Is cognitive bias really present in analyst forecasts? The role of investor sentiment

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ABSTRACT

This paper analyses four key markets within the European context. In this context, where the level of analyst coverage is lower than in the US setting, we aim to ascertain whether the origin of optimism in analyst forecasts in these markets is mainly strategic or whether it also contains an element of cognitive bias. Despite the fact that forecast errors lack the explanatory power to account for a significant percentage of the relationship between market sentiment and future stock returns, our new tests based on selection bias (SB1 and SB2), in conjunction with an analysis of abnormal trading volume, confirm the presence of both cognitive bias and strategic behaviour in analyst forecasts. This shows that, although regulation can reduce analyst optimism bias, the benefits are constrained by the fact that optimism bias is partly associated with cognitive bias.

Keywords: Analyst forecasts, Optimism, Investor Sentiment, Strategic Behaviour, Cognitive Bias

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1-Introduction

Financial analysts play an important role collecting, processing and distributing financial information about firms to investors. They issue value-relevant information for end-users about corporate data, although there is widespread evidence that they fail to fully reflect all the available information in their forecasts. This stream of research has also shown extensively that analysts are optimistic in their Earnings Per Share (EPS) forecasts (see Brown, 1997 and Chopra, 1998, among others). This circumstance produces two opposite effects. On the one hand, if analysts are optimistic, their accuracy is lower and, consequently, their credibility and ranking may suffer. On the other hand, upward-biased forecasts generate investment banking business or commissions for analysts' brokerage houses, which could compensate for the previous negative effect.

Several studies have investigated the causes of this optimism because its potential correction and consequences are clearly linked to its origin. Recent studies have re-ignited the debate about whether the observed optimism is due to strategic behaviour by analysts (see Ertimur *et al.*, 2011 or Karamanou, 2011) or if it is mainly motivated by their cognitive bias (see Qian, 2009 or Hribar and McInnis, 2012).

One of the variables associated with cognitive bias is investor sentiment. This is a variable that reflects optimism or pessimism about stocks in general (Baker, *et al.* 2012) or investor opinion, usually influenced by emotion, about future cash flows and investment risk (Chang, *et al.* 2012). The existence of high or low sentiment in the market may affect all the participants therein, including financial analysts. Hribar and McInnis (2012), analysing the US market, find that when sentiment is high, analyst forecasts are relatively more optimistic for hard-to-value stocks. They also find that forecast errors account for a sizeable percentage of the explanatory power of the sentiment variable for cross-sectional futures returns, thus providing support for the argument that investor sentiment affects earnings expectations in this type of stocks.

European financial markets are subject to less analyst coverage than the US market, as noted by Jegadeesh and Kim (2006), who found levels of around 90% for US firms and no higher than 25% for European firms during the period 1993-2002. This characteristic enhances the attractiveness of the European setting for the purposes of our study, because it means that we are likely to find less cognitive bias because the type of stocks being followed by analysts are less prone to behavioural biases. This makes the European setting a suitable framework in which to test for significant levels of cognitive bias in analyst forecasts, using the investor sentiment as the measuring instrument, this being the main objective of our paper.

To explore this issue, we begin by testing whether investor sentiment affects EPS forecasts and whether the impact varies with stock type. Our results reveal that investor sentiment affects forecast errors, especially in hard-to-value stocks. The next question is whether analyst forecast errors play a role in the sentiment-return relationship as an indicator of expectation errors, which would confirm the presence of cognitive bias. Our results, unlike those obtained by Hribar and McInnis (2012) for the US market, show that forecast errors lack the power to provide a significant part of the explanation for the link between investor sentiment and future stock returns. Thus, we have no evidence of the presence of cognitive bias in these markets. Nor, however, do we have any evidence to prove its absence. In order to shed further light on the issue, therefore, we check for the presence of strategic behavior and cognitive bias in analyst forecasts by running two new tests based on selection bias (which is when analysts decline to make any forecast rather than issue a negative one). We run these tests in conjunction with an analysis of abnormal trading volume in hard-to-value versus less hard-to-value stocks, in order to discern between different causes in the event of the tests proving inconclusive. The combined results of these tests confirm the presence of a significant degree of both biases (strategic and cognitive) in analyst forecasts. Despite the contrasting characteristics of the markets considered, the results are robust, which increases their generalizability. The fact that no significant differences emerge between the UK (representative of the Anglo Saxon financial system) and the other European markets (representative of the Continental financial system) is an indication that issues relating the type of financial system do not significantly alter the impact of strategic or cognitive bias on the degree of optimism in analyst forecasts.

This paper contributes to the literature in various ways. Firstly, we conduct our analysis in the previously unstudied context of European financial markets, which, as already stated, contrast with the US market by having a lower level of analyst coverage.

Secondly, the analysis of four key European countries (France, Germany, Spain and the UK) with different stock characteristics (Corredor *et al.,* 2013a), corporate governance structures (see La Porta *et al.,* 1998), and cultural dimensions (see Hofstede, 2001) will enable us to check the robustness of the results to these differences within that context[1]. Despite constraints due to the small number of countries considered, we also test to see whether the UK, as a representative of the Anglo Saxon system, presents significant variation with respect to the other three, which can be taken to represent the continental system. This enables us to compare the impact of this kind of differences with that of analyst coverage levels, when trying to determine what drives the optimism in analyst forecasts.

Thirdly, as a methodological contribution, we develop new tests based on the concept of selection bias (Selection Bias 1, SB1 and Selection Bias 2, SB2). SB1 enables us to test for the presence of strategic bias in analyst forecasts. SB2 is a modified version of SB1 for use with more sentiment-prone stocks in the presence of high investor sentiment. When combined with an analysis of abnormal trading volume, SB2 enables us to test for the presence of cognitive bias or strategic bias linked to the level of investor sentiment[2]. It should be emphasized that these statistics enable us to detect strategic bias both conditional on and unconditional on investor sentiment, a distinction that was not possible with other approaches. This type of joint analysis enables us to see whether the optimism in analyst forecasts is strategic (be it conditional on sentiment or not), cognitive, or a mixture of the two. Previous studies analysing the origin of such optimism have focused on just one of these biases, sometimes using non-conclusive testing methods.

The practical implications of these results are very important because, any demonstrated cognitive element in the observed analyst bias will reduce the effectiveness of regulations aimed at correcting potential bias in analyst behaviour.

The paper is organized as follows: the second section presents the theoretical framework. The third describes the database, the European setting, details of the construction of the investor sentiment proxy and the calculation of EPS forecast errors. Section four examines the effect of investor sentiment on EPS forecast errors. The results of the analysis of expectation errors as a driver of the sentiment-return relationship and the different tests to determine whether cognitive bias is really present in analyst forecasts appear in sections 5

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[1] Our work will include both individual and aggregate analyses of these markets, in order to increase the generalizability of the results. The analysis of individual markets will enable us to check the robustness of our findings to cross-country differences. Note that our aim is not to test the impact of any single factor (stock characteristics, corporate governance structure or cultural dimensions) on a specific result, since this would require us to investigate a very large number of countries in order to isolate any other differentiating features.

[2] Strategic bias may be unconditional on sentiment (tested by the SB1 statistic) or conditional on sentiment (tested by the SB2 statistic). The latter case is when analysts are aware that investors are optimistic due to high market sentiment and decide to issue more optimistic forecasts than they would under other circumstances, simply because they think investors will believe them, not because they themselves are led by the level of market sentiment.

and 6, respectively. Finally, section seven presents the main conclusions that emerge from the paper.

2-Theoretical framework

The literature on EPS forecast errors has widely shown that they are positively biased (Brown, 1997, Chopra, 1998; Richardson, *et al*., 2004, and Qian, 2009, among others). The incentives to issue optimistic forecasts are diverse. There is a link between analyst optimism bias, their career development, and their facility of access to non-public information (Das *et al*., 1998, Lim, 2001, Hong and Kubik, 2003, Chen and Matsumoto, 2006, among others). Optimism in EPS forecasts is also associated with subsequent investment banking business and commissions for analysts' brokerage houses (Lin and McNichols, 1998, Michaely and Womack, 1999, Lim, 2001, Cowen *et al*., 2006, Barber *et al*, 2007 and Agrawal and Chen, 2008, among others). This evidence reflects companies' preference for positive rather than negative forecasts, which could induce the bias detected.

Francis (1997) suggests the existence of three different types of bias that could produce the optimism observed in analyst forecasts. Reporting bias reflects an explicit intention to mislead by artificially inflating earnings expectations. Selection bias is observed when analysts prefer not to issue a report rather than issue negative information about a company. The third, cognitive bias, is due to analysts inadequately processing the available information, and thereby being unable to produce unbiased forecasts. Although there are incentives to offer biased forecasts, the ultimate cause of analyst optimism is far from clear and there is an interesting ongoing debate with empirical evidence favourable to both explanations: strategic behaviour or cognitive bias (see Karamanou, 2011 and Ertimur *et al*., 2011 or Qian, 2009 and Hribar and McInnis, 2012, as recent examples of different conclusions regarding this issue).

As already noted, investor sentiment is a variable that reflects optimism or pessimism about stocks in general and can therefore affect financial analysts. Baker and Wurgler (2006, 2007) show that, when investor sentiment is high/low, stock returns suffer an over/undervaluation which later revert to their fundamentals.

The two main channels through which sentiment can affect pricing are sentiment-based demands and arbitrage constraints. In the first, sentimental demand shocks vary across stocks while arbitrage limits are constant. Interpreting sentiment as the propensity to speculate, sentiment increases the relative demand for stocks that are vulnerable to speculation, whose valuations are subjective and difficult to determine, and whose contemporaneous returns are higher than is justifiable. Specifically, small stocks, high volatility stocks, extreme growth stocks, distressed stocks, young stocks and non-dividend-paying stocks, are the most difficult to price and, therefore, the most vulnerable to investor sentiment. In the case of the second channel, the effect of changes in sentiment will be uniform while the difficulty of arbitrage will differ across stocks. Some papers, such as Baker and Wurgler (2006 and 2007), have shown that arbitrage is particularly costly and risky with certain stock types (young stocks, small stocks, unprofitable stocks, extreme growth stocks and distressed stocks). These two channels appear to affect the same type of stocks. The most speculative stocks are also the hardest to arbitrage and will therefore be the most strongly influenced by investor sentiment. Lemmon and Portniaguina (2006) find this effect to be predominantly present in small stocks and those with less institutional ownership. Baker and Wurgler (2006, 2007) find that small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks are the most heavily affected and likely to suffer from over- or under-pricing, depending on investor sentiment.

