Analyst Forecast Error and investor sentiment in cross-sectional returns

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Abstract:

Forecasted earnings constitute an essential source of information to market participants in the process of stock valuation. Consequently, the observed financial analysts' optimism would be reflected in the investor sentiment. This paper examines the effect of the investor sentiment on cross-sectional stock returns by embedding the effect that financial analysts have on investor sentiment. Using all firms listed on LSE from 1992 until 2015, the results confirm previous studies that analysts are overall optimistic. We show that financial analysts' error is a major component of the investor sentiment. Higher than average forecasts lead to higher sentiment levels. Furthermore, we show that sentiment levels partially explain the value premium phenomenon. While stock returns are significantly positively affected by sentiment levels, growth stocks appear to be more sensitive to shifts in sentiment than value stocks.

1. Introduction

Behavioural scholars in finance show a strong belief in sentiment as a major player in stock markets (Chen (2010), Brown and cliff (2005), Baker and Wurgler (2006)). Market expectation is a key factor in their argument regarding the existence of sentiment. According to Brown and Cliff (2004), sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be". This leads to divergence from the intrinsic value making market prices for example look vulnerable and prone to behavioural bias. Many aspects in finance have been investigated from a sentiment perspective. Daniel et al. (1998) suggest that market price momentum is partially driven by investor's overconfidence. Schmelling (2009) and Baker and Wurgler (2006) find that investor sentiment affects negatively future stock returns. Bergman and Roychowdhury (2008) argue that a firm's board is likely to change its disclosure policies depending on the market sentiment level.

In light of this matter, one cannot talk about market expectations without mentioning analyst forecasts. Financial analysts are an important source of information briefing the market with rich analysis and recommendations on a daily basis. Such source had a fare share of academic studies investigating its role and consequences. Analysts are found to be overall optimistic regarding companies' future earnings (Capstaff et al. (2001), Gu and Wu (2003), Easterwood and Nutt (1999), Ciconne (2005), Larocque (2013)). Capstaff et. Al. (1995) argue that financial analysts might have the incentives to issue optimistic forecasts in order to increase the trading volumes generated after their forecasts. Abarbanel and Bernard (1992) finds that stock prices drift after earnings announcement are partially driven by inefficient forecasts made throughout the year. Mest and Plammer (2003) explain that optimism in analysts' forecasts facilitate the access to management's private information specially for hardly predictable firms. Baron, Biard and Liang (2013) focused on the timing of the analyst forecast depending on its type. They found that a pessimistic forecast is issued later than the other forecasts on average, which may explain why the last quarter of a fiscal year is less optimistic in terms of earnings forecast.

Consequently, this research studies the possibility that forecast error made by financial analysts is a major component of sentiment in London Stock exchange. The idea is that when forecast error is positive, that is having an optimistic forecast, sentiment is likely to be high due to the high expectation been built by analysts. The impact of sentiment on stock returns could be partly traced optimistic behaviour of financial analysts. Following Baker and

Wurgler (2006), sentiment index is estimated using principal component analysis based on seven proxies. The sample employed spans over January 1992 to December 2015 and covers all companies listed in London stock exchange.

The results confirm previous findings in the literature on stock returns being driven by investor sentiment. However, we provide original findings on the role of financial analysts in influencing the sentiment of the overall market. Results show that forecast error is positively correlated with the investor sentiment index. In addition, stock returns appear to increase in high sentiment compared to low sentiment. The value premium shrinks significantly when sentiment become high. This is due to the significant impact of sentiment on growth companies rather than value companies. As a result, small stocks, growth stocks and stocks with weak profitability appears more prone to sentiment shifts than value, large and stocks with robust profitability. These findings support the theory that growth firms are harder to value thus turn to change dramatically when sentiment jumps.

The remaining of this paper is as follow: the second section discusses the background, literature and rational of the study. The third section explains the sample and methodology used. The fourth section navigates through discussions and interpretations. The last section concludes.

2. Rational and background:

a. Forecast error and stock returns

Past studies suggest that there is a relationship between analysts' forecasts and consequent abnormal returns. Bernhard and Campello (2007) report that following downward forecast revisions, abnormal returns appear to be large following earnings announcement. They claim that as aggregate analysts revise their forecast downwards, the probability of getting positive surprise after the announcement increases (probability of having the actual earnings per share being higher than the forecasted earnings per share). Consistent with Bernhard and Campello (2007), Bartov et al. (2002) claim that firms that meet or beat analysts' forecasts (previously referred to as a positive surprise), report higher stock returns over the quarter compared to the ones that fail to meet their forecasts.

Clearly, a lot of effort was made in the past to understand whether analysts forecast error is systematic or random. The behavioural side of the systematic bias in forecast revisions is discussed by De Bondt and Thaler (1990) who report that earnings forecasts are too extreme

to be rational and that analysts' forecast revisions show a trend of overreaction to previous forecasts. De Bondt and Thaler (1990) conclude that analysts are subject to overreaction emphasizing on the behavioural explanations for the anomalous trends. Hribar and McInnis (2012) find that the forecast error is positively significantly affecting stock returns and that it absorbs the impact of sentiment index on the return of the SMB portfolio. They indicate that "it appears that analyst forecast errors are significant intermediating variable in the cross-sectional patterns documented between sentiment and stock returns" (Hribar and McInnis (2012 p. 306)). However, such a relationship has never been investigated before.

b. Sentiment

Sentiment surrounding the stock market is considered a very important factor in affecting investment decisions. As human beings, investors are subject to sentiment and it sometimes leads to inappropriate interpretations of given information. Daniel et al. (1998) suggests that market price momentum is partially driven by sentiment such as investors overreact to private signals and underreact to public information. Similarly, Schmelling (2009) finds that sentiment is negatively related to future returns and mostly in the short and medium term horizons. Scheinkman and Xiong (2003) claims that investors' overconfidence plays a big role in bubble markets by stimulating prices, volatility and trading volume, that is, by creating more speculative trading driven by heterogeneous beliefs. Consistently, Odean (1998) had found that overconfident traders trade more aggressively than rational ones and this is due to their superior self-belief in private information. As a result, trading volume and price volatility increase. According to the author, investors do not only overvalue their private information but they also misinterpret it. Baker and Wurgler (2006) define sentiment, in the context of financial markets, as the tendency to speculate, such that it drives the relative demand for speculative investments. Also, Brown and Cliff (2004) states that "sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be". The empirical findings in Brown and Cliff (2005) confirm their statement by finding that sentiment levels push stock prices to higher levels surpassing the intrinsic values leading to negative stock returns in the following periods.

