the results obtained on the predictive regressions for long-short portfolios confirm the patterns indicated by the sorts' analysis in relation to the impact of sentiment in the cross-section of stock returns. Especially, the impact of sentiment in the studied characteristics portfolios is higher when sentiment is measured by the orthogonalized Investor Sentiment Index (ISI<sup>⊥</sup>) than when sentiment is measured through the standardized Consumer Confidence Index (CCI). The regression analysis also confirms that in periods of high (low) sentiment, small stocks, extreme volatility stocks, unprofitable stocks, non-dividend-paying stocks, less tangible stocks, extreme growth stocks and distressed stocks tend to earn subsequent low (high) returns.

Table 10.

### Time Series Regressions of Portfolio Returns, 1993 to 2013

Results (coefficients and p-values in brackets) of the predictive regressions for long-short portfolios, using the orthogonalized Investor Sentiment Index ( $ISI^{\perp}$ ) and the Consumer Confidence Index (CCI) as sentiment measures, and for four distinct time horizons: 1, 6, 12 and 24 months.  $ISI^{\perp}$  consists in the first principal common component of six orthogonalized sentiment proxies: share turnover (TURN), number of IPOs (NIPO), average first-day returns on IPOs (RIPO), share of equity issues (S), dividend premium ( $P^D - N^D$ ) and volatility premium. This index is controlled for six macroeconomic conditions, such as: industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), policy interest rate (INTR) and employment growth (EG). CCI is the standardized consumer confidence index published by DG ECFIN. The sentiment measures are calculated on a monthly basis. The long-short portfolios are constructed based on several firm characteristics: size (ME), total risk ( $\sigma$ ), dividend policy (D), profitability (E), asset tangibility (PPE/A and RD/A) and growth opportunities and/or distress (BE/ME and EF/A). When sentiment is measured by CCI, the regression's independent variables are the sentiment index (CCI) and the macroeconomic variables (IPI, CPI, GDP, INFR, INTR and EG). High corresponds to a stock in the top three deciles, low describes a stock in the bottom three deciles and stock in the four middle deciles represents medium



		Time horizon															
		1 month				6 months				12 months				24 months			
		ISI $\perp$		CCI		ISI $\perp$		CCI		ISI $\perp$		CCI		ISI $\perp$		CCI	
		d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)
<b>Size portfolio</b>																	
<b>ME</b>	SMB	-0.21	[0.00]	-0.27	[0.00]	0.53	[0.00]	-0.17	[0.00]	-1.42	[0.00]	-0.28	[0.00]	-0.33	[0.00]	-0.08	[0.00]
<b>Total risk portfolio</b>																	
<b><math>\sigma</math></b>	High-Low	-0.03	[0.00]	-0.03	[0.00]	-0.08	[0.00]	-0.02	[0.00]	-0.03	[0.00]	-0.03	[0.00]	-0.57	[0.00]	-0.01	[0.00]
<b>Profitability portfolio</b>																	
<b>E</b>	>0 - <0	1.58	[0.00]	0.19	[0.00]	0.47	[0.00]	0.10	[0.00]	0.98	[0.00]	0.13	[0.00]	0.82	[0.00]	-0.19	[0.00]
<b>Dividend policy portfolio</b>																	
<b>D</b>	>0 - =0	-0.01	[0.00]	0.04	[0.00]	0.89	[0.00]	0.29	[0.00]	2.12	[0.00]	0.32	[0.00]	1.63	[0.00]	0.52	[0.00]
<b>Tangibility portfolios</b>																	
<b>PPE/A</b>	High-Low	-0.75	[0.00]	0.26	[0.00]	1.17	[0.00]	0.12	[0.00]	-1.65	[0.00]	0.15	[0.00]	1.59	[0.00]	0.04	[0.00]
<b>RD/A</b>	High-Low	-0.73	[0.00]	0.11	[0.00]	-0.52	[0.00]	-0.04	[0.00]	-0.40	[0.00]	-0.001	[0.00]	-0.63	[0.00]	-0.02	[0.00]
<b>Growth opportunities and Distress portfolios</b>																	
<b>BE/ME</b>	HML	1.38	[0.00]	0.23	[0.00]	0.16	[0.00]	0.29	[0.00]	-0.34	[0.00]	0.23	[0.00]	0.30	[0.00]	0.22	[0.00]
<b>EF/A</b>	High-Low	-1.94	[0.00]	-0.21	[0.00]	-0.53	[0.00]	-0.10	[0.00]	0.99	[0.00]	-0.17	[0.00]	0.21	[0.00]	-0.14	[0.00]
<b>Growth opportunities portfolios</b>																	
<b>BE/ME</b>	Medium-Low	1.04	[0.00]	0.12	[0.00]	0.58	[0.00]	0.08	[0.00]	-0.29	[0.00]	0.10	[0.00]	0.36	[0.00]	-0.05	[0.00]
<b>EF/A</b>	High-Medium	-1.41	[0.00]	-0.14	[0.00]	-2.64	[0.00]	0.05	[0.00]	-1.10	[0.00]	-0.20	[0.00]	-0.23	[0.00]	-0.02	[0.00]
<b>Distress portfolio</b>																	
<b>BE/ME</b>	High-Medium	-0.81	[0.00]	-0.12	[0.00]	-0.50	[0.00]	-0.11	[0.00]	-0.07	[0.00]	-0.11	[0.00]	-0.23	[0.00]	0.03	[0.00]
<b>EF/A</b>	Medium-Low	0.85	[0.00]	0.12	[0.00]	1.09	[0.00]	-0.12	[0.00]	0.61	[0.00]	0.10	[0.00]	0.96	[0.00]	0.08	[0.00]

### *5.3.3. Systematic Risk*

Table 12 presents the results obtained for the regressions of long-short portfolio returns on the market risk premium (RMRF) and the market risk premium interacted with ISI<sup>L</sup> and CCI, for four distinct time horizons: 1, 6, 12 and 24 months.