To the best of our knowledge, very few papers have analysed the relationship between investor sentiment and analyst optimism, by testing for the presence of sentiment as a component of analyst optimism, and they focus on the US market. Bergman and Roychowdhury (2008) and Qian (2009) present evidence of the association between sentiment and the bias in analyst earnings forecasts without making any in-depth exploration to determine whether the origin of analyst optimism is strategic or cognitive. Qian (2009) shows that analysts issue more optimistic earnings forecasts when sentiment is high, especially in smaller assets and value stocks. Hribar and McInnis (2012) also find this relationship. They also show that forecast errors are an intermediating variable in the relationship between sentiment and future stock returns. This finding supports the presence of cognitive bias in analysts.

The different levels of analyst coverage in the US and European markets and their potential influence, particularly on the role of cognitive bias in the level of optimism in analyst forecasts, make it all the more worthwhile to take European markets as our framework of analysis in order ascertain whether it is possible to generalize the findings of Hribar and McInnis (2012). The four key European countries selected for analysis (France, Germany, Spain and the UK) have contrasting features stemming from their different financial systems: the Anglo Saxon system (UK) and the continental system, as well other market-specific differences.

We base our analysis on a set of tests taken from the literature, and two new methodological proposals of our own tests based on selection bias, SB1 and SB2, which allow us to test for the presence of strategic behaviour (both conditional on and unconditional on sentiment) and cognitive bias in analyst forecasts.

3-Database

3.1 The European setting

There are notable differences between the US market and European markets that can justify our interest in testing for the presence of strategic behaviour and cognitive bias in analyst forecasts. For one thing, the level of cross-listing in Europe is considerably lower than in the US and this has its implications. According to some estimates, clearing and settlement costs for European transactions are nine times higher than they are for US transactions, and the costs of cross-border transactions in Europe can be as much as forty-six times higher than they are in the United States (London Stock Exchange 2001). Furthermore, despite a gradual convergence in the way European and the US stock markets work, some institutional differences still remain. The US regulatory authority is concentrated into a single agency, the SEC, which is responsible for setting standards. In Europe, however, a history characterized by individual stock markets subject to domestic legislation has given way to an era of member-state-negotiated legislation under the direction of the European Union. In addition, European stock markets are not subjected to harmonized rules and the reforms introduced by the Directive do not mandate specific market structure rules beyond transparency requirements. Higher transaction costs, together with impediments to effective regulation might suggest a stronger analyst bias.

Also, and more importantly for the objective in hand, there is a clear difference in the level of analyst coverage between US and European markets. Thus, Jegadeesh and Kim (2006) show that analyst coverage of US firms for the period 1993-2002 reached a level of around 90%, while in Europe it was never any higher than 25%. In particular, according to data collected by Jegadeesh and Kim (2006, Table I) the number of US firms with at least two active recommendations in the IBES database is 5.86 times the number of British firms, 12.72 times the number of French firms, 16.05 times the number of German firms and 39.94 times the number of Italian firms, the last of these being very similar to the number of Spanish firms. Although we use the FactSet as our reference database, the difference in analyst coverage between the US and Europe is no less important.

Due to the very nature of the type of stocks followed by analysts, lower coverage implies less consideration of those stocks that are hard to value and to arbitrage, which are precisely the ones on which behavioural biases, such as those driven by investor sentiment, tend to have the strongest impact (see Baker and Wurgler, 2006, 2007 or Kumar, 2009).

In order to address this issue, this study uses data from four of the main European markets in terms of capitalization: France (FR), Germany (GE), Spain (SP) and the United Kingdom (UK). According to the World Federation of Exchanges classification for 2011, the London SE Group is the largest group in Europe in terms of capitalization, followed by NYSE Euronext (Europe), the Deutsche Börse and the BME Spanish Exchanges.

The reason for this choice of countries is to enable us to make reasonably homogeneous comparisons among assets and, thus, to control as much as possible for the potential influence of the level of development of the stock market in these comparisons. Our choice is based not only on the importance of the markets but also on the need to consider countries that differ with respect to cultural dimensions, corporate governance and the quality of the legal environment, and to include representatives of both the Anglo-Saxon and the Continental financial systems. The UK belongs to the Anglo-Saxon system, which is characterized by shareholder dispersion and a wider separation between ownership and control, while Germany, France and Spain form part of the Continental system, which has a highly concentrated ownership structure that promotes stability and commitment, although it reduces capital market liquidity. Another key feature of the Continental system is the presence of control groups, which means that managers are kept under strict control unless they belong to the power group. Most firms are under owner-management. Cross-share holdings are another widespread feature. These characteristics mean that firms based on the Continental, or insider, model are quite different from those based on the Anglo-Saxon model, which is characterized by shareholder dispersion and a wider separation between ownership and control. In terms of institutional investor type, the majority of institutional investors in Continental Europe are banks, which take an active part in firm management, whereas, in the Anglo-Saxon system, they are predominantly mutual funds and pension funds. The Anglo Saxon system's clearer orientation towards the stock market might give financial analysts a more prominent role in these markets. It has no direct implications for the potential impact of their strategic behaviour, however, because, although the higher trading volume associated with their activity might increase their incentive to act strategically, their actions are, by the same token, likely to come under stricter control. Thus, variation in the magnitude of the impact of this type of behaviour in analyst forecasts is an empirical issue. Furthermore, the fact that the magnitude of cognitive bias is apparently easier to relate to stock characteristics or cultural influences on market agents than to strictly institutional factors prevents us from developing the specific hypothesis that it varies with the type of financial system. The analysis described in this paper, as well as examining the various markets individually, studies them overall and by type of financial system (Anglo Saxon vs Continental), in order to determine whether the latter has any implications for the findings.

The study sample covers the period 1994-2007. The accounting variables and stock prices are taken from the Datastream database (Thomson Financial) and the data relating to analyst activity are obtained from the FactSet database, which is affected by survival bias. Thus, the analysis covers all stocks currently and formerly listed in the four European markets considered and for which data from both databases are available for the study period. Following Ince and Porter (2006), we have screened and corrected the database. We have removed padded zero-return records at the end of delisted firms, we have removed all nonlocal firms and all listings other than those on the primary exchange and all listings with Type not equal to Equity. We include only those firms that checked YES in the "Primary quote" field. Based on these criteria, the final sample for the first year includes an average of 134 firms from France, 35 from Germany, 39 from Spain and 150 from the United Kingdom. The average number of firms follows an overall upward trend. In 2007, specifically, these figures increase to 372 from France, 233 from Germany, 89 from Spain and 387 from the United Kingdom.

During the period of this study, 1994-2007, there were significant EU accounting and reporting issues leading towards harmonized financial reporting in the EU that probably had an impact on investor markets and analysts' attitudes and perceptions[3]. These changes may have caused convergence of the attitudes of Anglo-Saxon and Continental analysts. In order to analyse this question, we test for time-period related variation in the differences between Anglo-Saxon and Continental results for the 1997-2004 and 2005-2007 sub-periods.

The stock characteristics used are book-to-market ratio (BTM)[4], market value (SIZ), volatility (VOL)[5] and dividend per share ratio (DIV). We measure all data in Euros, with the exception of the UK data which are expressed in pounds.

3.2 - Investor Sentiment Measurement

Previous studies have used various indicators for the measurement of the sentiment variable, although there is no consensus on the best way to measure this unobservable

[3] For example, in 1995, the EC announced support for the International Accounting Standards Committee's international harmonization efforts. In 2000, the EC's "EU Financial Reporting Strategy: the way forward" led to the use of IAS by EU listed companies starting in 2005. In 2002, the EU Parliament and Council issued the IAS accounting regulation for listed companies. We are grateful to the anonymous reviewer #1 for this information.
[4] We remove stocks with negative book-to-market values.
[5] Volatility is obtained as the standard deviation of stock returns for the previous twelve months.

variable. The indicators used in the literature include investor survey findings (Brown and Cliff, 2005, and Lemmon and Portniaguina, 2006), mutual fund flows (Brown *et al*., 2003; Frazzini and Lamont, 2008), the dividend premium (Baker and Wurgler, 2004a and b), the closed-end fund discount (Zweig, 1973; Lee, *et al.,* 1991; Swaminathan, 1996, and Neal and Wheatley, 1998), trading volume or turnover (Jones, 2001; Scheinkman and Xiong, 2003; and Baker and Stein, 2004), and, more recently, composite sentiment indexes (Brown and Cliff, 2004; Baker and Wurgler, 2006, 2007).

In recent papers, the tendency is to construct global sentiment indexes, which include local sentiment proxies. Baker *et al.* (2012) construct investor sentiment indexes for six major stock markets and compose them into one global sentiment index. Chang *et al. (*2012) use the first main component of US, UK, French and German sentiment as a measure of global investor sentiment. In this paper, we construct a global sentiment index because, as well as this being the current trend in studies analysing market sentiment, we consider it particularly relevant given the global environment in which financial analysts operate. Financial intermediaries have expanded internationally, have obtained membership in multiple exchanges and trading venues, and have grown both through a larger network of clients and through increased consolidation in the investment banking business. For these reasons, we take the common component in US and Europe sentiment[6] as a measure of global investor sentiment.

As a proxy of US sentiment, we use the composite index constructed by Baker and Wurgler (2006, 2007) (*SentUS*) which is made up of 6 sentiment indicator variables: the closed-end fund discount, stock turnover, the number of IPOs and the average first-day returns, the share of equity issues in total equity and debt issues and the dividend premium[7]. The European sentiment index (*SentEU*) collects information about the investor sentiment of four key European markets: France (*SentFR*), Germany (*SentGE*), Spain (*SentSP*) and the UK (*SentUK*). Following Baker and Wurgler (2006) and Baker *et al* (2012), we use principal components analysis to isolate the common component. We build a composite sentiment index of these four markets. Firstly, we obtain four local composite indexes. The variables included in each local sentiment index are: turnover, the volatility premium and the consumer confidence index[8]. In line with Baker and Wurgler (2006), we start with the estimation of the first main components of these three variables and their

[6] Due to lack of data, we exclude the Japanese sentiment index and all other Asian references.

