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Modeling the effects of investor sentiment and conditional volatility in international stock markets

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Abstract

Behavioral finance argues that some properties of asset prices are most reasonably considered as deviations from fundamental value and they are caused by the presence of traders who are not fully rational hence called noise traders. Noise trader approach assumes that sentiment traders exert greater influence during high-sentiment periods than during low-sentiment periods, and sentiment traders misestimate the variance of returns weakening the mean-variance relation.

This study's main objective is to provide a framework to model conditional volatility regarding the changes in the investor sentiment by measuring the effect of noise trader demand shocks on the volatility of stock market indexes of the various countries. GARCH, TARCH, and EGARCH models are used to test whether earning shocks have more influence on the conditional volatility in high sentiment periods weakening the mean-variance relation.

This paper takes an international approach using weekly and daily returns of Nasdaq, Dow, S&P500, Nikkei225, HangSeng, FTSE100, CAC40, DAX, and ISE indexes. Weekly and daily trading volume changes of these indexes are used as a proxy for investor sentiment and significant evidence is found that there is asymmetric volatility in these market indexes and earning shocks have more influence on conditional volatility when the sentiment is high.

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1 Introduction

The efficient market hypothesis was acknowledged in general by academic financial economists a generation ago. It was widely assumed that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. The accepted thought was that when new information is released, the news spreads very fast and is reflected into the prices of securities without delay [1]. So, neither technical analysis, which is the study of past stock prices in an attempt to predict future prices, nor even fundamental analysis, which is the analysis of financial information such as company earnings and asset values to help investors select "undervalued" stocks, would enable an investor to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks, at least not with comparable risk.

The efficient market hypothesis mentioned above states that any mispricing in the market would be arbitraged away and the market will return to its equilibrium prices. But the history of the stock market is full of incidents contradicting with the theory such as The Great Crash of 1929, the Tonics Boom of the early 1960s, the Go-Go Years of the late 1960s, the Nifty Fifty bubble of the early 1970s, and the Black Monday crash of October 1987. The conventional finance model, where unemotional investors always force the markets to equal to the rational present value of expected future cash flows, has a considerable difficulty fitting these patterns [2].

Behavioral finance is a new approach in financial markets that has emerged as a response to the complications faced by the traditional finance theory. In general, behavioral finance argues that some financial phenomena can be better apprehended using models in which some players are not fully rational. More definitely, it investigates what happens when one or both of the tenets that underlie individual rationality is relaxed [3]. These financial phenomena that can be better understood by other means than efficient market hypothesis include short-term momentum, long-run reversals in addition to prediction patterns based on valuation parameters and firm characteristics such as dividend yields, P/E multiples, size effect and value/growth stocks.

A stock's price equals to its fundamental value, which is the discounted sum of expected future cash flows, in the traditional framework that players are rational and there are no frictions. Efficient Market Hypothesis (EMH) states that actual prices reflect fundamental values. Behavioral finance argues that some properties of asset prices are most reasonably considered as deviations from fundamental value, and that these deviations are caused by the presence of traders who are not fully rational. When there is a deviation from the fundamental value- a mispricing- an attractive investment opportunity appears. Behavioral finance argues that when these investment opportunities are created, they are hard to be exploited immediately stating that the mispricing can be both risky and costly thus the mispricing can remain unexploited.

The most evident risk that an arbitrageur faces is the fundamental risk which can be hedged to a limit by shorting a substitute security but substitute securities are not always perfect making it impossible to remove all the fundamental risk. The arbitrageur will still be subject to risk that is specific to the portfolio he's holding. In addition to fundamental risk, there is also the noise trader risk which is an idea first introduced by De Long et al. [4] studied further by Shleifer and Vishny [5]. Noise trader risk means that if the arbitrageur continues to exploit the mispricing, the situation becomes worse in the short-run. Even if the arbitrageur finds a perfect substitute for shorting, one is still subject to the risk that pessimistic investors who cause the stock to be undervalued in the first place become even more pessimistic and lower the price of the stock even more.

This research depends on noise trader approach which is an alternative to the efficient market theory. This approach is based on two main assumptions. First, not all the investors are fully rational and their demand for risky assets is influenced by their beliefs or sentiments that are not absolutely justified by fundamental news. Basically, the investors are subject to sentiment. Second, arbitrage which is stated as trading fully by rational investors not subject to any sentiment is risky, thus limited [6]. So, betting against sentimental investors are costly and risky which can be stated limits to arbitrage in the language of modern behavioral finance.

Even though, there is some debate considering the significance of sentiment traders, one can logically make two cases. First, greater influence is exerted by sentiment traders during high-sentiment periods than during low-sentiment periods, since they are reluctant to take short positions in low-sentiment periods. It is also stated by empirical evidence that sentiment traders participate and trade more aggressively in high-sentiment periods [7]; [8]. The second case is that sentiment traders, who are naive and inexperienced, are likely to have a poor judgement of how to measure risk and as a result likely to misestimate the variance of returns which weakens the mean-variance relation.

Regarding the above indications, it must be noted that there is a critical role for investor sentiment in the mean-variance relation. When sentiment is low, there is a strong tradeoff between mean and variance as stated by the rational asset pricing theory which implies a positive relation over time between the market's expected return and variance. But there is little tradeoff when sentiment is high because there is greater participation of traders that are driven by sentiment in the market when the investor sentiment is high which causes the prices to deviate from levels that would otherwise reflect a positive mean-variance tradeoff. Although there is considerable debate regarding the importance of sentiment driven traders, two cases can be considered. First of all, since sentiment traders are more reluctant to take short positions in low-sentiment periods, they have much more effect on prices during high sentiment periods [9]. Secondly, sentiment traders are likely to misestimate the variance of returns impairing the mean-variance relation since they tend to have a poor understanding of how to measure risk [10].