Systematic risk can be explained in two ways. The first explanation suggests that the systematic risks (beta loadings) of stocks with certain characteristics fluctuate with the sentiment proxies used as sentiment measures (despite the attempt to isolate them from macroeconomic conditions). Looking at table 12 to analyse the time-varying betas, it is possible to conclude that, in general, the coefficient  $\beta f$  enters with the opposite sign than those obtained in table 10.

A second explanation maintains stocks' betas fixed and allows the risk premium to vary with sentiment. This suggests that high and low beta stocks fluctuate in proportion to the differences in returns. However, the results obtained contradict this assumption. In fact, the results indicate that the predicted effect of several characteristics varies in magnitude, as well as in sign over time.

The results obtained through the study of systematic risk are in line with those found by Baker and Wurgler (2006) and suggest that, in general, the results do not reflect compensation for classical systematic risks.

**Table 12.**

**Conditional Market Betas - using  $ISI^{\perp}$  and CCI as a sentiment measure, 1993 –2013**

Regressions of long-short portfolio returns on the market risk premium (RMRF) and the market risk premium interacted with SENTIMENT, measured by  $ISI^{\perp}$  and CCI. The long-short portfolios are constructed according to several firm characteristics, such as: size (ME), total risk ( $\sigma$ ), profitability (E), dividend policy (D), asset tangibility (PPE/A and RD/A) and growth opportunities and/or distress (BE/ME and EF/A). High corresponds to a stock in the top three deciles, low describes a stock in the bottom three deciles and stock in the four middle deciles represents medium. Monthly returns are matched to *SENTIMENT*, lagged 1, 6, 12 or 24 months.  $ISI^{\perp}$  consists in the first principal common component of six orthogonalized sentiment proxies: share turnover (TURN), number of IPOs (NIPO), average first-day returns on IPOs (RIPO), share of equity issues (S), dividend premium ( $P^{D-ND}$ ) and volatility premium (PVOL). This index is controlled for six macroeconomic conditions, such as: industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), policy interest rate (INTR) and employment growth (EG). CCI is the standardized consumer confidence index published by DG ECFIN. The sentiment measures are calculated on a monthly basis. For each sentiment in each time horizon it is presented the  $\beta f$  coefficient and the respective p-values in brackets.

Time horizon

		1 month				6 months				12 months				24 months			
		ISI $\perp$		CCI		ISI $\perp$		CCI		ISI $\perp$		CCI		ISI $\perp$		CCI	
		$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$	$\beta f$	$t(\beta f)$
<b>Panel A: size and risk</b>																	
<b>ME</b>	SMB	-0.04	[0.00]	0.06	[0.00]	-0.21	[0.00]	-0.08	[0.00]	-0.14	[0.00]	0.01	[0.00]	0.02	[0.00]	0.02	[0.00]
$\sigma$	High-Low	-0.02	[0.00]	0.01	[0.00]	0.07	[0.00]	-0.01	[0.00]	-0.04	[0.00]	0.01	[0.00]	-0.03	[0.00]	0.01	[0.00]
<b>Panel B: Profitability and Dividend Policy</b>																	
<b>E</b>	>0 - <0	0.11	[0.00]	0.04	[0.00]	0.04	[0.00]	0.02	[0.00]	-0.29	[0.00]	-0.08	[0.00]	0.07	[0.00]	-0.04	[0.00]
<b>D</b>	>0 - =0	0.46	[0.00]	-0.01	[0.00]	0.24	[0.00]	-0.03	[0.00]	0.34	[0.00]	-0.003	[0.00]	-0.02	[0.00]	0.05	[0.00]
<b>Panel C: Tangibility</b>																	
<b>PPE/A</b>	High-Low	-0.05	[0.00]	0.06	[0.00]	-0.31	[0.00]	0.02	[0.00]	-0.06	[0.00]	0.02	[0.00]	-0.002	[0.00]	-0.004	[0.00]
<b>RD/A</b>	High-Low	-0.09	[0.00]	0.03	[0.00]	0.02	[0.00]	-0.01	[0.00]	0.01	[0.00]	0.02	[0.00]	-0.03	[0.00]	-0.003	[0.00]
<b>Panel D: Growth opportunities and Distress</b>																	
<b>BE/ME</b>	HML	0.31	[0.00]	0.01	[0.00]	-0.02	[0.00]	0.03	[0.00]	-0.25	[0.00]	0.05	[0.00]	0.15	[0.00]	0.04	[0.00]
<b>EF/A</b>	High-Low	0.01	[0.00]	-0.04	[0.00]	-0.04	[0.00]	0.11	[0.00]	-0.09	[0.00]	0.01	[0.00]	-0.14	[0.00]	0.09	[0.00]
<b>Panel E: Growth opportunities</b>																	
<b>BE/ME</b>	Medium-Low	0.07	[0.00]	-0.02	[0.00]	-0.06	[0.00]	0.001	[0.00]	-0.16	[0.00]	0.01	[0.00]	0.16	[0.00]	-0.002	[0.00]
<b>EF/A</b>	High-Medium	0.03	[0.00]	0.02	[0.00]	0.03	[0.00]	0.05	[0.00]	-0.04	[0.00]	0.05	[0.00]	0.23	[0.00]	-0.02	[0.00]
<b>Panel F: Distress</b>																	
<b>BE/ME</b>	High-Medium	-0.03	[0.00]	0.03	[0.00]	0.13	[0.00]	0.04	[0.00]	0.02	[0.00]	0.03	[0.00]	-0.15	[0.00]	0.03	[0.00]
<b>EF/A</b>	Medium-Low	-0.01	[0.00]	-0.04	[0.00]	-0.05	[0.00]	0.01	[0.00]	-0.01	[0.00]	-0.02	[0.00]	-0.23	[0.00]	0.03	[0.00]

## 6. Conclusions

This dissertation investigates the impact of investor sentiment in the aggregated stock market and in the cross-section of stock returns, on the French market. Sentiment is measured using two sentiment indexes: the orthogonalized Investor Sentiment Index ( $ISI^\perp$ ) and the Consumer Confidence Index (CCI).  $ISI^\perp$  is constructed through market data, thus constituting an indirect measure of investor sentiment. CCI is a survey that directly asks investors about their expectations regarding the stock market, hence representing a direct measure.