[7] The BW index data are available on the website of Wurgler http://www.stern.nyu.edu/~jwurgler

[8] The reason for the consideration of these three variables is their relationship with the level of sentiment. Details of the construction of the volatility premium are available in Baker *et al*. (2012). Finally, consumer confidence has been used in numerous studies such as Brown and Cliff (2005) and Lemmon and Portniaguina (2006), among others. The index of consumer confidence data comes from the website of the European Commission http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm

lags. This gives a first stage with six loadings and the variable index is included in t or t-1, depending on which is most highly correlated with the first-stage index. After obtaining the four local composite indexes, they are included in the construction of the European sentiment index. The European sentiment index coefficients are:

$$SentEU_t = 0.32 * SentFR_t + 0.43 * SentGE_t + 0.34 * SentSP_t + 0.27 * SentUK_t \qquad (1)$$

This main component explains 51.87% of the total variance.

Finally, as a measure of overall sentiment (*SentG*), we form a composite index that captures the common component in the *SentUS* and *SentEU* indexes. This first main factor explains 81.15% of the sample variance, enabling us to conclude that one factor captures much of the common variation. The resulting index is:

$$SentG_t = 0.55 * SentUS_t + 0.55 * SentEU_t \qquad (2)$$

The *SentUS* and *SentEU* indexes show positive and significant correlation (0.65), while the correlation of each of these indexes with the *SentG* is 0.908. Note that each sentiment index is likely to include a sentiment component as well as a common economic cycle component. For this reason, we construct a new global index that explicitly removes the effect of possible changes in the economic cycle[9].

3.3-Calculation of EPS forecast errors

Analyst forecasts and annual EPS data are obtained from the Factset database[10]. We collect consensus (median) quarterly EPS forecasts, from January 1994 to December 2007. EPS forecast errors are defined as the difference between actual EPS for the fiscal year y, minus the quarterly consensus (median) forecast for the fiscal year y, scaled by the absolute value of the EPS consensus forecast. In order to reduce the EPS skewness effect, we

[9] Following Baker and Wurgler (2006) and Schmeling (2009), the macroeconomic variables considered are the industrial production index, consumption of durable and non-durable goods and the rate of unemployment. The construction of this new index is similar to the previous one. However, the three initial individual measures are orthogonalized on these macroeconomic variables.

[10] As well as the major international firms that regularly send their recommendations to I/B/E/S, contributors to this database include some domestic analysts, which results in wider coverage in European countries. Nevertheless, like other forecast databases, FactSet is affected by potential survivorship bias, and also selection bias, because it collects recommendations and forecasts from brokerage houses that collaborate on a voluntary basis. Correction of these two biases is not possible.

consider median consensus instead of mean consensus[11]. The choice of the variable used to scale the errors is not obvious. The literature has provided several alternatives for scaling forecast errors. The most common option appearing in previous works is to scale by stock prices (Brown, 1997; Chopra, 1998; Gu and Wu, 2003 and Richardson, *et al*, 2004). Nevertheless, in line with the arguments put forward by Qian (2009), when stock prices are used to scale forecast errors they are "artificially" reduced in the case of high stock prices. As an alternative, Qian (2009) scales errors by the total asset per share and the book value of equity, while Hribar and McInnis (2012) use the absolute value of the consensus forecast. We adopt the approach used by Hribar and McInnis (2012)[12]. In further agreement with these authors, we reduce the sensitivity of the results to small EPS by removing stocks with absolute earnings forecasts of less than 0.10 euros. Following Gu and Wu (2003) and Qian, (2009), the sample is limited to stocks whose fiscal year ends in December and we exclude EPS forecasts issued less than 90 days before the earnings report dates[13].The EPS forecast error is calculated as follows:

$$FE^{i}_{t,y} = \frac{EPSactual_{i,t,y} - EPSFY1consensus(median)_{i,t,y}}{ABS(EPSFY1consensus(median))_{i,t,y}} \qquad (3)$$

where $FE^{i}_{t,y}$ is the EPS forecast error of stock i in quarter t for the fiscal year y, $EPSactual_{i,t,y,}$ is the actual EPS of asset i in quarter t for the fiscal year y and EPSFY1consensus $(median)_{i,t,y}$ is the consensus (median) EPS forecast of stock i in quarter t for the fiscal year y. Finally, ABS denotes the absolute value of a variable.

A negative value of the EPS forecast error ($FE^{i}_{t,y}$) indicates analyst optimism, since the EPS forecast issued is greater than the company's actual EPS for this fiscal year.

In order to observe the impact of sentiment on different stocks, we group them into quintiles by size, volatility, BTM ratio and dividend per share. Thus, each quarter, we sort the assets into quintiles by the characteristic j. We then compute the average EPS forecast errors in the following quarter. This procedure allows us to compare the two extreme quintiles (the first and the fifth), since a greater sentiment effect is expected in quintiles with assets whose characteristics are associated with difficulty of valuation and arbitrage (i.e., the first quintile in size and dividends per share and the fifth quintile in volatility).

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[11] However, the analysis has been carried out with both measurements of consensus recommendations and the results are virtually the same.

[12] We do not have total asset per share data. However, as a robustness test, we have also scaled EPS forecast errors by the price and the book value of equity and the results, in general, are similar to those shown in Table II, despite the inconvenience of some loss of observations due to the elimination of data with negative book value. Results are available on request from the authors.

[13] The initial (final) numbers of observations following application of the above-mentioned criteria are: France 15,194 (14,547), Germany 6,571 (5,925), Spain 4,531 (4,092) and UK 15,786 (15,319).

In Panel A of Table I, we present the average and median values of analysts' EPS forecast errors for the entire set of assets. In Panel B, we present the results for the extreme quintiles of each stock characteristic. When we analyse the whole data set, the results are very clear in all four markets and show that EPS forecast errors are negative, confirming the analyst optimism that had been detected in other markets. Furthermore, median EPS forecast errors are less negative than the average, which indicates that the errors are negatively skewed. In general, comparison of the extreme quintiles of the stock characteristics allows us to affirm that hard-to-value and difficult-to-arbitrage stock quintiles show more optimism, on average, than their opposites. This result is evident in the smaller, more volatile and lower dividend-per-share stocks, in which EPS forecast errors are very important. Classification by BTM ratios yields less clear results. The difference between the extreme quintiles is only significant in the case of the Spanish and French markets, the first quintile being more negative. These results may be due to the effect of two stock dimensions that are related to the BTM ratio, namely, high growth (the first quintile), and high distress risk (the fifth quintile).

[Insert Table I]

4-The effect of sentiment on forecast errors

Previous results have shown that analysts tend to be optimistic, issuing earnings forecasts greater than the earnings companies actually obtain. One of the possible causes of this may be the reaction of analysts to variations in the level of sentiment. Hribar and McInnis (2012) find evidence supportive of this notion in the US market. However, lower analyst coverage of European markets limits our sample, by excluding some firms with high sensitivity to investor sentiment. This increases the importance of testing the following hypothesis:

Hypothesis H1: *In European markets, investor sentiment is positively and significantly related to analyst forecast errors*.

In order to test this hypothesis we estimate the following equation:

$$FE_t^c = \alpha^c + \beta^c SentG_{t-1}^{\perp} + \gamma^c Skew_t^{c\perp} + u_t^c \tag{4}$$

where FE_t^c is the EPS forecast errors consensus (median) for all of the stocks in country c and quarter t. $SentG^{\perp}$ is the investor sentiment variable orthogonal to the economic variables. Following Qian (2009), we also include a proxy for the skewness in analyst forecast errors ($Skew_t^{c\perp}$) as a control variable, because optimistic bias can result from analysts' efforts to improve forecast accuracy when the distribution of earnings is skewed (Gu and Wu, 2001). Finally, an AR (1) model is applied to correct for serial correlation. OLS estimation is used with the Newey and West (1987) standard errors.

The results obtained in the estimation of equation 4 are shown in Panel A of Table II. The data show that both the EPS forecast errors of the previous period and the skewness in analyst forecasts positively affect EPS forecast errors in the current period. The impact of investor sentiment on the EPS forecast errors is clearly significant and negative for the four European markets analysed. Obviously, the same result is obtained for the whole set of countries, with no significant differences being observed between those belonging to the Anglo Saxon and those belonging to the continental financial system. All of these results support the null hypothesis H1. This shows that latent market optimism makes analysts, on average, more optimistic, as reflected in higher earnings forecasts and, consequently, larger errors. Therefore, analysts appear to be influenced in their forecasts, either consciously or unconsciously, by investor sentiment. All of this enables us to conclude that the generalization of these results to all the European markets analysed is not diminished by the impact of their various differences.

[Insert Table II]

Given that, as the literature has shown, investor sentiment has a stronger impact on hard-to-value or difficult-to-arbitrage stocks (see Baker and Wurgler 2006, 2007 or Corredor et al, 2013a) and taking into account findings by Hribar and McInnis (2012) showing that in the US market these stocks are associated with more optimistic EPS forecasts, it is worth testing this hypothesis for the European market. The specific hypothesis is as follows:

Hypothesis H2: *In European markets, the positive relationship between investor sentiment and forecast errors is stronger in hard-to-value or difficult-to-arbitrage stocks.*

To test hypothesis 2, we estimate a system of equations adapted to the two extreme quintiles of each characteristic j

$$FE_{q,t}^{c,j} = \alpha_q^{c,j} + \beta_q^{c,j} SentG_{t-1}^{\perp} + \gamma_q^{c,j} Skew_{q,t}^{c\perp} + u_{q,t}^{c,j} \qquad \text{c=1 to 4} \qquad (5)$$

where $FE_{q,t}^{c,j}$ is the average of the EPS forecast errors in the stocks belonging to quintile q (first and fifth) for country c, characteristic j and quarter t. We include the skewness in the analyst forecast errors of each quintile orthogonal to investor sentiment and, finally, the investor sentiment variable orthogonal to macroeconomic variables.

