The role of extreme investor sentiment on stock and futures market returns and volatilities in Taiwan

Hsiang-Hsi Liu

hsiang@mail.ntpu.edu.tw

Graduate Institute of International Business

National Taipei University

Chun-Chou Wu*

wucc123@seed.net.tw

Department of Finance

National Kaohsiung First University of Science and Technology

Yi-Kai Su

jerrysu89540551@gmail.com

Graduate Institute of Finance

National Taiwan University of Science and Technology

JEL codes: G12, G14.

* Corresponding author. Address: 2 Jhuoyue Rd., Nanzih, Kaohsiung City 811, Taiwan, R.O.C. Tel: 886-7-6011000 ext. 4015 Fax: 886-7-6011041

The role of extreme investor sentiment on stock and futures market returns and volatilities in Taiwan

Abstract

This study uses different volatility models to describe the conditional volatility pattern and incorporates extreme sentiment indicators into the models for the dynamic structure of returns. This research tries to design different grades for abnormal trading volume as a proxy for extreme investor sentiment to detect the relationships between extreme investor sentiment and market returns. Meanwhile, the direct and indirect effects of these sentimental factors on market returns are examined. The empirical results clearly indicate that the extreme bright and dark sentiment indicators have various effects on market returns. Additionally, we also discuss the impacts of the Financial Tsunami on returns and volatility structure. We can infer that the extreme sentiment indicator still plays a critical role in exploring changes in market returns. Finally, incorporating the specific sentiment indicators in the short and long volatility structures would have an indirect influence on market returns.

Keywords: Abnormal Trading Volume, Extreme Sentiment Indicators, Component Volatility

1. Introduction

The sentiment indicator for investors has been accepted as a key took for analyzing change in market returns. Several prior studies state that trading volume could be viewed as a proxy of the investor sentiment factor and furthermore that the abnormal trading volume could also be considered an irrationally sentimental reaction. Nevertheless, the transmission mechanism between the latent sentiment indicators and market returns are still ambiguous. In this paper, we document that extreme investor sentiment drives the market returns in direct and indirect ways. We use the most representative financial markets, Taiwan's securities markets, to discuss this subject, as in these markets individual traders occupy more than 70% of the trading volume.

The influences between noise trade and expected returns were first constructed by De Long, Shleifer, Summers, and Waldmann (1990, hereafter DSSW). In practice, we treat investor sentiment as the proxy of noise traders' behavior. Based on their argument, investor sentiment could affect the expected returns in both transitory and permanent ways. In general, the transitory influence can be classified as the hold-more and the price-pressure effects that indicate the direct influences of noise traders' activities on their expected returns, which are simultaneously ascribed to variations in investor sentiment. The permanent form can be divided into two sub-types, namely, the Friedman and the create-space effects. The permanent effect can indicate the indirect influences of noise traders' activities on their expected returns, which also follow the action of variations in sentiment on the volatility of returns.

This paper offers some interesting insights for the extreme sentiment indicator (hereafter ESI) that may have salient influences on market returns through direct and indirect processes.

In order to avoid offsetting by the insignificant interference of trivial sentiment from non-extreme trading volume, it is reasonable to extract the extreme trading volume as a proxy for the latent sentiment index. Baker and Stein (2004) point out that the high trading volume reflects high investor sentiment and leads to low expected returns. Baker and Wurgler (2007) and Hong and Stein (2007) have analogous viewpoints that trading volume can also be used as a proxy for investor sentiments. However, to our knowledge, the interactions among trading volume, volatility and market returns remain unclear for stock markets and futures markets. It is intuitive to classify the quantity of trading volume, using volumes greater or smaller than a standard deviation from the mean for a time interval as different measurements of ESI. Retail traders are usually much more concerned about the occurrence of extreme trading volume than are institutional traders. Kumar and Lee (2006) find that the trading activities of retail traders can be viewed as a proxy for the sentiment factor.

Generally speaking, as the trading volume becomes abnormal, investors will show much more expectation in trading behavior than they will in normal trading situation. Thus, it is quite natural to decompose different trading grades to denote different sentiment responses. We conjecture that the various sentiment responses will have different effects on expected returns through direct and indirect behaviors. Again, Baker and Wurgler (2007) conclude that the different grades of sentiment will reflect asymmetric average returns on different types of stocks. Baker and Stein (2004) and Barber, Odean and Zhu (2009) argue that abnormal trading volume can be considered a signal of irrational investor sentiment. Based on these references, this research infers that the abnormal trading volume can be introduced as an ESI for discussing the change of market returns. Brown (1999) proposes that the asset volatilities are affected partly by investor sentiment. It seems that investor sentiment will affect asset returns directly or through interim volatility to affect asset returns. The component volatility model proposed by Engle and Lee (1999) is among the appropriate approaches for dissecting this interesting subject. The component volatility model helps to decompose the conditional volatility into long- and short-term components that can aid in the discussion of the transition between returns and its volatility. Additionally, this paper will continue to fit the ESI into mean, long- and short-term volatility structures, and it will attempt to describe the influence through such a rigorous setting. Lee, Jiang and Indro (2002) state that the investor sentiment can cause a shock in both the formation of conditional volatility and expected returns approved from three market indices, namely, DJIA, S&P500, and NASDAQ.[1] Furthermore, Lee, Jiang and Indro (2002) also incorporate both bullish and bearish sentiments into their model for discussing the conditional volatility structure. Meanwhile, fitting the conditional variance into the mean equation and then inferring this parameter can explain its role in mediating influence. Indeed, many relative literatures have agreed that the component volatility model proposed by Engle and Lee (1999) could capture more completely dynamic process and perform well in model fitting for financial market volatility.[2] These findings offer a meaningful, workable direction for using the component volatility model in exploring the relationships among market returns, volatility and investors' sentiment responses.

This study attempts to examine the ESI as an influence on market returns through direct and indirect processes in three major financial markets in Taiwan, namely, the TAIEX, the TAIFEX and OTC (over-the-counter) markets. One of the noticeable properties is that the proportion of average individual investor trading volume is found to be about 76.8% in TAIFEX, 72.3% in TAIEX and 87.3% in OTC during the investigative period. One of the purposes for this paper is trying to assist traders in finding significant factors in asset price

[1] Lee, Jiang and Indro (2002) select the Investors' Intelligence of New Rochelle sentiment index as the proxy for a sentiment factor.