The Investor Sentiment Index (ISI) corresponds to the first principal component of six underlying proxies: market turnover (TURN), number and average first-day returns on IPOs (NIPO and RIPO, respectively), the share of equity issues (S), dividend premium ( $P^{D-ND}$ ) and volatility premium (PVOL). In order to control for some macroeconomic conditions, each of the underlying proxies are regressed with six macroeconomic variables: industrial production index (IPI), inflation rate (INFR), consumer price index (CPI), policy interest rate (INTR), employment growth (EG) and the gross domestic product (GDP). The residuals obtained are cleaner proxies for investor sentiment and are used to construct the orthogonalized Investor Sentiment Index ( $ISI^\perp$ ). The Consumer Confidence Index (CCI) represents the standardized consumer confidence indicator, from the Directorate General for Economic and Financial Affairs (DG ECFIN).

The analysis of the characteristics of  $ISI^\perp$  indicates that more than a 1/3 of the index's variance is explained by the first common component among the six underlying proxies. All the orthogonalized proxies enter the index with the respective timing, suggesting that proxies based on investor demand or investor behavioural precede firm supply variables. Looking at the variables' signs, the results indicate that the market turnover, the average first day return on IPOs, the dividend premium and the volatility premium have a positive impact on  $ISI^\perp$ . Conversely, the number of IPOs and the share of equity issues relate negatively with sentiment. The results obtained in this dissertation differ from those demonstrated by Baker and Wurgler (2006), in relation to the interaction of the share of equity issues, the number of IPOs and the dividend premium with the sentiment index. In the U.S. stock market, the dividend premium has a negative impact on sentiment and the number of IPOs and the share of equity issues have a positive influence on sentiment. The difference between the French and the U.S. markets results can be attributed to the size and importance of the IPOs' market in these two countries. The U.S. IPOs'

market has a much greater impact on its financial market than in the French case. The importance of paying dividends also differs from market to market, which may also justify this difference (Baker et al., 2012).

The inclusion of two sentiment measures, built from different information sources, aims to provide a better understanding of the potential differences on the explanatory power of both measures, whether at an aggregated market level or at a cross-section level of stock returns. Therefore, analysing and comparing the results obtained allows the study of their characteristics and adequacy to different contexts.

The study of the correlation between the two investor sentiment measures and the evolution of both during the investigation period leads to the conclusion that they are in fact substantially different from one another. The  $ISI^L$  and CCI present a correlation of, approximately, -0.02, suggesting that they capture different influences and move in opposite directions. As for the evolution of the two measures, it suggests that the CCI is intimately related to the economic environment and the financial tendencies captured in the French market. On the other hand,  $ISI^L$  shows a greater stability throughout time.

The first objective of this dissertation is to assess the impact of investor sentiment (measured by  $ISI^L$  and CCI) in the aggregated stock market returns for four distinct time horizons: 1, 6, 12 and 24 months. When studying the explanatory power of investor sentiment in this context, the results found support two main conclusions. First, when investor sentiment is captured using CCI, it reveals a significant negative impact on the aggregated market returns in all time horizons. Second, when resorting to  $ISI^L$ , solely for the 24 months' time horizon, the aggregated market returns show to be positively influenced by investor sentiment. For the remaining, shorter time horizons, using  $ISI^L$ , investor sentiment displays no impact. Thus, overall results support the conclusion that CCI is the most suitable index to study the explanatory power of investor sentiment on aggregated market returns.

The second major objective is to examine the impact of investor sentiment (measured by  $ISI^L$  and CCI) on different types of stocks. To achieve this, a cross-section of stock returns is performed considering distinct firms' characteristics, namely size, total risk, profitability, dividend policy, asset tangibility, growth opportunities and/or distress. To study the impact of investor sentiment on these particular types of stocks, three approaches are applied: sorts, predictive

regressions for long-short portfolios and systematic risk. Overall, results show the impact of sentiment in the studied characteristics portfolios to be higher when sentiment is measured by the ISI<sup>L</sup> than when sentiment is measured through the CCI. Hence, results reveal ISI<sup>L</sup> as the most adequate index to assess the impact of investor sentiment on the cross-section of market returns.

Similarly to the previous findings by Baker and Wurgler (2006) and Baker et al. (2012), using ISI<sup>L</sup>, both the sorts and the predictive regressions for long-short portfolio analysis arrive to the same conclusions. Results support that small, high volatility, unprofitable, non-dividend-paying, less tangible, extreme growth and distressed stocks tend to earn subsequent higher (lower) returns after periods of low (high) sentiment. Results also show that changes in investor sentiment have a higher impact on these type of stock returns, which can be explained by the fact that these characteristics are harder to value and more difficult to arbitrage.

This dissertation also suggests that the conditional characteristics effects that were previously presented, do not reflect compensation for classical systematic risks. These results are consistent with Baker and Wurgler (2006).

Another relevant conclusion can be inferred from the fact that the most suitable index for the study of the aggregate market returns differs from the one most adequate to the analysis of the cross-section market returns. The CCI yields better results in an aggregated context. This falls in line with the previous finding that CCI tracks much more closely the economic events and the financial market trends experienced in the French market. As for the ISI<sup>L</sup>, its adequacy towards the cross-section market returns, leads to the conclusion that when investor sentiment is calculated using actual market variables, the results are more susceptible to capturing subtle differences in distinct types of actions.

Further research should focus on the study of other sentiment proxies to capture the investor sentiment in the financial markets. Is it vital to understand the idiosyncratic characteristics of the country that is under analysis, in order to understand what the results obtained using a certain proxy of investor sentiment is really capturing. Current literature presents clear evidence that the investor sentiment affects stocks returns. However, it is important to continue to study and develop new sentiment measures and understand its influence in financial markets. Specifically, further studies should focus on its correlation with political, social and economic variables, specific

to an individual country. Understanding this issue, will allow a better understanding of the measures more adequate to study each specific country.

Another aspect that needs further research is the set of a firm's characteristics that are sensitive to sentiment. Other characteristics such as social responsibility, a firm's core business and its nationality, among many others, should be included in further research in order to contribute towards a better understanding of which firms are more prone to be influenced by investor sentiment.