The impact of investor sentiment on EPS forecast errors for each quintile is shown in Panel B of Table II[14]. The results are in line with our expectations and support hypothesis H2. The results of the analysis of volatility portfolio are unanimous for the four markets. The impact of sentiment on the more volatile stocks is greater than observed in less volatile stocks, and the difference between the two groups is significant for the four markets analysed. In the case of the UK, in the analysis of portfolios classified by size and dividend-per-share, the first quintile (which contains the stocks most sensitive to investor sentiment) has coefficients superior in magnitude to those of the fifth quintile, the differences being significant in both cases. The coefficients of these characteristics are also higher in the first quintile in the other stock markets, although they are not significant[15]. When we study portfolios sorted by BTM, the impact is higher in the first quintile than in the fifth, but the differences are in no case significant[16].

Table II summarizes the findings for all the markets analysed. We also show the results for full sample, continental subset and the differences in coefficients between the Anglo Saxon and Continental subsets. As in the case above, the results for the whole set of European markets support the main reported finding that the positive relationship between investor sentiment and forecast errors is significantly stronger when volatility and DPS are used as an approximation of the sensitivity of stocks to investor sentiment. The results for the Continental subset are similar in overall terms to those obtained for the entire sample. In agreement with the above finding, the various tests performed show that there are no significant differences associated with the market belonging to the Anglo Saxon vs the Continental financial system. Finally, in spite of the significant EU accounting and reporting issues leading towards harmonized financial reporting in the EU, we do not find significant variations in the differences between the Anglo Saxon and Continental financial systems for the 1997-2004 and 2005-2007 sub-periods. This result could be due either to the progressive nature of the harmonization process or to the brevity of the last sub-period.

To sum up, analyst optimism is related to the level of investor sentiment. This relationship is stronger in hard-to-value and difficult-to-arbitrage stocks, especially when

[14] The impact of the AR(1) and skewness variables is similar to that shown in A Panel. The results are available on request from the authors.
[15] When we analyse size for the French stock market the observations were winsorized at the 99% level due to the presence of extreme values.
[16] The recent decrease in analyst optimism reported in the literature motivated us to extend our sample period back to 2001 in order to test for any associated variation in the impact of market sentiment on forecast errors. The results reveal a significantly negative sentiment effect throughout the whole sample period, suggesting that the reduction in optimism does not seriously affect our reported results.

these characteristics are proxied by stock volatility[17]. Given that the main effect of sentiment on EPS forecast errors appears in the high volatility portfolio, the following analysis is restricted to these assets only. In fact, Baker and Wurgler (2006), Chang et al (2012), Joseph et al (2011), Baker et al (2012) and Corredor et al (2013a,b) use volatility portfolios to proxy for hard-to-value and difficult-to-arbitrage stocks because the observed effects are stronger than for other characteristics.

5. Do errors-in-expectations drive the relationship between sentiment and future stock returns?

Baker and Wurgler (2006, 2007) and Chang, *et al.* (2012), among others, analyse the relationship between sentiment and stock returns and find long-term price reversal to fundamentals. Hribar and McInnis (2012) include EPS forecast errors in the relationship between stock returns and investor sentiment and try to determine whether EPS forecast error is an intermediating variable between sentiment and returns and whether its inclusion reduces or even eliminates the explanatory power of sentiment. They obtain favourable evidence for the US market. Based on their work, we propose the following hypothesis:

Hypothesis H3: *In the European setting EPS forecast error is an intermediating variable between sentiment and returns.*

As noted by Hribar and McInnis (2012), confirmation of the above hypothesis implies the presence of cognitive bias in analysts. The cited authors formulate the following regression

$$R^c_{high,t} - R^c_{low,t} = \alpha^c_k + \beta^c_k DSentG_t + \gamma^c_k FE^c_{diff,t} + \delta^c_k RMRF^c_t + \omega^c_k SMB^c_t + \lambda^c_k HML^c_t + u^c_{k,t} \quad (6)$$

where $R^c_{high,t} - R^c_{low,t}$ is the self-financed portfolio return based on volatility for country c and and month t. $DSentG_t$ is the dummy variable, which is equal to 1 if investor sentiment in December of year t-1 is above the median level and equal to 0 otherwise. $FE^c_{diff,t}$ is the difference between the two portfolios in terms of forecast errors. As the results may be due to the significant exposure of the volatility portfolio to traditional risk factors, Fama and French (1993) factors (*RMRF*, *SMB* and *HML*) are included for each market[18].

[17] DPS variable is only significant at the 10% level for the full sample, while volatility is significant at the 1% level. The empirical evidence for the BTM variable yields mixed results, due to the fact that both high and low volatility can proxy for high sensitivity to sentiment. Finally, analysts' bias towards large stocks makes size a poor proxy for hard-to-value and difficult-to-arbitrage stocks.

[18] See Fama and French (1993) and Jegadeesh and Titman (2001) for details of the construction of risk factors and the construction of the return variable, respectively. Due to the observed causality of investor sentiment on

In our view, however, this relationship would be better specified as follows:

$$R^{c}_{high,t+k} - R^{c}_{low,t+k} = \alpha^{c}_{k} + \beta^{c}_{k} SentG^{\perp}_{t} + \gamma^{c}_{k} FE^{c}_{diff,t} + \delta^{c}_{k} RMRF^{c}_{t} + \omega^{c}_{k} SMB^{c}_{t} + \lambda^{c}_{k} HML^{c}_{t} + u^{c}_{k,t} \quad (7)$$

where $R^{c}_{high,t+k} - R^{c}_{low,t+k}$ is the self-financed portfolio return based on volatility for country c and holding period k, $SentG^{\perp}_{t}$ is the investor sentiment variable, orthogonal to economic variables, and defined as a continuous variable. The remaining variables are the same as those specified in (6).

Our reason for proposing specification (7) is that investor sentiment, as has been abundantly shown in the literature, has a more notable mid-term impact, and cannot be fully captured by analysing a portfolio with a month-long holding period. However, the inclusion of portfolios with k holding periods raises problems due to autocorrelation and heteroskedasticity of overlapping observations. To address these issues, the portfolio return is computed in calendar time, following Jegadeesh and Titman (2001). In addition, we use a continuous variable (instead of a dummy variable) as the sentiment proxy, which we orthogonalize to macroeconomic variables to control for economic cycle effects.

Table III presents the results of the estimation of equation (6) (with $DSentG_t$ [6.1], with $SentG_t$ [6.2], and with $SentG^{\perp}_{t}$ [6.3]) and equation (7) for a holding period of 12 months for the full sample of markets considered, using dummy variables to represent France, Germany and Spain, in order to facilitate comparison between the Anglo Saxon and Continental financial systems. We estimate equation (6) in order to make more direct comparisons between our findings and those of Hribar and McInnis (2012) and rule out methodological issues as the source of any differences. However, we also estimate equation (7) using the $SentG_t$ [7.1] variable and our final proposal using $SentG^{\perp}_{t}$ [7.2].

Despite the different specifications of the two equations, the conclusions are identical. The estimates in columns [6.1], [6.2], [6.3], [7.1] and [7.2] show the effect of sentiment on future returns in line with Baker and Wurgler (2006, 2007). The results also show that the impact of sentiment on future returns is negative and significant in all the models. The explanation of this phenomenon is that high sentiment produces overpricing followed by reversion to equilibrium. This effect is more predominant in high volatility stocks, as shown by the negative sign on the estimated coefficient.

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the stock returns, the market factor is orthogonalized to the sentiment index to control for multicollinearity among the independent variables.

These results are clearly consistent with those obtained in the literature on the relationship future returns-sentiment. Baker and Wurgler (2006, 2007), Baker, *et al.* (2012), Chang, *et al* (2012) and Corredor et al (2013a) found this same pattern for both the American market and international markets.

[Insert Table III]

The coefficient of EPS forecast error is not significant in any of the cases analysed[19]. Therefore, this variable does not in itself seem to have any impact on future returns. These results permit us to reject hypothesis 3 while also casting doubt on the possibility that the detected relationship between sentiment and EPS forecast errors is due to error- in-expectations. These results clearly differ from those presented by Hribar and McInnis (2012) for the US market, by showing that EPS forecast errors help to explain the future stock returns-sentiment relationship found by Baker and Wurgler (2006). This difference in results cannot be attributed to methodological factors, however, because the specification (6) is the one used by Hribar and McInnis (2012) and yields the same results as the rest. In addition, the results hold both for the full sample and the subset of Continental European-type markets, no significant differences having been observed between their average values and those of the UK market. Finally, we find no significant time-period-related variation in the differences between the two financial systems for the 1997-2004 and 2005-2007 sub-periods.

The evidence that the undermining effect of forecast errors on the predictive power of sentiment for future returns is driven by errors-in-expectations would confirm the presence of cognitive bias. Nevertheless, analysts can still fall prey to cognitive bias, even though forecast errors cannot explain future returns. Thus, the rejection of hypothesis 3 does not necessarily rule out cognitive bias as the driver of analyst optimism. In fact, our first analysis has shown that sentiment is a key explanatory factor of forecast errors that might be consistent with the presence of cognitive bias. The results may be an indication that the relationship between sentiment and stock returns is more complex or that lower analyst coverage may reduce the suitability of using analyst forecast errors as a means to measure errors-in-expectations by investors in European markets[20].

[19] Observation of the data for individual markets shows that this coefficient is significant for the French stock market, although this does not undermine the explanatory power of investor sentiment.

[20] A survey of 365 analysts by Brown et al (2013) aimed at revealing the forces that motivate analysts' decisions shows that single most important determinant of their compensation and main input in their forecasts and recommendations is industry knowledge. The second most important factor is broker votes (a measure of client satisfaction). Analysts claim that the most useful way to obtain information is through private telephone calls, adding that it is essential for them to keep in close touch with company managers. The cited study does not directly analyse optimism or its explanatory factors. Future research in that direction might further

6-Does cognitive bias significantly affect analyst forecasts?