[2] Engle and Lee (1999), Fleming, Kirby, and Ostdiek (2008), and Adrian and Rosenberg (2008) show that the component volatility model performs well in the stock market. Christoffersen, Jacobs, and Wang (2006) find that use of the component volatility model price options could increase the accuracy.

discovery, arbitrage and hedging in Taiwan financial markets. Our empirical results can explicitly show the influence of the ESI on market returns.

The remainder of this article proceeds as follows. Section 2 introduces the data properties and discusses the sentiment indicator. Section 3 describes the main empirical results. Section 4 discusses the Financial Tsunami of 2008 and its impacts on the ESI. The last section provides some concluding remarks.

2. Data sources and sentiment indicators

In Taiwan's financial markets, the individual traders are the major participants for liquidity trading. Therefore, it is suitable to dissect the interaction for sentiment indicators and market returns based on previous statements. The main data for this article include trading volumes and market returns for the TAIEX, the TAIFEX and the OTC market, which are collected from TEJ. The research period is from January 3, 2001 to May 27, 2009. Daily data are collected in order to obtain the estimation (also see Merton, 1980).

To construct the ESI, this study extracts the values for trading volumes that are smaller or greater than one standard deviation from the mean, i.e., those values that are greater than one standard deviation from the mean can be regarded as a proxy for an extreme bright sentiment indicator (hereafter EBSI), and those that are smaller than one standard deviation from the mean can be a proxy for the extreme dark sentiment indicator (hereafter EDSI). The purpose is to point out the relationship between the different grades of abnormal trading volumes and the influence of various extreme sentiments. Thus, it is suitable to take the extreme sentiments as latent signals to discuss their influence on changes in market returns. The daily returns are calculated from the daily data for closed prices on TAIEX, TAIFEX and OTC. The market returns are defined as follows.

Returns of TAIEX $= 100 \times [\ln(P_t^{close}) - \ln(P_{t-1}^{close})]$

Returns of TAIFEX $= 100 \times [\ln(F_t^{close}) - \ln(F_{t-1}^{close})]$

Returns of OTC $= 100 \times [\ln(O_t^{close}) - \ln(O_{t-1}^{close})]$

where P_t^{close} denotes the TAIEX closing price at time t, F_t^{close} denotes the TAIFEX closing price at time t, and O_t^{close} denotes the OTC closing price at time t.

Descriptive statistics for these daily market returns and trading volume are reported in Table I. The average daily market returns for the whole sample period are 0.0161% for TAIEX, 0.0168% for TAIFEX, and 0.0008% for OTC, respectively. The values for the maximum and minimum returns for the stock markets show that the existence of seven percent upper and lower bounds as a result of government regulation. All market returns and trading volumes are apparently not following a normal distribution by Bera-Jarque criterion. Furthermore, the kurtosis for all market returns exhibits a fat-tailed shape. At first glance, the GARCH family model seems appropriate to fit these trading data.

[Table I]

The relationship between investor sentiment and market returns is discussed below. This study specified two classifications for trading volume, scaled volume and deviated volume, as proxies for investor sentiments.[3] Using a simple regression model can roughly express the relations between investor sentiments and market returns.

$$R_{i,t} = c_{i,1} + c_{i,2} S_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the daily market returns for TAIEX, TAIFEX, and OTC, $S_{i,t}$ is the investor sentiment proxy for the ith market at time t that can be replaced by scaled volume or deviated volume, and $\varepsilon_{i,t}$ is the error term based on the regression model. Panel A and panel B of Table II report the estimated results of MLE regression for three different markets. The coefficient for c_2 shows that the scaled volume evidently has a positive influence on spot market returns and that the deviated volume has significantly negative influence for all market returns. These results are not quite explicit enough to completely describe the influence of investor sentiment on the change of market returns. It seems that the scaled volume contains some noise information and that the results implicitly show an influence on market returns. In order to outline the influence of investor sentiment on trading volume, this study selects the deviated volume variable to represent the effective sentiment indicator for empirical discussion later. A special specification is to separate the deviated trading volumes into two parts denoting the bright and dark sentiment indicators. The ESI in such a model structure can easily describe the different aspects of investors' moods. Thus, below is the modified model based on Eq. (1) which decomposes the sentiment variable for the ESI into two parts

$$R_{i,t} = c_{i,1} + c_{i,2} S\_H_{i,t} + c_{i,3} S\_L_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $S\_H_{i,t}$ and $S\_L_{i,t}$ represent EBSI and EDSI for traders respectively. Again, the regression results are shown in Table II. For the coefficients of c_2 and c_3 on Panel C, they are

[3] Let the variable for trading volume be q. The scaled volume can be calculated by using the standardization of the trading volume (Fleming et al., 2008), the scaled volume can be expressed as follows. Scaled volume equals [q-E(q)] / SD(q). The variable for deviated volume is formed by sorting out the values of trading volume that are greater or smaller than one standard deviation of the mean and defined as follows. Deviated volume = max{q-[E(q)+SD(q)],0} ∪ abs{min{q-[E(q)-SD(q)],0}}. In this paper, we define deviated volume as the abnormal trading volume.

mostly significant as depicting that the ESI explicitly affects market returns. The EBSI and EDSI represent different market moods for traders. First, the specification of investor sentiment is quite important unsuitable specification may lead confused results. Secondly, the dark sentiment (c_3) has a negative influence for all market returns. The bright sentiment (c_2) generates positive market returns for the spot markets. However, it has a negative influence for futures market returns. Furthermore, the magnitude of negative influence is greater than that of positive influence, according to Panel C, Table II. This finding also explains why a negative influence can dominate all market returns through deviated volume on Panel B, Table II. Basically, these debatable empirical results offer contributions for incorporating investor sentiment indicators to investigate market return behavior.

[Table II]

In Figure 1, the ESI for TAIEX, TAIFEX and OTC are respectively graphed. In order to clearly distinguish the EBSI and EDSI, we use a negative quantity to denote the EDSI. It is apparent that the same aspect of ESI roughly displays clustering. This finding supports taht the ESI derived from abnormal trading volume will be a critical role in the change of market returns.

[Figure 1]

3. Model setup and the effects for ESI to returns and volatilities

Due to the kurtosis coefficient's being greater than three for return processes in Table I, it is reasonable to adopt GARCH(1,1) model in order to estimate and check the relationship between ESI and the volatility of market return. Later, we discuss the direct and indirect impacts of ESI for different market returns. Finally, the component volatility model proposed by Engle and Lee (1999) is introduced to describe the complete dynamic volatility process. Meanwhile, we analyze the detailed influences on market returns through two distinct ESI respectively.