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## 8. Appendices

**Table 1.**  
**Sentiment proxies' data**

The table present all variables collected to construct the raw and the orthogonalized Investor Sentiment Index (ISI and ISI $\perp$ ) and the Consumer Confidence index (CCI). For each variable, it is presented the source and the code in the database. The data is collected on the first day of each month and is computed on a monthly basis. All variables are expressed in euros. The period under analysis starts at January 01, 1993 and ends on December 31, 2013, combining a total of 252 months.

Item	Code	Source	Period	Periodicity
<b>Turnover (<i>TURN</i>)</b>				
Turnover by Volume	VO	Datastream	January 1993 – December 2013	Monthly
Market Value	MV	Datastream	January 1993 – December 2013	Monthly
<b>IPO volume (<i>NIPO</i>) and IPO first-day returns (<i>RIPO</i>)</b>				
IPO flag	IPO	SDC	January 1993 – December 2013	Monthly
Stock price at close of offer / First trade	PRSDAY	SDC	January 1993 – December 2013	Monthly
Offer price	P	SDC	January 1993 – December 2013	Monthly
<b>Equity issues (<i>S</i>)</b>				
Common equity as % of capitalization after offering	CCAP	SDC	January 1993 – December 2013	Monthly
<b>Dividend Premium (<math>P^D - ND</math>)</b>				
Market to book value	MTBV	Datastream	January 1993 – December 2013	Monthly
Dividends per share	DPS	Datastream	January 1993 – December 2013	Monthly
<b>Consumer Confidence Index (<i>CCI</i>)</b>				
Consumer Confidence Index		DG ECFIN	January 1993 – December 2013	Monthly
<b>Volatility Premium (<i>PVOL</i>)</b>				
Stock return	RI	Datastream	January 1993 – December 2013	Monthly
Market value	MV	Datastream	January 1993 – December 2013	Monthly
Market to book value	MTBV	Datastream	January 1993 – December 2013	Monthly

**Table 2.**  
**Firm-level data**

The table present all variables collected for different firms' characteristics under and to compute stock market returns. For each variable, it is presented the source and the code in the database. The data is collected on the first day of each month and is computed on a monthly basis. All variables are expressed in euros. The period under analysis starts at January 01, 1993 and ends on December 31, 2013, combining a total of 252 months.

<b>Item</b>	<b>Code</b>	<b>Source</b>	<b>Period</b>	<b>Periodicity</b>
<b>Returns</b>				
Stock return	RI	Datastream	January 1993 – December 2013	Monthly
<b>Size</b>				
Market Equity	WC08001	Datastream	January 1993 – December 2013	Monthly
<b>Profitability</b>				
Net income before extraordinary items/preferred dividends	WC01551	Datastream	January 1993 – December 2013	Monthly
Deferred income taxes and investment tax credit on income statements	WC04101	Datastream	January 1993 – December 2013	Monthly
Preferred dividend requirements	WC01701	Datastream	January 1993 – December 2013	Monthly
Total shareholders' equity	WC03995	Datastream	January 1993 – December 2013	Monthly
Deferred taxes on balance sheets	WC03263	Datastream	January 1993 – December 2013	Monthly
<b>Dividend policy</b>				
Dividends per share	DPS	Datastream	January 1993 – December 2013	Monthly
Total shareholders' equity	WC03995	Datastream	January 1993 – December 2013	Monthly
Deferred taxes on balance sheets	WC03263	Datastream	January 1993 – December 2013	Monthly
<b>Asset tangibility</b>				
Property, plant and equipment	WC02301	Datastream	January 1993 – December 2013	Monthly
Research and development	WC01201	Datastream	January 1993 – December 2013	Monthly
Total assets	WC02999	Datastream	January 1993 – December 2013	Monthly
<b>Growth opportunities and/or distress</b>				
Dividends per share	DPS	Datastream	January 1993 – December 2013	Monthly
Total shareholders' equity	WC03995	Datastream	January 1993 – December 2013	Monthly
Deferred taxes on balance sheets	WC03263	Datastream	January 1993 – December 2013	Monthly
Market equity	WC08001	Datastream	January 1993 – December 2013	Monthly
External financing	WC04500	Datastream	January 1993 – December 2013	Monthly

**Table 4.****Macroeconomic variables**

The table presents the macroeconomic variables used to control for macroeconomic conditions. For each macroeconomic variable it is presented the source and the code in the database. The data is collected on the first day of each month on a monthly basis. The period under analysis starts at January 01, 1993 and ends on December 31, 2013, combining a total of 252 months.

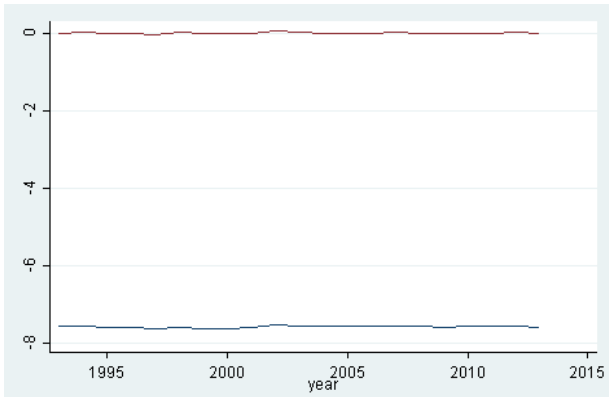
<b>Item</b>	<b>Code</b>	<b>Source</b>	<b>Period</b>	<b>Periodicity</b>
<b>Industrial production</b>	FRIPTOT.G	Datastream	January 1993 – December 2013	Monthly
<b>Inflation rate</b>	FRCPANNL	Datastream	January 1993 – December 2013	Monthly
<b>CPI</b>	FRCONPRCE	Datastream	January 1993 – December 2013	Monthly
<b>Interest rate</b>	FRPRATE.	Datastream	January 1993 – December 2013	Monthly
<b>Employment growth</b>	FRSURFETQ	Datastream	January 1993 – December 2013	Monthly
<b>GDP</b>	FRML2103Q	Datastream	January 1993 – December 2013	Monthly