The dilemma lies in building a model to estimate investor sentiment. Both direct (survey primary data) and indirect (quantitative market proxies-secondary data) methods have been employed in previous studies. Brown and Cliff (2004) provide a comprehensive study

about the different measures of investors sentiment. They found that both methods (direct and indirect) provide common features. A common feature of the direct method is using consumer confidence surveys as a proxy of investor sentiment[2]. Fisher and Statman (2003) use the Michigan Consumer Confidence index and the American Association of Individual Investors, and find a positive relationship between the change in individual investor's sentiment and change in consumer confidence. Furthermore, they find a positive significant relationship between individual investor's confidence and returns on small stocks. In the same manner, Lemmon and Portniaguina (2006) find that the sentiment component of consumer confidence can forecast returns on stocks primary held by individuals.

On the other hand, several studies employ indirect measures of investor sentiment[3]. For instance, Baker and Wurgler (2006) apply an indirect quantitative approach where they construct a sentiment index using principal component analysis based on six proxies: Closed end fund discount, return on IPOs, number of IPOs issued, turnover ratio, share of equity issued and dividend premium. The results from their analysis show a negative impact of investor sentiment over subsequent returns. In particular, when sentiment level is low, subsequent stock return appear to be high for small stocks, young stocks, non-dividend paying stocks, highly volatile and distressed stocks. Baker and Wurgler (2006) base their interpretation on the assumption proposed by Shleifer and Vishny (1997) and that is, since asset mispricing is a result of a demand shock, a shift in sentiment levels would affect stocks that are more sensitive to speculative demand, harder to value, and stocks that are riskiest and costliest to arbitrage to a greater extent.

While most of the empirical findings suggest that changes in sentiment level tend to affect small, growth, harder to value stocks, as well as stocks that are dominantly held by individual investors (see for example, Fisher and Statman (2003) and Lee, Shleifer and Thaler (1991)), there are still discrepancies in the literature. For instance, Baker and Wurgler (2006) and Waggle and Agrrawal (2015) find that investor sentiment significantly influence the returns of growth stocks rather than value stocks. On the contrary, Lemmon and Portniaguina (2006) find no evidence in support of the relationship between sentiment and value premium. Moreover, Schmelling (2009) finds that the impact of sentiment on returns is significant for both value and growth firms but economically stronger for value firms than

[2] See for example Bergman and Roychowdhury (2008), Chen (2010), Lemmon and Portniaguina (2006) and Schmeling (2009).
[3] See for example Baker and Wurgler (2006), Baur, Quintero and Stevens (1996), Brown and Cliff (2005), Hribar and McInnis (2012), Neal and Whealley (1998).

growth firms. There is clearly a need for further investigation on this matter. We, therefore, intend to distinguish the effect of investor sentiment on stock returns relative to firm characteristics.

Henceforward, combining the above associations together raises few critical questions about the nature of relationship between sentiment, forecast error and stock returns. On the one hand, investors continue to fall in the trap of earnings surprise yet they already know the significant repetitive optimistic forecasts and systematic downward forecast revisions found in many papers[4]. It is important to notice that forecast errors are not limited only to small and growth firms but apply as well to large firms even though they have more accurate earnings forecasts. Hence, it is essential to account for forecast optimism when estimating investor sentiment. Rather than taking forecast errors as an intermediating variable, investor sentiment index is calculated as a function of forecast error using the principal component analysis in order to capture the common component between forecast optimism and Baker and Wurgler (2006) sentiment variables.

On the other hand, there is evidence that upward shifts in investor sentiment (measured either directly or indirectly) pushes stock prices in the short term and affects future returns negatively in the medium and long term. However, the evidence on the stronger relationship between sentiment and small and growth stocks is still debatable.

This paper contributes to the literature in two ways. First, it proposes a new indirect measure of investor sentiment index that embeds analysts forecast errors for all London Stock Exchange (LSE) companies from 1992 to 2015. This is motivated by the fact that the forecast error substantially absorbs the impact of investor sentiment on cross-sectional stock returns. Second, it to address the relationship between investor sentiment, as a function of forecast error, and patterns in cross-sectional stock returns. We distinguish the sentiment effect relative to firm characteristics to examine whether it plays a part in exacerbating return anomalies, such as value premium.

[4] See for example Bernhard and Campello (2007), Bartov, Givoly and Hayn (2002), Yu and Ke (2006), among others.

3. Methodology and sample selection:

The first step in the analysis is to calculate analysts forecast error. For simplicity, the following equation is used:

$$\textbf{a)} \qquad FE_{hT} = \frac{F_{ht} - E_t}{|E_t|}$$

Where FE is average forecast error made in month h for year t , F ht is the EPS forecast in monthly horizon h for year ending t, Et is the actual EPS at year ending t. "h" is the monthly distance (11 to 1 horizon) from which the forecast was made until earnings announcement date. The forecast error is calculated monthly to fit into the time series analysis. For each month, forecast error is simply defined as the difference between monthly forecast and the yearly reported earnings per share, deflated by the reported earnings per share. This will produce a percentage of error made by forecasters when forecasting the end of year performance. It's important to remind about the purpose of this research which is to find how the aggregate forecast error made each month in LSE can contribute to the sentiment level, regardless whether this error is subject to biasness. Note that the denominator is kept in absolute value in order to save the sign of the nominator, which would tell whether the forecast is optimistic or pessimistic.