All in all, the mean-variance relationship, which is the main tradeoff in finance, sets forth a strong tow-regime pattern and that investor sentiment can distinguish these two regimes uniquely. When investors that are driven by sentiment have a greater market participation which makes the sentiment high, this distorts prices away from levels that would otherwise reflect a positive mean-variance tradeoff.

This study's main objective is to provide a framework to model conditional volatility regarding the changes in the investor sentiment by measuring the effect of noise trader demand shocks on the volatility of stock market indexes of the various countries. TARCH and EGARCH models are used to test whether earning shocks have more influence on the conditional volatility in high sentiment periods weakening the mean-variance relation.

2 Literature review

2.1 Noise Trader Approach & Effect of Sentiment

If one assumes that the efficient markets hypothesis was a publicly traded security, its price would be extremely volatile. After Samuelson [11] has proved that stock prices should follow a random walk if rational competitive players in the market require a fixed rate of return and Fama [12] has demonstrated that stock prices are, in fact, close to a random walk, stock in the efficient markets hypothesis rallied. After the publication of Shiller's [13] and Leroy and Porter's [14] volatility tests, the stock in the efficient market hypothesis had a bear period, since these studies have showed that stock market volatility was far greater than could be justified by changes in dividends. Just after the studies of Kleidon [15] and Marsh and Merton [16], the hypothesis has found strong ground again. However, the papers of Schleifer and Summers [6] and DeLong et al. [4] have demonstrated another aspect as noise trader risk that must be considered in addition to market volatility besides the rational expectations.

First assumption in the noise trader approach is that not all the investors in the market are fully rational and their demands for risky assets might be affected by their beliefs or sentiments which do not fully result from fundamental news. Second assumption is that arbitrage is subject to such sentiment, thus risky and therefore limited. Recent empirical studies have shown that cognitive biases and misguided beliefs that lead to suboptimal trading decisions might not be arbitraged away immediately, since individual investors are not only prone to biases as the population at large but also they might show over-confidence, herding behavior, and speculation [3]. The common result of all these studies is that news alone does not move stock prices: uninformed changes in demand also move them too. These irrational demand changes seem to be a response to changes in expectations or sentiment which is not fully justified by information. In light of all these insights, it is concluded that investor sentiment plays an important role in the price determination of the stocks and, as a result, volatility modeling of the markets.

2.2 Defining and Measuring Investor Sentiment

There has been no single widely acknowledged definition of investor sentiment to date. The definitions that exist in the literature vary from vague statements about investors' failures to more explicit psychological biases that are model-specific [17]. Additionally, the term itself is classified in a wide spectrum and used in variety of ways by academic researchers, financial analysts, and the media [18]; [19]; [20]; [21]; [17]; [2]. For instance, some researchers might accredit investor sentiment as an inclination to trade on noise instead of information, while the same term is employed particularly to make reference to investor optimism or pessimism. The sentiment term is also associated with emotions, thus the media accredit it as investor fear or risk-aversion.

In this research, it is subscribed to the approach that investor sentiment should be regarded in terms of beliefs. The classical definition of a rational investor is the one who has well-defined choices and develops accurate beliefs through Bayesian logic. It can be assumed that the former is always correct but the latter must be focused which means that investors are prone to incorrect beliefs but are otherwise rational in the sense that their choices fulfill standard preference axioms. So, throughout this paper investor sentiment is defined as the representation of market players' beliefs about future cash flows in connection with some objective standard which is the correct fundamental value of the stock. In plain English, investors that are subject to sentiment might develop their beliefs not only through news about fundamentals but also irrelevant noisy signals and they might do so in a statistically incorrect way [22].

Quantifying the investor sentiment has been a great concern in the finance literature and plentiful studies have been made since throughout the history of the financial markets there have been numerous historical events and empirical puzzles that are inconsistent with the efficient market hypothesis and other standard financial theories. Currently there are many sentiment measures which range from measures that are developed for academic intentions to daily indexes employed by traders for adverse objectives like closed-end fund discount, consumer confidence indices, investor intelligence surveys, market liquidity, implied volatility of index options, ratio of odd-lot sales to purchases, net mutual fund redemptions. Since there are numerous measures, it may be concluded that there is no consensus about which sentiment measure is more accurate and efficient. The disagreement is especially between the academic community and professionals because the latter one is employing these sentiment indexes as an investment tool, while the former's sole purpose is to form arguments for or against market efficiency or to explain some irrationalities in the market.

The measurement of sentiment is examined in two subdivisions in this part of the thesis: Market based proxies for sentiment and direct surveys. The first one is the market based approach that looks for extracting sentiment indirectly from financial proxies such as closed-end fund discount or put-call ratio. The second approach is measuring sentiment directly from investors using surveys and questionnaires. University of Michigan's Consumer Confidence Index and the Yale School of Management's Stock Market Confidence Index are examples for this kind of investor sentiment measure.

2.2.1 Market Proxies for Sentiment

There are many supporters for using market proxies for sentiment and they claim that specific financial data procure a dependable basis for sentiment approximation, although it is one step removed from quantifying actual investor beliefs. Most of the market-based proxies are derived from empirical puzzles like closed-end fund discount and IPO under-pricing.

If it is accepted that markets are efficient and arbitrage opportunities are exploited immediately, the fact that closed-end funds are traded at a discount is one of the most puzzling remarks in financial markets. Lee et al, in their 1991 study [23], claim to demonstrate this anomaly in relation to investor sentiment. Ross [24], Berk and Stanton [25], Spiegel [26], Chan et al. [27], Malkiel [28], and Zweig [29] have provided rational explanations for this puzzle such as agency costs, illiquidity of assets, and tax liabilities. Although CEFD is used as a consistent proxy for investor sentiment in many studies, Qiu and Welch [20], Ross [24], Chan et al. [27] have provided significant evidence that CEFD alone may not be sufficient to account for all investor sentiment because of omitted variable problem or confounding variables. Lee et al. [23] have demonstrated that if decreases in the CEFD are positively correlated with asset returns held disproportionally by noise traders, then changes in the CEFD should be correlated negatively with retail sentiment. The authors showed confirming evidence that small firms outperform large firms when the CEFD decreases.