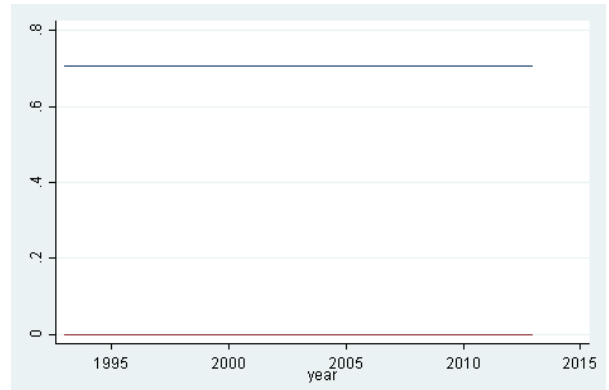
**Figure 1.**  
**Investor sentiment proxies**

Panel A plots the log turnover. Turnover (TURN) is calculated as the ratio of total value of shares traded during a month divided by the market capitalization of the previous month. Panel B exhibits the equity share in new issues. The equity-share of new issues (S) represents the percentage of gross equity in total capitalization after the issuing. Panel C represent the number of IPOs over a given month (NIPO). Panel D shows the average first-day returns of IPOs (RIPO). RIPO is calculated as the difference between the first trading price and the offer price divided by the offer price. Panel E presents the dividend premium ( $P^{D-ND}$ ) and is calculated as log ratio of the value-weighted average market-to-book ratio of payers and non-payers. Panel F plots the volatility premium (PVOL). The volatility premium represents the natural log of the ratio of the value-weighted average market to book ratio of high volatility stocks to that of low stocks. TURN,  $P^{D-ND}$  and PVOL are obtained through Datastream and S, RIPO and NIPO are obtained through SDC. The blue line stands for the raw data. Each measure is regressed with six macroeconomic conditions - industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), policy interest rate (INTR) and employment growth(EG). The red line is the residuals from this regression and the red one plots the raw proxies.

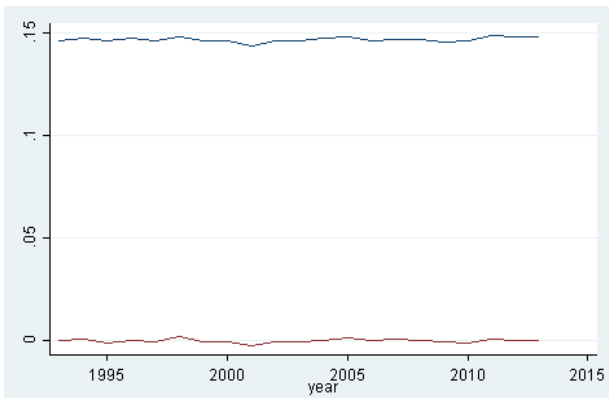
**Panel A. Turnover**



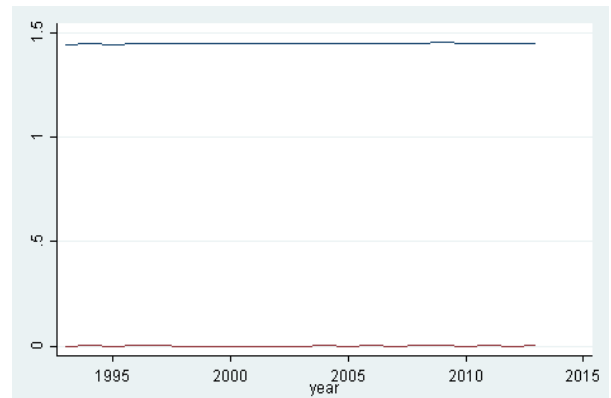
**Panel B. Equity share in new issues**



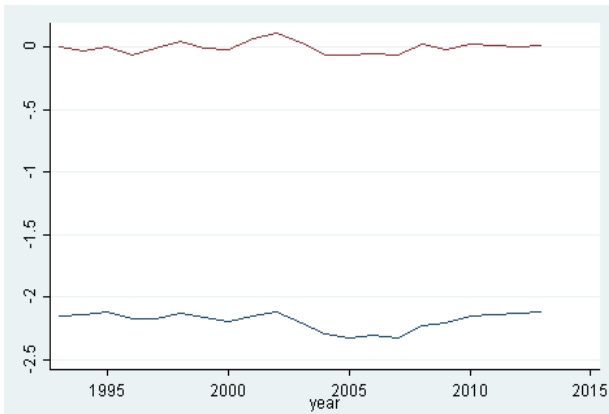
**Panel C. Number of IPOs**



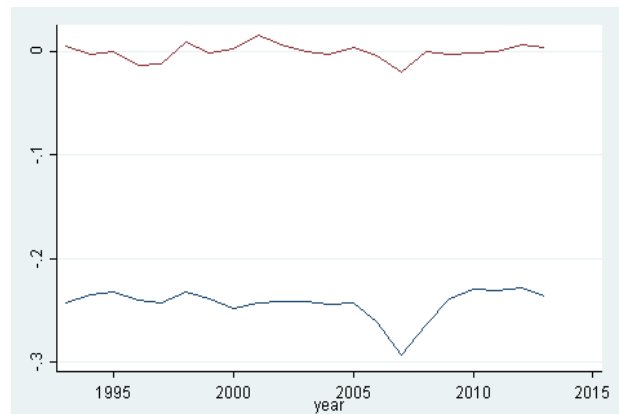
**Panel D. Average first-day return on IPOs**