The next step is to calculate the investor sentiment index. Prior work suggests a number of proxies as stated in the previous sections. However, there is no definite answer to such behavioural estimation. This research follows a popular index is proposed by Baker and Wurgler (2006) who use six proxies in order to estimate the investor sentiment index: closed-end fund discount, LSE share turnover, the total number of IPOs issued monthly, the monthly average of first day return on the IPOs, the share of equity issues in LSE, and dividend premium. In this research, the analyst forecast error is added as the seventh proxy.

The definitions, sources and expected sign of each proxy come as follow: Closed-end fund discount (CEFD) is the average difference between net asset value (NAV) of closed-end fund stocks and their market prices. Baker and Wurgler (2006) suggest that the coefficient of this variable is expected to be negative. The Share Turnover (Turn) is the ratio of reported trading volume over average shares listed in LSE. This ratio is a proxy of liquidity and is supposed to be positively related to sentiment (Baker and Stein (2004)). The variables related to CEFD and NAV are collected using Thomson Reuters Datastream. NIPO is the total number or IPOs listed in each month between 1992 and 2015 and is expected to be have a positive sign with sentiment index. RIPO is the monthly average return on first day of LSE IPOs and is

expected to be positively associated with sentiment with high first day return viewed as a sign of excitement. The share of equity issues SE is the percentage of equity issues in total monthly equity and debt issues of LSE. Similar to IPO signs, SE is expected to be positively correlated with sentiment index. Bloomberg Terminals database is used to get the IPO data as well as debt and equity issuances. The sixth proxy is dividend premium Divp, which is the difference in market to book ratio between firms that pay dividend and those that don't. This proxy is believed to be inversely correlated to sentiment levels according to Baker and Wurgler (2007) and is available from Thomson Reusters Eikon terminals. The last proxy of sentiment is FE (forecast error) which is the difference between average forecasted earnings per share and actual reported earnings per share at the end of the year, divided by reported earnings per share.

A positive sign of FE suggests an optimistic forecast and vice versa. The expected relationship between forecast error and sentiment index is expected to be positive, that is, optimistic earnings forecast signal high sentiment and pessimistic earnings forecast signal a low sentiment. Forecasting data are downloaded from IBES which is available on Datastream database.

All public companies listed in London Stock Exchange were used as available from 1992 to 2013. Starting from 1992 was important to insure that analysts had adopted the third financial reporting standard (FRS3) in the UK. As stated in the previous chapter, the introduction of FRS3 has forced public companies to disclose more detailed information. It was clear that such introduction had an impact on financial analysts, specially when it comes to earnings per share forecasts (Acker, Horton and Tonks (2002)). Moreover, companies listed in LSE were collected as available in each year and this is important in order avoid the survivorship effect as each year the number of listed companies vary due to mergers, acquisitions, new entrants or companies leaving the index. At a particular month, companies followed by less than 3 forecasters were eliminated due to reliability issues and consistent with the literature.

Table 1.

Summary statistics and correlations of sentiment index and sentiment components. Sentiment is the index estimated using the first principal component based on seven proxies: $CEFD_t$ is the monthly, value-weighted average discount on closed-end mutual funds. The second measure $TURN_t$ is the detrended natural log Turnover (5 years moving average) which is the ratio of reported trading volume over average shares listed in LSE. The third measure $NIPO_t$ is the monthly total number of initial public offerings issued in LSE. The fourth measure $RIPO_{t-1}$ is the average monthly first-day returns of initial public offerings, issued the previous month. The fifth measure SE_t is the share of monthly equity issuance to total equity and debt issuance. The sixth measure $DIVP_{t-1}$ is the lag of natural log of the value-weighted average ratio of market-to-book ratio of dividend payers to non-payers. The last proxy FEt_{-1} is the analyst forecast error as a ratio of the difference between earnings per share monthly forecast and end of year reported earnings per share, divided by end of year reported earnings per share. Each of the seven components are regressed against the growth in industrial production, the growth in durable, nondurable, and services consumption, and a dummy for recession (2 consecutive negative growth of GDP). The orthogonalised proxies are then used in this analysis.

	Summary Statistics					**Correlation matrix**							
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**sentiment**	**CEFD**	**TURN**	**NIPO**	**RIPO**	**SE**	**DIVP**	**FE**
$sentiment_t$	258	0.000	0.864	-3.356	2.417	1							
$CEFD_t$	288	-4.137	1.191	-27.544	30.321	-0.1679*	1						
$TURN_t$	288	7.063	3.862	2.709	41.182	0.6121**	-0.1367	1					
$NIPO_t$	288	4.066	23.975	-10.556	259.000	0.8041***	-0.0141	0.3911***	1				
$RIPO_{t-1}$	288	7.191	6.676	0.000	31.000	0.8257***	-0.0982	0.3513***	0.4165*	1			
SE_t	280	30.928	3.665	0.000	100.000	0.2467**	-0.184**	0.1276	0.2068**	0.032	1		
$DIVP_{t-1}$	288	-19.121	22.606	-1.016	0.473	-0.3184**	0.0812	-0.1312	-0.2321*	-0.1093	-0.201**	1	
FE_{t-1}	288	9.911	6.357	-3.451	35.553	0.4227***	-0.416**	0.3094***	0.1432	0.2451**	0.1334	-0.275*	1