Although the lack of significance of forecast errors in the relationship between sentiment and futures returns casts some doubt on the importance of cognitive bias in analyst behaviour, it does not completely invalidate this explanation. If analysts are aware of the state of investor sentiment, they will be able to exploit it by issuing more optimistic forecasts than they would have otherwise. This will bring them personal profit in the form of commissions from brokerage houses and from increased trading. Thus, sentiment-driven optimism in EPS forecasts may be due to analysts' strategic use of investor sentiment. Nevertheless, it is also possible that, when sentiment is high, analysts may be unconsciously led by the tone of the market and issue abnormally optimistic earnings forecasts. The observed effect may, of course, also be due to a combination of both these factors.

In order to analyse this issue in this paper, we propose two new tests based on selection bias (SB1 and SB2), which we apply in conjunction with an analysis of abnormal trading volume in hard-to-value stocks versus less hard-to-value stocks[21]. The first (SB1) will show us whether analysts behave strategically, but unconditional on the level of investor sentiment in the market. The second (SB2), which takes into account the impact of sentiment on selection bias for some types of stock, will, together with the analysis of abnormal trading volume, allow us to test for the additional presence of cognitive bias or strategic bias conditional on the level of investor sentiment.

6.1. Strategic behaviour unconditional on the level of investor sentiment

We will begin by examining the possibility of strategic behaviour unconditional on investor sentiment by testing the following null hypothesis:

Hypothesis H4: *Analysts operating in the European setting do not behave strategically in issuing optimistic forecasts*.

In order to test for the presence of strategic behaviour unconditional on investor sentiment, we begin by running a test (SB1) based on selection bias. Selection bias is the result of analysts opportunistically choosing the moment to release market information. When acting strategically, analysts will adjust their forecasts upward in the presence of

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understanding of the personal motives behind analysts' actions. We are grateful to the anonymous reviewer #1 for this observation.

[21] Hribar and McInnis (2012) perform two additional strategic behaviour checks which we also perform. We first test for variation, in the form of a decrease, or reversal, in the impact of sentiment on forecast errors when measured over shorter horizons. We then test whether analyst optimism translates into recommendations, which are their final output to investors. The results are not reported here for the sake of clarity. The first test does not find strategic behaviour but the second one suggests this behaviour in financial analysts.

positive news and will not adjust them downwards in the presence of negative news. When cognitive bias alone is present, however, any revision, whether upward or downward will be random. SB1 compares the ratio of upward revisions to pieces of positive news (R^U) and the ratio of downward revisions to pieces of negative news (R^D). This reveals whether analysts handle information strategically.

$$R^U = \frac{Upward\ Revisions}{PositiveNews} \quad \text{and} \quad R^D = \frac{Downward\ Revisions}{NegativeNews}; \quad SB1 = R^U - R^D \qquad (9)$$

Under the assumption of non-intentionality, both ratios should diverge only by chance, and the statistic will therefore have a value of 0. Furthermore, negative values of the statistic will also be inconsistent with the presence of strategic behaviour by investors. Therefore confirmation of the null hypothesis, H4, implies that the statistic SB1≤0. However, if their behaviour is strategic, and assuming that there are incentives for analysts to issue optimistic forecasts and recommendations, the R^U ratio should be significantly greater than the R^D ratio. Thus, in the presence of strategic behaviour by analysts unconditional on investor sentiment, the statistic will have positive values (H_4^{SB}: SB1>0).

6.2 Cognitive bias and Strategic behaviour conditional on investor sentiment

Having tested for the presence or absence of strategic behaviour by analysts unconditional on investor sentiment, we test for the presence of cognitive bias or strategic bias that is conditional on investor sentiment. Note that analysts can also act strategically in the presence of high investor sentiment, under the assumption that high optimism among investors at such times will camouflage their inflated price forecasts. Based on these considerations, we propose the following null hypothesis:

Hypothesis H5: *In the European setting, the level of investor sentiment does not influence the level of analyst bias.*

Confirmation of the null hypothesis would indicate that the level of investor sentiment does not drive the aforementioned effect on strategic behaviour by analysts or lead to cognitive bias affecting the level of analyst optimism.

To test this hypothesis, we perform a second test (SB2), which is a modified version of SB1 and takes into account the effect of sentiment on the relationship between news and EPS revisions. Assuming that high investor sentiment increases the level of optimism in the EPS forecasts for hard-to-value and difficult-to- arbitrage stocks, the R^U ratio in these stock types could increase or decrease significantly. Note that, under the assumption of strategic behaviour, the question of whether analysts make more upward or more downward revisions in relation to the number of pieces of positive news in hard-to-value and difficult-to-arbitrage stocks will depend on the strength of the opposing incentives. In other words, they will have to weigh up the incentives or pressures to issue optimistic forecasts when SEO and IPO activity is at a peak against the potential reputation costs of issuing over-optimistic forecasts that fail to materialize due to medium-term price reversal in these stock types (see Baker and Wurgler, 2006 and Corredor et al, 2013a). It is important to emphasize that, during periods of high market sentiment, the level of trading volume is sufficient to obviate the need for analysts to use optimistic forecasts to increase their business. In this line, Bergman and Roychowdhury (2008) show that managers strategically reduce the frequency of long-horizon earnings announcements during high sentiment periods. Thus, if analysts are not under too much pressure to issue optimistic forecasts, the net effect could be fewer upward revisions. However, if the origin of analyst optimism lies in a cognitive bias, a high level of investor sentiment will lead to an increase in their optimism and a greater effect should be observed in hard-to-value and difficult-to-arbitrage stocks, which are the stocks on which investor sentiment has the most noticeable effect. Thus, a decrease in R^U will provide the necessary evidence with which to conclude that the primary source of analyst optimism lies in their strategic intentions. But if R^U is positive, the origin may be strategic (if the incentives or pressures to issue optimistic forecasts outweigh the reputational costs) or cognitive.

The SB2 test compares the expected R^U and R^D ratios that are conditional on high level sentiment (HS) to their respective unconditional ratios.

$$SB2^U = E(R^U / HS) - E(R^U) \quad \text{and} \quad SB2^D = E(R^D / HS) - E(R^D) \qquad (10)$$

Under the null hypothesis of the absence of any effect of investor sentiment in the R^U and R^D ratios, the $SB2^U$ and $SB2^D$ statistics should be zero ($H_{5,0}$: $SB2^U=SB2^D=0$).

The alternative hypotheses (analysts behaving strategically conditional on investor sentiment, H_5^{StB}, or cognitive bias, H_5^{CgB}) may significantly alter the behaviour of the $SB2^U$ statistic for the most volatile stocks (which are the most sensitive to investor sentiment).

Under the alternative hypothesis of cognitive bias in analyst behaviour, H_5^{CgB}, the $SB2^U$ statistic will be positive (H_5^{CgB} : $SB2^U > 0$).

The alternative hypothesis of strategic behaviour by analysts, H_5^{StB} depends on whether or not reputational costs outweigh the remaining incentives for analysts. In particular, the $SB2^U$ statistic should be negative if the reputational costs for analysts outweigh either their incentives to make the most of high investor sentiment to drive up trading volume or the pressures they are under to issue optimistic forecasts in order to support SEOs or IPOs. ($H_{5,1}^{StB}$: (Reputational costs > Firms pressure) $SB2^U < 0$). But the $SB2^U$ statistic should be positive if it is due to strategic behaviour when the reputational costs do not outweigh the remaining incentives ($H_{5,2}^{StB}$: (Firms pressure > Reputational costs) $SB2^U > 0$).

Thus, the results for the SB2 statistic can indicate any of three possibilities: If the $SB2^U$ statistic is not different from zero, it will indicate the absence of cognitive bias or strategic behaviour linked to the pattern of investor sentiment. If the $SB2^U$ statistic is negative, it will indicate the presence of strategic bias. If the $SB2^U$ statistic is positive, it will raise the problem of origin identification, since the origin could be cognitive or strategic. We can overcome this problem, by tracing the source of the optimism by means of a complementary analysis of abnormal trading volume in hard-to-value stocks versus bond-like stocks during periods of high market sentiment. If analysts are strategically selecting hard-to-value stocks, the latter will have significantly higher abnormal trading volume than bond-like stocks. If, however, the difference in abnormal trading volume between these two stock types is negligible or even reversed, the only compatible explanation will be that analyst optimism is driven by cognitive bias.

[Insert Figure 1]

In the case of the $SB2^D$ statistic, the effect should be less pronounced than in the $SB2^U$ statistic. When strategic behaviour is present, a positive or not different from zero $SB2^D$ statistic is expected. Because negative news is more informative during periods of high sentiment, analysts taking into account the reputational costs, tend more frequently to revise downwards. Note, however, that pressures for analysts to issue optimistic forecasts to support SEO and IPO activity also have this effect. If optimism is mainly motivated by their cognitive bias, a negative or not different from zero $SB2^D$ statistic is expected, because negative news is not confirmed by their own expectations and they are not likely to revise their forecasts downward. Finally, the expected sign of the statistics for low volatility stocks is the same as that expected for high volatility stocks, but the statistics should probably not be significantly different from zero because, in these stocks, investor sentiment has less impact and the magnitude of the optimism bias will also be smaller.

6.3 Measuring SB1 and SB2

The first step in computing SB1 and SB2 is to choose the stocks to construct the portfolio. For this purpose, each quarter, we sort the stocks by their volatility and group them into quintiles. We then calculate the percentage of quarters that each stock appears in each of the extreme quintiles, i.e., the first and fifth. Finally, the stocks selected as high (low) volatility will be those that, for more than 60% of the quarters, appear in the fifth (first) quintile and for less than 10% of the quarters in the first (fifth) quintile[22]. The number of upward and downward EPS revisions is obtained from Factset and we compute the number of revisions issued by the analysts following a firm during the last month of the quarter. The proxy for news is the unexpected stock return (20% extreme). As Antoniou *et al* (1998), Engle and Ng (1993) and Pagan and Schwert (1990) argue, it is typical to define news as the unexpected component of returns, u_t. Let r_t be the return on a stock from t - 1 to t and Φ_{t-1} be the information set containing all relevant information up to time, t-1. The conditional expected return, ρ_t, is defined as $E(r_t | \Phi_{t-1})$ so news is defined as $u_t = r_t - \rho_t$. Moreover, Engle and Ng (1993) assert that a large value of u_t implies that the news is "significant" and it is critical to distinguish between positive and negative return shocks by examining the magnitude of a piece of news. To do this, they proposed identifying the more extreme values using the αth percentile of the set of $\{u_t\}$. Blasco *et al* (2010) find that using the top and bottom quintiles of the residual is a good proxy for good and bad news, respectively. For the sake of homogeneity, each quarter, we compute the total number of pieces of positive or negative news for each stock during the last month of the quarter.