It has been widely argued that initial public offerings (IPOs) can be explained by investor enthusiasm. Rational firms ought to exploit the dominating market sentiment to raise new equity so, IPOs might come in waves which relates to periods of over- or under-valuation. In addition to this, IPOs are subject ample under-pricing. The equity that the companies sell tends to be under-priced resulting in a considerable price increase on the first day of trading, when these companies first go public.

Based on the above explanations and facts, it is assumed by some researchers that data on IPOs can be used as a proxy for investor sentiment. Qiu and Welch [20] have constructed an index in their study based on violations of the law of one price in new equity issues. Baker and Wurgler [2] have used high first-day returns on IPOs or IPO volume as a measure of investor eagerness. Even though IPOs and investor sentiment seems correlated, basing a sentiment measure solely on this data might not explain the situation properly and there might be confounding factors.

It is argued that the inexperienced retail or individual investor is more prone to investor sentiment than the professionals. It has been found that younger investors were more likely than older investors to buy stocks at the peak of the Internet Bubble [30]. Kumar and Lee [31] have suggested in their paper to construct a sentiment index for retail investors based on whether such investors are buying or selling.

It has been proposed by Brown et al. [32] that a general market sentiment measure based on how fund investors are moving into and out of safe government bond funds to risky growth stock funds. Acknowledging evidence has been suggested [33] by using fund flows as a proxy for sentiment for individual stocks that when there is a considerable inflow to funds that hold a specific stock, the consecutive performance of that stock is relatively weak.

Trading volume, or more commonly liquidity, can be used as a proxy for investor sentiment. It was noted in previous studies of Baker and Stein [34] that if short-selling is costlier than opening and closing positions, when irrational investors are optimistic and buying climbing stocks rather than when they are pessimistic and buying falling stocks, it is likely that they might want to trade and so, add liquidity. Kaniel et al. [35] also formed an investor sentiment index called Net Investor Sentiment (NIS) by using individual buy and sell dollar volumes in NYSE and provided evidence that individual investors who trade on the NYSE are likely to react to the liquidity needs of institutions, and at least in the short run, gain abnormal returns by exploiting their counterparties demand for immediacy.

Instead of using a single sentiment measure, Baker and Wurgler [2] developed a sentiment index which averages six commonly used proxies for investor sentiment: trading volume based on NYSE turnover, the dividend premium, the closed-end fund discount, the number and first-day returns on IPOs, and the equity share in new issues. Each proxy is regressed on macroeconomic variables(industrial production, real growth in durable, non-durable, and services consumption, growth in employment, and NBER recession indicator) to get rid of the economic fundamental effects. Then principal component analysis is used to extract the common features into an averaged index. Baker and Wurgler [2] have stated that when the sentiment is low (high), speculative stocks have greater (lower) future returns on average than bond-like stocks which shows that riskier stocks sometimes have lower expected returns inconsistent with classical asset pricing theories.

2.2.2 Survey Measures of Sentiment

Since survey measure of sentiment is a direct approach rather than using in direct market proxies for sentiment, using survey data for sentiment is a better way to capture the changes in the investors' mood, even though these survey measures of sentiment are subject to methodological issues and response biases.

Since 1978, the Michigan Consumer Research Center supplies a consumer confidence index derived from monthly surveys of consumers. The survey is based on 500 telephone interviews with adult men and women from United States and five questions are asked to respondents to capture their mood swings and current confidence in the economy.

Lemmon and Portniaguina [36] have used Michigan Consumer Confidence Index as a proxy for investor sentiment in their recent work, A time series framework is adopted in their study and it is shown that consumer confidence helps to reveal the time variation in equity portfolio returns, specifically size premium. The authors have employed a similar method as Baker and Wurgler [37] has used in which the proxy for sentiment is regressed on a group of macroeconomic variables. In addition to CEFD, Qiu and Welch [20] have also used Michigan Consumer Confidence to show that sentiment changes effect the excess return of stocks especially with small market capitalization.

Brown [38] has used the direct measure of investor sentiment data collected for the American Association of Individual Investors (AAII) Sentiment Survey. Since 1987, AAII has selected randomly a group of its members and surveyed them on a weekly basis. They ask their respondents where they think the stock market will be in six months: bullish, bearish or neutral. Brown has provided strong evidence that individual investor sentiment is related to increased volatility in closed end funds (CEF) which is also a supporting evidence both for the reason that why CEFD is employed as an investor sentiment proxy and DSSW theory that irrational investors acting together on a noisy signal like sentiment can effect asset prices and create added risk.

Not all the studies are focused only on returns since there are recent works that also inquire the effect of investor sentiment on conditional volatility using the above stated sentiment proxies. Lee et al. [39] utilized Investors' Intelligence of New Rochelle which is recognized as a reliable forecaster of market movements. 135 independent advisory services are read and rated by the editor of Investors' Intelligence's editor each week. Letters are rated as bullish, bearish or correction depending on the prediction of the market. The sentiment index is calculated as the ratio of the number of bullish investment advisory services relative to the total number of all bullish and bearish investment advisory services. Lee et al [39] employed a GARCH-in-mean model to test for the effects of sentiment on returns and volatility and showed that changes in the sentiment are negatively correlated with the market conditional volatility which means volatility goes up (goes down) if investors become more bearish (bullish).

It is also investigated by Verma and Verma [40] that fundamental and noise trading has relative effects on conditional volatility and unlike previous studies they focus on both the rational and noise components of investor sentiment and their relative effects on volatility making a separation between rational and irrational investor sentiment. Unlike the study of Lee et al. [39], AAII investor sentiment index is employed in this research and instead of a GARCH model they have used EGARCH model to test for the asymmetric effects of sentiment. They have found that there is greater effect of bullish than bearish investor sentiments on the volatility of stocks. They have also stated that stock returns' effect on individual investor sentiment (institutional investor sentiment) is significant (insignificant) which suggests that individuals are mostly positive feedback traders.