*****, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.**

The choice of time at which each proxy is expected to have an impact on investor's sentiment is another challenge since some variables might reflect a shift in sentiment earlier than others. Following Baker and Wurgler (2006), the first stage is to run the principal component analysis using each proxy and its lagged values and this results in a preliminary index with 12 loadings, one of each variable and its lagged proxy. After computing the correlation between the preliminary index and all 12 variables, the second stage consists of choosing the variables that are the most correlated with the index either lead or lagged, then run again the first principal component using the chosen variables. The six proxies chosen are then standardised so that the index has unit variance.

$$\text{b)} \quad Sentiment_t = -0.2698\, CEFD_t + 0.4493\, TURN_{t-1} + 0.4439\, NIPO_t + 0.3986\, RIPO_{t-1} + 0.2419\, SE_t - 0.3125\, DIVP_{t-1} + 0.4617\, FE_{t-1}$$

Equation b is the result of the second stage analysis. First thing to notice is that the sign of each loading appears as expected. Nevertheless, as the sample is withdrawn from a long period of time, it is a must to distinguish between business cycles and investor sentiment cycles. To do so, a third stage principal component analysis is run after controlling for macroeconomic factors. Therefore, each of the six chosen proxies is regressed on growth in consumer durables; consumer nondurables and consumer services; a dummy variable of recession (A consecutive 2 quarters of negative GDP); and growth in industrial production index. The residuals of each regression are then taken as the orthogonalised variables and used to run the first principal component.

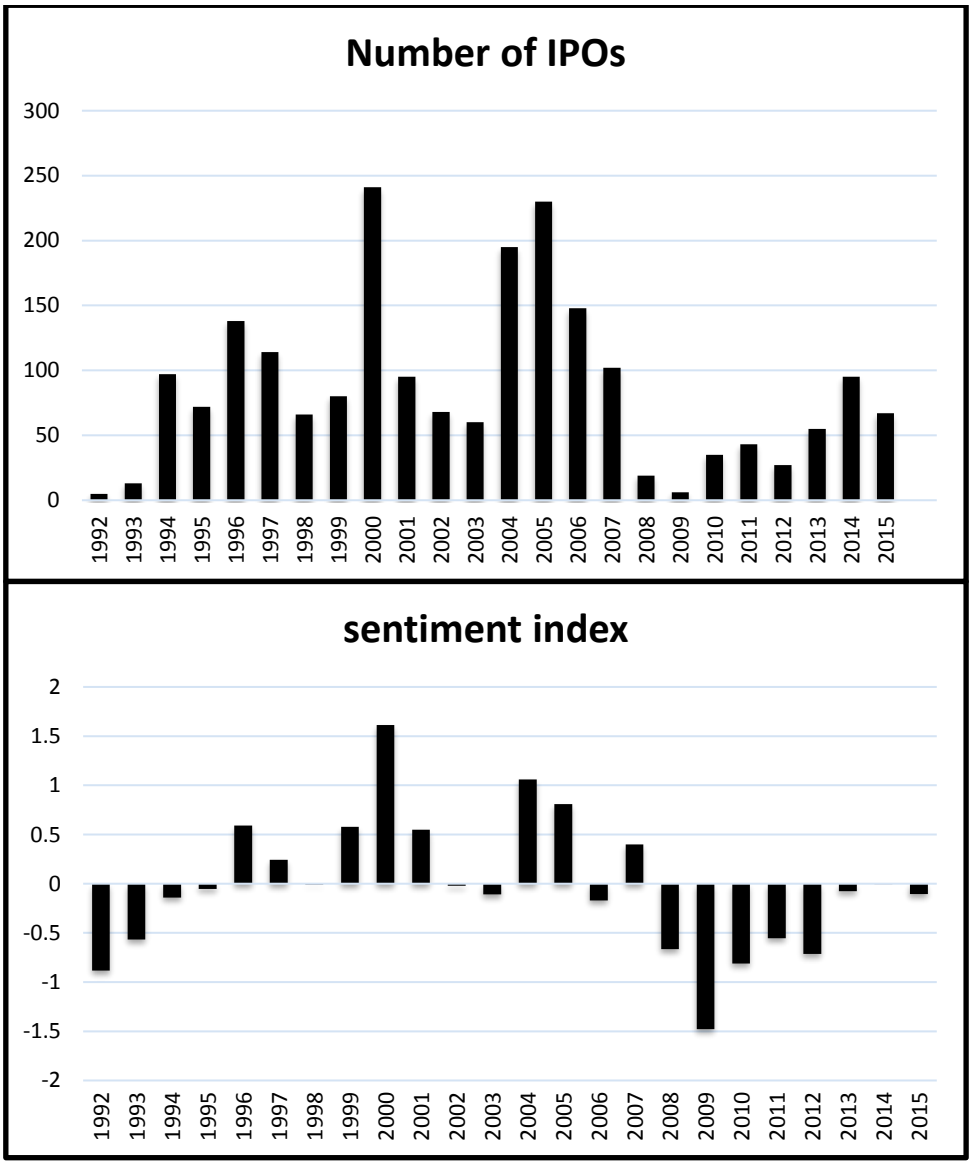
$$\text{c)} \quad Sentiment_t = -0.2798\, CEFD_t + 0.4473\, TURN_t + 0.4422\, NIPO_t + 0.4042\, RIPO_{t-1} + 0.2423\, SE_t - 0.304\, DIVP_{t-1} + 0.4603\, FE_{t-1}$$

Notice that the coefficient of each factor didn't change much from the previous equation and the correlation between Sentiment index of equation c and b is 93%, but more importantly, it captured 49% of the sample variance. Table 1 shows the descriptive statistics of each component as well as the calculated sentiment. One thing to notice in the correlation matrix is the low coefficient of CEFD (-16.7%) compared to previous studies. Despite having the same sign as previous studies suggest (Baker and Wurgler (2006); Hribar and McInnis (2012)), it is still normal considering that open-ended funds became much more popular in recent years

than closed-end fund (in the UK, open-ended funds occupy 69% of total mutual funds). Another interesting point is how dominant RIPO and NIPO appear to be with correlations of 80.2% and 82.5% respectively. Figure 1 clearly shows how the number of IPOs for example was seriously depending on the sentiment index. The year with the highest number of IPOs was 2000, during which it recorded the highest level of sentiment as well at 1.61 on average. Similarly, 2009 recorded the lowest number of IPOs issued (total of 5) in a year where sentiment index was at the lowest figures (-1.47 on average).