Finally, we compute the ratio of the number of upward EPS revisions (the number of downward EPS revisions) to the number of pieces of positive (negative) news on a quarterly basis[23]. It should be pointed out that our interest lies in the ratio of pieces of positive or negative news to the number of upward or downward revisions of forecasts, rather than the exact time they occur or their simultaneity (which, in any case, would be difficult to ascertain). The number of pieces of news and number of revisions, in aggregate, are informative about analyst behaviour and can therefore support our research aims.

6.4 Empirical results

Table IV presents the average values of the R^U and R^D ratios for the entire set of stocks and for the extreme volatility portfolios, and the SB1 statistic (R^U-R^D) with the p-value of the t-test of difference in means. The results of the SB1 test show that, in 3 of the 4

[22] To ensure that the results are not firm-specific, the number of stocks in each market is greater or equal to 10.
[23] For the sake of homogeneity, both variables are standardized.

individual market analyses and in the full sample analysis[24], the ratio of positive revisions to pieces of positive news (R^U) is significantly greater than the ratio of negative revisions to pieces of negative news (R^D), which enables us to reject the null hypothesis of the absence of strategic behaviour by analysts (H4). It is important to emphasize that these results are not conditional on investor sentiment. They are a consequence of analysts behaving strategically in response to their incentives. We find no differences between the Anglo Saxon and Continental systems and no significant variation in this result between sub-periods (1997-2004 and 2005-2007)[25].

[Insert Table IV]

The results of these SB2 tests are shown in Table IV. The $SB2^U$ test, the difference between the expected R^U in the conditional and unconditional cases, for the high volatility portfolio is significant in two of the four individual markets analysed (the UK and Spain), and also for the full sample and the Continental subset. In the other two markets, when the R^U ratio is conditional on high sentiment, it displays a higher average than when it is not, although the variance is too high to obtain $SB2^U$ tests significantly different from zero. The results of the $SB2^D$ test, the difference between the expected R^D in the conditional and unconditional cases, for the high volatility portfolio in no case differ significantly.

To sum up in two of the individual markets considered, for the sample as a whole, and indistinctly for both financial systems (Anglo Saxon and Continental[26]), we are able to reject the null hypothesis, H5, of absence of biases linked to the level of investor sentiment. However, given that the $SB2^U$ statistic is positive in all cases, we perform an additional analysis based on the abnormal trading volume of hard-to-value versus bond-like stocks during periods of high market sentiment, in order to determine the root cause of the rejection of the null (cognitive bias or strategic behaviour conditional on sentiment).

To carry out this complementary analysis, we need to compute the mean abnormal trading volume for the volatility portfolios used to compute SB2, which is the variable we use as the proxy indicator of hard-to-value stocks, during periods of high investor sentiment. To compute the average trading volume for each portfolio, the trading volume of each stock is standardized by its historical mean and the abnormal trading volume is obtained by subtracting from this the average volume for the past 12 months. Thus, at the

[24] No significant differences emerge for the Continental subset, or between these and the UK (which does show a significant degree of strategic bias). These incoherencies may be due to the high volatility of the data.
[25] Although the sign of the statistic SB1 is negative, suggesting some lessening of selection bias during the second sub-period, this reduction is not significant at conventional levels.
[26] Given that, throughout the entire 2005-2007 sub-period, there were only 3 quarters with high investor sentiment, we were unable to obtain sufficient observations to compute the SB2 test.

end of every three-month period, we obtain the abnormal trading volume of each stock in the last month, which enables us to compute the abnormal trading volume of the various quintiles. Table V shows the results of the test of difference of means between the top and bottom quintiles for each of the markets considered.

[Insert Table V]

The results are highly revealing. Indeed, in all the markets considered, the abnormal trading volume of the high-volatility portfolio is clearly lower than that of the low-volatility portfolio, except in the case of Germany, where the difference between the two is not significant (which is the reason for the lack of any significant differences when either the full sample or the Continental subset is considered[27]). This finding is in no way compatible with strategic behaviour on the part of analysts, since the stocks on which most of the optimism is concentrated generate less trading activity and therefore significantly less direct or indirect earnings for analysts. Given that the quintile-based portfolios include both stocks with buy recommendations and stocks with sell recommendations, we repeat the analysis using portfolios constructed exclusively from stocks with strong buy recommendations during the study period. Basically, the same results hold, thus ruling out the possibility of any skewness due to this characteristic. Finally, we construct portfolios from the three-month average returns, instead of the past month's returns, obtaining the same results both in the overall analysis and in the screening for strong buy recommendations[28].

In combination, the results of SB1 and SB2 provide empirical evidence of both strategic behaviour and cognitive bias linked to the level of investor sentiment, suggesting that the joint effect observed in analyst behaviour in the European markets considered can only be explained by the concurrence of both phenomena. The fact that past forecast errors fail to fully explain the effect of market sentiment on returns, as shown, does not detract from the explanatory power of cognitive bias with respect to analyst behaviour. The relationship between the level of sentiment, forecast errors, and future stock returns may be too complex to be captured by the linear regression model proposed by Hribar and McInnis (2012). Thus emerges an interesting avenue for future research.

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[27] The high volume of abnormal trading in the first quintile for Germany results in a highly volatile statistic that prevents us from rejecting the null hypothesis for the full sample or the Continental subset. There is also no difference between the results for the Continental system and those of the Anglo Saxon system, where the presence of cognitive bias is detected. In conjunction with the result for the three individual markets, this enables us to assert (as the most plausible hypothesis overall) that the optimism in analyst forecasts is due to the presence of cognitive bias.

[28] These results are available upon request from the authors.

7-Conclusions

This study focuses on the debate regarding the source of optimism in analyst forecasts. Recent papers have rekindled the debate about whether the optimism observed is due to analysts behaving strategically (see Karamanou, 2011 or Ertimur *et al.*, 2011) or is a consequence of cognitive bias (see Hribar and McInnis, 2012).

In this paper, we analyse the effect of investor sentiment on analyst expectations in the European context, where the level of analyst coverage is lower than in the US setting, from which most of the previous empirical evidence has emerged. In pursuing this objective, we study the four most important European markets in terms of capitalization, which exhibit significant differences in stock characteristics, financial systems (Anglo Saxon vs Continental) and cultural dimensions that will ensure the robustness of our results. The results confirm the presence of optimism bias in analyst forecasts. Moreover, we find that investor sentiment significantly affects forecast errors in all of the markets analysed (thus confirming the null hypothesis, H1), a bias which is more pronounced in assets with high sensitivity to investor sentiment, namely, those that are hard to value or difficult to arbitrage (thus confirming the null hypothesis, H2). Despite the fact that forecast errors lack the explanatory power to account for a significant percentage of the relationship between market sentiment and future stock returns (thus allowing us to reject the null hypothesis, H3), the results from our new tests based on selection bias (SB1 and SB2) confirm the presence of both cognitive bias and strategic behaviour in analyst forecasts. In particular, the results enable us to reject the null hypothesis, H4, that analysts do not behave strategically unconditional on market sentiment. We are also able to reject the null hypothesis, H5, that the level of market sentiment does not influence the degree of behavioural biases affecting analysts. The positive sign of the SB2 statistic, in conjunction with the results of an analysis of abnormal trading volume, support the alternative hypothesis, H_5^{CgB}, by revealing the presence of cognitive bias in analysts that is conditional on investor sentiment.

Findings by Ertimur et al (2011) or Karamanou (2011) reveal the presence of strategic behaviour in analysts' actions. Furthermore, although cognitive bias could have less impact because analyst coverage is lower in the European markets, our results show that it, too, has a significant impact on analyst forecasts, which is consistent with the findings of Hribar and McInnis (2012) for the US market.

It is important to emphasize the homogeneity of these findings across the various European markets considered. Indeed, the joint analysis of these markets reveals no significant cross-country variation[29] or differences associated with the nature of the financial system (Anglo Saxon vs Continental) to which they belong. This last result may also be due to significant EU accounting and reporting issues leading towards harmonized financial reporting in the EU context.

The main practical implication of our results is that regulation can reduce analyst optimism because part of this optimism is strategic. However, the fact that the rest of this optimism is associated with a cognitive bias suggests limited regulatory effectiveness. The effect of this bias is greater in hard-to-value and difficult-to-arbitrage assets, which means that, in times of high investor sentiment, the EPS forecasts will be more upwardly biased for these types of assets, so investors should approach analysts' predictions with a degree of caution.

