Investor Sentiment and ETF Liquidity
-Evidence from Asia Markets[1]

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ABSTRACT

This study aims to analyze the effect of investor's sentiment on the Exchange Traded Funds(ETF) liquidity, and to capture the variations of investor's sentiment, the Volatility Index (VIX) is used to observe the market characteristics as a proxy variable. In addition, our sample data mainly focus on the Asia ETF market. The empirical results show that the degree of market investor sentiment plays an important role in the ETF liquidity within these Asia countries. We employ GARCH model to capture the volatility-clustering effect in the study. The empirical result shows ETF has liquidity and volatility-clustering effect, which is, when in a specific period there is a better or poor liquidity phenomenon. Especially, when the market condition presents different characteristics, namely the difference of trading systems, regulations and so on, the relationship between VIX and ETF liquidity is also significant difference. From the viewpoints of hedging market risk and portfolio investment, this paper also suggests that investor should consider the sentiment factors into their investment decision, and timely readjust the investment weight of ETF product.

Keywords: Investor's Sentiment, ETF Liquidity, Liquidity-volatility-clustering Effect, Volatility Index

[1] ICMSDM-TW.

1. INTRODUCTION

The global ETF Industry experienced best growth ever pushing AUM (Asset Under Management) to \$2.6 trillion by the end of 2014 reaching a new record. ETF trading activity up 13% in 2014 reaching \$18.7 trillion and will continue to rise, and ETF markets advance globally with no sign of slowing down. According to ETF flows the researcher finds that investors preferred less risky assets. Deutsche Bank expect global ETF assets to pass \$3 trillion in 2015.[2] The rapid capital formation of ETF these years, making it one of the favorite inverstment products of retail investors, especially the ETF product, which has lower investment cost for investors , as its overall management cost is lower than index fund. Gradually, ETF also becomes one important investment product in customer's investment portfolio of Bank wealth management; Due to lower trading cost, ETF is one of the most popular underlying asset. Besides the others equity products, many policy holders will also choose ETF to accumulate their account value in life insurance and variable annuity products. The main reason why customer chooses ETF is that they want to be involved of market growth, especially in the era of low interest rates, to avoid their growing wealth lost by inflation . When they are bullish about the market, they can be involved without spending time and effort to choose stocks or any equilty products. When they choose ETF as their investment product, they will first consider about the issuer, trading platform, product potential value, and liquidity, however they often ignore the investment sentiment might cause price volatility, which will influence the liquidity of inverstment product itself and cause the decrease of trading volume .

Review the literature on the research of ETF product features, which mainly focuses on capturing the behavior of ETF product return. Fujiwara(2006) finds that there is a correlation between the changes in the discount rates and the small capital stock index, but these phenomena were not observed in an ETF. And Li *et al.*(2012) introduce a U-shaped and an L-shaped intraday pattern for trading volume and return volatility, as they find a significant increase of trading volume and turnover ratio of all ETFs during and after the financial crisis. As there is correlation between ETF and capital market , variable type of ETF in investment portfolio can be a hedging target, when financial criss happens. Boscaljon and Clark(2013) find that during a financial criss, there is a positive abnormal return for equities in SPDR Gold Share(GLD) exchange traded funds(ETF), if VIX increases 25%. Ivanova *et al.* (2013) introduce that price discovery are differently influenced by the temporal behavior of the exchange traded funds price discovery metric, in the spot and futures markets across indexes. The

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market investor's transaction will might be influenced by his or her individual sentiment, especially when there is high uncertainty risks in the market. Investor's trading behavior will change significantly, i.g. feedback trading will cause widly price fluctuation. Recent researches, such as Chau *et al*. (2011) believe that the presence of sentiment-driven noise trading will largely generate feedback trading activity. For regulators and investors, investment sentiment and market dynamics are directly relevant, so when we study on the ETF, we need not only focus on ETF return, but pay more attention to investor sentiment.

Besides sentiment, liquidity is also very important, especially facing markets with different development degrees, i.g. ETF product volatility in developed markets and newly emerging Asian markets varies significantly. （Gutierrez *et al*. 2009）· The difference in volatility value might be caused by the information spreading speed, the product features and investor's holding information.（Chiu *et al*. 2012）. Different volatility will also cause the change on liquidity. In this research , we assume that the poor liquidity of financial product can lower the transaction will of new financial product, decrease the institute investor profit , and hinder government to promote new financial product.

