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Abstract

This paper investigates how investor sentiment affects stock market returns and evaluates the predictability power of sentiment indices on U.S. and EU stock market returns. As regards the American example, evidence shows that investor sentiment indices have a negative influence on stock market returns. Concerning the European market instead, investigation provides weak results. Moreover, comparing the two markets, where investor sentiment of U.S. market tries to predict the European stock market returns, and vice versa, the analyses indicate a spillover effect from the U.S. to Europe.

Keywords: Bayesian econometrics; Portfolio choice; Sentiments; Stock Market Predictability.

JEL Codes: C11; C22; G11; G12.

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1. INTRODUCTION

Optimism in financial markets could create situations of mispricing, leading investors to lower returns than they expected. Due to these movements in sentiment that conduct distance from fundamentals, it becomes an issue of interest. Is it optimism, and consequently pessimism, a factor of influence in financial markets? Accordingly, investor sentiment, which captures these fluctuations, is increasingly a topic of research relevance.

Several studies of behavioural finance have been conducted in order to examine the presence and the effects of sentiment in financial markets. Investors are driven by fluctuations of sentiment. Before of an investment, investors behave differently. According to their propensity to the risk and the future expectations, they are divided into rational and irrational traders. Sentiment could be expressed through different measurements, but there is no academic consensus on a theory or a right formula to quantify it. The literature confirmed that arbitrage is limited and many individuals, in making decisions, underreact or overreact to fundamentals and returns. Overconfidence, conservatism, and representativeness explain this concept. Indeed, Baker, Wurgler, and Yuan (2012) state that "when sentiment is high, future returns are low on relatively difficult to arbitrage and difficult to value stocks." Therefore, evaluation and decision-making are biased with the result of mispricing, i.e. moving from its fundamental value.

The majority of studies investigates this relationship with American stock markets, because of their financial significance and the higher likelihood to access the data. One of the few exception is Fernandes, Gonçalves, and Vieira (2013) that provide an examination of the Portuguese market. This research would like to contribute to the literature by analysing and comparing a strong and stable market like U.S. to a smaller one but with economic significance, like Europe. Analysing only the rational component of the regression, as in Lemmon and Portniaguina (2006), this paper carries a limitation on the irrational part, i.e. the residual inspection, and on availability of data.

The aim of this paper is to investigate whether it exists a relationship between the investor sentiment and the stock market returns. We apply Bayesian inference allowing us to set priors such as that the posterior distribution of the parameters of the predictive return regression can better learn from the data. We also evaluate the predictability power of investor sentiment acting on this association and interpret the economic effects of the findings. Using various indices, which measure sentiment both in an implicit and explicit way, the U.S. and the European market are studied, over the period 1990-2014 and 2001-2017, respectively, in order to find the investor sentiment ability in forecasting stock returns. The forecasts in both examples start from the year 2008 because of its economical relevance due to the financial crisis. It is compelling to observe the consequences of the movements of sentiment correlated to stock returns over this period. Further analyses compare the two markets to each other, searching for a spillover effect. In this case, investor sentiment of U.S. market tries to predict the European stock market returns, and vice versa.

As regards the American example, we find that sentiment indices have a negative impact on the stock market returns and provide accurate predictions of next month stock returns. With respect to the European market, evidence show weak findings. Indeed, there is no relationship between the Economic Sentiment Indicator and stock market returns of Europe. Only a consumer confidence index provides evidence of predictive power is the Consumer Confidence Index. Finally, the results show the presence of spillover effect between the two markets. From an economic standpoint, Europe that has been affected from globalisation and quick communication is more prone to follow the influence of the American sentiment, because of the U.S. stronger economy.

The structure of the paper is the following: section 2 provides the literature review, deepening what is investor sentiment and diversifying between its measurements. Section 3 deals with the methodology, the empirical applications and the relative results. Section 4 sums up the conclusion and suggests issues for future works.

2. LITERATURE REVIEW

This chapter provides a brief definition of investor sentiment, supported by theories, extended to behavioural reasons and effects, and empirical analyses of the relationship with markets, conducted by various authors in the past years.

2.1 Investor sentiment

First of all, it is pivotal to define what the investor sentiment is and why it has become more important in recent times. Investor sentiment is also known as *market sentiment* since it reveals the movements in the financial markets dictated by the psychological perception of determined operations or trades. Investors are subject to the sentiment of the market, i.e. to the belief about future expectations and investment risks that are not consistent with the statistical data or real facts. When the business performance is driven by emotions, a distortion of the price from its fundamental value occurs, entailing the risk in itself to be misunderstood from the investors and worsen the situation. Therefore, sentiment represents generally the attitude of economic agents, from consumers to investors, towards the market.

Barberis, Shleifer, and Vishny (1998) introduce an investor sentiment, focusing on overreaction and underreaction. They explain that information could be misleading. Indeed, optimistic announcements drive the investors to an exaggerated optimism about future news, and therefore to overreaction, which leads stock prices to increase. Unfortunately, the following "news announcements are likely to contradict his optimism, leading to lower returns" (Barberis, Shleifer, and Vishny, 1998). This idea simply resumes the evidences that optimistic investors tend to overreact and in the end receive less of what they expected. Furthermore, another mechanism arises: conservatism, which "states that individuals are slow to change their beliefs in the face of new evidence" (Barberis, Shleifer, and Vishny, 1998). Then, investors, divided into optimistic and pessimistic traders, behave differently according to the weight they designate to a particular announcement, and are unlikely to change their mind, even though a strong proof is supplied. This wrong assessment conducts to persistent mispricing and a deterioration of the final wealth.