Wang et al. [41] have used GJR-GARCH, EGB_2, and SWARCH models to investigate for the sentiment effect on the Taiwan Futures Exchange. Wang [42] has developed an investor sentiment index for each type of trader based on their current total positions and historical extreme values as follows:

$$SI_t = (Open_t - min[Open_t]) / (max[Open_t] - min[Open_t])$$

where SI_t is the sentiment index, $Open_t$ is the open interest position at day t, and $max[Open_t]$ and $min[Open_t]$ are maximum and minimum positions over the sample period. A more recent work has been Yu and Yuan's [10] research which also uses GARCH models and Baker and Wurgler's [37] composite sentiment index which is mentioned before. They separated the sampling period into two as high sentiment regime and low sentiment regime. The mean-variance relation is tested with the following model:

$$R_{t+1} = a + bVar_t(R_{t+1}) + \varepsilon_{t+1} \text{ and}$$

$$R_{t+1} = a_1 + b_1Var_t(R_{t+1}) + a_2D_t + b_2D_tVar_t(R_{t+1}) + \varepsilon_{t+1}$$

where R_{t+1} is the monthly excess return, $Var_t(R_{t+1})$ is the conditional variance, and D_t is the dummy variable for the high sentiment period, which is, D_t equals one if month t is in a high sentiment period. The empirical results found in the study support the aspect that mean-variance tradeoff changes with the sentiment. It is found that there is a significantly positive tradeoff in the low sentiment period (b_1 is 13.075 with a t-statistic of 2.45) but this is dramatically weakened (b_2 is -13.714 with a t-statistic of -2.64) in the high sentiment period.

DeLong et al. [4] prediction is that stocks disproportionally held by sentiment (noise) traders are disproportionally subject to investor sentiment. Based on not only on empirical but also theoretical evidence, it is commonly understood that investor sentiment should be mean-reverting. Baker and Wurgler's [2] sentiment index followed a mean-reverting walk. It has also been argued that overconfidence might lead to a mean-reverting difference of opinions among different investors [43]. Since the sentiment follows a mean-reverting process, the distribution of sentiment conditional when the investor sentiment is high should have a longer right tail. Higher sentiment would push the prices up and lowers the expected returns so, the return distribution would be left skewed. Accordingly, noise (sentiment) traders have more effect on prices of the stocks in high sentiment periods. So, one might expect to find that all the moments of realized variance in high sentiment periods are greatly higher than low sentiment periods which shows that prices are more volatile when the investor sentiment is high.

It has been widely argued that investor sentiment has an adverse effect on returns and volatility of stock markets and all the studies mentioned before provide sustainable evidence for the importance of investor sentiment regarding stock valuations in the financial the markets. But the investor sentiment might have adverse effects on different kind of stock. For example, small or illiquid stocks may be more prone to the changes in the investor sentiment that changes in the investor sentiment might have more severe effects on returns and volatility of these stocks. These adverse effects might also be high book-to-market ratio or nature of the stock such as being an industrial, technological, service etc. Thus, the effect of the investor sentiment on these market anomalies and the effect of the investor sentiment on the stock market volatility regarding these stock-inherent anomalies should be investigated.

Chan and Fong [44] have employed a parsimonious method to test the forecasting capability of the announcement of the individual investors' sentiment for the coming week's return by regressing weekly return on the percentage of optimistic stock investors in the preceding Friday Evening Survey. Fisher and Statman [45] employed a similar methodology and investigated whether the release of individual investor sentiment data temporarily affects the prices hence the returns of the stocks in a market where investor sentiment is likely to be influential. They have found that publication does not, in fact, predict the coming week's return on large, medium, or small stocks but it was observed that the publication affects the daily closing prices of medium and small stocks, but not large stocks where the effect was stronger for small stocks than for medium stocks.

Baker and Wurgler [2] has defined some stocks as speculative regarding their risky appeal that they are harder to arbitrage. The stocks are divided in several ways such as firm age, market capitalization, dividend payment, profitability, growth and distress indicators like market-to-book ratio, asset growth or sales growth. They have stated that older, larger, dividend paying, profitable stocks are easier to arbitrage. The effect of investor sentiment on the returns of different kind of stocks according to these indicators is investigated and it has been found that sentiment betas increase as stocks become more speculative and harder to arbitrage meaning that the changes in the sentiment has more effect on speculative stocks' returns.

The effect of investor sentiment on small stocks is investigated by other researchers too. Qiu and Welch [20] have stated their hypothesis that sentiment changes disproportionally influence small stocks and found that Michigan Consumer Confidence Index exerts an influence on the small firm spread more than it does for stocks with large market capitalization.

Besides these researches that investigate the relation between investor sentiment and stock returns, there has also been some evidence regarding the effects of investor sentiment on volatility of returns concerning stocks with different attributes. As mentioned before, Lee et al. [39] have focused on the relation between the changes in the sentiment index and the market volatility and demonstrated that the most important effect was on NASDAQ's volatility which is consistent with the study of Lee et al. [23] since, individual investors are not only dominant readers of independent investment advisory newsletters but also the prevailing shareholders of small capitalization stocks. But this research did not focus on the effect of sentiment on stock inherent market anomalies and their relation regarding the mean-variance tradeoff since the study only observed the main indices NASDAQ, S&P500, and DJIA and not evaluate the effects on stock basis employing these effects as a variable in the main model without elaborating on them specifically.

3 Data and methodology

This paper takes an international approach using weekly and daily returns of Nasdaq, Dow, S&P500, Nikkei225, Hang Seng, FTSE100, CAC40, DAX, and ISE indexes. Instead of using survey data or other sentiment indexes, weekly and daily trading volume % changes of these indexes are used as a proxy for investor sentiment.