**Panel E. Dividend premium**



**Panel F. Volatility premium**

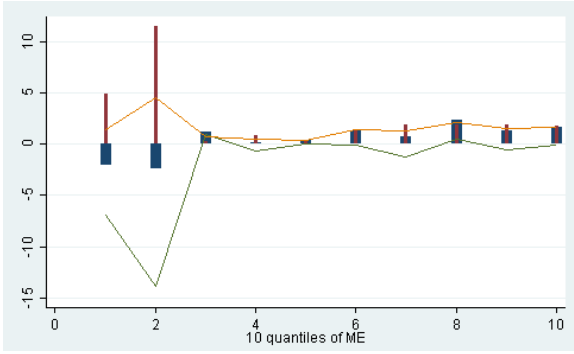


**Figure 3.**

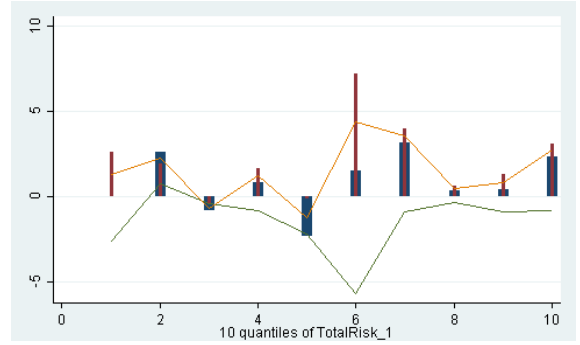
**Sorting approach: Future returns by ISI<sup>L</sup> and firm characteristics, France 1993 – 2013**

For each month, it was constructed 10 equally-weighted portfolios according several firm characteristics and the level of ISI<sup>L</sup> on the previous year, such as: size (Panel A), total risk (Panel B), profitability (Panel C), dividend policy (Panel D), asset tangibility (Panel E and F) and/or distress (Panel G, H and I). The blue bars correspond to positive periods of ISI<sup>L</sup>, whereas the red bars are associated with negative periods of ISI<sup>L</sup>. The orange line show the average across both periods and the green line plots the difference.