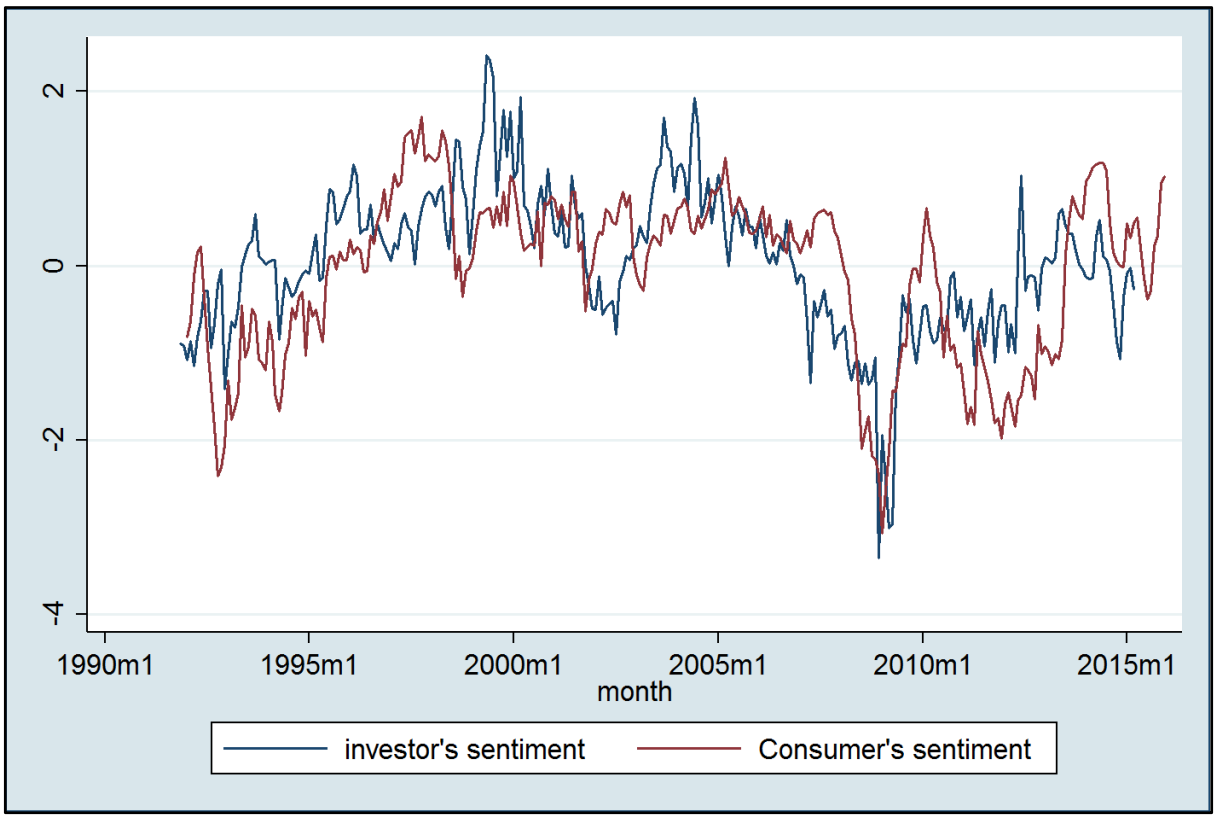
***Figure* 1**

Total number of IPOs issued yearly from 1992 until 2015, compared to the sentiment index SENT. Sentiment is the yearly average of monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues.



As noted previously, it seems evident for many scholars that consumer confidence index is a powerful proxy for investor's sentiment index (Bergman and Roychowdhury (2008), Chen (2010), Fisher and Statman (2003), Schmelling (2009)). Therefore, figure 2 compares the Sentiment index calculated in this study with consumer confidence survey conducted by the UK General Affair of Finance (accessed through Thomson Reuters Eikon). The correlation between the two indices is 51%. The time series plot in figure 2 illustrates how both indices showed signs of optimism during the internet bubble period (between 1995 and 2000), with another side of pessimism during the latest financial crisis particularly between 2007 and 2013. During the whole sample of study, there are 141 months of pessimism and 149 months of optimism (when Sentiment index is below or above 0 respectively). If consumer confidence index was considered as the benchmark, there would exist 175 pessimistic months against 115 optimistic ones.

Figure 2
Time series plot of consumer confidence index and investor's sentiment index from 1992 until 2015 in the UK. Consumer confidence index is a survey data collected monthly by the UK General Affair of Finance (accessed through Thomson Reuters Datastream). Investor Sentiment is a monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues.



4. Empirical Tests and discussion:

The new index is believed to have an impact on stock returns and the value premium phenomenon in particular. In order to test for such phenomenon, firms are sorted first depending on size, BTM, profitability and investment aggressiveness, then compared during periods of different sentiment levels. Where B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Investment is the percentage change in total assets between the end of fiscal year t-1 and t-2. Profitability is the operating profitability divided by book equity. Size is the market cap at fiscal year end t. For each month, firms are sorted to 5 value-weighted portfolios of book-to-market quintiles, with low book-to-market firms which belong to the first quintile are called growth firms and value firms are the ones belonging to the fifth book-to-market quintile. The same sorting is applied using investment and profitability quintiles. Regarding size, firms are sorted into three different portfolios using 33% and 66% as breakpoints, as well as 5 portfolios of size quintiles. The Sentiment index follows a slightly different procedure where months are divided into low (months during which sentiment percentile is less or equal to 33%), and optimistic (months during which sentiment percentile is above or equal to 66%). Sentiment is called neutral if its percentile is between 33% and 66%.