The GARCH model has been extensively cited and analyzed. Bollerslev, Chou and Kroner (1992) suggest that the GARCH(1,1) model is the most parsimonious volatility model to fit most financial data. Based on such a survey, this study applies the GARCH(1,1) model to fit market return processes in the beginning. The mean equation is represented by Eq. (2) previously. The error term in Eq. (2) $\varepsilon_{i,t} \sim N(0, h_{i,t})$, and the conditional volatility equation can be shown as

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \theta_{i,1} S\_H_{i,t-1} + \theta_{i,2} S\_L_{i,t-1}, \tag{3}$$

where $h_{i,t}$ is the conditional volatility and the coefficients $\theta_{i,1}$ and $\theta_{i,2}$ represent the influences for the EBSI and EDSI to conditional volatility. We also consider the possible influence from volatility effect to returns. After incorporating the volatility term into Eq. (2), the mean equation can be modified as[4]

$$R_{i,t} = c_{i,1} + c_{i,2} S\_H_{i,t} + c_{i,3} S\_L_{i,t} + c_{i,4} h_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where $c_{i,4}$ denotes the magnitude of indirect influence from ESI shocks.

Table III reports the empirical results for the simple GARCH(1,1) model and the GARCH-in-mean model with the influence of ESI. Panels A and B of Table III provide GARCH(1,1) estimated coefficients indicating that the ESI has a substantial influence on

[4] The risk premium term established on GARCH-in-mean model could cite lagged conditional volatility (Brooks, 2004, p.480).

both market returns and conditional volatility for all markets. Such an inference can be mostly be confirmed by the estimates for c_2, c_3, θ_1 and θ_2. One of our findings is that the direct influence of EDSI is noticeably controlled by the price-pressure effect for all markets and that the magnitudes are -0.493 for the TAIEX, -0.581 for the TAIFEX, and -0.606 for OTC on Panel A of Table III. However, the direct influence for EBSI is dominated by the hold-more effect in the spot markets and is dominated by the price-pressure effect in the futures market. The sizes of the direct influence for EBSI are 0.292 for the TAIEX, 0.323 for OTC, and -0.487 for the TAIFEX on Panel A of Table III. These results not only support that the GARCH volatility model is suitable for fitting market trading data but also convincingly point out that it is appropriate to incorporate the risk premium term triggered by ESI. Nevertheless, the ESI's effect on risk premium seems insignificant on Panel C of Table III for these three markets. These findings are in agreement with previous literatures that the compensations of risk bearing are often hard to recognize based on a time-series framework.[5] In order to obtain more complete blueprint for these relationship, we use component volatility model to detect the ESI's effects on the risk premium.

[Table III]

The component volatility model proposed by Engle and Lee (1999) could substantially decompose the conditional volatility into long- and short-term components. This approach can assist analysts to realize the complex process for conditional volatility and the dynamical relationship between risk and return. Thus, this study tries to make a few modifications to the traditional component volatility model for performing the research purpose. The ad hoc specification model is presented below:

[5] Also see Baillie and DeGennaro (1990), Glosten, Jagannathan, and Runkle (1993), and Guo and Whitelaw (2006).

$$R_{i,t} = c_{i,1} + c_{i,2} S\_H_{i,t} + c_{i,3} S\_L_{i,t} + c_{i,4} q_{i,t-1} + c_{i,5}(h_{i,t-1} - q_{i,t-1}) + \varepsilon_{i,t}, \tag{5}$$

$$q_{i,t} = \omega_i + \rho_i q_{i,t-1} + \varphi_i(\varepsilon^2_{i,t-1} - h_{i,t-1}) + \theta_{i,1} S\_H_{i,t-1} + \theta_{i,2} S\_L_{i,t-1} \tag{6}$$

$$h_{i,t} = q_{i,t} + \alpha_i(\varepsilon^2_{i,t-1} - q_{i,t-1}) + \beta_i(h_{i,t-1} - q_{i,t-1}) + \theta_{i,3} S\_H_{i,t-1} + \theta_{i,4} S\_L_{i,t-1}. \tag{7}$$

where $q_{i,t-1}$ is the long-term volatility and can be viewed as the unconditional variance, and $(h_{i,t-1} - q_{i,t-1})$ represents the short-term volatility. The coefficients $c_{i,2}$ and $c_{i,3}$ represent the influence of the EBSI and the EDSI, respectively. These influences can be viewed as the direct effects of the ESI on returns. Namely, these are the direct effects of extreme sentiments on returns. Additionally, the estimated coefficients $c_{i,4}$ and $c_{i,5}$ are two exhibited risk premia brought through long- and short-term volatilities, respectively. The risk premia can be regarded as indirect effects when the ESI shows substantial performance under the component volatility structure. Based on equations (6) and (7), if the ESIs are statistically significant for either long- or short-term volatility, then volatility predominately impacts market returns. At the same time, it means that the indirect influence coming from sentiment indicators exists.

One of the advantages of using the component volatility model to express the indirect influence is that we could get meaningful information such as the effect of short- and long-term volatility on market returns. On the contrast, the direct effect includes permanent (long-term) and transitory (short-term) volatility information. It is necessary to realize the precise indirect influence, as the different intermediaries would bring dissimilar results. When an ESI affects market returns through permanent volatility, it shows in agreement with market returns' responding to the ESI through past volatility. Meanwhile, market returns react to the ESI through unexpected shocks lagged only one period. Applying more rigorous econometric tests, we calculate the model selection criterion with the Bayesian information criterion (BIC) to compare the performance between GARCH-in-mean and component volatility models.[6] According to this model selection criterion, the BIC values for GARCH-in-mean models are 3.963 for the TAIEX, 4.183 for the TAIFEX, and 4.111 for OTC, but the component volatility models are 3.874 for the TAIEX, 4.120 for the TAIFEX and 4.040 for OTC. Therefore, we can infer that the component volatility model performs more truly than the GARCH-in-mean model from the empirical results.

