Progress Of the Study on The Impact of Investor Sentiment on Stock Returns

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Abstract. Traditional pricing models do not reckon investor sentiment as a systematic factor of stock returns. However, past market events around the world have shown considerable return anomalies that are unexplainable by well-known market factors alone. It has inspired researchers to develop behavioral finance, that is, the study of investor irrationality and how it influences the stock market in a less efficient setting. This essay reviews three popular methods to research the impact of investor sentiment on stock returns in stock markets: conventional regression models, the GARCH model family, and the DSSW model, proposed by De Long et al. It is found that conventional regressions links investor sentiment with a significant effect on stock returns, with different patterns that reflect past data and predict future prices. The GARCH family explores the sentiment-return relationship in more detail, considering factors such as volatility, while the DSSW model gives a more behavioral account and captures the complexity of such patterns of effect. In the research of this paper, investor sentiment does influence stock returns as well as volatility in both markets, which implies a deeper understanding of the stock markets and calls for attention of retail investors, institutional investors, and financial regulators.

Keywords: Investor sentiment; asset pricing; GARCH family model; DSSW model; stock return.

1. Introduction

Throughout the history of stock markets, there are some noticeable circumstances when a bubble gradually builds up, followed by an eventual burst. Consequently, the market crashes and most stocks will plummet in value. For the American market, according to Baker and Wurgler [1,2], notable stock booms and crashes in the past started with the 'Tronic Boom in the early 1960s. This wave of demand for small growth stock sent by 1962 but was followed by another boom later in the decade, referred to as the Go-Go Years. Later events include the Nifty Fifty Bubble at the start of the 1970s, the high-tech boom from the late 1970s to mid-1980s, and finally, the Internet bubble around 2000 [1]. However, at their times, these speculative episodes lack even the most basic ex-post characterization [1]. Besides, the nascent Chinese stock market has also seen several bubbles and troughs since the 2000s. A number of anomalies apart from market crashes, such as the closed-end fund puzzle and distressed securities, have been examined in depth.

Since the 1980s, researchers have been analyzing the cause of market crashes and how particular factors affect the whole stock market. With the development of behavioral finance theory, investor sentiment has become an important consideration, and many researchers have analyzed the nuances of its impact on the market. To begin with, investor sentiment has various definitions, but two of them are most commonly used. The first one points to the propensity of stock investors to speculate for extra profits. The second one is more straightforward, since it regards investor sentiment as investors' overall optimism or pessimism towards the market [2].

In light of the previous contributions of the investor sentiment problem, this essay reviews three methods to investigate the influence of investor sentiment for a broad view. The first one is conventional regression models. A simpler model to connect sentiment with returns, it manages to verify empirical sentiment accounts and to predict future returns. The second one is the GARCH model. This econometric model assumes more realistic conditions in the stock market and gives a further explanation of excess price drifts from fundamentals. The third method is the one proposed by De Long et al. (DSSW model thereafter), which has a more appropriately behavioral sense of the research topic.

2. Literature review

The purpose of this article is to provide a overview of the channel by which investor sentiment impact stock returns by citing existing articles. After examining the reading and analysis of the literature on such influence, this article sorts the examples by research methodology. In this article, 18 articles are reviewed, all of which demonstrate a strong pattern in general.

2.1 Conventional regression models

Baker and Wurgler [1] started their regression model from the view that mispricing of the market due to investor sentiment comes from the competition between rational arbitrageurs and sentimental investors [1]. Hence systematic mispricing is a combined result of an unexpected demand shock among sentimental investors and existent limits of arbitrage [1]. In this case, the shift in demand causes stock prices to drift from their fundamentals, and in the absence of arbitrage, such drift is possible and even persistent [1]. Two types of analysis are proposed. One assumes that sentiment have different impact on different stocks, while keeping the difficulty of arbitrage constant, and the other changes the arbitrage difficulty across stocks, with the condition that the investor sentiment influence has no cross-sectional variations [1]. The former evinces the impact of investor sentiment on stocks for which it is difficult to value and so whose perceived target price differ considerably among analysts [1]. The latter reveals that the swing in stock prices is susceptible to the difficulty for stocks to arbitrage [1]. In practice, these two types of stocks perfectly overlap. They both tend to be younger or began to sell their stocks to the public more recently, have more volatile stock prices, earn less profit, pay less dividend, or face imminent financial dangers [2]. Different kinds of sentiment may cancel out in unconditional returns, thus smoothing out the impact of some proxies of sentiment [2]. Baker and Wurgler [2] have indeed found that some of the firm characteristics concerned lack absolute capacity of predicting unconditional returns, but they exhibit strong influence patterns when conditioning on that sentiment.