Data in which the variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, are said to suffer from heteroscedasticity [46]. The standard warning is that when there is heteroscedasticity in the data, the regression coefficients for an ordinary least squares regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision. When deviations from an idealized random walk can't be modeled by a simple autoregressive process, such as ARMA which capture the variation over time in conditional means, a new type of stochastic processes was needed to model the non-constant variances conditional on the past. ARCH and GARCH models assume heteroscedasticity as a variance to be modeled instead of addressing this as a problem to be fixed. Thus, not only are the shortcomings of least squares amended, but a forecast is calculated for the variance of each error term. The purpose of such models is to provide a volatility measure - like a standard deviation- that can be employed in financial decision making regarding risk analysis, portfolio selection and asset pricing.

If h_t is used to define the variance of the residuals of a regression

$$r_t = m_t + \sqrt{h}_t \varepsilon_t.$$

The most simple generalized GARCH model for variance looks like this:

$$h_{t+1} = \omega + \alpha(r_t - m_t)^2 + \beta h_t = \omega + \alpha h_t \varepsilon_t^2 + \beta h_t$$

where the problem is to forecast the constants ω, α, β. The GARCH model that has been demonstrated is typically called GARCH(1,1). The first number in the parentheses refers to how many autoregressive lags, or ARCH terms exist in the equation whereas the second term refers to how many moving average lags are specified which is called the number of GARCH terms.

Engle [47] modeled ARCH processes which are mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances. In the first ARCH model, introduced by Engle, h_t, conditional variance, is a function of past squared returns; in GARCH models, which are developed by Bollerslev, additional dependencies were put in the conditional variance equation.

The EGARCH modeled by Nelson constructs conditional variance in logarithmic form. By employing logarithmic form imposing non-negativity constraints is not necessary. In EGARCH a negative shock leads to a higher conditional variance in the following period than a positive shock [48]. Another model that allows for nonsymmetrical dependencies is GJR-GARCH, which is developed by Lawrence Glosten, Ravi Jagannathan, and David Runkle [49]. Glosten et al. showed that the standard GARCH-M model is misspecified. They readdressed the problem and altered the model to allow positive and negative innovations to returns to have different impacts on the conditional variance. They also demonstrated that the results did not change when they used EGARCH-M specification. The paper suggested a negative relation between volatility and expected return and it is also found that persistence of volatility is quite low in monthly data.

As mentioned before, Lee et al. [39] employed Investors' Intelligence Index as sentiment proxy and used GARCH-M model which has synchronous changes in investor sentiment in the mean equation and lagged changes in the magnitude of investor sentiment in the conditional volatility equation. Verma and Verma [40] used E-GARCH method instead of GARCH-M and employed AAII investor sentiment as a proxy. One of the most recent works that uses GARCH methods is the study of Wang et al. [41]. They have employed GJR-GARCH, EGB_2 and SWARCH methods to test the impact of investor sentiment on the Taiwan Futures Exchange. The GJR-GARCH model to test the asymmetric effects of the sentiment is as follows:

$$\mu_t = \theta_0 + \theta_1 h_t + \theta_2 \Delta SI_t + \varepsilon_t$$

and

$$h_t = \gamma_0 + \gamma_1 \varepsilon^2_{t-1} + \gamma_2 \varepsilon^2_{t-1} I_{t-t} + \gamma_3 h_{t-1} + \gamma_4 R_f + \gamma_5 (\Delta SI_{t-1})^2 D_{t-1} + \gamma_6 (\Delta SI_{t-1})^2 (1-D_{t-1})$$

where D_{t-1} is a dummy variable that $D_{t-1} = 0$, if $\Delta SI_{t-1} < 0$; and $D_{t-1} = 1$ if $\Delta SI_{t-1} > 0$. Another recent study of Yu and Yuan [10] have shown the investor sentiment has a dramatic effect on the mean-variance tradeoff using GARCH (1,1) and asymmetric GARCH (1,1).

In this study TGARCH (threshold GARCH) and EGARCH (Exponential GARCH) models are used. The mean equation and the variance equation for the TGARCH model are as below:

$$\mu_t = \theta_0 + \theta_1 h_t + \theta_2 AR(1) + \theta_3 MA(1) + \theta_4 \Delta SI_t + \varepsilon_t$$

and

$$h_t = \gamma_0 + \gamma_1 \varepsilon^2_{t-1} + \gamma_2 \varepsilon^2_{t-1} I_{t-1} + \gamma_3 h_{t-1} + \gamma_4 |\Delta SI_t|\, D_{t-1} + \gamma_5\, |\Delta SI_t|\, (1-D_t)$$

In order to overcome the negativity constraints in the TGARCH model, EGARCH model is also used in the study. Similarly, the mean and the variance equation for the EGARCH model are presented as below:

$$\mu_t = \theta_0 + \theta_1 h_t + \theta_2 AR(1) + \theta_3 MA(1) + \theta_4 \Delta SI_t + \varepsilon_t$$

and

$$\log (h_{t-1}) = \gamma_0 + \gamma_1 \left[\, |\varepsilon_{t-1}|/\sigma_{t-1} - \sqrt{2/\pi}\right] + \gamma_2\, (\varepsilon_{t-1}/\sigma_{t-1}) + \gamma_3 \ln (h_{t-1}) + \gamma_4 |\Delta SI_t|\, D_{t-1} + \gamma_5\, |\Delta SI_t|\, (1-D_t)$$

In the mean equations, h_t is the conditional volatility of the market index, AR(1) is the First-Order autoregressive term, MA(1) is the First-Order moving average term, ΔSI_t is the daily or weekly percentage change in the trading volume of the market index which is used as a proxy for sentiment and a measure of noise trader risk. ARMA process has been tested for every index with daily and weekly data and the terms are included in the model according to their contribution to the model's accuracy. In the variance equations, ε_{t-1} is the First-Order autoregressive lag term. I_t in TGARCH model stands for the dummy variable for the asymmetric effects of earning shocks due to good or bad news. I_t is 1 for bad news ($\varepsilon_{t-1} < 0$) and 0 for good news ($\varepsilon_{t-1} > 0$) which means bad news generates more volatility then good news. Absolute value of the ΔSI_t is used to catch the magnitude effect of investor sentiment. D_t stands for the dummy variable to state the high and low sentiment periods where D_t is 1 for the high sentiment periods and 0 for low sentiment periods (1 if $\Delta SI > 0$ and 0 if $\Delta SI < 0$).