Three model specification empirical results are shown in Table IV. The volatility component equations including both the EBSI and the EDSI are reported as specification 1. First, the direct influences on market returns through the ESI are still statistically significant. The magnitudes of the direct influence of EBSI are 0.545 for the TAIEX, -0.673 for the TAIFEX, and 0.586 for OTC, but those of EDSI are -0.765 for the TAIEX, -0.627 for the TAIFEX, and -0.912 for OTC. This finding is consistent with our previous empirical outcome confirming that negative (positive) market returns are triggered by EDSI (EBSI) for spot markets. However, simply negative market returns are induced by both EDSI and EBSI in the futures market. In other words, dark sentiment is dominated by a price-pressure effect for all markets, and bright sentiment is dominated by a hold-more (price-pressure) effect in the spot (futures) market. As suggested by DSSW(1990), the hold-more effect suggests that the noise traders are compensated for bearing more risk by holding more risky assets relative to the arbitrageurs. The price-pressure effect resulting from the overreaction of asset prices reduces the expected returns. Secondly, both the EBSI and the EDSI approximately exhibit significant effects in the long- and short-term volatility equations. This finding supports that the component volatility model performs more comprehensively than the GARCH-in-mean model for market trading data. Moreover, the component volatility model could avoid the

[6] GARCH-in-mean and component volatility model are non-nested. Adrian and Rosenberg (2008) point out that using BIC to compare models is applicable, as models are non-nested.

offsetting for the indirect influence of ESI. The indirect influence is revealed on the spot markets through short-term volatility—the sizes are 0.725 for the TAIEX and 0.762 for OTC—but on the futures market through long-term volatility, the size is 0.042. It seems to demonstrate that the indirect influence on market returns is subject to the entirety of the ESI. It is of interest to prudently group the single-aspect ESIs in the component volatility equations for inspecting whether the interaction of indirect influence originating from the whole ESI exists.

[Table IV]

We can focus on the effect of the distinguishable ESI, relating it to the different degrees of market returns with volatilities. Furthermore it is reasonable to estimate the real trading data for three markets by taking a single ESI in the component volatility equations. The empirical results of the model specifications 2 and 3 are reported in Table IV. Even when we divide the whole ESI into two parts and proceed to reconsider the influences of ESI, the estimated results of direct influences on market returns through ESI are quite similar to those reported on Table III. These statistical results support that the model setting used for this study is relatively steady. We discover that the impacts of short-term volatility affected by ESI have been changed, especially for TAIFEX and OTC. On the Panel C of specification 2 the estimated coefficient θ_3 becomes positive and significant for the TAIFEX, and for specification 3, the estimated coefficient θ_4 becomes negative and insignificant for OTC. In addition, the estimations of indirect influence on these three market returns also exhibit an apparent disparity. Generally speaking, the sizes of indirect influence on specification 2 are 1.006 for the TAIEX, 0.039 for the TAIFEX, and 0.479 for OTC; but those for specification 3 are -0.475 for the TAIEX, and 0.036 for the TAIFEX. We got a hint that the interactions generated by the ESI in component volatility equations exist. Furthermore, this interaction may cause a biased estimation of indirect influence for market returns, especially for spot markets. The intermediary influence on market returns is purely that of short-term volatility for spot markets but is simply that of long-term volatility for the futures market. This finding not only agrees with model specification 1 on Table IV but also highlights the fine-moving process. As shown on Table IV, the indirect influence of ESI is apparently affected by different aspects of ESI for these three markets. Moreover, the indirect influence of EBSI is approximately dominated by a create-space effect in these three markets, but the indirect influence of EDSI is dominated by a create-space effect for TAIFEX and by a Friedman effect for TAIEX.

The short-term component can be interpreted as having transitory volatility driven by instant market shocks. On the contrary, the long-term component is stated as the level of risk over a long period. Therefore, we demonstrate that the indirect influence of ESI only affects short-term volatility for spot markets. Although the ESI can partly affect the estimation of long-term volatility, this impact cannot be transmitted to spot-market returns. Since the ESI can deeply affect the spot market returns, the indirect influence of ESI is manifested in the long-term volatility in the futures market.

[Figure 2]

In Figure 2, we plot the unconditional volatility series and scaled trading volume for those three different markets. It is apparent that the pattern of trading volume and unconditional volatility are approximately co-movements. The phenomenon of co-movement explains that the moving of unconditional volatility follow the process of sentiment. This result is in line with the outcome in panel B of Table IV; it plots three different specifications simultaneously. It is obvious that that the signs of the estimates are the same but that the magnitudes are different. Last, we discover that the oscillation in unconditional volatility for in futures market is larger than those in two spot markets (TAIEX and OTC). This result is consistent with the descriptive statistics on Table I.

4. The impacts for the 2008 Financial Tsunami

The financial crisis occurring during 2008-2009 was ignited by the Financial Tsunami in September 2008.[7] These dramatic financial episodes not only caused many global financial institutions to collapse but may have brought the changes in market returns and volatility. Therefore, exploring and re-estimating the sub-period, January 3, 2001-August 31, 2008, excluding the September 2008 Financial Tsunami is necessary. In order to discuss the influence of the ESI and offer a clear comparison with Table IV, we evaluate the three specifications of the component volatility model as in the previous arrangement. The empirical results are reported on Table V.

Before the Financial Tsunami, the indirect influence and the estimated coefficients $\theta_{i,2}$ and $\theta_{i,4}$ have notable changes between specification 1 and other specifications for all markets. These results show that the interaction of specification 1 of Table V does exist and also is consistent with the findings of Table IV. The next step is to compare the results on Table IV and Table V and discussing the impacts of the Financial Tsunami. On Table V, the direct influence of the ESI on market returns is roughly consistent with the estimations over the whole period. Nevertheless, the indirect influence for model specifications 1 and 2

[7] Preston (2009) has clear discussion on the date of financial tsunami.

dominated by the create-space effect brings the obvious changes in futures market returns. In other words, medium-term volatility is replaced by short-term volatility for the futures market. Overall, the medium affecting market returns is just short-term volatility on specification 2 for all markets; the magnitudes of the effects are 0.923 for the TAIEX, 0.081 for the TAIFEX, and 0.503 for OTC. On specification 3, the medium is simply short-term volatility for the TAIEX market, and the magnitude is -0.472; the medium is purely long-term volatility for the futures market, and the magnitude is 0.041. Only the indirect influence of EDSI is dominated by the Friedman effect for the TAIEX market. All in all, the ESI still plays a significant role in estimating the market returns in direct and indirect ways. Furthermore, the September 2008 financial tsunami has indeed changed the indirect influence of EBSI on the conditional volatility, especially in the case of the futures market.