Baker and Wurgler (2006) argue that the issue of mispricing derives from an "uninformed" sentimental demand shock or the limitation of arbitrage. According to behavioural finance, there is a strong debate on market efficiency, since the allocation of capital could be prone to encounter several risks (for example, fundamental and noise trader risk) during the investment and imply costs due to mispricing (Barberis and Thaler, 2003). An arbitrage is an investment strategy that offers riskless profits at no cost (Barberis and Thaler, 2003), where *arbitrageurs* are the rational traders and *noise traders* are the irrational ones. But the previous statement hides some information. Indeed, theoretical evidence of behavioural finance proves that arbitrage is de facto limited, and any type of mispricing is a persistent phenomenon difficult to eradicate, because of implementation costs, or horizon and synchronisation risks.

For this reason, it is deducible that analyses on investor sentiment and attention to it are strongly needed other than a fundamental indicator of future trends in the market. Baker and Wurgler (2006) add that investor sentiment "drives the relative demand for speculative investments, and therefore causes cross-sectional effects even if arbitrage forces are the same across stocks".

2.2 Empirical investigation

Various authors have contributed to influence the scientific field with a great number of papers regarding the investor sentiment and its effects. Hereafter, brief summary of the most worthy and appropriate previous studies on this topic.

Fisher and Statman (2000) investigate three different groups of investors: individuals, newsletter writers, and Wall Street strategists. While the first two are almost perfectly correlated, there is no correlation of them with the last group. The study reveals that the future S&P500 returns have a negative and statistically significant relationship with individual investors and strategists of Wall Street.

Also Brown and Cliff (2005) prove that sentiment is negatively related to future returns. Then, if the investor sentiment is high (low), it will imply lower (higher) stock returns in the future. Smaller companies tend to be less affected by sentiment, while large firms even in long horizon are more influenced, with a consequent higher level of predictability power.

Baker and Wurgler (2006) explore the effect of the investor sentiment on cross section of stock returns. The results suggest that the sentiment is inversely proportional to stock returns – small, young, extreme growth, unprofitable, distressed, high volatility, and non-dividend-paying stocks. Another salient conclusion is that firm characteristics, that theoretically should not exercise any unconditional predictive power, show instead conditional patterns (for example, the U shape) as the sentiment is conditioned. This outcome can be explained as a compensation for the systematic risks, where some countermeasures, as the orthogonalisation of the investor sentiment index to macroeconomic circumstances, demonstrate inconsistency with this interpretation.

Baker and Wurgler (2007) examine theoretically and empirically in depth the investor sentiment, looking for an optimal way to measure it and to discern and quantify the consequences of it. They confirm that sentiment influences the cost of capital, with effects on the allocation of investments.

Lemmon and Portniaguina (2006) investigate the time-series relationship between investor sentiment and stock returns using consumer confidence as a measure of investor optimism. Lemmon and Portniaguina (2006) distinguish from a rational and an irrational part (the letter is situated in the residuals) in the regression. They find that a negative relationship between the sentiment and the stock market returns exists, even if a mispricing seems to be eventually corrected by noise traders.

From an international point of view, Schmeling (2009) researches if the consumer confidence could have an impact on the expected stock returns in 18 industrialised countries. As before, Schmeling (2009) shows that sentiment has a negative relationship with forecasts of aggregate stock market returns. In addition, he provides a cultural explanation of why some countries have higher sentiment; indeed, most of them are more prone to overreact and to have a herding behaviour.

On the other hand, Verma and Soydemir (2006) point out that rational and irrational factors are both constituent parts of the investor sentiment, individual as well as institutional. Furthermore, they brought to light a significant phenomenon: the contagion effect. The exploration consists of searching for an influence of one country’s sentiment upon the assets of other markets. Their research evidences that the U.S. investor sentiment affects Mexico and Brazil, at an institutional stage, and U.K. at both institutional and individual level.

Verma, Baklaci, and Soydemir (2008) consider the impact of arbitrageurs and noise traders' sentiment on both the Dow Jones Industrial Average and the S&P500 returns. They find that irrational investor sentiment has a stronger effect on stock returns than rational one, justifying it with the speed of processing information about economic fundamentals.

Chung, Hung, and Yeh (2012) also inspect investor sentiment in the business cycles and report that the predictability of the sentiment is meaningful only during the expansion, while in periods of recession state there is no significance. Therefore, the investor sentiment results to be regime-dependent.

Huang, Jiang, Tu, and Zhou (2014) propose a new investor sentiment, denoted as *aligned*, which outperforms the others, in terms of fitting, reducing incredibly the noise component, and predictability, with good results even in the out-of-sample forecasting method. Widely basing on the previous predictor of Baker and Wurgler (2006), they compare the results between the BW sentiment and aligned SPLS (PLS, since it is the procedure they follow to construct the index).