Table 2.

Average monthly percent of returns for portfolios formed on size and BTM ratio (Book to market), from January 1992 until December 1995 (288 months). Where B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Stocks are sorted into five size groups (small to big) taking the market cap quintiles as breaking points. Stocks are also sorted according to the BTM quintiles from low to high. The combination of the two sorting produces 25 value weighted portfolios.

	Book-to-market quintiles						
Size quintiles	Low	2	3	4	high	**HML**	**Average**
small	-3.8610	-3.36626	-2.59356	-1.80512	-0.81516	3.04591	-2.48823
2	-1.6657	-1.48035	-0.73735	-0.29106	0.4823	2.14805	-0.73844
3	-0.0443	-0.02775	0.45653	0.56164	1.27611	1.32041	0.444446
4	0.62727	0.86072	1.08581	0.85486	1.64943	1.02216	1.015618
big	0.67046	0.74106	0.69115	0.84927	1.70973	1.03927	0.932334

Table 2 shows the percentage of stock returns on size and BTM portfolios using the quintile sorting for both variables (5 x 5). Consistent with the literature, the value premium

can be clearly seen in this analysis as high BTM firms produce higher returns on average than low BTM firms. In every size row, most of stock returns gradually increases from low to high BTM but on a different rate or change. Fama and French (2015) find that the value premium is more evident in smaller firms. Results in table 2 also show a similar trend as smaller firms record higher differences in returns between firms with high and low BTM ratios. Moreover, HML monotonically decreases as firm size increases. For example, the average monthly return for big companies increases from 0.67% to 1.709% between growth and value companies respectively.

Nonetheless, stocks that are extremely small (the first row) appear to have a very low return. Even more, the worst average return is recorded for the extremely small companies that have an extremely low BTM ratio (-3.861% monthly return)

Preliminary results regarding the impact of sentiment on stock returns could be seen in table 3. Returns in neutral periods are very hard to interpret as they they consist of mixed signs and no exceptional behavioural feature. Consequently, the main focus in this research is on the extreme sides of Sentiment index which are low and high. Concerning size, panel A show that big companies outperform small ones in all sentiment periods. This difference, however, slightly decreases during high sentiment than low sentiment. By looking at each column separately, while small companies improve on average by 1.03% from low to high sentiment, big companies improve by 0.34%. Stock returns are thus better during high Sentiment for all groups, but small companies are more prone to sentiment shifts than big ones.

Panel B indicates how a shift in sentiment level can affect returns of growth and value firms. Despite an average return being higher in high sentiment compared to low sentiment, HML (High minus Low) seems to be stronger in low sentiment periods. By looking at the first column in panel B, growth firms have higher returns during high sentiment periods compared to low sentiment, with an average difference of 0.608%. Value firms, however, don't look very subject to sentiment conditions as there was almost no difference between their average return in high and low sentiment. This result supports Baker and Wurgler (2006) claiming that sentiment levels affect mostly stocks that are more sensitive to speculative demand and harder to value. fact that returns on value firms remained unchanged between low and high sentiment levels followed by an increase in returns of growth firms during high sentiment levels, led HML to appear weaker in high sentiment.

A different pattern can be seen in panel C. Investment quintile is a measure of investment aggressiveness having 1 (conservative investing) and 5 (aggressive investing). Firms having a conservative month of investment appear to have lower returns, only in low sentiment. During high sentiment, firms that are investing aggressively have a slightly lower returns than conservative firms with a monthly difference CMA of 0.209% (conservative minus aggressive). The fact that aggressive firms earn more during low sentiment might be a sign of strength specially during a period of general pessimism, resulting in an overreaction to this sign.

Panel D talks about the return on profitable companies during different sentiment levels. In this panel, profitable firms barely improve their monthly return when sentiment shifts from low to high. Contrarily, returns on firms with weak operating profitability jumps significantly from -0.652% to 1.04171% after sentiment index improved from low to high. As a result, RMW (robust minus weak) drops from 1.87% to 0.388%. Again, this finding supports the theory that unprofitable firms are harder to value and tend to be more affected by Sentiment.

The remaining is to verify whether the relationship between Sentiment and value premium is statistically significant or not. To do so, the difference between returns on value and growth stocks HML was taken as a dependant variable against Sentiment index calculated in the previous section, in addition to Fama and French (2015) factors.

d) $$HML_{it} = \alpha_t + \beta_1 SENTIMENT_t + \beta_2 MP_t + \beta_3 SMB_t + \beta_4 RMW_t + \beta_4 CMA_t + \varepsilon_t$$

Where HML is return on companies with high minus low book to market (according to Book to market quintiles) at time t for portfolio i; Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term. Unfortunately, the first attempt to regress HML against Sentiment solely gave a non-significant coefficient. Findings didn't change even after adding Fama and French (2015) factors. Findings in table 4 do not confirm preliminary results discussed above. The only significant figure was the negative coefficient of operating profitability with -0.157 significant at 5% confidence level.

Table 3.

Average monthly percent of returns for portfolios formed on Sentiment and BTM ratio (Book to market); Sentiment and investment; Sentiment and profitability, from January 1992 until December 1995 (288 months). Where B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Investment is the percentage change in total assets between the end of fiscal year t-1 and t-2. Profitability is the operating profitability divided by book equity. Stocks are sorted according to the BTM quintiles from low to high. Months are sorted into three groups of sentiment (using 33% and 66% as the break-point percentiles). The combination of BTM and Sentiment groups produces 18 value weighted portfolios. The same thing applies to Investment with Sentiment, and Profitability with Sentiment. SMB is small minus big. HML is high minus low BTM. CMA is conservative minus aggressive investing. RMW is robust minus weak profitability.