After the 2008 financial criss happened, investors increased their requirement of multiple financial product to avoid investment risk. In recent years, the increasing requirement to avoid risks makes various countries begin to develop the diversity of financial derivatives. Generally speaking, investor sentiment will influence his or her trading behavior, in another word, investor behavior mainly impact on their trading strategy. When the market liquidity is measured by the trading volume, the investor sentiment will of course become a critical factor, so this paper aims to analyze wether the liquidity of ETF is influenced by investor sentiment with evidence.

According to Chiu *et al*. (2012) research findings that with an increase in funding illiquidity during the subprime crisis period, in which a corresponding increase in the bid–ask spread and a decrease in market depth is found, indicating a general reduction in equity liquidity, According to the related introduction on ETF liquidity change(Chiu *et al*. 2012), researchers's previous finding demonstrates that ETF liquidity will be influenced by volatility value, which is seldom discussed by present literatures. They mentioned and believed with clear evidence that liquidity shock and continuous bad market information will cause the pressure of ETF redemption and the change of financial liquidity, which will influence the liquidity of ETF itself. However they did not explain why investor sentiment might be the reason to cause this type of liquidity change. Investors are influenced by the market information, which will impact the fluctuation of investor sentiment, and possibly futher influences the liquidity of ETF. This paper extends the reseach on ETF liquidity, considering the sentiment factor.

Chau *et al*. (2011) find statistically significant evidence suggesting that the negative relationship between autocorrelation and volatility, sentiment influence seems to be stronger during the bullish market. They find evidence on the direct impact of investor sentiment on the momentum-style feedback trading strategies, and those results are very important in contributing to the current debate on the role of investor sentiment in asset pricing and investment behaviour. They focuse on the evidence research of relationship between investor sentiment and trading behavior. Although there is significantly negative correlation between autocorrelation and volatility as they mention, according to the statistic data of measuring investor sentiment, which demonstrates that investor sentiment will influence the change of volatility to make different trading behaviors. However, there is no futher explanation or discussion on investor sentiment and volatility change.

The key point of above two articles is that investor sentiment is an abstract qualitative factor, which influnces ETF returns by volatility to show its liquidity. In addition, our paper inherits their discussion on investor sentiment.

Gutierrez *et al*. (2009) find that the overnight volatility is higher than daytime volatility, both U.S. returns and local Asian market returns explain the Asian ETF returns. The trade location and investor sentiment effects are further supported by the high return correlation between Asian and U.S. ETFs.

The bi-directional Granger causality in volatility between the U.S. and the six Asian markets analyzed are found in this article. Their finding demonstracts that local market information can be used to explain the ETF volatility and return in Asia, but the discussion on the source of volatility is not discussed in details. On the other hand, they find that the ETF volatility and return are influenced by each other depending on different trading regions, so that the relationship between investor sentiment and volatility might be overlooked.This paper combined the interaction of findings of these three papers to observe how investor sentiment can influence ETF returns and ETF volatility using valitility.

This paper researches on the ETF samples of five main countries in Asia-Pacific region, including Japan, South Korea, Taiwan, Malaysia and Singapore, from 2005, January 31st to 2015, January 30th, including the global financial crisis period, to prove the effect of financial crisis on liquidity .The empirical data indicates that trading volume and investment sentiment have significant impact on the sample countries ETFs liquidity. We review previous data, and find liquidity has the feature of volatility cluster, which means liquidity will perform well or badly in specified period. We adopt GARCH model to analyze the sample data, and the empirical result proves that investment sentiment has significant impact on overall ETF volume. The empirical results will be significantly different in time of crisis, and we believe that this is caused by the difference of financial environment, system or investment sentiment in these countries, which is also proved by our empirical results. We found that the phenomenon of ETF liquidity volatility cluster apparently exists in Malaysia and South Korea, but this phenomenon becomes less apparent in the financial market such as Japan, Singapore, and Taiwan, where its ETF product is more maturely developed. For countries ETF liquidity inconsistencies, we inference that is based on the country financial environment, change on transaction system, maturity of ETF products and investment sentiment.