[Table V]

5. Conclusion

In light of behavioral finance theory, investor sentiment indeed becomes noticeable in evaluating expected returns. Following DSSW'(1990) proposal that the four effects generated by noise trader risk could interfere with expected returns, it seems to show that the individual investing activities are endowed with the ability for pricing. These four effects can be generalized in two parts, direct and indirect effects. The explanations of these effects in the previous paper appear imperfect. This paper attempts to employ the component volatility model to cope with the process of these effects in its entirety. In addition, we select the abnormal trading volume to investigate and treat the abnormal trading volume as a signal leading the variety of market returns. In our specification, we define the abnormal trading volume as the ESI and then separate them into EBSI and EDSI. We find that the interaction between the EBSI and EDSI really exists and that it can cause a biased estimation of its mediating influence on market returns; therefore we estimate two different aspects of ESI through the component volatility model.

The main empirical finding is that the EDSI directly affects market returns for all markets through a price pressure effect. However, the EBSI directly affects market returns through hold more effect on spot markets than on the futures market. We detect that the intermediary indirectly affecting market returns is the short-term volatility for spot markets but is the long-term volatility for futures market, although most of the ESIs have a significant influence on both long- and short-term volatility. The findings explain that extreme investor sentiment truly has a direct and indirect influence on market returns and that the magnitude depends on different factors. We consider that extreme investor sentiment belongs to instantaneous contagious shocks; therefore, the indirect effect is shown through short-term volatility for spot markets. Moreover, this phenomenon appears to be the reverse for futures market returns. We believe that it could be concluded that the characteristics of the futures market are different from those of the spot market. Thus, the indirect effect is shown as being long-term volatility in the futures market.

Finally, we also show the empirical results before September 2008, the date of the Financial Tsunami. Afterward, we investigate the impact of this episode. Our main finding is that the mediating influence of the EBSI clearly varies from short-term volatility to long-term volatility for the futures market. Overall, the ESI still plays a significant effect on the mean and volatility of market returns in two distinct ways.

BIBLIOGRAPHY

Adrian T., & Rosenberg, J. (2008). Stock returns and volatility: Pricing the short-run and long-run components of market risk. Journal of Finance, 63, 2997-3030.

Baillie, T. R., & DeGennaro, R. P. (1990). Stock returns and volatility. Journal of Financial and Quantitative Analysis, 25, 230-214.

Baker, M., & Stein, J. (2004). Market liquidity as a sentiment indicator. Journal of Financial Markets, 7, 271-299.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives, 21, 129-151.

Barber, B. M., Odean, T., & Zhu, N. (2009). Systematic noise. Journal of Financial Markets, 12, 547-569.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31, 307-327.

Bollerslev, T., Chou, R., & Kroner, K. (1992). ARCH modeling in finance: A review of the theory and empirical evidence. Journal of Econometrics, 52, 5-59.

Brooks, C. (2004). Introductory econometrics for finance (1st ed.). Cambridge: Cambridge University Press.

Brown, G.W. (1999). Volatility, sentiment, and noise traders. Financial Analysts Journal, 55, 82-90.

Christoffersen, P., Jacobs, K., & Wang, Y. (2006). Option valuation with long-run and short-run volatility components (working paper). McGill University.

De Long, J. B., Shleifer, A., Summers, L.G., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy, 98, 703-738.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of U.K inflation. Econometrica, 50, 987-1008.

Engle, R. F., & Lee, G. J. (1999). A permanent and transitory component model of stock return volatility. In R. F. Engle, & H. White (Eds.), Cointegration, causality, and forecasting: A festschrift in honor of Clive W.J. Granger. Oxford: Oxford University Press.

Fleming, J., Kirby, C., & Ostdiek, B. (2008). The specification of GARCH models with stochastic covariates. Journal of Futures Markets, 28, 911-934.

Glosten, L. R., Jagannathan, R., & Runkle, D.E. (1993). On the relation between expected value and the volatility of the nominal excess return on stock. Journal of Finance, 47, 1779-1801.

Guo, H., & Whitelaw, R. (2006). Uncovering the risk-return relation in the stock market. Journal of Finance, 61, 1433-1463.

Hong, H., & Stein, J. (2007). Disagreement and the stock market. Journal of Economic Perspectives, 21, 109-128.

Kumar, A., & Lee, C.M. (2006). Retail investor sentiment and return comovements. Journal of Finance, 61, 2451-2486.

Lee W.Y., Jiang, C.X., & Indro, D.C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. Journal of Banking and Finance, 26, 2277-2299.

Merton, R.C. (1980). On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics, 8, 323-361.

Preston, P. (2009). The other side of the coin: Reading the politics of the 2008 financial tsunami. British Journal of Politics and International Relations, 11, 504-517.

Shleifer, A. (2000). Inefficient Markets (1st ed.). Oxford: Oxford University Press.

Table I

Descriptive statistics for daily TAIEX, TAIFEX and OTC returns and trading volumes for January 3, 2001 to May 27, 2009

	TAIEX	TAIFEX	OTC
Panel A: market returns			
Observations	2078	2078	2078
Mean	0.0161	0.0168	0.0008
Maximum	6.5246	6.8931	5.8672
Minimum	- 6.9123	- 8.7758	- 6.9679
Standard deviation	1.5661	1.8169	1.6799
Skewness	- 0.1175	- 0.1788	- 0.3065
Kurtosis	4.8602	5.7910	4.3814
Bera-Jarque	304.385 [< 0.001]	685.541 [< 0.001]	197.781 [< 0.001]
Q(8)	14.893 [0.061]	14.295 [0.074]	65.156 [< 0.001]
$Q^2(8)$	287.260 [< 0.001]	424.430 [< 0.001]	419.820 [< 0.001]
Panel B: trading volume			
Observations	2079	2079	2079
Mean	3895.277	35.866	50.997
Maximum	11631.230	172.208	204.673
Minimum	856.000	3.169	7.611
Standard deviation	1591.640	26.330	27.231
Skewness	1.0599	1.7051	1.4169
Kurtosis	4.5523	6.3478	5.7633
Bera-Jarque	598.012 [< 0.001]	1978.258 [< 0.001]	1357.092 [< 0.001]
Q(8)	9287.900 [< 0.001]	11333.000 [< 0.001]	10808.000 [< 0.001]
$Q^2(8)$	4592.200 [< 0.001]	6973.400 [< 0.001]	6576.700 [< 0.001]

Note. This table provides descriptive statistics for daily TAIEX, TAIFEX and OTC returns and trading volume over the period from January 3, 2001 to May 27, 2009. Normality tests are based on the Bera-Jarque statistics. Q(8) is the Ljung-Box (1978) test for serial correlation up to the 8^{th} order in the standardized residuals, $Q^2(8)$ is the Ljung-Box test for serial correlation up to 8^{th} order in the squared standardized residuals. Significant at the 5% level is denoted by *. The number in bracket is p-value.