Panel A: Size

entiment	small	2	3	4	big	SMB	verage
low	-2.46338	.66039	.49567	.15282	.07723	-3.54061	).07961
neutral	-2.71936	.34725	.01231	.37549	.29082	-3.01018	.682522
high	-1.42511	.24133	.89495	.53112	.41984	-2.84495	532426
ifference	1.03827	.90172	.39928	).3783	.34261		

Panel B: Book-to-market quintiles

entiment	Low	2	3	4	high	HML	verage
low	0.59172	.79329	.81657	.22577	.16002	1.5683	117474
neutral	0.28357	.24532	.46127	.34028	).6437	0.36013	258716
high	1.20036	.50352	.11016	.74054	.19409	0.99373	549734
ifference	0.60864	.71023	.29359	.51477	.03407		

Panel C: Investment quintiles

entiment	onservative	2	3	4	gressive	CMA	verage
low	0.8215	.10511	.83745	.67244	.84281	-1.02131	055862
neutral	0.2115	.26301	).0649	.14191	.08825	0.12325	.07119
high	1.32989	1.28986	1.2771	0.989	1.12014	0.20975	1.201198
Difference	0.50839	0.18475	0.43965	0.31656	-0.72267		

Panel D: Profitability quintiles

Sentiment	weak	2	3	4	robust	RMW	average
low	-0.65238	1.08359	0.58851	1.18647	1.21728	1.86966	0.684694
neutral	-0.45799	-0.4738	-0.2353	0.10438	0.43305	0.89104	-0.125932
high	1.04171	0.20369	1.14792	1.20611	1.4304	0.38869	1.005966
Difference	1.69409	-0.8799	0.55941	0.01964	0.21312		

Equation e is the another way to examine the robustness of the effect of sentiment on value premium. This time, instead of using HML as a dependant variable, excess return on value firms and excess return on growth growth firms were regressed separately to compare the difference in Sentiment coefficient.

a) $r_{it} - r_{ft} = \alpha_t + \beta_1 SENTIMENT_t + \beta_2 MP_t + \beta_3 SMB_t + \beta_4 RMW_t + \beta_4 CMA_t + \varepsilon_t$

where r_{it} is the return on portfolio of growth stocks or value stocks, all else is the same as equation d. Using Newey-West regression is essential in order to control for the serial correlation present in the sample. Coefficients, raw standard errors and adjusted standard errors can be seen in table 5. Panel A represents the OLS regressions where coefficients of growth and value firms' samples can be seen. Panel B shows the same coefficients, but with robust standard errors. In all regressions, MP, SMB, RMW and CMA are used as control variables following Fama and French (2015).

Table 4.

Regression analysis of HML on Sentiment, and HML on sentiment and Fama and French (2015) factors using OLS and Newey-west robust standard errors, 1992 to 2015 (288 months). Where HML is return on companies with high minus low book to market (according to Book to market quintiles); Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

HML	**OLS**		**Robust SE/Newey west**		**Robust SE/Newey west**	
	coef	**se**	**coef**	**se**	**coef**	**se**
Sentiment	-0.08421	(0.06416)	-0.0842189	(0.0737)	-0.02158	(0.08016)
MR-RF					0.16391	(0.11158)
SMB					0.01862	(0.11942)
RMW					-0.157**	(0.0747)
CMA					0.07332	(0.0881)
Constant	0.00454	(0.0601)	0.0045449	(0.06755)	-0.02575	(0.0702)

se: standard errors

***** p<0.01, ** p<0.05, * p<0.1**

Table 5.

Regression analysis of excess returns on Sentiment index, and Fama and French (2015) factors using OLS and Newey-west robust standard errors. Where excess return is return on portfolio of growth or value stocks minus risk free rate (one month treasury bill), Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus return on big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

Panel A: OLS				
Excess	**Growth**		**Value**	
Return	**coef**	**se**	**coef**	**se**
Sentiment	0.228***	(0.0394)	0.145***	(0.0338)
MP	0.827***	(0.0426)	0.833***	(0.0365)
SMB	-0.0987**	(0.0430)	-0.186***	(0.0369)
RMW	-0.00461	(0.0394)	-0.0850*	(0.0338)
CMA	-0.00553	(0.0376)	0.0738*	(0.032)
Constant	-0.0788**	(0.0371)	-0.0732	(0.0318)
R-squared	0.655		0.596	

Panel B: Robust SE/Newey-West				
Excess	**Growth**		**Value**	
Return	**coef**	**se**	**coef**	**se**
Sentiment	0.228***	(0.0525)	0.145***	(0.0435)
MP	0.827***	(0.0641)	0.833***	(0.0507)
SMB	-0.0987	(0.0670)	-0.186***	(0.0419)
RMW	-0.00461	(0.0623)	-0.0850*	(0.0438)
CMA	-0.00553	(0.0517)	0.0738*	(0.0434)
Constant	-0.0788	(0.0771)	-0.0732	(0.0642)

se: standard errors

***** p<0.01, ** p<0.05, * p<0.1**

A very interesting point is that Sentiment coefficient in the growth panel is greater than the coefficient of sentiment in the value panel. The slope of the relationship between sentiment and excess returns on growth stocks is 0.228 compared to 0.145 for value stocks. Both coefficients being statistically significant at 1% confidence level, this finding supports the hypothesis that growth firms are more sensitive to sentiment than value firms, which is

reflected in stock returns as a result. It is important to note that the impact of sentiment index on stock return is a short term one since this index consists of four components that are lagged to one-month (FE, Turn, RIPO and DivP). Taking for example the coefficient of RIPO, combining figures from equation c and table 5 allow us to say that the average monthly return on IPOs affected positively subsequent monthly stock returns of companies in LSE. This short term impact of RIPO was also evident in forecast error FE. Since sentiment index affects positively stock returns; and since sentiment index is positively significantly correlated with forecast error, an increase in forecast error is likely to lead to an increase in excess returns. In other words, excess returns are more likely to be positive following a month of optimistic consensus forecasts.