The remainder of the paper is organised as follows. Section 2 briefly reviews the related literature and Section 3 decripes the varibales and empirical research models used in our investigation. The data and descriptive statistics are provided in Section 4 presents basic statistics of variables in the research and discusses the main empirical results and robustness checks. Finally, Section 5 concludes the paper.

2. LITERATURE REVIEW

2.1 Sentiment, Trading behavior, and Voladility

After the 2008 financial criss happened, investors increased their requirement for multiple financial product to avoid risk, making various countries begin to develop the diversity of financial derivatives in recent years, and ETF is One of the biggest. The recent research on ETF volatility points out that the Investor sentiment, which might be influenced by certain exceptional events, will impact investor' trading behavior, depending on the investor's positive or negative expectation.What's more, this will further affect the trading volume in direct proportion. In the past literatures, Edelen *et al,* (2010) introduce setiment fluctuations regarded as risk tolerance, or overly optimistic or pessimistic forecast cash flow investment environment. In both cases, the setiment impact on asset pricing should be obvious influence from fundamentals. The research on Investor sentiment usually focuses on the discussion on target returns, Investor sentiment and trading. Glabadanidis (2014), proves that abnormal return is generated by a moving average (MA) trading strategy ,but Investor sentiment cannot fully explain its performance. This reseach shows that it is impossible to use Investor sentiment to explain abnormal return generated by trading policy, as one empirical research shows that abnormal return generated from using trading strategy might exclude the influence on target price performance caused by Investor sentiment. However, another empirical research believes that Investor sentiment can be used to improve the investment portfolio performance. According to Basu, Hung, Oomen, and Stremme (2006), sentiment can improve the performance of dynamically managed portfolio strategies for standard market-timers as well as for momentum-type investors.

The recent research points out that Investor sentiment will affect the trading behavior of average investor or institute investors. (Edelen *et al*., 2010), Feedback trading in the E-mini index futures markets in microstructure setting is examined by Kurov (2008), and he finds that traders in index futures markets are positive feedback traders and their feedback trading tend to be more intense in period of high Investor sentiment. There are normally three types of Investor sentiment, and the degree of each sentiment will impact on the sensitivity on target price, the trading volume, or product selection. In the case of positive sentiment, Chau *et al*, (2011) find that there is a significant positive feedback trading in the U.S. ETF markets, and the intensity of which tends to increase when investors are optimistic, consistented with the view that the market is less rational and inefficient during high-sentiment periods, due to higher participation by noise traders in such periods. In the case of negative sentiment, Chiu *et al*, (2014) show that when the fearful market-based sentiment increases (decreases) in the state of bearish institutional investor expectation, net buying volume and market liquidity will decrease (increase) more significantly than in normal times, as for the interaction between fearful market-based sentiment and institutional investor expectation. Therefore, the variation of Investor sentiment will impact on the investment product and trading volume, especially on product selection, which will impact on these investment portofilio. ETF can meet investor's requirement of avoiding risks, or reaching expected return, so the trading volume of ETF changed obviously in recent years. According to the above, the literatures in the past indicate that impact factors such as sentiment is not ignorable, especially to Risk-averse Investor. The positive sentiment in market will increase the volatility risk and affect the ETF return, which implies that market trading volume will be influenced, so does the liquidity.