Finally, Fernandes, Gonçalves, and Vieira (2013) provide an examination of the "small" Portguese stock market. Starting from the same hypothesis of the majority of the essays cited before, they investigate whether there exists predictability not only of aggregate stock returns, but also at industrial indices levels for Portugal, over the period 1997-2009. Using the residuals of the Economic Sentiment Indicator (ESI) for Europe and applying the principal component analysis technique to obtain macroeconomic factors, they document that sentiment shows a negative relation to returns. In addition, they inspect for the presence of a contagious effect of the U.S. investor sentiment on the local market.

2.3 Sentiment Measures

Many different indicators have been proposed as investor sentiment index. As well, there are several different measurement mechanisms to build it. They can be divided mostly into two macro-categories: direct and indirect measures. Direct measures are all the indices, where the data are obtained through surveys conducted to consumers, investors or other agents, who explicitly give a response and their sentiment towards some specific questions and issues. The indirect measure is, instead, a financial or pure mathematical index used as a proxy to define the new sentiment indicator.

In the surveys, investors usually divide into bull, neutral or bear. Alternatively, they are asked to express an opinion, through numbers indicating high or low expectations. Some examples are the American Association of Individual Investors (AAII), which officially conducts and publishes surveys on investors; the Conference Board Consumer Confidence Index, which elaborates the surveys on individuals' expectations about issues in macroeconomics; and others that can deal with businesses or industrial sectors.

The literature provides many example of indirect measurements that can be assumed as sentiment indices. The more applied are: the IPOs, the number and average of first-day returns on Initial Public Offerings; NYSE turnover, measuring trading volume; CEFD, closed-end fund discount, since it seems to be inversely correlated to sentiment; dividend premium, which is the difference between average market-to-book ratios of payers and non-payers. All these proxies are considered as subject to sentiment, even though with probably different timing. Consequently, Baker and Wurgler (2006), and Huang, Jiang, Tu, and Zhou (2014) combine more of these proxies to create one unique index.

3. METHODOLOGY

The first intent of this section is to replicate the model tested by Huang, Jiang, Tu, and Zhou (2014) on a more recent dataset and then to investigate if the same approach can be generalized to other markets, in particular the European stock market. Another attempt will be that of verifying whether there exists a spillover effect of the U.S. market on the European one and vice versa.

3.1 Hypotheses

Huang, Jiang, Tu, and Zhou (2014) and before Baker and Wurgler (2006, 2007) study how the investor sentiment works and which factors are its constituents. They construct two different indices from the same set of variables. Indeed, both the BW investor sentiment, created by Baker and Wurgler (2006, 2007), and the aligned one (here-hence denominated as SPLS), created by Huang, Jiang, Tu, and Zhou (2014), are obtained from the following six individual sentiment proxies:

- Close-end fund discount rate (CEFD),
- Share turnover (TURN),
- Number of IPOs (NIPO),
- First-day returns of IPOs (RIPO),
- Dividend premium (PDND),
- Equity share in new issues (EQTI).

In constructing the sentiment index, Huang, Jiang, Tu, and Zhou (2014) and Baker and Wurgler (2006) use equal structure and same choice of proxies (see above). The reference equation to create investor sentiment is written as follows:

$$Sent_t = CEFD_t\ \beta_1 + TURN_t\ \beta_2 + NIPO_t\ \beta_3 + RIPO_t\ \beta_4 + PDND_t\ \beta_5 + EQTI_t\ \beta_6$$

However, the coefficient values are different, since the sample size changes in the two studies. Another difference relates to the method of combination. Indeed, while Baker and Wurgler (2006) apply a first principal component (denoted as PC method), Huang, Jiang, Tu, and Zhou (2014) prefer the partial least squares (PLS method). According to Huang, Jiang, Tu, and Zhou (2014), PC fails to produce significant forecasts because it can accumulate approximation errors coming from parts of the variations of the proxies. Hence, every one of the aforementioned proxy is moved on average with six months smoothing, standardised and elaborated upon other regressions on industrial production, durable and nondurable consumption, service consumption, employment and a series of dummy variables in order to reduce the business cycle variation. In addition, the residuals coming from these regressions are used as proxy to be combined to build a new investor sentiment index. This procedure is the orthogonalisation to macro variables in order to compensate for systematic risk and to prevent high correlations, if the raw data are conditioned from macroeconomic factors.

In order to comply with the purpose of predicting stock market returns, the linear regression model considered, according to Huang, Jiang, Tu, and Zhou (2014), is the following:

$$R_{t+1} = \alpha + \beta\ Sent_{t,k} + \varepsilon_{t+1}, \qquad k = 1, \ldots, K$$

where R_{t+1} is the excess market return at time $t+1$, $Sent_{t,k}$ is the investor sentiment at time t, and k is one of the K alternative investor sentiment indices.