4 Results

The results of the TGARCH and EGARCH models for daily and weekly data are presented in the Appendix A and B. To see the volatility feedback effect, coefficient θ_1 is checked which shows whether higher volatility has negative impact on returns. The only significant negative volatility feedback is in EGARCH model with weekly DAX data where else in ISE, FTSE and HSI there is significant positive volatility feedback. To see the effect of higher sentiment on returns coefficient θ_4 is checked which indicates whether higher investor sentiment has a negative effect on returns. θ_4 is significant and negative for all the markets except ISE, NIKKEI and HSI in both TGARCH and EGARCH models which shows that as the investor sentiment and the participation of noise traders increase, the returns go down.

To check the asymmetric volatility in TGARCH model, the coefficient γ_2 should be checked. As long as γ_2 is significant and positive, negative shocks have a larger effect on h_t than positive shocks. For all the markets that are examined in the study, γ_2 is positive and significant which shows that there is asymmetric volatility in all of them. This result highlights a negative leverage effect, thereby showing that bad news causes more volatility. Also in EGARCH model coefficient γ_2 is evaluated in order to examine the asymmetric volatility. In EGARCH model, if γ_2 is significant and negative, negative shocks have a larger impact on h_t than positive shocks. Again for all the markets, γ_2 is significant and negative which points out like TGARCH model that bad news generate more volatility.

The γ_3 parameter measures the persistence in conditional volatility irrespective of anything that occurs in the market. When as γ_2 is relatively large, then volatility takes a long time to die out following a crisis in the market. In TGARCH model, all the coefficients γ_2 are significant. For daily data, DOW, ISE and NIKKEI markets have high persistence where else for weekly data, almost every market have high persistence. To overcome the negativity constraints on the coefficients, we have also used EGARCH model. Both for daily and weekly data, all the markets show very high persistence when EGARCH model is employed which might point out that long term variance ought to be modeled also.

γ_4 and γ_5 are the coefficients to be checked in order to evaluate the effects of investor sentiment during high and low sentiment periods. It is expected that γ_4 should be positive and γ_5 should be negative since heavy presence of sentiment investors during high-sentiment periods should undermine an otherwise positive mean-variance tradeoff in the stock market. In TGARCH model, γ_4 is positive and γ_5 is negative for all the markets except DAX. The effects of sentiment traders can be distinguished more clearly with the EGARCH model. When EGARCH model is used, γ_4 is positive and γ_5 is negative for all the markets. These results show that a rise in investor sentiment increases the volatility in high sentiment periods whereas it lowers the volatility in low sentiment periods. Noise trader theory suggests that in high investor sentiment periods, earning shocks have more influence on the conditional volatility meaning that high sentiment should weaken the mean-variance relation. The results of the study support this theory as the large effect of sentiment traders in the high sentiment periods weakens the positive mean-variance tradeoff.

5 Conclusion

Weekly and daily returns of nine different market indexes are evaluated and their conditional volatility is modeled using TGARCH and EGARCH models according to the changes in the investor sentiment. Weekly and daily trading volume changes of these market indexes are used as a proxy for investor sentiment.

There is not significant evidence of negative volatility feedback in the observed markets except DAX index so, higher volatility does not have negative impact on returns. There is strong evidence that higher investor sentiment has a negative effect on returns. During high-sentiment periods when noise traders participate more, the returns decline for all the markets except ISE, NIKKEI and HSI in both models.

Asymmetric volatility effects are also evaluated with both models. The results showed that there is asymmetric volatility in all the markets which means there is negative leverage effect. So, bad news (negative earning shocks) cause more volatility than good news (positive earning shocks).

Persistence in the markets are also examined in the study. Most market indexes showed a high persistence when TGARCH model is used. EGARCH model is also employed in order to overcome the negativity constraint in the TGARCH model. All the markets have demonstrated high persistence both for daily and weekly data. This may point out to a problem in the long term variance and the long term variance might be modeled using component ARCH methods.

Both in the TGARCH and EGARCH models there is asymmetric effect of the investor sentiment on the volatility. An increase in the investor sentiment also increases the volatility when the investor sentiment is high where else it decreases the volatility in low sentiment periods. These results from the study provided evidence that in high investor sentiment periods, the mean-variance relationship is undermined as suggested by the noise trader theory. The stocks and their volatilities in these particular 9 indexes should also examined regarding to the changes in the investor sentiment since the investor sentiment might affect each stock differently according to their attributes. The markets might also be compared according to their sensitivity because investor sentiment might affect some markets more than others due to their characteristics.

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Appendix A

TARCH model

$\mu_t = \theta_0 + \theta_1 h_t + \theta_2 AR(1) + \theta_3 MA(1) + \theta_4 \Delta SI_t + \varepsilon_t$

and

$h_t = \gamma_0 + \gamma_1 \varepsilon^2_{t-1} + \gamma_2 \varepsilon^2_{t-1} I_{t-t} + \gamma_3 h_{t-1} + \gamma_4 |\Delta SI_t|\, D_{t-1} + \gamma_5\, |\Delta SI_t|\, (1-D_t)$