Table II
Regression analysis for the relationship between market returns and the proxies for sentiment indicator
January 3, 2001 to May 27, 2009

regression model: $R_{i,t} = c_{i,1} + c_{i,2}S_{i,t} + c_{i,3}R_{i,t-1} + \varepsilon_{i,t}$

	c_1	c_2	c_3	Q(8)
Panel A: scaled volume				
TAIEX	0.016 (0.471)	0.218 (6.295)**	0.025 (1.129)	9.020 [0.341]
TAIFEX	0.017 (0.438)	- 0.015 (- 0.367)	- 0.030 (- 1.374)	12.644 [0.125]
OTC	< 0.001 (0.010)	0.214 (5.778)**	0.122 (5.544)**	10.025 [0.263]

	c_1	c_2	c_3	Q(8)
Panel B: deviated volume				
TAIEX	0.064 (1.595)	- 0.180 (- 2.318)**	0.053 (2.417)**	9.443 [0.306]
TAIFEX	0.118 (2.645)**	- 0.488 (- 4.987)**	- 0.036 (- 1.657)*	14.326 [0.074]*
OTC	0.049 (1.152)	- 0.190 (- 2.251)**	0.150 (6.890)**	12.819 [0.118]

modified regression model: $R_{i,t} = c_{i,1} + c_{i,2}S\_H_{i,t} + c_{i,3}S\_L_{i,t} + c_{i,4}R_{i,t-1} + \varepsilon_{i,t}$

	c_1	c_2	c_3	c_4	Q(8)
Panel C: sentiment indicator					
TAIEX	0.064 (1.628)	0.209 (2.132)**	- 0.661 (- 6.204)**	0.029 (1.296)	9.822 [0.278]
TAIFEX	0.120 (2.707)**	- 0.407 (- 3.510)**	- 0.675 (- 4.312)**	- 0.036 (- 1.654)*	14.664 [0.066]*
OTC	0.051 (1.224)	0.155 (1.485)	- 0.670 (- 5.691)**	0.130 (5.936)**	10.681 [0.220]

Note. This table reports the regression models, expressed by Eq. (1) and (2), for TAIEX, TAIFEX and OTC over the whole period from January 3, 2001 to May 27, 2009. The proxies of sentiment indicator including scaled volume and deviated volume are considering in regression model. We group deviated volume into high and low sentiment indicators and then incorporate these sentiment indicators into modified regression model. Q(8) is the Ljung-Box (1987) test for serial correlation up to the 8^{th} order in the standardized residuals. Significant at the 5% level is denoted by **, at the 10% level by *. The number in brackets is p-value, in parentheses is standard error.

Table III

Comparison to GARCH(1,1) model and GARCH(1,1)-mean model, Daily January 3, 2001 to May 27, 2009

$$R_{i,t} = c_{i,1} + c_{i,2} S\_H_{i,t} + c_{i,3} S\_L_{i,t} + c_{i,4} h_{i,t-1} + \varepsilon_t$$
$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \theta_{i,1} S\_H_{i,t-1} + \theta_{i,2} S\_L_{i,t-1}$$

Simple GARCH:	c_1	c_2	c_3	c_4			
Panel A: mean equation without lagged conditional volatility							
TAIEX	0.078**	0.292**	- 0.493**				
	(2.540)	(3.538)	(- 4.549)				
TAIFEX	0.110**	- 0.487**	- 0.581**				
	(3.507)	(- 3.965)	(- 3.357)				
OTC	0.069*	0.323**	- 0.606**				
	(1.881)	(3.882)	(- 4.780)				
	ω	α	β	θ_1	θ_2	Q(4)	Q(8)
Panel B: conditional volatility equation							
TAIEX	0.010**	0.055**	0.930**	0.101**	0.067**	6.678	11.097
	(2.336)	(7.274)	(108.04)	(5.513)	(2.898)	[0.154]	[0.196]
TAIFEX	0.035**	0.075**	0.905**	0.242**	0.080*	2.896	6.799
	(4.722)	(8.654)	(93.401)	(3.909)	(1.977)	[0.575]	[0.558]
OTC	0.019**	0.066**	0.923**	0.043**	0.050*	49.068**	51.496**
	(2.543)	(8.741)	(111.03)	(3.547)	(1.770)	[<0.001]	[<0.001]
GARCH-in-mean:	c_1	c_2	c_3	c_4			
Panel C: mean equation with lagged conditional volatility							
TAIEX	0.087	0.263**	- 0.608**	0.009			
	(1.351)	(3.176)	(- 5.541)	(0.362)			
TAIFEX	0.086	- 0. 126**	- 0.640**	0.030			
	(1.465)	(- 4.427)	(- 3.689)	(1.383)			
OTC	0.033	0.286**	- 0.671**	0.026			
	(0.431)	(3.382)	(- 5.336)	(1.057)			
	ω	α	β	θ_1	θ_2	Q(4)	Q(8)
Panel D: conditional volatility equation							
TAIEX	0.213**	0.162**	0.743**	0.076	0.167**	6.410	13.173
	(28.747)	(7.516)	(38.294)	(1.511)	(2.219)	[0.171]	[0.106]
TAIFEX	0.216**	0.138**	0.769**	0.710**	0.224**	5.298	16.280*
	(28.446)	(8.109)	(48.423)	(4.951)	(2.135)	[0.258]	[0.039]
OTC	0.364**	0.181**	0.694**	- 0.121**	0.204**	50.016**	55.255**
	(27.575)	(8.235)	(37.579)	(- 2.952)	(2.028)	[<0.001]	[<0.001]

Note. Panel A and B are the empirical result for the estimations of GARCH(1.1) model with sentiment indicator in conditional volatility equation. Panel C and D are the empirical result for the estimations of GARCH(1,1)-in-mean model incorporating sentiment indicator in both mean and conditional volatility equations. Q(4) and Q(8) are the Ljung-Box (1987) test for serial correlation up to the 4^{th} and 8^{th} order with the standardized residuals. In order to simplify the estimated results, our specification on mean equation ignores the autoregressive term for the time being. The number in brackets is p-value and in parentheses is standard error. Significance at the 5% level is denoted by **, at the 10% level by *.