Huang, Jiang, Tu, and Zhou (2014) applies OLS estimation, but we extend their analysis with Bayesian inference. Barberis (2000), Kandel and Stambaugh (1996) and Hodrick (1992) are among the first papers to advocate the use of Bayesian inference for investigating stock market predictability. Bayesian inference allows to set priors such as that the posterior distribution of the parameters of the predictive return regression can better learn from the data. For example, priors can be set to improve long-term asset allocation and to remove biases. Recently, Pettenuzzo, Timmermann and Valkanov (2014) document that economic constraints based on prior beliefs systematically reduce uncertainty about model parameters, reduce the risk of selecting a poor forecasting model, and improve both statistical and economic measures of out-of-sample forecast performance. Moreover, prior information helps to reduce parameter uncertainty when the sample size is small. This is possible the case with our European data example.

We apply a prior such as that the mean of the posterior coefficient for sentiment indices is negatively distributed, see Koop (2003) for exact value the equation can be solved to get the prediction at time *t+1*.[1] The estimation is run recursively. Up to the last observation posterior distributions and predictive densities are computed to predict the following value. At next period, when new data are available, the process is repeated to get further predictions.

3.2 Data

The data span from January 1990 until December 2014 (300 months) for the U.S. example, whereas the European example range from June 2001 through April 2017 (191 months). The European sample is unfortunately quite limited since the data are not available before the selected start point for all the components of the variables considered. As for the U.S. example, the length of the sample ends in 2014, because the data for the Baker and Wurgler's investor sentiment (2006, 2007, 2012) and the aligned investor sentiment calculated by Huang, Jiang, Tu, and Zhou (2014) are available only until that year.

First of all, it is meaningful to clarify the variables used in this study. The dataset for the analysis in the U.S. market consists of the following variables:

- *Stock excess market returns of US market*, SEMRUS: calculated from price of S&P500, including dividends and in excess of the risk free rate (3-month US treasury bill);
- *Continuous compounding of S&P500*, COMPOUND: calculated without dividends, in excess of risk free rate (10-year US treasury bill);
- *Investor sentiment index*, BW: calculated by Baker and Wurgler (2006), through the PC method;
- *Orthogonalised investor sentiment index*, BWORT: calculated by Baker and Wurgler (2006), the orthogonalisation is applied in order to reduce the systematic risk;
- *Aligned investor sentiment index*, SPLS: calculated by Huang, Jiang, Tu, and Zhou (2014), through the PLS method;
- *Orthogonalised aligned investor sentiment index*, SPLSORT: calculated by Huang, Jiang, Tu, and Zhou (2014), the orthogonalisation is applied for the same reasons as before;

[1] We also try to apply uniform flat priors and results are identical. The posterior distribution of parameter β has only negative support on both cases, indicating the likelihood support only negative values.

- *Conference Board Consumer Confidence Index of US*, CB_CONS: calculated through surveys on expectations about business conditions, employment and income, from consumers over a six-month horizon;
- *Bullish sentiment percentage of S&P500*, BULLISH: represents the share of pessimistic investors from the AAII Investor Sentiment Survey;
- *CBOE's Volatility of S&P500*, VIX: annualised standard deviation, also known as uncertainty index, it is calculated from near expectations (one-month horizon) about stock market volatility.

On the other hand, the dataset for the European consists of the following variables:

- *Stock excess market returns of EU market*, SEMREU: calculated from price of Euro Stoxx 50, including dividends and in excess of the risk free rate (3-month Euribor);
- *Continuous compounding of Euro Stoxx 50*, COMPOUND: calculated without dividends, in excess of risk free rate (10-year German government bond);
- *Economic Sentiment Indicator of European countries*, ESI_EU: published monthly by the European Commission, it consists of five sectoral confidence indicator (based on results from business surveys), which are: industry (40%), services (30%), consumers (20%), construction (5%) and retail trade (5%);
- *Economic Sentiment Indicator of Eurozone*, ESI_EUZONE: composite calculated only for the Eurozone countries;
- *Consumer Confidence Indicator of Europe*, CONSCONF: calculated from surveys on the financial situation of households, the general economic situation, unemployment expectations and savings, over one year horizon;
- *Industrial Confidence Indicator of Europe*, INDUCONF: calculated from surveys on production expectations, order books and stocks of finished products;
- *Economic Sentiment Indicator of Germany*, ZEW_DEU: calculated from surveys on expectations about macroeconomic development, financial and industrial profit situation over the following six months;
- *Ifo Business Climate Index*, IFO: dealing with the assessments of business situation and future expectations, it is calculated from surveys on different sectors from enterprises, such as manufacturing, construction, wholesaling and retailing, over a six-month horizon.

3.3 Empirical results

3.3.1 The U.S. Market

This section deals with the analysis and interpretation of the U.S. example. As already mentioned before, the example follows Huang, Jiang, Tu, and Zhou (2014) and predicts stock market returns through the aligned investor sentiments.

The dependent variable the excess market return, continuously compounded log return on the S&P 500 index (including dividends), minus the risk-free rate. The risk free rate is represented by the 3 months U.S. Treasury bill.