Investor sentiment does not only affect on trading behavior, but also correlate with volatility, and further impact on the return of investment product. A contemporaneous relation between changes in Investor sentiment and U.S. stock market returns is introduced by Brown and Cliff (2004). Even Investor sentiment can be used to predict stock return, Lemmon and Portniaguina (2006) find the returns on small size stocks can be predicted by Investor sentiment. In recent years, the research on the correlation between Investor sentiment and volatility is expanding. The relation between the expected return and volatility of the U.S. stock market hinges on Investor sentiment are founded by Yu and Yuan (2011). Furthermore, a positive relationship between shifts in sentiment and stock returns is found by Li and Zhang(2008) in the Chinese stock market, and the shifts in sentiment are negatively correlated with market volatility. These emprirical research shows that Investor sentiment is obviously correlated with volatility and return, and many variations exisits in this correlation. Such as, the asymmetry in the predictive power of Investor sentiment in stock returns in times of flourishing economic environments when investors become more optimistic, and in times of economic downturns when investors are more pessimistic is captured by Chung *et al*. (2012) . Furthermore, Baker and Wurgler (2006) prove that the Investor sentiment is related to the expected returns and risks of the market. Undervalued stocks are likely to be undervalued more strongly, when Investor sentiment is low and Investor sentiment is high and vise versa. However, some empirical results are different with investor’s idea. Schmeling (2009) finds that in most of the 18 industrialized countries, future stock returns tend to be lower, when consumers have high confidence. Besides, according to Ho and Hung (2009), the explanatory power of asset pricing models for stock returns are enchanced by incorporating Investor sentiment in modeling the dynamics of risk exposures. In these studies, they found that although there are variations in correlation between Investor sentiment and volatility, investor sentiment is still a good explanatory power for investment return. Chiu *et al*. (2012) recently advance an opinion on the research on ETF liquidity that the fund flow and liquidity will change in correlation greatly, when big events happen. The trading volume of ETF increases significantly in recent years, making the research on ETF financial products attract more attention.

2.2 Trading behavior, and Voladility

In order to discuss the correlation between investor sentiment and trading behavior, the trading behavior and volatility need also be included. The difference on time zone or trading hours willcause the feature that product price volatitliy increases or decreases drastically. Masahiro (2008) introduces a hump-shaped relation between trading volume and information precision, and a positively correlation between trading volume and absolute price changes. The volatility and correlation of stock returns in the highly volatile and strongly correlated equilibrium will be increased by accurate information. Besides, many paper discuss on the correlation between trading behavior and volatility. According to Nielsen and Shimotsu (2007), there is weak evidence of fractional cointegration between realized volatility and trading volume for most of the stocks considered. Recent research on momentum effect discovers in hehavior finance field may provide evidence to the existence of long-term memory. Rossi and Magistris (2013) find in most cases, volume and volatility are long memory but not fractionally cointegrated. They also find right tail dependence, which is informative on the behavior of the volatility and volume when large surprising news impact the market, in the volatility and volume innovations. These researches almost all demonstrate that the correlation between trading behavior and volatility are significant.

2.3 Voladility, And Liquidity

As the expansion of fund market scale and the maturity of institute investor scale, the requirement of institute investor on market liquidity is increasing, and the risk management of liquidity receives larger attention. If the the trading volume of financial product is not large, or the liquidity is poor, it will cause the concern from institute investor and government financial regulation department, so the liquidity becomes an important research topic. In order to perfect the trading diversity in fund market, government needs pay more attention to the liquidity of newly promotion product. Academically, the past research compared the relative results under positive and negative sentiment, and the research outcome can be used to maintain liquidity in a low trading level during negative Investor sentiment to avoid poor liquidity. The past discussion on poor liquidity mainly focuses on the pricing mechanism problem, i.g. too large difference, opaque pricing, and lack of market maker. So it is very important to understand liquidity change of financial product, because the poor liquidity will lower the trading will, and further cause the sharp fall of institute investor's profit and hinder the government to promote new financial product. At the beginning of research on liquidity, Pastor and Stambaugh (2003) firstly report the return sensitivity to market liquidity finding. And then, there are more studies on liquidity and volatility, Chordia *et al*. (2005) also find that the innovations to stock and bond market is greatly correlated to liquidity and volatility, so the common elements , which will drive liquidity and volatility in stock and bond markets are inferred. Then, the correlation between volatility and liquidity are getting increasingly attention. According to the research of Karoly *et al.* (2012), they interpret the results as evidence for the demand-side theory that liquidity commonality is greater during times of high market volatility, in countries with a greater presence of international investors and more correlated trading activity. Recently, researchers try to find out the measurement for volatility and other factors. He *et al*. introduce that all liquidity measures of SEO(Seasoned Equity Offering) firms improve significantly after SEO events. Relative offer size, the change in stock price and in volatility with expected signs are greatly associated with the magnitudes of reductions in transaction cost measures of illiquidity. This research discovers the importance of liquidity issues, which not only the government financial supervision department must face, but an important global risk management topic for liquidity after 2008 financial criss.