In table 6 a separate regression of excess return is run for each BTM quintile. This gives more detailed coefficients about the role of Sentiment in each panel of companies. Consistent with previous results, excess returns of Panel 1 appear to be the most affected by Sentiment index with a coefficient of 0.228 significant at 1% level. Sentiment coefficient decreases almost monotonically when BTM increases from quintile 1 to quintile 5. Moreover, one can also induce that a shift in forecast error have a higher impact on growth firms than value firms. A possible reason is that growth firms are harder to predict and have less followers than value firms, which is again consistent with the theory that growth firms are harder to value.

Results in this study adds to findings of some previous studies but contradicts with others. Few articles such as Baker and Wurgler (2006, 2007), support the idea that sentiment index affects negatively future stock returns (in the long run), this study finds that sentiment affects positively stock returns (in the short run) on a monthly period. Overall, it comes consistent with Ciner (2014) who states that sentiment affects positively stock returns in the short term and negatively in the long term but only for small firms.

In addition, this study shows that this pattern is significant in the UK for growth and value firms, but stronger for growth and small firms. However, it contradicts results in Brown and Cliff (2004) who document that sentiment affects returns on large and institutionally owned companies. It also comes inconsistent with Schmelling (2009) who report that sentiment impact is qualitatively more powerful on value firms than growth firms.

Furthermore, this study doesn’t agree with McInnis and Hribar (2012) regarding the use of forecast error as an intermediary between sentiment and stock returns. As a reminder,

McInnis and Hribar (2012) report a positive relationship between forecast error and stock returns and claim that forecast error is an intermediary of sentiment as it absorbs most of the impact power shown by sentiment alone on stock returns. One possible reasons could be the common component shared between sentiment index and forecast error, resulting in forecast error being collinear with sentiment index. In fact, this particular point is addressed by the present research as the correlation between forecast error and sentiment index proved to be significant and equal to 42.2%. Based on this argument, this study shows how sentiment index, as a function of forecast error and other traditional components, still has a powerful impact on stock return without one replacing the other.

Table 6.

Regression analysis of excess return on Sentiment index, and Fama and French (2015) factors Newey-west robust standard errors. Data was divided into five BTM panels from 1 to 5 (low to high). Where excess return is return on portfolio of growth or value stocks minus risk free rate (one month treasury bill), Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

	Newey-West Regression				
Excess Return	**BTM Quintiles**				
	1	**2**	**3**	**4**	**5**
Sentiment	0.228***	0.223***	0.228***	0.163***	0.145***
	(0.0525)	(0.0441)	(0.0420)	(0.0501)	(0.0435)
MP	0.827***	0.839***	0.830***	0.778***	0.833***
	(0.0641)	(0.0633)	(0.0603)	(0.0795)	(0.0507)
SMB	-0.0987	-0.165***	-0.114***	-0.0632	-0.186***
	(0.0670)	(0.0405)	(0.0436)	(0.0557)	(0.0419)
RMW	-0.00461	0.00757	-0.185***	-0.126***	-0.0850*
	(0.0623)	(0.0593)	(0.0495)	(0.0463)	(0.0438)
CMA	-0.00553	-0.0691	0.0901*	0.0526	0.0738*
	(0.0517)	(0.0499)	(0.0501)	(0.0491)	(0.0434)
Constant	-0.0788	-0.0650	-0.0914	-0.0820	-0.0732
	(0.0771)	(0.0687)	(0.0652)	(0.0679)	(0.0642)

Standard errors in parentheses

***** p<0.01, ** p<0.05, * p<0.1**

5. Conclusion:

In this study, we review the relationship between investor sentiment and documented patterns in cross-sectional stock returns. Using the principal component analysis, a sentiment index is estimated following Baker and Wurgler (2006) six proxies and an additional proxy (analyst forecast error of earnings) is appended to the model. All companies in London Stock exchange are investigated from January 1992 until December 2015. The use of forecast error is essential to fulfil the assumption that forecast optimism is a main component of investor sentiment and that it influences future stock returns.

The first stage analysis show that sentiment index is positively significantly correlated with forecast error, that is, when monthly aggregate earnings forecast is optimistic, investor sentiment tends to be high in the following month and vice versa.

More interestingly, sentiment index is found positively related with stock returns meaning that stock returns increase over the short-term period when sentiment is higher. While big companies appear to have larger returns in general, small and growth companies seem to be more prone to sentiment shifts than large and value firms. In particular, we find that the value premium varies substantially with the sentiment level. The HML portfolio generates 50% more in low sentiment levels than in high sentiment levels and 5 times more than in neutral levels of sentiment.

Furthermore, firms having a conservative month of investment appear to have lower returns, only in low sentiment periods. During high sentiment, however, firms that are investing aggressively have lower returns than conservative firms do. Even more, stocks with high operating profitability barely improve their monthly return when sentiment increases from low to high. These findings support Baker and Wurgler (2006) who state that harder to value, young, small and uncertain companies get more affected by shifts in market sentiment.

Having a significant positive correlation between forecast error and sentiment index, it becomes possible to interpolate that stock returns and forecast error share a positive relationship as well, such that, stock returns increases when earnings forecasts are more optimistic.

To conclude, this research provides a different dimension of the role of analyst forecast error in stock markets. It offers a valid argument that aggregate sentiment should be looked at as a function of forecast error which in return affects short term stock returns.

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