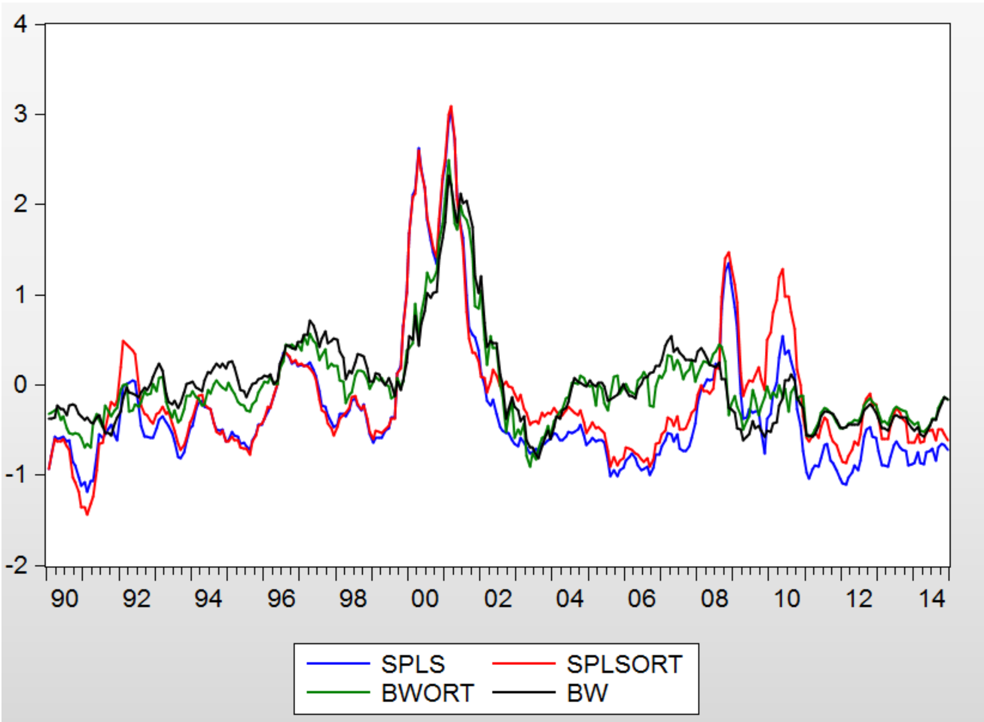
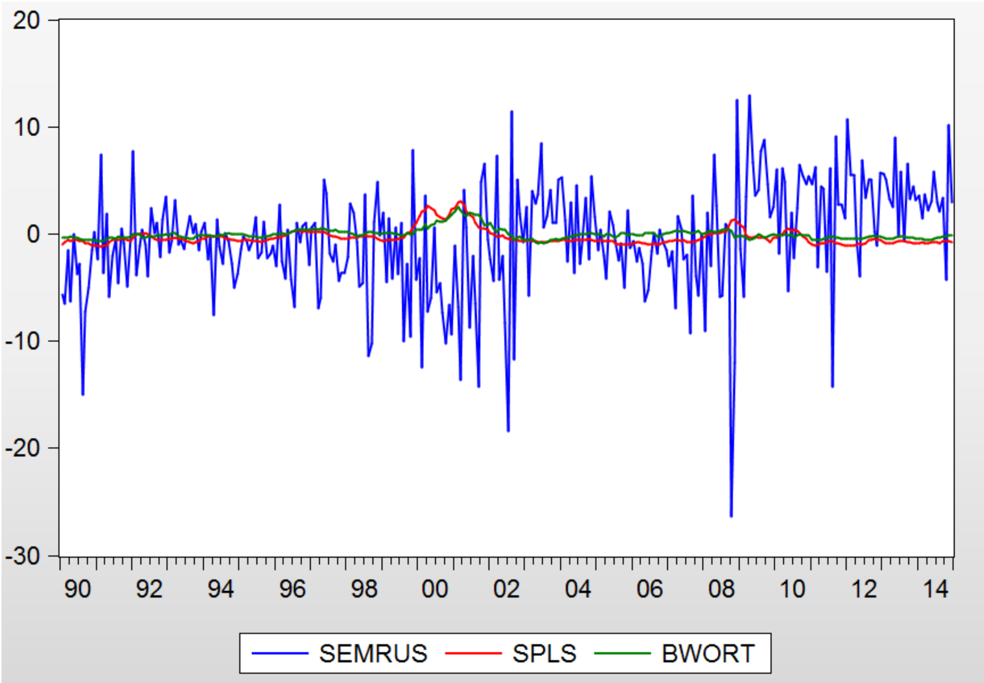


Figure 1: Plot of the sentiment indices group for the entire range, 1990-2014.

Figure 1 shows the sentiment indices used for the U.S. market. Both the BW index and the SPLS have a similar pattern, since they are constructed starting from the same six variables, even though using different methods (PC and PLS, respectively). For this reason, the sentiment indices cannot be applied all together, but regress in separate equations.

Figure 2 reports two sentiment indices, SPLS and BWORT, and stock market returns and it document that the latter variable is much more volatile than the sentiment, with great positive and negative peaks in short periods. As discussed in Baker and Wurgler (2006, 2007), first, orthogonalisation applied to sentiment indices reduces the systematic risk. Second, the sentiment changes are more difficult to be detected, and its volatility expressed only in periods of high speculation.



Graph 2: Plot of the sentiment indices, SPLS and BWORT, and the stock market returns, SEMRUS, for the entire range 1990-2014.