This method is rather versatile since it applies to both cross-section and aggregate analysis. Between the two cases, Zhao and Qu [3] proved it useful to analyze the sentiment-return relationship across industries in the Chinese stock market. The B&W index is also used in analyzing other anomalies. Stambaugh et al. [4] investigate 11 stock price anomalies by the B&W index, including financial distress, net operating assets, momentum and investment to assets, all of which are believed to cause sentiment to bias stock returns. Examples exist where researchers modify the proxies for the B&W model or even the model itself. Gao and Yang [5] use four proxies to suit the need to investigate the futures market.

Researchers also use some variations of the B&W model, and an example is the “aligned” sentiment index [6]. This index improves the B&W index by its different composition, though the proxies are the same [6]. It aims to eliminate the approximation error that influences each proxy by aligning the investor sentiment estimation towards future stock return forecasts [6]. Specifically, two steps of OLS regressions are implemented to emulate a partial least square (PLS) approach [6]. The index generally fits the past anecdotal accounts of major sentimental periods, and it tends to outperform the original one, especially when a common noise factor is present as well [6]. Using the overnight returns as a sentiment proxy, Aboody et al. [7] capture the forecasted future returns by the total returns of the subsequent weeks. For the next 4 weeks, the daily stock returns are compounded into weekly total returns, and for each subsequent week, the difference in returns between the highest and lowest decile is computed [7].

2.2 The GARCH family

2.2.1 The original GARCH model

For a deeper understanding of the influence mechanism of investor sentiment, researchers draw upon a more complex statistical model: the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, first proposed by Bollerslev [8]. It is presented as a generalization of the Autoregressive Conditional Heteroskedastic (ARCH) process, allowing for past conditional variances as a factor of current conditional variance equation, so as to capture a more flexible lag structure and to take account of the longer memory in empirical work [8]. With different indexes of sentiment, the GARCH model is still applicable and generates reasonable results. In an investigation by Da et al., the daily excess return of the market portfolio and the FEARS index are simultaneously modelled by a GARCH model. In addition, the model considered dynamic conditional correlation since the combined dynamics between the market return and the index are equally important to be examined [9]. The conditional variance is confirmed to have a substantial positive correlation of 7.17% with the return [9].

2.2.2 The GARCH-M model

Since the introduction of the original GARCH model in 1986, researchers have modified it to suit the need for different situations. An earlier one is the GARCH-in-mean (GARCH-M) model. Engel et al. extended the GARCH model to make the conditional variance a factor of the current risk premium, so that one can forecast mean returns more directly [10]. Three different data sets of bonds were examined to apply this model, and conditional volatility was revealed to be a significant factor of bond holding yields, showing that risk premiums do vary with time [10].

Ample examples exist where the model is applied to other signs of investor sentiment. For instance, the connection between sin stock (that of alcohol, tobacco, and gaming industries) returns and investor sentiment is constructed by a GARCH-M model. According to Liston [11], by the model, the returns of sin stocks can be successfully decomposed into rational and sentimental components, with the latter having some explaining power for sin stocks' overperformance in recent empirical records [11]. The model allows to consider vital complications such as conditional variance effects, volatility clustering, and leverage effect [11]. It gives a more reliable result that investor sentiment, whether individual and institutional, is priced into sin stock returns [11]. Another study by Zheng [12] turns to metal futures returns instead of stocks. Nevertheless, it captures a highly negative correlation by a combination of the Vector Autoregressive (VAR) model and GARCH-M model, as well as a nonlinear pattern that is significantly skewed to the pessimistic side [12].

2.2.3 Further extensions of the GARCH-M model

The GARCH-M model also has other extensions for a better fit for stock market data, one of which is the Time-Varying (TVA)-GARCH-M model. In 1987 when the former was first proposed, researchers noticed that it could possibly apply to more general models of uncertainty and risk. Under the capital asset pricing model (CAPM), with a varying risk beta, uncertainty may better explain returns [10]. To explain the specific channel flowing from investor sentiment to stock returns, He et al. [13] proposed a model, arguing that investor sentiment interferes by affecting the link between investor risk compensation (IRC) and stock returns. To take into account the fact that the market volatility apparently varies with time and tend to cluster around specific periods, they used the TVA-GARCH-M model [13]. This model is an extension of the original one and it allows the conditional variance to vary with time instead of being constant, as is the case with the simple GARCH-M model [13]. Since the required risk premium can change with people's decision-making process in the real market, the paper takes into account people's endogenous risk compensation, prior risk compensation, as well as prior unexpected risk premiums to test this model [13]. With time-varying results by regression analysis and consideration of a varying required risk premium, current risk compensation is shown to affect stock returns positively while the past one lowers stock returns [13]. Both effects sustain under the assumption of high or low states of investor sentiment, while having no influence from the level of sentiment [13].