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Table I: **Descriptive Statistics for Analysts' Earnings Forecast Errors**

Panel A: All Stocks

	Mean	Median	St.Dv	Min	Max	Per10%	Per90%
France	-0.150	-0.128	0.113	-0.526	0.068	-0.288	-0.027
Germany	-0.141	-0.133	0.172	-0.469	0.132	-0.401	0.077
Spain	-0.045	-0.018	0.120	-0.387	0.184	-0.206	0.078
United Kingdom	-0.047	-0.027	0.077	-0.165	0.028	-0.165	0.028

Panel B: Stock Characteristics

		Mean	Median	Mean	Median	Mean	Median	Mean	Median
		SIZE		SIGMA		BTM		DPS	
France	1Q	-0.727	-0.741	-0.001	-0.002	-0.221	-0.160	-0.364	-0.342
	5Q	-0.069	-0.039	-0.421	-0.422	-0.114	-0.139	-0.059	-0.037
	p-value	0.00		0.00		0.09		0.00	
Germany	1Q	-0.262	-0.429	-0.077	-0.069	-0.155	-0.097	-0.223	-0.231
	5Q	-0.064	-0.060	-0.322	-0.350	-0.168	-0.223	-0.109	-0.145
	p-value	0.02		0.00		0.81		0.06	
Spain	1Q	-0.198	-0.153	0.009	0.004	-0.141	-0.059	-0.484	-0.225
	5Q	0.017	0.015	-0.170	-0.132	0.013	-0.023	0.121	0.052
	p-value	0.02		0.02		0.00		0.00	
United Kingdom	1Q	-0.075	-0.048	0.001	0.010	-0.054	-0.006	-0.122	-0.038
	5Q	-0.021	-0.004	-0.198	-0.111	-0.068	-0.010	-0.035	-0.002
	p-value	0.07		0.00		0.73		0.04	

Mean and Median for the quarterly EPS forecasts errors series. Panel A shows the descriptive statistics of the sample data for each country. Panel B shows the descriptive statistics for stocks sorted by their volatility and grouped into quintiles based on size (SIZ), volatility (VOL), BTM ratio (BTM) and dividend per share (DPS). 1Q (5Q) is the portfolio of stocks belonging to the first (fifth) quintile. P-value is the significance level for the t-test for a difference in means between the two extreme quintiles.

Table II: **Effect of Investor Sentiment on Analysts' Earnings Forecast Errors**

Panel A: All Stocks

	France		Germany		Spain		United Kingdom	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Sent⊥	-0.035	0.01	-0.057	0.00	-0.034	0.01	-0.032	0.00
Skew⊥	0.016	0.00	0.017	0.00	0.018	0.00	0.009	0.00
AR(1)	0.457	0.00	0.632	0.00	0.375	0.00	0.020	0.77

	Full Sample		Continental		Ang-Sax vs Cont		Ang-Sax vs Cont 2005-2007 vs 1997-2004	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Sent⊥	-0.040	0.00	-0.042	0.00	0.010	0.49	-0.081	0.24
Skew⊥	0.015	0.00	0.017	0.00	-0.008	0.01	-0.006	0.35
AR(1)	0.371	0.00	0.488	0.00	-0.468	0.00	-0.326	0.15

Panel B: Stock Characteristics

	SIZE					VOL				
	1Q		5Q		DIFF	1Q		5Q		DIFF
	Coeff.	p-value	Coeff.	p-value	p-value	Coeff.	p-value	Coeff.	p-value	p-value
FR	0.011	0.81	-0.008	0.29	0.68	-0.018	0.02	-0.090	0.03	0.08
GE	-0.090	0.11	-0.065	0.00	0.53	-0.025	0.09	-0.083	0.04	0.17
SP	-0.044	0.29	-0.006	0.10	0.39	-0.013	0.11	-0.220	0.00	0.00
UK	-0.122	0.00	-0.034	0.00	0.00	-0.017	0.00	-0.082	0.03	0.08
Full Sample	-0.062	0.01	-0.026	0.00	0.16	-0.019	0.00	-0.115	0.00	0.00
Continental	-0.042	0.16	-0.024	0.00	0.55	-0.019	0.00	-0.126	0.00	0.00
Ang-Sax vs Cont	-0.078	0.13	-0.011	0.31	0.20	0.001	0.89	0.044	0.37	0.40
Ang-Sax vs Cont 2005-2007 vs 1997-2004	0.092	0.79	-0.022	0.78	0.77	0.039	0.63	0.287	0.46	0.49

	BTM					DPS				
	1Q		5Q		DIFF	1Q		5Q		DIFF
	Coeff.	p-value	Coeff.	p-value	p-value	Coeff.	p-value	Coeff.	p-value	p-value
FR	-0.040	0.07	-0.020	0.60	0.64	-0.017	0.61	-0.016	0.34	1.00
GE	-0.065	0.00	-0.016	0.66	0.24	-0.074	0.02	-0.027	0.01	0.19
SP	-0.020	0.74	0.001	0.98	0.80	-0.122	0.22	-0.008	0.40	0.27
UK	-0.017	0.59	-0.043	0.13	0.55	-0.118	0.00	-0.055	0.00	0.07
Full Sample	-0.033	0.02	-0.020	0.21	0.52	-0.077	0.00	-0.028	0.00	0.07
Continental	-0.039	0.03	-0.012	0.51	0.29	-0.065	0.03	-0.019	0.01	0.14
Ang-Sax vs Cont	0.021	0.51	-0.030	0.40	0.28	-0.051	0.42	-0.035	0.03	0.80
Ang-Sax vs Cont 2005-2007 vs 1997-2004	0.246	0.18	0.119	0.66	0.80	0.064	0.85	-0.027	0.80	0.96

Panel A shows the results of the regression for the whole sample data set for each country. The dependent variable is the consensus (median) EPS forecast errors for all stocks in country c and quarter t. The independent variables are the investor sentiment variable $Sent^{\perp}$orthogonal to macroeconomic variables (the industrial production index, durable and non-durable goods consumption, and the unemployment rate)) and a proxy of skewness in analyst forecast errors ($Skew^{C\perp}$). Panel B shows the results for stocks grouped into quintiles by size (SIZ), volatility (VOL), BTM ratio (BTM) and dividend per share (DPS). 1Q (5Q) is the portfolio of stocks belonging to the first (fifth) quintile. DIFF shows the p-value of the test for the difference between the beta coefficient of the sentiment variable for two extreme quintiles for each stock characteristic. AR (1) model is applied to correct for serial correlation. OLS estimation is used with the Newey and West (1987) standard errors. Results are shown for each market analysed: France (FR), Germany (GE), Spain (SP) and the United Kingdom (UK). "Full sample" shows the results for all the markets considered. "Continental" shows the results for the sample made of data from the French, German, and Spanish stock markets. "Ang-Sax vs Cont" shows the estimates of the difference in coefficients between the aggregate results for the Continental subset versus those for the UK, together with their levels of significance. Ang-Sax vs Cont 2005-2007 vs 1997-2004 shows the estimated difference in coefficients between the Continental versus UK aggregate results for the period 2005-2007 versus those for the period 1997-2004, together with their levels of significance

Table III: **Effect of Investor Sentiment on future volatility portfolio returns and analysts' earnings forecast errors**

	[6.1]		**[6.2]**		**[6.3]**		**[7.1]**		**[7.2]**	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
c	0.005	0.11	-0.002	0.47	-0.003	0.26	-0.024	0.00	-0.025	0.00
DumFR	-0.003	0.52	-0.003	0.48	-0.003	0.47	0.017	0.00	0.016	0.00
DumGE	-0.013	0.16	-0.011	0.14	-0.012	0.14	-0.005	0.45	-0.005	0.44
DumSP	0.006	0.25	0.003	0.51	0.003	0.48	0.021	0.00	0.021	0.00
Sent⊥	-0.019	0.00	-0.013	0.00	-0.010	0.00	-0.014	0.00	-0.010	0.00
Sent⊥*DumFR	0.000	0.97	0.000	0.98	-0.001	0.77	-0.004	0.40	-0.007	0.16
Sent⊥*DumGE	-0.001	0.92	-0.003	0.64	-0.007	0.23	-0.008	0.17	-0.011	0.04
Sent⊥*DumSP	-0.004	0.68	0.003	0.66	0.002	0.69	0.007	0.12	0.005	0.24
Fediff	0.004	0.45	0.004	0.41	0.005	0.37	-0.013	0.17	-0.008	0.36
Fediff*DumFR	0.002	0.83	0.002	0.83	0.001	0.90	0.026	0.01	0.021	0.03
Fediff*DumGE	0.010	0.36	0.013	0.22	0.011	0.32	0.011	0.24	0.007	0.45
Fediff*DumSP	0.003	0.75	0.002	0.88	0.001	0.90	0.008	0.45	0.004	0.73
MKT	0.701	0.00	0.686	0.00	0.698	0.00	0.503	0.00	0.520	0.00
MKT*DumFR	0.390	0.01	0.404	0.01	0.390	0.01	0.350	0.00	0.341	0.00
MKT*DumGE	0.223	0.09	0.271	0.04	0.235	0.07	0.467	0.00	0.438	0.00
MKT*DumSP	-0.158	0.28	-0.135	0.36	-0.142	0.32	0.143	0.17	0.128	0.21
SMB	0.428	0.00	0.416	0.00	0.416	0.00	0.514	0.00	0.511	0.00
SMB*DumFR	-0.117	0.37	-0.105	0.42	-0.105	0.42	-0.165	0.08	-0.161	0.09
SMB*DumGE	-0.277	0.05	-0.250	0.07	-0.259	0.06	-0.261	0.04	-0.263	0.04
SMB*DumSP	-0.453	0.00	-0.432	0.00	-0.431	0.00	-0.520	0.00	-0.517	0.00
HML	-0.140	0.34	-0.132	0.34	-0.118	0.39	-0.194	0.15	-0.181	0.18
HML*DumFR	-0.004	0.98	-0.010	0.96	-0.017	0.94	0.149	0.38	0.163	0.34
HML*DumGE	-0.079	0.70	-0.070	0.72	-0.101	0.61	0.114	0.52	0.093	0.60
HML*DumSP	-0.109	0.67	-0.105	0.68	-0.123	0.63	0.049	0.79	0.034	0.86
Sent Ang-Sax vs Cont		0.80		0.96		0.63		0.64		0.28
FE Ang-Sax vs Cont		0.48		0.44		0.54		0.12		0.26
Sent Ang-Sax vs Cont 2005-2007 vs 1997-2004		0.16		0.24		0.54		0.19		0.41
FE Ang-Sax vs Cont 2005-2007 vs 1997-2004		0.16		0.25		0.23		0.35		0.14