Table IV
Comparison to component volatility model in mean on three specifications, Daily January 3, 2001 to May 27, 2009

$$r_{i,t} = c_{i,1} + c_{i,2}S\_H_{i,t} + c_{i,3}S\_L_{i,t} + c_{i,4}q_{i,t-1} + c_{i,5}(h_{i,t-1} - q_{i,t-1}) + \varepsilon_t$$

$$q_{i,t} = \omega_i + \rho_i q_{i,t-1} + \varphi_i(\varepsilon^2_{i,t-1} - h_{i,t-1}) + \theta_{i,1}S\_H_{i,t-1} + \theta_{i,2}S\_L_{i,t-1}$$

$$h_{i,t} = q_{i,t} + \alpha_i(\varepsilon^2_{i,t-1} - q_{i,t-1}) + \beta_i(h_{i,t-1} - q_{i,t-1}) + \theta_{i,3}S\_H_{i,t-1} + \theta_{i,4}S\_L_{i,t-1}$$

Sample period	January 3, 2001-May 27 2009								
Specification 1	TAIEX	TAIFEX	OTC						
Specification 2				TAIEX	TAIFEX	OTC			
Specification 3							TAIEX	TAIFEX	OTC
Panel A: mean equation									
c_1	0.104**	0.050	0.171**	0.121**	0.052	0.167**	0.059	0.054	0.077
c_2	0.545**	- 0.673**	0.586**	0.542**	- 0.653**	0.542**	0.299**	- 0.621**	0.329**
c_3	- 0.765**	- 0.627**	- 0.912**	- 0.526**	- 0.560**	- 0.610**	- 0.769**	- 0.616**	- 1.020**
c_4	- 0.009	0.042**	- 0.039	0.005	0.039**	- 0.023	- 0.012	0.036*	- 0.017
c_5	0.725**	- 0.061	0.762**	1.006**	- 0.028	0.479**	- 0.475*	- 0.083	- 3.245
Panel B: long term component									
ω	0.773**	1.777**	1.710**	1.087**	2.169**	1.993**	2.842**	3.690**	2.777**
ρ	0.988**	0.979**	0.992**	0.992**	0.984**	0.994**	0.994**	0.993**	0.987**
φ	0.053**	0.083**	0.059**	0.054**	0.084**	0.058**	0.066**	0.088**	0.081**
θ_1	0.113**	0.258**	0.054**	0.091**	0.219**	0.060**			
θ_2	0.034	0.102**	0.032				- 0.005	0.064*	0.032
Panel C: short-term component									
α	0.011	- 0.063**	0.020**	0.010	- 0.064**	0.030**	0.012	- 0.068**	- 0.002
β	0.767**	0.070	0.830**	0.743**	0.095	0.758**	0.847**	0.083	0.827**
θ_3	- 0.176**	0.040	- 0.090**	- 0.158**	0.119**	- 0.177**			
θ_4	0.169**	- 0.212	0.126**				0.199**	- 0.264	- 0.048

Note. This table reports the estimations of component volatility model on three specifications over the whole period from January 3, 2001 to May 27, 2009. Component volatility model including two aspects sentiment indicators in volatility equations is shown in specification 1. Specifications 2 and 3 are presented that model containing just high and low sentiment indicator individually. Significant at the 5% level is denoted by **, at the 10% level by *.

Table V
The estimated results of component volatility model in mean on three specifications before 2008 financial tsunami

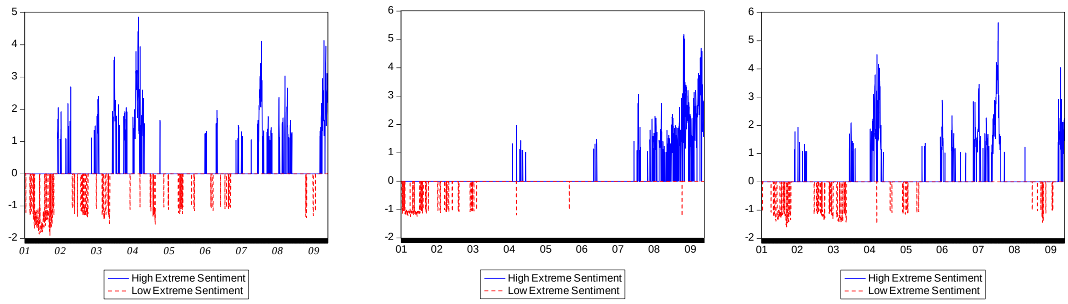
$$r_{i,t} = c_{i,1} + c_{i,2}S\_H_{i,t} + c_{i,3}S\_L_{i,t} + c_{i,4}q_{i,t-1} + c_{i,5}(h_{i,t-1} - q_{i,t-1}) + \varepsilon_t$$

$$q_{i,t} = \omega_i + \rho_i q_{i,t-1} + \varphi_i(\varepsilon_{i,t-1}^2 - h_{i,t-1}) + \theta_{i,1}S\_H_{i,t-1} + \theta_{i,2}S\_L_{i,t-1}$$

$$h_{i,t} = q_{i,t} + \alpha_i(\varepsilon_{i,t-1}^2 - q_{i,t-1}) + \beta_i(h_{i,t-1} - q_{i,t-1}) + \theta_{i,3}S\_H_{i,t-1} + \theta_{i,4}S\_L_{i,t-1}$$