Besides the TVA-GARCH-M model, the Generalized Error Distribution (GED)-Exponential (E) GARCH-M model is also favorable in researches about industry-wide investor sentiment. It proves useful and versatile in a paper about the industry sentiment in Chinese markets by Zhao and Qu [3]. They regarded it as a useful tool since it relaxed the requirement of non-negative coefficient and allows for the existence of stock return leverage and hence its non-normal errors [3]. This model relaxes the assumption of normally distributed time series and adds asymmetrical terms to identify the different impacts between positive and negative sentiment shocks [3]. To rule out possible false regressions, the authors also did a test of smoothness across all the 17 industries concerned [3]. In an extensive analysis across the stocks of different industries, they discovered that the transportation, steel, and textile industries were particularly sensitive to sentiment, and that the industries exhibited similar patterns over time under different sentiment states [3]. A result of the GED-EGARCH (1,1)-M model, mining, chemical, and home appliance industries possessed strong leverage effects, when they were particularly vulnerable to negative shocks in investor sentiment [3].

2.3 DSSW model

Another model is devised by De Long, Shleifer, Summers, and Waldmann (DSSW thereafter), which has become increasingly popular since its first launch in 1990. Instead of trying to bridge the connections between investor sentiment and stock returns directly, it starts with introducing two types of market participants: noise traders and rational arbitrageurs [14]. Noise traders irrationally react to trivial information and think that such information will give them an edge to earn excessive returns [14]. If the arbitrageurs worry about prolonged mean reversions and the chances that the noise traders' beliefs will be more extreme, they may take limited positions due to their shorter investment horizon [14]. Such noise trader risk actually yields risk premiums for the irrational themselves, hence their sentiment leads to higher and persistent expected returns [14].

The DSSW model is widely applied under different markets and time horizons. A notable example is a study of Chinese stock markets by Chen and Lu [15]. The paper used the DSSW model throughout its analysis and investigated the sentiment-return relationship in both short and long horizons. Based on the setup of the original model, it divides the market into noise traders and rational arbitrageurs [15]. It also introduces their market shares, distribution of projected returns, and their goal to maximize their utility before deriving the expected utility functions [15]. By DSSW optimization, the paper presents a pricing model determined by both types of investors [15]. The stock returns are decomposed into fundamental values and irrational noises, and Chen and Lu [15] argue that the difference of long-term and short-term impact of sentiment only depends on different distribution of future prices of risky assets. From long term to short term, the expected mean of stock prices decreases, but the volatility increases [15]. Specifically, investor sentiment draws down prices in the short run but increases the latter in the long run [15]. It generally agrees with the short-run persistence and long-run reversion of investor sentiment as a means to affect stock returns.

In another study of the Chinese market, He et al. [16] used the DSSW model with adjusted assumptions. Of the three conditions that they assume, the first one is that a risk-free asset and a risky asset are the only securities available in the market [16]. The second one assumes both noise traders and arbitrageurs to be subject to sentiment, considering the greater share of retail investors in the market [16]. The third assumption sets the expected deviation from expected price to follow a normal distribution, while the fourth one represents the investor utility as an invariant risk aversion function [16]. Except for the second one, the assumptions are largely for simplicity. In the absence of completely rational arbitrageurs, their research still hassimilar results [16]. When the sentiment is high, the market sees a positive expected price deviation, but its volatility decreases [16]. Therefore, it extends the DSSW model to explore the nonlinearity of sentiment effects, i.e., the more volatile the market sentiment, the lower the stock market returns [16]. It only exists under pessimistic sentiments, which reveals the asymmetric property of the sentiment effect [16].

Baker et al. [17] referred to the DSSW model to explain the contrarian predictability of global investor sentiment on country-level returns. Noise traders' risk, the variability of investor sentiment, corrects when noise traders' unrealistic beliefs correct [17]. Instead of using the model in a different context, Yang and Wu [18] improve the model by setting the "chasers" to extract signals and thus determine the demand for some stock. However, their analysis is consistent in that it still follows a classic mechanism of irrational shocks and limits of arbitrage, as mentioned at the beginning of part 2.1 [18].

3. Conclusion

In sum, this essay presents three methods used by researchers to uncover the impact of investor sentiment on stock returns. The results generally showed that investor sentiment is priced in the stock market, and that the waves of sentiment affect individual stocks and the whole market in a discernible, important, and regular way. This finding is borne out by subsequent studies even if they use different methods, namely GARCH and the DSSW model, thus the investor sentiment theory is further extended. By the GARCH model, volatility also counts as a systematic determinant of stock returns to yield a more robust result, and different influence patterns can be revealed under different time horizons. The DSSW model sheds light on a more behavioral analysis of the asymmetric influence of sentiment. This essay contributes to the study of asset pricing incorporating behavioral factors by synthesizing three popular means to investigate the market anomalies from the aspect of investor sentiment and will be of some use for a closer look at the pricing of assets and the financial market during possible future crises. New models may still be needed for appropriate investment strategies and regulatory efforts.

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