Results of the regression for the whole sample data set for each country. The dependent variable ($R^c_{high,t+k} - R^c_{low,t+k}$) is the self-financed portfolio return based on volatility, for country c and holding period k. The independent variables are investor sentiment orthogonal to the macroeconomic variables ($SentG^{\perp}_t$) and the EPS forecast errors computed for the volatility portfolio as the difference between the average EPS forecast errors for high volatile stocks minus low volatile stocks($FE^c_{diff,t}$). Fama and French (1993) risk factors are also included for each market. To prevent the autocorrelation and heteroskedasticity problems associated with overlapping observations, the portfolio return is computed in calendar time approach following Jegadeesh and Titman (2001). OLS estimation is used with the Newey and West (1987) standard errors. Results are shown for each market analysed: France (FR), Germany (GE), Spain (SP) and the United Kingdom (UK). "Ang-Sax vs Cont" shows the level of significance of the difference in coefficients between the aggregate results for the Continental subset versus those for the UK. Ang-Sax vs Cont 2005-2007 vs 1997-2004 shows the estimated difference in coefficients between the Continental versus UK aggregate results for the period 2005-2007 versus those for the period 1997-2004, together with their levels of significance

Table IV: **Selection bias and investor sentiment**

	FR	GE	SP	UK	Full Sample	Continental	Ang-Sax vs Cont	Ang-Sax vs Cont 2005-2007 vs 1997-2004
R^U	0.264	0.274	0.223	0.225	0.244	0.255	-0.030	0.309
R^D	-0.062	0.158	0.136	-0.758	-0.256	0.042	-0.256	0.723
SB1	0.326	0.116	0.087	0.983	0.500	0.213	0.227	-0.414
p-value	0.07	0.92	0.00	0.07	0.06	0.23	0.45	0.60
$SB2^U5Q$	0.173	0.155	1.222	0.700	0.794	0.935	-0.235	
p-value	0.905	0.783	0.079	0.094	0.019	0.093	0.686	
$SB2^D5Q$	0.085	0.063	-0.241	0.002	-0.501	-0.092	0.095	
p-value	0.69	0.92	0.52	1.00	0.99	0.61	0.33	
$SB2^U1Q$	0.075	0.195	0.008	-0.425	-0.032	0.092	-0.517	
p-value	0.76	0.91	0.99	0.13	0.93	0.85	0.58	
$SB2^D1Q$	0.070	-0.263	-0.205	0.114	-0.027	-0.062	0.176	
p-value	0.70	0.81	0.54	0.85	0.92	0.84	0.38	

Average values of the R^U and R^D ratios, by country, for the entire set of stocks. Results of the SB1 and SB2 tests. To compute the SB2 test each quarter stocks are sorted by their volatility and grouped into quintiles. Then we calculate the percentage of quarters that each stock appears in each of the extreme quintiles, the first and fifth. Finally, the stocks selected as more volatile (less volatile) will be those that, for more than 60% of the quarters, appear in the fifth quintile (first quintile) and for less than 10% of the quarters in the first quintile (fifth quintile). The number of upward and downward EPS revisions is obtained from the FactSet database and we compute the number of revisions issued by the analysts following a firm during the last month of the quarter. The proxy for news is the unexpected stock return (20% extreme). We define news as the unexpected component of returns, $u_t = r_t - \rho_t$, where r_t is the return on a stock from t - 1 to t and ρ_t, is defined as $E(r_t | \Phi_{t-1})$, where Φ_t is the information set at time t. R^U (R^D) is the ratio between the number of upward EPS revisions (the number of EPS downward revisions) and the number of pieces of positive (negative) news on a quarterly basis, the SB1 test statistic is the difference between R^U and R^D. $SB2^U=E(R^U/HS)-E(R^U)$ and $SB2^D=E(R^D/HS)- E(R^D)$ are the conditioned Selection Bias (SB) Tests during high sentiment periods computed as the differences between the results of the expected R^U and R^D ratios conditional on high level sentiment (HS) and their respective unconditional ratios. "Full sample" shows the results for all the markets considered. "Continental" shows the results for the sample made of data from the French, German, and Spanish stock markets. "Ang-Sax vs Cont" shows the estimates of the difference in coefficients between the aggregate results for the Continental subset versus those for the UK, together with their levels of significance. Ang-Sax vs Cont 2005-2007 vs 1997-2004 shows the estimated difference in coefficients between the Continental versus UK aggregate results for the period 2005-2007 versus those for the period 1997-2004, together with their levels of significance.

Table V: **Abnormal Trading Volume Analysis**

Panel A: Abnormal Trading Volume during High Sentiment Periods

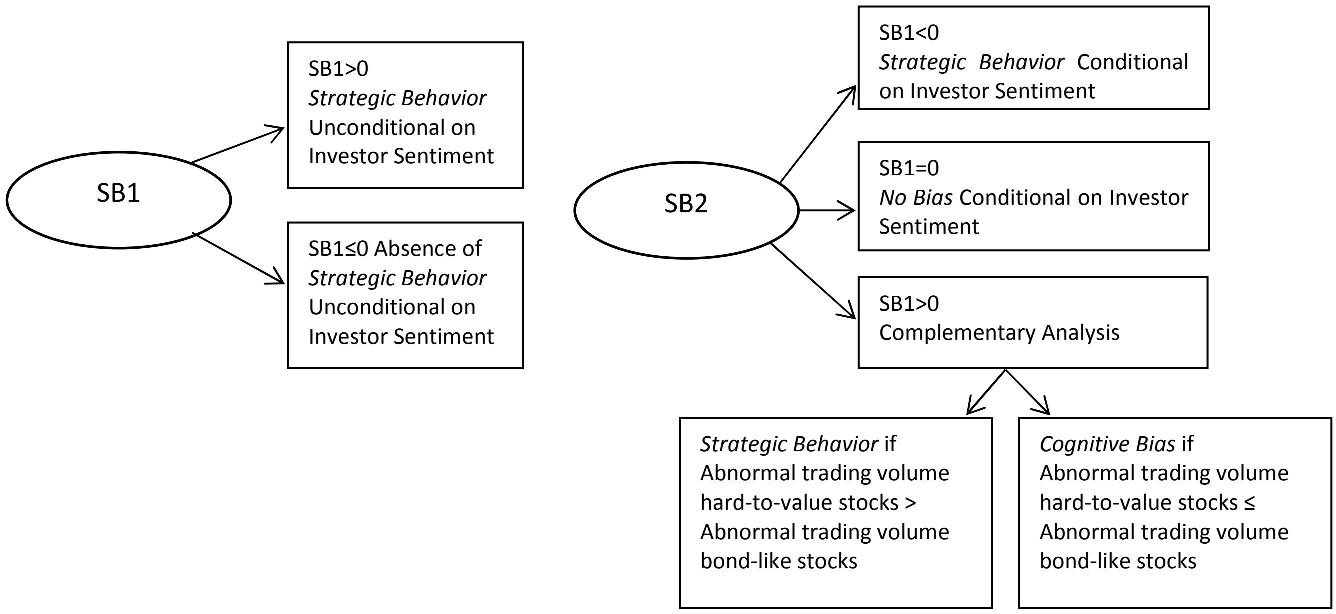
	FR	GE	SP	UK	Full Sample	Cont	Ang-Sax vs Cont
5Q	-0.148	-0.138	-0.099	-0.021	-0.102	-0.128	0.107
1Q	0.055	-0.234	0.037	0.123	-0.005	-0.047	0.170
p-value	0.02	0.51	0.08	0.01	0.48	0.14	0.64

Panel B: Control by Buy Recommendations during High Sentiment Periods

	FR	GE	SP	UK	Full Sample	Cont	Ang-Sax vs Cont
5Q	-0.333	-0.200	-0.136	0.004	-0.166	-0.223	0.227
1Q	-0.021	-0.185	-0.011	0.132	-0.021	-0.072	0.204
p-value	0.08	0.9	0.05	0.04	0.15	0.01	0.15

Results of the abnormal trading volume analysis during high sentiment periods. We calculate the results for the extreme quintiles, the first (1Q) and fifth (5Q) based on volatility (Panel A). We also compute the results using portfolios constructed exclusively from stocks with strong buy recommendations during the study period (Panel B). Results are shown for each market analysed: France (FR), Germany (GE), Spain (SP) and the United Kingdom (UK). “Full sample” shows the results for all the markets considered. “Cont” shows the results for the sample made of data from the French, German, and Spanish stock markets. “Ang-Sax vs Cont” shows the estimates of the difference in coefficients between the aggregate results for the Continental subset versus those for the UK, together with their levels of significance.

Figure 1: **Testing strategy**



Appendix.

BTM = book-to-market ratio characteristic used in the construction of the portfolios; we remove stocks with negative book-to-market values

SIZ = size characteristic proxied by market value

VOL = stock volatility measured as the standard deviation of past twelve-month returns

DIV = Dividend Per Share ratio

SentUS = proxy of US sentiment; this variable is used in Baker and Wurgler (2006) and available at http://pages.stern.nyu.edu/~jwurgler (see Section 3.2 for details)

SentEU = European sentiment index that captures the overall level of investor sentiment across four key European markets sentiment (see Section 3.2 for the details)

SentFR = French investor sentiment (see Section 3.2 for the details)

SentGE = German investor sentiment (see Section 3.2 for the details)

SentSP = Spanish investor sentiment (see Section 3.2 for the details)

SentUK = UK investor sentiment (see Section 3.2 for the details)

SentG = global sentiment; this is a composite index formed by the common component in the SentUS and SentUE indexes (see Section 3.2 for the details)

EPSFY1consensus (median) = one-year-ahead Earnings Per Share consensus median forecast for fiscal year y

EPSactual = actual Earnings Per Share obtained in this fiscal year y by the company

FE= Earnings Per Share forecast errors computed as the difference between EPSactual and EPSFY1 for the fiscal year y, scaled by the absolute value of EPSFY1consensus (see Section 3.3 for details)

$SentG^{\perp}$ = global investor sentiment orthogonal to economic variables to control for possible changes in the economic cycle; the macroeconomic variables considered are the industrial production index, durable and non-durable goods consumption and the unemployment rate

$Skew^{\perp}$ = proxy for the skewness in analyst forecast errors (Gu and Wu, 2001)

R_{high} - R_{low} = self-financed portfolio return.

DSentG = a dummy that is equal 1 if investor sentiment at the beginning of the year y is above the median, and zero otherwise.

SB1 = Selection Bias 1; defined as the difference between the R^u and R^d ratios

SB2 = Selection Bias 2; compares the expected R^u and R^d ratios that are conditional on high investor sentiment with their respective unconditional ratios.