Sample period	January 3, 2001-August 31 2008								
Specification 1	TAIEX	TAIFEX	OTC						
Specification 2				TAIEX	TAIFEX	OTC			
Specification 3							TAIEX	TAIFEX	OTC
Panel A: mean equation									
c_1	0.100*	0.099**	0.186**	0.078	0.094*	0.188**	0.053	0.093	0.062
c_2	0.522**	- 0.733**	0.598**	0.365**	- 0.798**	0.555**	0.267**	- 0.646**	0.336**
c_3	- 0.811**	- 0.489**	- 0.928**	- 0.536**	- 0.481**	- 0.630**	- 0.822**	- 0.517**	- 1.047**
c_4	0.003	0.022	- 0.051	0.014	0.027	- 0.030	- 0.007	0.041*	- 0.014
c_5	0.613**	0.058**	0.686**	0.923**	0.081**	0.503**	- 0.472*	0.006	- 2.833
Panel B: long term component									
ω	0.740**	0.879**	1.475**	1.184**	2.016**	1.716**	2.101**	2.199**	2.302**
ρ	0.981**	0.998**	0.989**	0.989**	0.996**	0.992**	0.989**	0.984**	0.981**
φ	0.051**	- 0.018**	0.053**	0.060**	0.029**	0.052**	0.069**	0.097**	0.082**
θ_1	0.133**	- 0.031**	0.054**	0.077**	- 0.031**	0.058**			
θ_2	0.046*	0.025**	0.033				< 0.001	0.116*	0.046
Panel C: short-term component									
α	0.015	0.074**	0.025**	0.020**	0.040**	0.030**	0.014	- 0.093**	- 0.003
β	0.819**	0.893**	0.835**	- 0.674**	0.903**	0.836**	0.863**	0.086	0.838**
θ_3	- 0.183**	0.279**	- 0.099**	- 0.429**	0.402**	- 0.126**			
θ_4	0.155**	0.053**	0.136**				0.191*	0.561*	- 0.055

Note. This table reports the estimations of component volatility model on three specifications over the sub-period from January 3, 2001 to August 31, 2008. Component volatility model including two aspects sentiment indicators in volatility equations is shown in specification 1. Specifications 2 and 3 are presented that model containing just high and low sentiment indicator individually. Significant at the 5% level is denoted by **, at the 10% level by *.



TAIEX extreme sentiment TAIFEX extreme sentiment OTC extreme sentiment

Figure 1: Extreme sentiment indicators for three markets

This figure plots the extreme sentiments separating into high (solid line) and low (dashed line) parts for three markets. These extreme sentiments are sorted from scaled trading volumes. We sort out the extreme scaled trading volumes and then plot the low extreme sentiment with negative quantity especially.

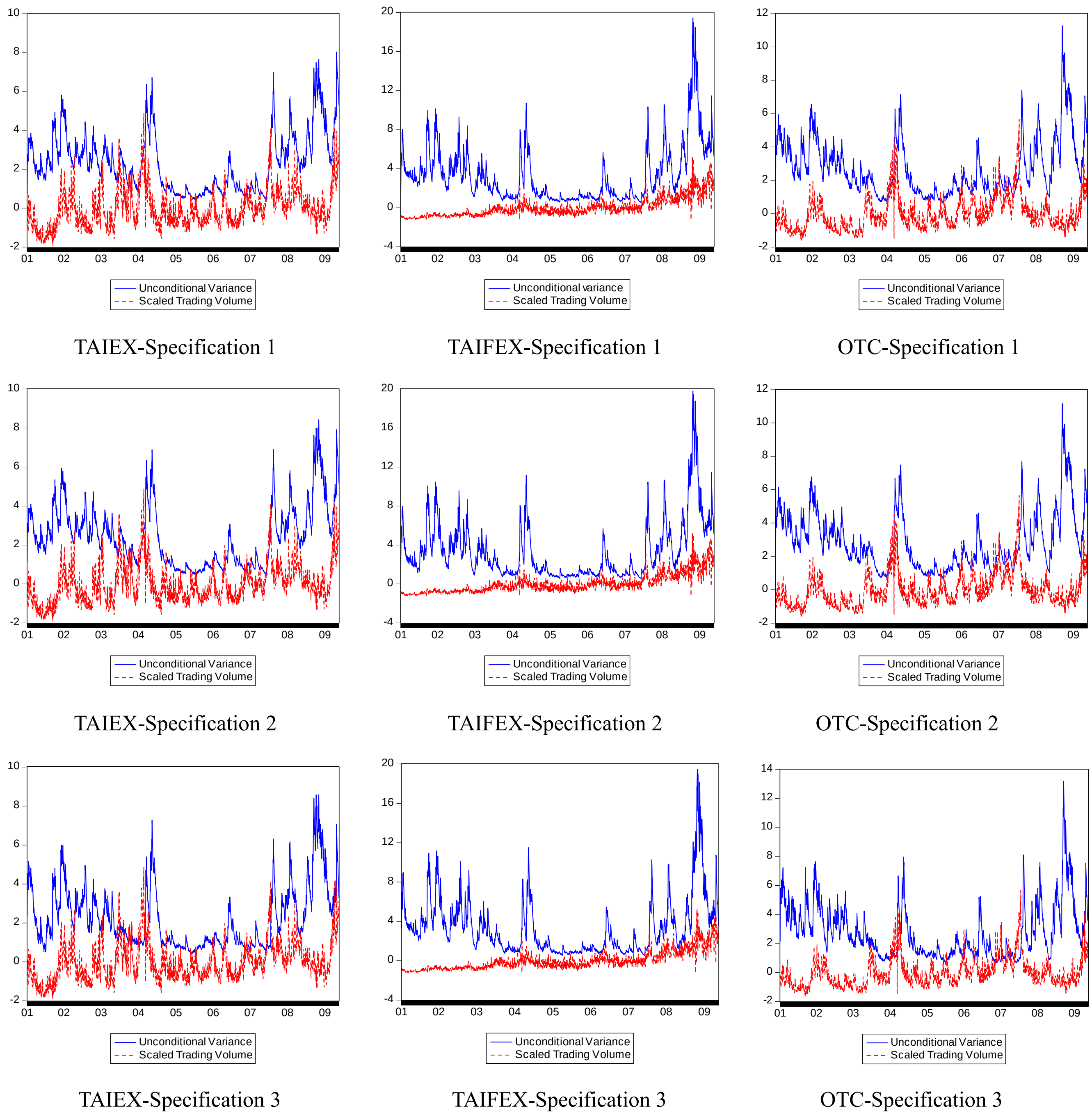


Figure 2: Unconditional variance and scaled trading volume for three markets

This figure plots the estimated unconditional variance (solid line) and scaled trading volume[8] (dashed line) at a daily frequency from January 3, 2001 to May 27, 2009. The estimated unconditional variance is modeled by three specifications including considering both two aspects of sentiment indicators in component volatility equations simultaneously (Specification 1) and considering single aspect of sentiment indicator respectively (Specification 2 and Specification 3). Specification 2 is described the component volatility equations containing only high sentiment indicator. However Specification 3 is pictured the component volatility equations containing only low sentiment indicator.

[8] The scaled trading volume is calculated by using standardization of the trading volume.