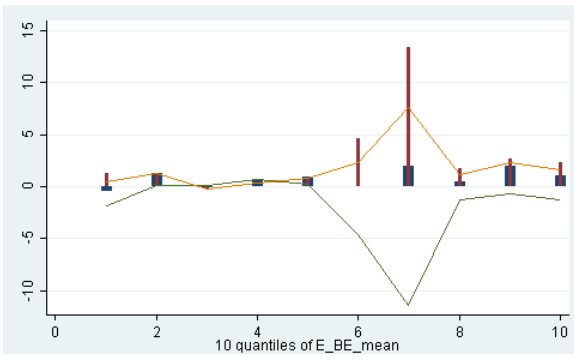
Panel A: ME



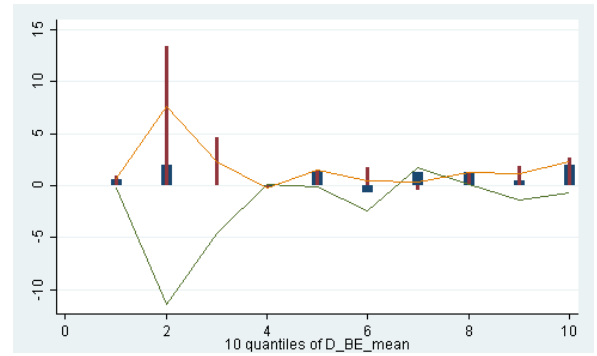
Panel B: Total risk



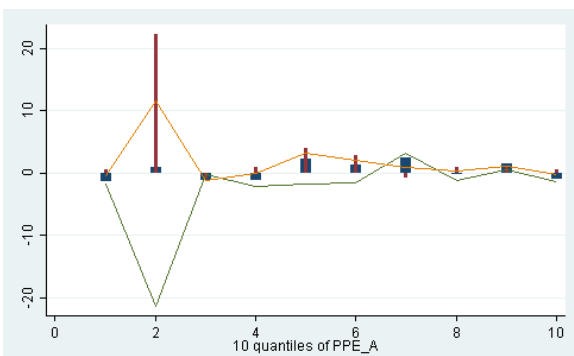
Panel C: Earnings



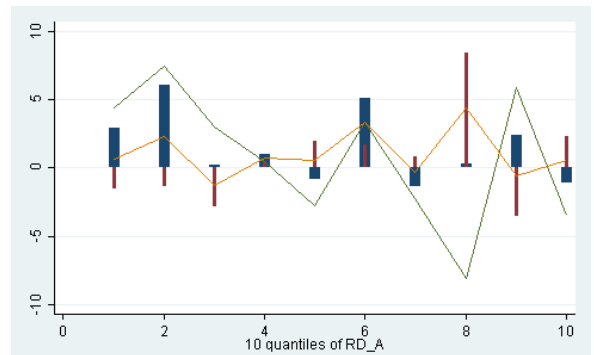
Panel D: Dividends



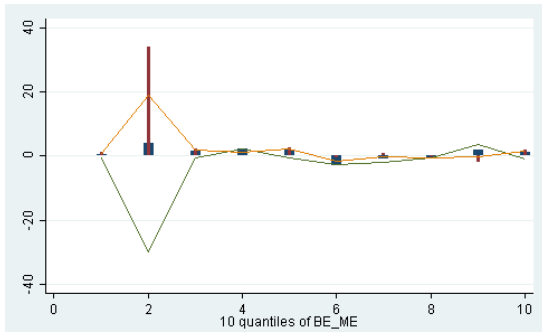
Panel E: PPE/A



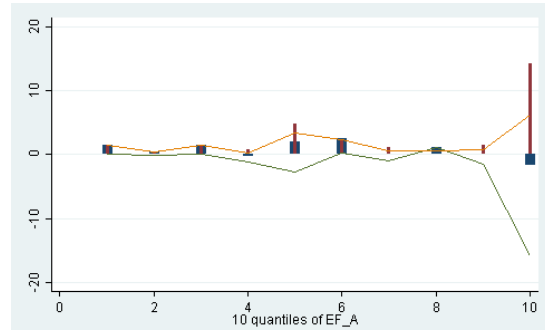
Panel F: RD/A



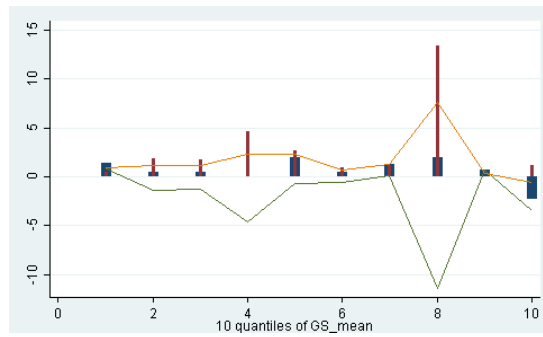
Panel G: BE/ME



Panel H: EF/A



Panel I: GS

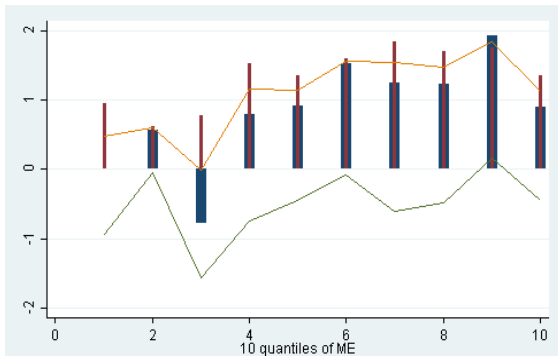


**Figure 4.**

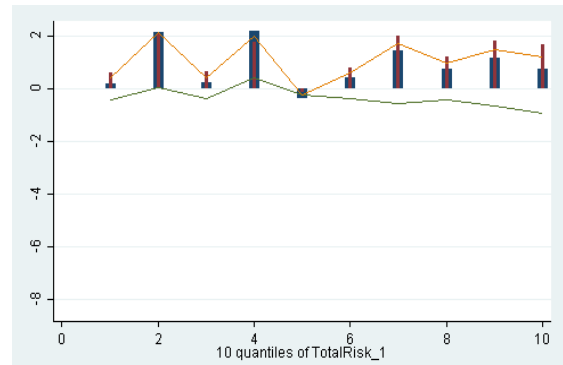
**Sorting approach: Future returns by CCI and firm characteristics, France 1993 – 2013**

For each month, it was constructed 10 equally-weighted portfolios according several firm characteristics and the level of CCI on the previous year, such as: size (Panel A), total risk (Panel B), profitability (Panel C), dividend policy (Panel D), asset tangibility (Panel E and F) and/or distress (Panel G, H and I). The blue bars correspond to positive periods of CCI, whereas the red bars are associated with negative periods of CCI. The orange line show the average across both periods and the green line plots the difference.