There are many research on Investor sentiment and trading behavior, trading behavior and Volatility, volatility and liquidity in the past, however the correlation between Investor sentiment and liquidity are seldom touched. This paper will try to make deduction based on the past theory foundation, and analyze research data using related model, to prove the correlation between Investor sentiment and liquidity.

3. VARIABLES, INFORMATION AND RESEARCH METHODS

This study is to explore whether there is a significant correlation between investor sentiment and ETF liquidity, and by adding a dummy variable to represent the pessimistic period of investor sentiment. In addition, set another model to perform a paired observation on the influence change of fluidity in the panic period. We also use the GARCH model to capture whether the liquidity has the effect of volatility cluster. In terms of the information, we use American panic index to represent the investor sentiment, and the ETF information use world's largest ETF issuing platform. We select five Asia-Pacific countries, namely Japan, South Korea, Taiwan, Malaysia and Singapore, to analyze and study Black Rock's iShare. The study period was from Jan. 31, 2005 to Jan. 30, 2015, covering the period of the financial tsunami. The settings, definitions and verifications which relate to the variables and models are described as follows:

3.1 Variables

(1). ETF liquidity ratio

We select the ETF of Japan, Korea, Taiwan, Malaysia and Singapore from iShare platform, and we useKarolyi *et al*. (2012) to calculate ETFliquidity, this paper calculates the liquidity ratio as follows:

$$L_{i,t} = \left[-log\left(1 + \frac{|R_{i,t}|}{V_{i,t}}\right)\right] \times 10^6 \qquad (1)$$

where $R_{i,t}$ and $V_{i,t}$ are the returns and trading volume for the country ETFi on day *t*, respectively. The liquidity ratio, $L_{i,t}$, is increasingin the liquidity for country ETFi.

(2). Volume

This paper uses trading volume in shares as in Wang (2013) to calculate the liquidity ratio. In addition, we also use the trading volume as an important variable, in order to observe the correlation between trading volume change and ETF liquidity change.

(3). Investor Sentiment-VIX index measures

Market Volatility Index ("VIX") is a measure of the implied volatility S & P 100 index option. Often referred toas the "investor fear index"(Whaley, 2000), we use this index as a proxy variable of investor sentiment. VIX index was introduced by CBOE (Chicago Board Options Exchange) in 1993, it is an index obtained after weighting average of index option implied volatility. Index reflects how much costs investors are willing to pay to treat their investment risk, it is widely used to reflect the investor's panic degree regarding the aftermarket, also known as the "fear index". When the index is higher, it means the investors are more anxious about the stock market status; when the index is lower, it indicates the stock index change of the market will tend to slow down. The calculation of VIX is to select total eight sequences of the recent-month and the following-month put and call options of S & P100 index option that are closest to the at-the-money, and respectively calculates its weighted average of implied volatility to obtainthe index.Later, the index was amendedin 2003.The selected subject was changed from S&P100 to S & P500, and changes the closest at-the-money put and call options sequences to all of the sequences, through the broader subject matter basis to provide market participants an indicator that could better reflect the overall broader market trend.The empirical period of this paper will use the new VIX index amended in 2003 to conduct the estimation.

(4). Dummy Variable ($\mathrm{PESS} - \mathrm{Dummy}_{i,t}$)

When investor sentiment ($VIXR_{i,t}$) fluctuation is over (less than) a standard deviation (7.01%), the dummy variable of pessimistic (optimistic) sentiment is expressed as 1, on the contrary as 0. This study through the setting of cross-multiplying term of pessimistic dummy variable and investor sentiment ($VIXR_{i,t} \times PESS - Dummy_{i,t}$) observes the influence of investor sentiment on liquidity in the panic period, in order to observe the influence degree of the pessimistic market-investment atmosphere on each country's ETF liquidity.