Table 1 reports the results of the U.S. regression on the period 1990-2007. The sample is constituted of the first 216 months, since the aim of the paper is to inspect the observations after the financial crisis of 2008. This operative procedure is justified by the economical relevance of that time, considering that it could be a demonstration of much volatile sentiment towards some investments with respect to others.

Table 1
Set of regressions run on the U.S. market

Variable	Post Mean ß	Bayesian T-stat	Positive Post. Distr.	RMSE
SPLS	-1.2468	-3.5530	0.0005	6.6137
BW	-1.9778	-3.8589	0.0002	6.3537
SPLSORT	-1.1229	-3.1213	0.0020	6.8303
BWORT	-2.0276	-4.0636	0.0001	6.5051
CB_CONS	-0.0432	-3.5288	0.0005	6.3270
BULLISH	16.2195	6.4154	0.0000	7.1693
VIX	-0.1980	-4.3907	0.0000	7.0222

Table 1 shows the results for the seven indices considered in the analysis. The first four variables refer to sentiment indices; the last three to consumer or market indices. All coefficients except Bullish have negative posterior means, almost all the posterior mass has negative mass as the Bayesian tstatistics confirms and the posterior distribution assigns probability to positive numbers lower than 1%. The coefficient and the forecasts evaluation are consistent with the literature, proving that there exists a negative relationship between stock market returns and investor sentiment, supported by Baker and Wurgler (2006, 2007) and Huang, Jiang, Tu, and Zhou (2014). Bullish has a positive relationship due to the negative nature of the index. Economically, one-percentage change in the dependent variable is associated with an average decrease of -1.98 (for the BW) in the excess market return.

As next step, we produce one-month forecasts from January 2008 to December 2014 using an expanding window approach. We compute root mean square errors (RMSE) by comparing each (point) forecast to the realization. Lower RMSE stands for higher likelihood of a good model.

Among the sentiment indices, we find that BW provides the most accurate predictions of stock market returns. This result contrasts with Huang, Jiang, Tu, and Zhou (2014), who found the SPLS being more accurate in the out-of-sample analysis. Adding the recent 4-year observations in the investigation and reducing the sample size (1990-2014 versus the analysed 1965-2010 period in the literature) explain the difference.

When comparing to other indices, we find that the Conference Board Consumer Index, which is constituted of surveys, outperforms all the other variables, including the BW and SPLS, as also affirmed in Huang, Jiang, Tu, and Zhou (2014). The VIX index seems to be also a good measure to predict stocks returns and many strategists observe it before operating in the market. However, even though VIX is a “financial” variable, an index like the CB_CONS, which is made up of opinions and should be more inclined to errors, seems to be more appropriate to represent the investor sentiment, performing a greater predictability power.

3.3.2. The European Market

In this section, we deal with the analysis and interpretation of the EU example. The procedure used is the same as that applied to the U.S. market. The excess stock market returns re constructed from the Euro Stoxx 50 and we try to predict them through different sentiment indices from Europe.

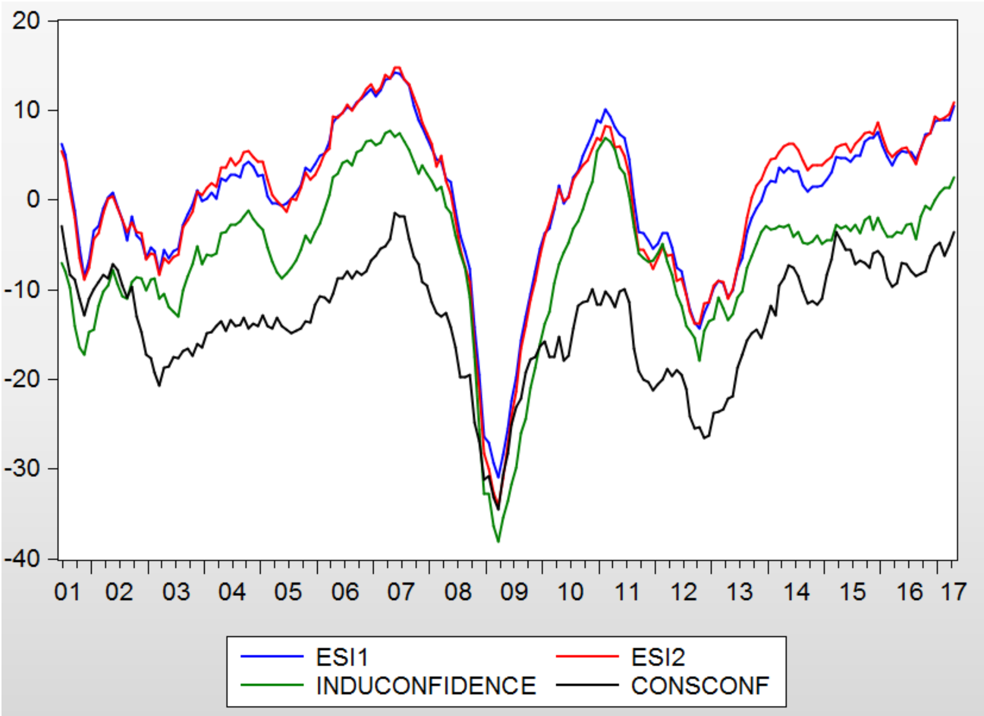


Figure 3: Plot of the sentiment indices group for the entire range, 2001/06-2017/04.