Daily

tarch(daily)																		
	spx		dow		nasdaq		ftse		dax		cac		xu100		nikkei		hsi	
	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.
θ_0	-0.000332	0.00026	-0.000147	0.00019	0.000026	0.000424	-0.000333	0.000221	-0.000371	0.000408	-0.000461	0.000472	-0.001006*	0.000536	-0.000304	0.000354	-0.001087**	0.000388
θ_1	2.248145	1.640376	2.433289	1.491918	-0.846524	1.359993	3.609022**	1.629856	2.005896	1.581147	3.423898*	1.94316	4.478931**	1.404921	0.981744	1.787561	6.436487**	1.720293
θ_2	-0.07265**	0.021909	-	-	-	-	-	-	-	-	-	-	-0.709084**	0.136014	-0.019971	0.021867	-	-
θ_3	-	-	-	-	-0.046543**	0.021931	-	-	-0.008802	0.023743	-	-	0.710991**	0.136464	-	-	-	-
θ_4	-0.002167**	0.000938	-0.001951**	0.000683	0.001314	0.001142	-0.000927	0.000668	-0.002779**	0.000488	-0.002052**	0.00065	0.010451**	0.001139	0.003298**	0.001142	0.000324	0.000591
γ_0	0.0000135**	1.33E-06	0.000000139	4.93E-07	0.0000407**	3.27E-06	0.0000128**	1.05E-06	0.0000552**	5.77E-06	0.0000607**	2.85E-06	0.000000186	2.57E-06	-0.00000175	1.29E-06	0.0000461**	3.4E-06
γ_1	0.06278**	0.015701	-0.006934	0.006243	0.101972**	0.017638	0.165943**	0.019553	0.124695**	0.023141	0.180384**	0.024415	0.058791**	0.010569	0.023209**	0.009261	0.179065**	0.019564
γ_2	0.338845**	0.039031	0.155856**	0.013527	0.286048**	0.040316	0.1932**	0.030853	0.26024**	0.040724	0.170959**	0.039024	0.130441**	0.018643	0.109166**	0.013619	0.192234**	0.038327
γ_3	0.597007**	0.024367	0.910374**	0.008586	0.609653**	0.017377	0.572532**	0.005975	0.595453**	0.029811	0.465434**	0.013434	0.765146**	0.016363	0.890875**	0.011153	0.449103**	0.012902
γ_4	0.000202**	2.09E-05	0.0000363**	4.72E-06	0.000181**	3.85E-05	0.0000816**	1.18E-05	-0.000000301**	1.67E-05	0.0000978**	2.31E-05	0.00042**	0.000027	0.000197**	0.00002	0.000253**	1.84E-05
γ_5	-0.0000334**	5.58E-06	-0.0000149**	2.18E-06	-0.000119**	5.43E-06	-0.0000192**	5.22E-06	-0.0000887**	1.51E-05	-0.0000667**	8.27E-06	-0.0000748**	1.15E-05	-0.000091**	9.26E-06	-0.00014**	6.84E-06

Weekly

tarch(weekly)	spx		dow		nasdaq		ftse		dax		cac		xu100		nikkei		hsi	
	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.
θ_0	-0.0000171	0.001245	0.000428	0.001294	0.001553	0.001539	0.000585	0.001065	0.006536	0.006207	-0.002955	0.004416	0.001918	0.003124	0.00074	0.003041	0.002045	0.001707
θ_1	-0.290044	2.229836	-0.296492	2.454939	-1.408783	1.384994	0.056344	2.306487	-2.135399	3.174392	1.074964	3.225743	0.351065	1.476628	-1.349814	3.136597	-0.858624	2.116889
θ_2	-0.090574**	0.038939	-0.099478**	0.037091	-	-	-0.918684	0.046449	-	-	-0.117071*	0.067488	-0.628049**	0.295175	0.982699**	0.007846	-0.04489	0.046436
θ_3	-	-	-	-	-	-	0.927181	0.044135	-	-	-	-	0.547776*	0.318995	-0.990542**	0.002657	-	-
θ_4	-0.007238**	0.002174	-0.007304**	0.002624	-0.007646**	0.003654	-0.005733**	0.002715	-0.000587	0.005973	-0.005976	0.00396	0.018852**	0.004915	0.0000938	0.003638	-0.003222	0.002998
γ_0	0.0000284**	1.33E-05	0.000051**	1.46E-05	0.0000707**	2.51E-05	0.0000237*	0.000014	0.000828**	0.000227	0.000793**	0.00024	0.0000153	0.000026	0.000266**	6.61E-05	-7.23E-07	7.03E-06
γ_1	-0.036294**	0.01512	-0.024167*	0.014002	-0.010048	0.034888	-0.017576	0.03447	0.083309	0.136068	-0.175557**	0.052836	-0.00472	0.021584	-0.023147	0.052237	0.005661	0.021425
γ_2	0.265515**	0.037351	0.368129**	0.058374	0.443948**	0.062934	0.426428**	0.062837	0.210085	0.151312	0.512688**	0.169085	0.064231**	0.026612	0.486245**	0.088403	0.158066**	0.026044
γ_3	0.825637**	0.030372	0.697506**	0.048605	0.713904**	0.043768	0.749034**	0.03937	0.460446**	0.157615	0.49852**	0.162103	0.893436**	0.020197	0.372679**	0.087372	0.894042**	0.027735
γ_4	0.000523**	0.000118	0.000604**	0.000126	0.000968**	0.000237	0.000233**+	9.11E-05	-0.0000995	0.000478	-0.000347	0.000366	0.001564**	0.000219	0.000985**	0.000324	0.000571**	8.88E-05
γ_5	-0.000346**	4.54E-05	-0.000319**	3.83E-05	-0.000553**	9.47E-05	-0.000044	3.09E-05	-0.000865**	0.000108	-0.000995**	0.000247	-0.000582**	0.000231	-0.0000628	0.000154	-0.00043**	0.000053

Appendix B

EGARCH model

$\mu_t = \theta_0 + \theta_1 h_t + \theta_2 AR(1) + \theta_3 MA(1) + \theta_4 \Delta SI_t + \varepsilon_t$

and

$\log(h_{t-1}) = \gamma_0 + \gamma_1[|\varepsilon_{t-1}|/\sigma_{t-1} - \sqrt{2/\pi}] + \gamma_2(\varepsilon_{t-1}/\sigma_{t-1}) + \gamma_3 h_{t-1} + \gamma_4|\Delta SI_t|\, D_{t-1} + \gamma_5\, |\Delta SI_t|\, (1-D_t)$