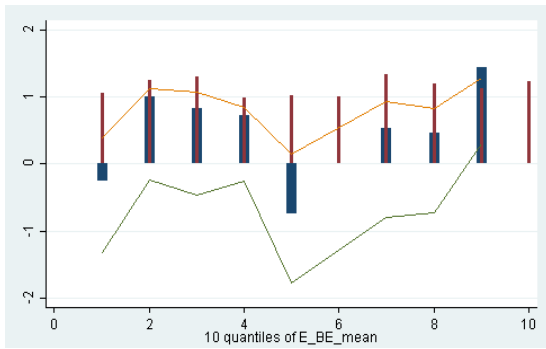
Panel A: ME



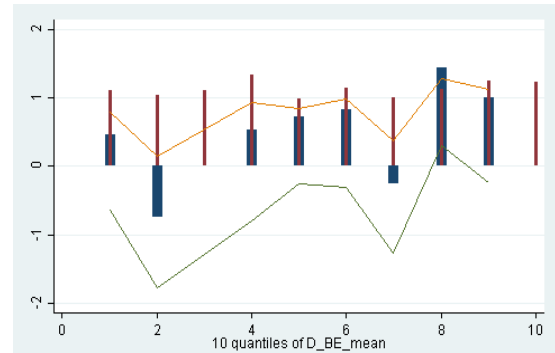
Panel B: Total risk



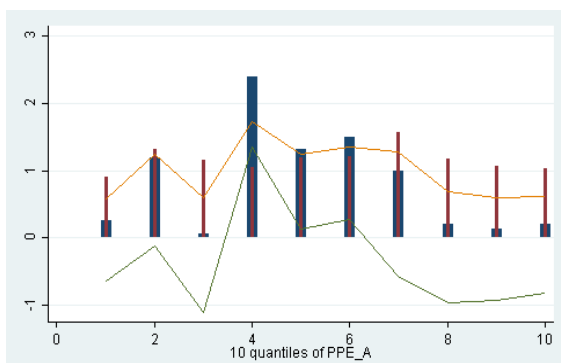
Panel C: Earnings



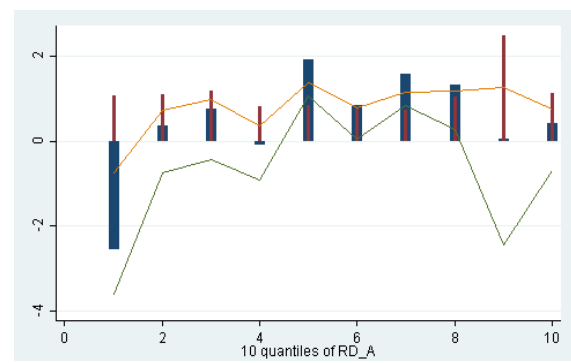
Panel D: Dividends



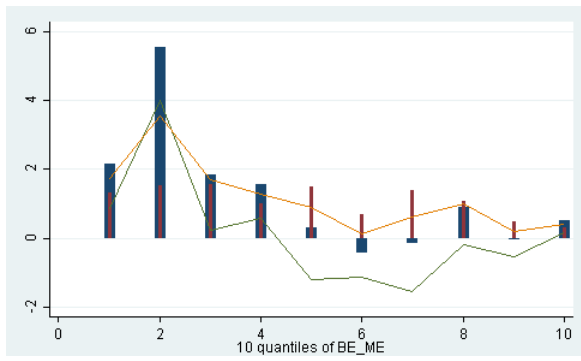
Panel E: PPE/A



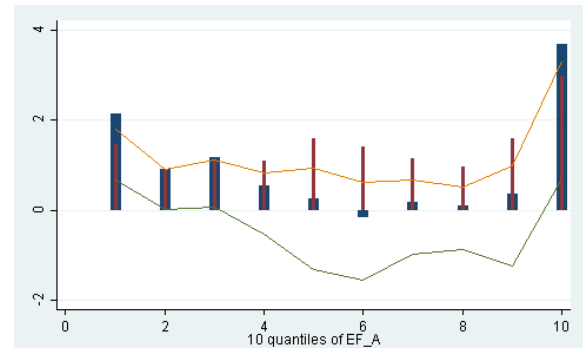
Panel F: RD/A



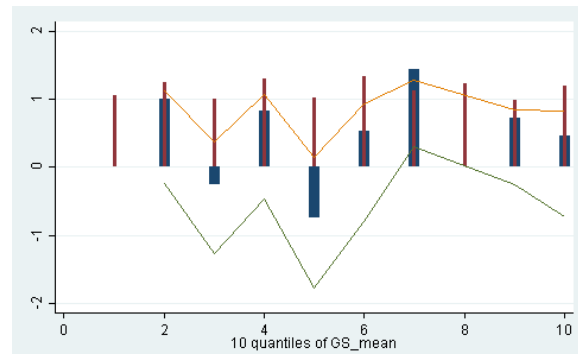
Panel G: BE/ME



Panel H: EF/A



Panel I: GS





**Table 11.**

**Time Series Regressions of Portfolio Returns controlling for the Fama-French factors, 1993 to 2013**

The table presents the results (coefficients and p-values in brackets) for the time series regressions of portfolio regressions controlling for the Fama-French factors, using the orthogonalized Investor Sentiment Index ( $ISI^{\perp}$ ) and the Consumer Confidence Index (CCI) as sentiment measures. The results are displayed for four distinct time horizons: 1, 6, 12 and 24 months.  $ISI^{\perp}$  consists in the first principal common component of six orthogonalized sentiment proxies: share turnover (TURN), number of IPOs (NIPO), average first-day returns on IPOs (RIPO), share of equity issues (S), dividend premium ( $P^D - N^D$ ) and volatility premium. This index is controlled for six macroeconomic conditions, such as: industrial production index (IPI), consumer price index (CPI), gross domestic production (GDP), inflation rate (INFR), policy interest rate (INTR) and employment growth (EG). CCI is the standardized consumer confidence index published by DG ECFIN. The sentiment measures are calculated on a monthly basis. The long-short portfolios are constructed based on several firm characteristics: size (ME), total risk ( $\sigma$ ), dividend policy (D), profitability (E), asset tangibility (PPE/A and RD/A) and growth opportunities and/or distress (BE/ME and EF/A). When sentiment is measured by CCI, the regression's independent variables are the sentiment index (CCI) and the macroeconomic variables (IPI, CPI, GDP, INFR, INTR and EG). High corresponds to a stock in the top three deciles, low describes a stock in the bottom three deciles and stock in the middle four deciles represents medium.

		Time horizon															
		1 month				6 months				12 months				24 months			
		ISI		CCI		ISI		CCI		ISI		CCI		ISI		CCI	
		d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)	d	p(d)
<b>Size portfolio</b>																	
<b>ME</b>	SMB	-0.23	[0.00]	-0.27	[0.00]	0.60	[0.00]	-0.15	[0.00]	-1.42	[0.00]	-0.30	[0.00]	-0.39	[0.00]	-0.10	[0.00]
<b>Total risk portfolio</b>																	
<b>σ</b>	High-Low	-0.06	[0.00]	-0.06	[0.00]	-0.06	[0.00]	-0.04	[0.00]	-0.05	[0.00]	-0.05	[0.00]	-0.57	[0.00]	-0.01	[0.00]
<b>Profitability portfolio</b>																	
<b>E</b>	>0 - <0	1.61	[0.00]	0.20	[0.00]	0.48	[0.00]	0.10	[0.00]	0.73	[0.00]	0.12	[0.00]	0.80	[0.00]	-0.18	[0.00]
<b>Dividend policy portfolio</b>																	
<b>D</b>	>0 - =0	2.10	[0.00]	0.07	[0.00]	1.04	[0.00]	0.29	[0.00]	1.98	[0.00]	0.37	[0.00]	1.60	[0.00]	0.54	[0.00]
<b>Tangibility portfolios</b>																	
<b>PPE/A</b>	High-Low	-0.79	[0.00]	0.26	[0.00]	1.12	[0.00]	0.14	[0.00]	-1.74	[0.00]	0.16	[0.00]	1.49	[0.00]	0.05	[0.00]
<b>RD/A</b>	High-Low	-0.72	[0.00]	0.12	[0.00]	-0.53	[0.00]	-0.03	[0.00]	-0.44	[0.00]	0.02	[0.00]	-0.60	[0.00]	-0.02	[0.00]
<b>Growth opportunities and Distress portfolios</b>																	
<b>BE/ME</b>	HML	1.40	[0.00]	0.23	[0.00]	0.11	[0.00]	0.29	[0.00]	-0.34	[0.00]	0.23	[0.00]	0.39	[0.00]	0.26	[0.00]
<b>EF/A</b>	High-Low	-1.97	[0.00]	-0.21	[0.00]	-0.54	[0.00]	-0.07	[0.00]	1.15	[0.00]	-0.17	[0.00]	0.22	[0.00]	-0.14	[0.00]
<b>Growth opportunities portfolios</b>																	
<b>BE/ME</b>	Medium-Low	1.07	[0.00]	0.12	[0.00]	0.56	[0.00]	0.08	[0.00]	-0.23	[0.00]	0.10	[0.00]	0.39	[0.00]	-0.04	[0.00]
<b>EF/A</b>	High-Medium	-1.41	[0.00]	-0.15	[0.00]	-2.48	[0.00]	0.07	[0.00]	-1.10	[0.00]	-0.21	[0.00]	-0.37	[0.00]	-0.02	[0.00]
<b>Distress portfolios</b>																	
<b>BE/ME</b>	High-Medium	-0.77	[0.00]	-0.12	[0.00]	-0.50	[0.00]	-0.11	[0.00]	-0.10	[0.00]	-0.11	[0.00]	-0.14	[0.00]	0.02	[0.00]
<b>EF/A</b>	Medium-Low	0.84	[0.00]	0.11	[0.00]	1.00	[0.00]	-0.12	[0.00]	0.63	[0.00]	0.09	[0.00]	0.95	[0.00]	0.08	[0.00]