Figure 3 represents, as for the U.S. example, the sentiment group on the entire sample, formed by the two Economic Sentiment Indicators, one for Europe and one for the Eurozone, and the Consumer and Industrial Confidence Index. For making visible the trend of the series, the mean value is subtracted to the variables ESI and ESI_EUZONE, levelling them to the other two indices. By comparing them and inspecting the correlations, it is clear that, similarly to the U.S. market, the sentiment cannot be used all together, because of multicollinearity issue. The explanation comes from the fact that INDUCONF and CONSCONF are two of the five components sectors of the ESI.

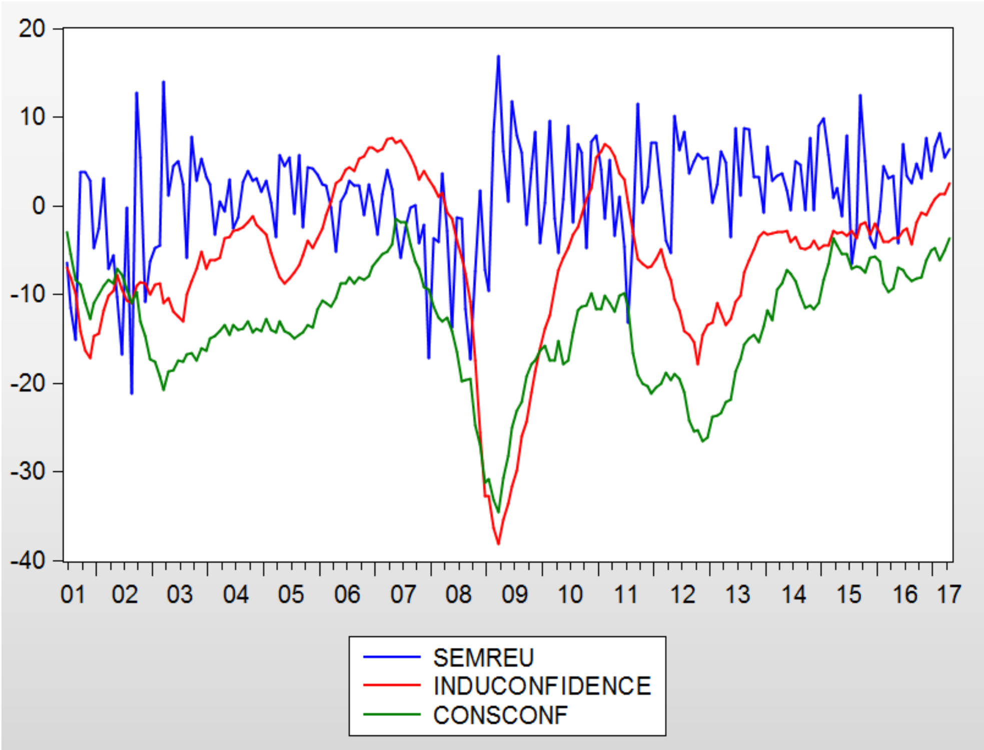


Figure 4: Plot of the economic indices, CONSCONF and INDUCONF, and the stock market returns, SEMREU, for the entire range 2001-2017.

Figure 4 show the volatile pattern of Euro Stoxx 50 compared to Consumer and Industrial Indices. Moreover, at the end of the 2008, it is evident the negative peak in sentiment indices due to the financial crises. On the contrary, on the same period, stock returns recorded an increasing evolution with positive peaks.

Table 2
Set of regressions on the EU market

Variable	Post Mean ß	Bayesian T-stat	Positive Post. Distr.	RMSE
ESI	-0.0449	-0.4191	0.6763	6.6414
ESI_EUZONE	-0.0384	-0.3432	0.7324	6.6394
CONSCONF	-0.4139	-2.7690	0.0070	6.6411
INDUCONF	0.0138	0.1343	0.8935	6.6547
ZEW_DEU	0.0168	0.7053	0.4827	6.8820
IFO	0.0500	0.5144	0.6084	6.8453

Table 2 shows the analyses on the EU market and the relative results. In this example, the Economic Sentiment Indicator and two specific components of it substitute the BW and SPLS indices are applied. The economic indicators we choose are European industrial confidence index, ZEW_DEU and IFO indicators. The choice of these two German indices comes from different reasons. First, Germany is considered as a leading country in Europe, with a stronger economic and political stability. Second, Germany is an industrial and financial centre, with contacts to many European regions. Finally, the surveys reflects optimistic and pessimistic share for the future expected economic development not only in Germany, but also in France, Italy and other relevant countries.