Daily

egarch(daily)																		
	spx		dow		nasdaq		ftse		dax		cac		xu100		nikkei		hsi	
	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.
θ_0	0.0000978	0.000183	0.000271*	0.000169	0.000306	0.000247	0.0000978	0.000189	0.000524**	0.00022	0.000269	0.000211	-0.001985**	0.000784	-0.000276	0.000313	0.000074	0.000214
θ_1	0.560263	1.494072	-0.627842	1.606823	-0.468712	1.121264	0.582325	1.671313	-1.112318	1.293076	-0.720983	1.367469	4.95382**	1.286792	0.663215	1.641621	0.465212	1.29557
θ_2	-0.089402**	0.02008	-0.084704**	0.019303	-	-	-0.047365**	0.0199	-	-	-0.05189	0.019522	0.987223**	0.006886	-	-	-	-
θ_3	-	-	-	-	-0.054461**	0.020038	-	-	-0.050694**	0.019305	-	-	-0.969852**	0.010038	-0.041212**	0.021178	-0.056867**	0.018517
θ_4	-0.001542**	0.00036	-0.00149**	0.000374	-0.001406**	0.000573	-0.00028	0.000312	-0.002213**	0.000549	-0.000663	0.000337	0.007198**	0.000745	0.003355**	0.00102	-0.000493	0.000537
γ_0	-0.175178**	0.024699	-0.157477**	0.022375	-0.183131**	0.023807	-0.204372**	0.029662	-0.14449**	0.023958	-0.134281	0.023852	-0.439284**	0.051339	-0.362212**	0.046569	-0.184647**	0.029208
γ_1	0.085592**	0.012714	0.081571**	0.011713	0.10233**	0.014904	0.110689**	0.014374	0.092665**	0.013909	0.07734	0.013778	0.122336**	0.018341	0.151613**	0.017786	0.126068**	0.015479
γ_2	-0.081759**	0.0086	-0.070187**	0.008525	-0.086944**	0.009854	-0.112442**	0.009802	-0.086423**	0.009926	-0.099646	0.010559	-0.11955**	0.009534	-0.095306**	0.010068	-0.057833**	0.009877
γ_3	0.989799**	0.002036	0.991778**	0.001821	0.989535**	0.002111	0.98812**	0.002734	0.991033**	0.001993	0.990662	0.002153	0.960237**	0.005137	0.975355**	0.004471	0.990416**	0.002452
γ_4	2.037658**	0.086274	2.027681**	0.081511	2.042969**	0.115944	0.973376**	0.077553	1.348696**	0.07832	1.319197	0.079615	1.560189**	0.071394	1.670374**	0.129427	2.137804**	0.099026
γ_5	-1.845881**	0.078127	-1.839363**	0.076155	-1.881221**	0.109209	-0.911809**	0.06207	-1.424812**	0.07053	-1.421682	0.068756	-1.397259**	0.069898	-1.275262**	0.117921	-2.161055**	0.098803

Weekly

egarch(weekly)	spx		dow		nasdaq		ftse		dax		cac		xu100		nikkei		hsi	
	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.
θ_0	0.001725	0.001134	0.001496	0.001163	0.004168**	0.002111	0.000578	0.001063	0.004313**	0.001607	0.002597*	0.001542	-0.001582	0.003652	0.001975	0.002368	0.001321	0.00161
θ_1	-2.382776	2.15805	-1.965818	2.286126	-2.153522	1.709078	-0.193292	2.388439	-3.670424**	1.883452	-2.939228	2.170827	5.764153**	1.593342	-2.834935	2.927212	-0.114461	2.132666
θ_2	-0.107566**	0.041833	-0.11348**	0.040028	0.987541**	0.00594	-0.934193**	0.029819	-0.824328**	0.061642	-0.137677**	0.049762	0.982405**	0.007643	-0.879601**	0.12525	-0.079242*	0.046488
θ_3	-	-	-	-	-0.997811**	0.001553	0.942056**	0.028018	0.792646**	0.074154	-	-	-0.969437**	0.009805	0.849822**	0.140705	-	-
θ_4	-0.003667	0.00245	-0.003554	0.002434	-0.002491	0.003509	-0.003203*	0.001958	-0.003835	0.002434	-0.004874**	0.002361	0.004661	0.003622	0.003633	0.002716	-0.001242	0.002682
γ_0	-0.364966**	0.094922	-0.464655**	0.1312	-0.261568**	0.067598	-0.424873**	0.115686	-0.177761**	0.063321	-0.29559**	0.119033	-0.117322**	0.021613	-2.443101**	0.489836	-0.15868	0.100516
γ_1	0.123909**	0.045842	0.115216**	0.046612	0.141364**	0.041705	0.135845**	0.039216	0.024531	0.025393	0.097627**	0.046326	-0.025622	0.020572	0.415156**	0.06844	0.097777**	0.050279
γ_2	-0.150074**	0.025474	-0.16094**	0.033437	-0.124032**	0.026792	-0.199822**	0.033724	-0.128435**	0.020184	-0.1688**	0.036565	-0.087994**	0.012598	-0.254029**	0.045055	-0.0639**	0.021484
γ_3	0.969216**	0.010432	0.957604**	0.014952	0.980291**	0.007094	0.962556**	0.013471	0.986016**	0.00743	0.973749**	0.01229	0.978574**	0.000322	0.711116**	0.06564	0.992057**	0.008987
γ_4	1.92128**	0.23583	1.934055**	0.220305	1.617228**	0.270305	0.925842**	0.151769	1.266471**	0.118155	1.237957**	0.156312	0.977393**	0.155972	0.863122**	0.26944	1.41482**	0.187404
γ_5	-1.594233**	0.227903	-1.504307**	0.257205	-1.480549**	0.275898	-0.597057**	0.160153	-0.727813**	0.117259	-1.008762**	0.181121	-1.046314**	0.142342	-0.481116**	0.184422	-1.293219**	0.194881