3.2 Model Specification

(1). Generalized Autoregressive Conditional Heteroskedasticity; GARCH)

In order to capture whether the liquidity has the volatility cluster and other characteristics, we added the detection of GARCH model in the model. Traditional econometric model and time sequence model both assume the variances of error term are fixed to conduct related deduction and research. However, the rationality of this assumption has been challenged by many scholars, because information of the general financial time sequence does not obey this assumption, i.e. the presentation of variances vary over time. Therefore, Engle (1982) proposed Autoregressive Conditional Heteroskedasticity (ARCH) Model. Bollerslev (1986) amended ARCH model and first proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, and he thought the conditional variances are not only affected by the previous time periods' error squared terms, but also affected by the previous time periods' conditional variances.Hence, the setting of GARCH(p, q) modelis as follows:

$$Y_t = X_t\beta + \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t)$$

$$\sigma_t = C + A\varepsilon_{t-1}^2 B\sigma_{t-1}$$

In the above expression (3), Ω_{t-1} means all the information setcan be obtained in t-1 time period. The Y_t and X_t represent the model′s explained variable vector and explanatory variable vector, and includes the column vectors of its exogenous variables or lagged dependent variables. β is the to-be-estimatedparameter vector.The parameters *C*, *A* and *B* are non-negative real numbers, to ensure the variances to be positive, and meet $A + B < 1$ thecondition of stationary state.Meanwhile, adopt the maximum likelihood estimation method, obtain the estimates of parameters *C*, *A* and *B*:

$$\text{Max}_{C,A,B} \quad L = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} Exp\left\{-\frac{X_t^2}{2\sigma_t^2}\right\}$$

Take log of the above expression:

$$\text{LL} = -\frac{T}{2} ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln\, \sigma_t^2 - \frac{1}{2}\sum_{t=1}^{T} \frac{X_t^2}{\sigma_t^2}$$

Finally, adopt repeated estimate algorithm to maximize the expression (5), to obtain the estimates ofparameters *C*, *A and B*.

(2). Empirical Models

This paper aims to explore if there is a significant correlation between investor sentiment and ETF liquidity. We adopted ordinary least squares (OLS) to set up. Model 1 adopts the trading volume ($\Delta\, Vol_{i,t}$) and investor sentiment ($VIXR_{i,t}$) to observe the correlation of each country's ETF liquidity ($\Delta L_{i,t}$); In Model 2, the pessimistic dummy variable was added ($PESS - Dummy_{i,t}$) into model 1 and combined with investor sentiment to form a cross-multiplying term ($VIXR_{i,t} \times PESS -$ *Dummyi,t*). This cross-multiplying term was used to represent the market panic period, in order to observe, when the market presenting a pessimistic atmosphere of investment, whether each country's ETF liquidity influence has difference.Therefore, the model settings of this study aredescribed as follows:

Model 1:
$$\Delta L_{i,t} = a_0 + a_1\Delta\, Vol_{i,t-1} + a_2 VIXR_{i,t-1} + \varepsilon_{i,t}$$

Model 2:
$$\Delta L_{i,t} = a_0 + a_1\Delta\, Vol_{i,t-1} + a_2 VIXR_{i,t-1} + a_3 VIXR_{i,t-1} \times PESS - Dummy_{i,t-1} + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} \sim \mathrm{N}(0, h_{i,t})$$