Except for the Consumer Confidence Index, posterior probabilities of other variables assign large probabilities to positive numbers. We remember our prior assumption restrict posterior mean of parameters of the sentiment indices to be positive, but leave coefficients for other parameters to be unrestricted. Therefore, apart from CONSCONF, there is no strong evidence on the role of sentiment indices to drive the EU stock market. From the economic point of view, this can be justified by the fact that Europe has not a strong financial impact comparable to the volumes of the U.S., which has been historically the leader of the worldwide markets. Fernandes, Gonçalves, and Vieira (2013) concluded that the Portuguese market has tendency to be affected by the sentiment, because of the high level of collectivism in the country. The herding is counterbalanced by the presence of institutional investors, which are considers as rational. This statement could lead to think that it is likely to notice a majority of rational investors in the EU market, because of institutional level, than noise traders. An argument in favour of this reasoning could be identified in the Consumer Index that demonstrates predictability power and is more influenced by investor sentiment. Therefore, consumers are the more affected by sentiment, since institutional traders are the rational agents.
The forecasting exercise over the sample 2008-2017 confirms evidence and all models perform similarly in terms of RMSE.

3.3.3. Spillover Effect

In this section, we consider the hypothesis of integrated markets. Our forecasting sample deals with the period during and after the financial crisis, which had a global effect. Therefore, we investigate the possibility that the markets are not independent, where booms and recessions spread around different geographic regions.

Table 3 shows the results of the regressions of mixed models. Indeed, the linear univariate model is again used, but the two markets are now combined. The purpose is predicting the stock market returns of Europe through the U.S. sentiment indices. The output demonstrates a spillover effect for almost all the variables, only VIX does not support this theory. The two factors created from surveys, i.e. BULLISH and CB_CONS, are the only with a positive coefficient. BW produces the lowest Root Mean Squared Error.

Table 3
Set of estimations run using the U.S. sentiment in order to predict the EU stock returns

Variable	Post Mean ß	Bayesian T-stat	Positive Post. Distr.	RMSE
SPLS	-3.8801	-3.0606	0.0030	6.4000
BW	-3.1945	-3.0552	0.0031	6.0258
SPLSORT	-4.9641	-3.5881	0.0006	7.0288
BWORT	-3.2829	-2.9024	0.0048	6.1059
BULLISH	12.2835	2.1015	0.0389	6.9441
CB_CONS	0.0965	2.2244	0.0290	6.8898
VIX	-0.1612	-1.5661	0.1214	6.9238

Table 4
Set of estimations run using the EU sentiment indices in order to predict the U.S. market

Variable	Post Mean ß	Bayesian T-stat	Positive Post. Distr.	RMSE
ESI	-0.1200	-3.9970	0.0001	6.6679
ESI_EUZONE	-0.1272	-4.3866	0.0000	6.5914
CONSCONF	-0.1912	-4.8621	0.0000	6.5208
INDUCONF	-0.1170	-3.5500	0.0005	6.7960

Table 4 reports the estimations of the U.S. stock returns through the European sentiment indices. As shown, all the variables have almost all the posterior mass in the negative support. Economically, it seems that the Economic Sentiment Indicator, elaborated by the European Commission, has a stronger link with American investors, enabling predictions on stock returns, than with the EU market. Again, evidence highlights that the Consumer Confidence Index can be suggested as the best model, in terms of predictability, providing the lowest Root Mean Squared Error. Zew and Ifo indices were not insert in this table, because of the unavailability of data for the entire range. However, in the end all the four variables are accurate predictors, with small differences in RMSE.

To sum up, Tables 3 and 4 document a link between financial markets and the two markets are not independent, but interdependent. Our regressions show interesting evidence of fitting with the data in predicting in both directions: first forecasts of the U.S. and then of the European stock returns.

4. CONCLUSION

The paper follows the work of Huang, Jiang, Tu, and Zhou (2014), using the sentiment index as a dependent variable in an univariate regression model, to predict the stock market returns, for the same market of the investor sentiment. Many measurements are experimented on this pattern model, from direct sentiment indices, like surveys, to indirect measures of investor sentiment, such as SPLS and BW, which are calculated by Huang, Jiang, Tu, and Zhou (2014) and Baker and Wurgler (2006, 2007), respectively. The regression is estimated for a set of variable to both the U.S. and EU markets. Differently than previous literature, we apply Bayesian inference to set priors such as that the posterior distribution of the parameters of the predictive return regression can better learn from the data and reduce parameter uncertainty due to the short sample, in particular for the European example.

As regards the American example, BW resulted to be the best variable for predictability stock markets. However, the Conference Board Consumer Index, which is a survey indicator, outperforms all the other models analysed. Consistent with the literature, the results showed that globally sentiment has a negative impact on the stock market returns.

With respect to the European market, evidence show weak findings. Indeed, there is no relationship between the Economic Sentiment Indicator, specially created from the European Commission to represents the EU sentiment, and stock market returns of Europe. The only variable providing results in terms of predictive power is the Consumer Confidence Index.

Finally, the results show the presence of spillover effect between the two markets. Therefore, it can be concluded that U.S. and EU are two interdependent markets. In the end, this idea can justify the weak outputs on the European markets. From an economic standpoint, affected from globalisation and quick communication, Europe could be more prone to follow the influence of the American sentiment, because of the stronger economy.

Unfortunately, due to unavailability of data, the analysis is conducted on a limited range. The short period and the choice of variables are a limitation on estimating the best model, since there could be omitted factors influencing the estimations. The use of Bayesian priors limits somewhat such effects. However, in future works it could be interesting to explore the difference between the rational and irrational factors of the sentiment, deepening the irrational analysis (i.e. the residual part).

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