$$h_{i,t} = \mathrm{C} + A\varepsilon_{i,t-1}^2 + Bh_{i,t-1}$$

for i=j, s, m, y, t to be proxies as countries ETF

In model 1 (7), $L_{i,t}$ represents the liquidity of ETF*i* on day *t*, $\Delta L_{i,t} = log\left(\frac{L_{i,t}}{L_{i,t-1}}\right)$, $\Delta L_{i,t}$ represents the liquidity fluctuations, taking first difference of liquidity ($L_{i,t}$) and then take log; $Vol_{i,t}$ represents the trading volume of ETF*i* on day t, $\Delta Vol_{i,t} = (Vol_{i,t} - Vol_{i,t-1})$, $\Delta Vol_{i,t}$ represents the trading volume changes on that day and the day before; $VIXR_{i,t} = log\left(\frac{VIX_{i,t}}{VIX_{i,t-1}}\right)$, $VIXR_{i,t}$ represents the investor sentiment fluctuation of ETFi on Day t, taking log of first difference of investor sentiment ($VIX_{i,t}$). On the model setting,it mainly observes each country's current-period ETF liquidity change, and therefore, at the right side of the equation, no matter it is $\Delta Vol_{i,t}$ or $VIXR_{i,t}$, we take both the previous period's data, which means each country's current-period ETF liquidity change is affected by the previous period's trading volume change and investor sentiment fluctuation. In Model 2 (8), add the $PESS - Dummy_{i,t}$, which is a dummy variable. When investor sentiment fluctuation of ETFi on day t is over a standard deviation,it means the pessimistic sentiment is increased, it is deemed the panic period, and the dummy variable is expressed as on the contrary as 0. Through forming a cross-multiplying term ($VIXR_{i,t}$×$PESS - Dummy_{i,t}$) with investor sentiment, when the market presenting a pessimistic atmosphere of investment, to observe whether each country's ETF liquidity influence has difference. Equations (9) and (10) are the conditional variance equations. They are mainly to estimate the coefficients of each country's ETFARCH effect (A) and GARCH effect (B), and to check if the ETF liquidity has a volatility-clustering (A+B<1, A and B >0) phenomenon.

4. SOURCE AND PROCESSING

This paper focuses our analysis on country ETFs issued by iShares, which is the world's largest ETF issuer and market leader owned by BlackRock.The sample period used in this paper is from Jan. 31, 2005 to Jan. 30, 2015 and the ETFs from 5 Asian countries with enough historical data and trading activity was adopted in this study to carry out the tests. All the data used in this study are obtained from the Datastream International database.

Table 1. Data Soucre and Description

Country	Ticker	Underlying index
Japan	EWJ	iSharesMSCI Japan Index
Singapore	EWS	iSharesMSCI Singapore Index
Malaysia	EWM	iSharesMSCI Malaysia ETF
South Korea	EWY	iSharesMSCI South Korea Capped ETF
Taiwan	EWT	iSharesMSCI Taiwan Index

Note: The table provides information on the sample of ETFs including the ticker and underlying index.This paper focuses our analysis on country ETFs issued by iShares, which is the world's largest ETF issuer and market leader owned by BlackRock.

4.1 Basic statistics

The influence of investor sentiment on liquidity was explored in this study; the study period was from Jan. 31, 2005 to Jan. 30, 2015. In the study period, there were the financial tsunami and some other major financial crises. The countries including Japan, South Korea, Taiwan, Malaysia and Singapore was researched here, covering several major countries in East Asia. There were total 2518 samples of trading-days, due to the model adopting the estimation with previous-day change; therefore, there were 2517 observation samples. The fluctuation of American panic index was used as the proxy variable of investor sentiment. In order to check whether the liquidity has volatility cluster and other characteristics, we added the detection of GARCH in the model. Furthermore, each data of variable sequence must be taken the unit root test prior to conducting each model estimation, to detect whether each variable obey the assumption of stationary sequence, in order to avoid the problem of spurious regression. In the test method, the ADF (Said and Dickey, 1984) and PP (Phillips and Perron, 1988) of traditional linearunit root test method was adopted to conduct the detection. The results shows that after all the data of empirical variables taking linear unit root test, all variables are at the 1%significance level, and all of them reject the null hypothesis of unit root, i.e. they obey the assumption of stationary state demand.

Table 1 is the description of the transaction code; Table 2 shows the descriptive statistics of data sample, and contains Jarque-Bera Normal Distribution test results. In the ETF returns part, take log of first difference of daily closing price of each country's index ETS as its remuneration, in order to check the fluctuation of daily price remuneration. From the value of standard deviation we can find that from Japan's 0.4566 to Malaysia's 0.6294, the daily price fluctuation of these five Asian countries' ETF is quite large. The proxy variables VIX index of the related investor sentiment also use taking log of first difference method to observe the daily volatility, the standard deviation of daily volatility is 0.07.

In coefficients of skewness and kurtosis, it is found that all variables showed in the results of non-normal distribution. At the 5% significance level and above, the ETF returns variable of all countries shows a positively skewed leptokurtic distribution except Singapore, which shows a negatively skewed leptokurtic distribution.VIXR data also shows a positively skewed leptokurtic distribution.In addition, the trading volume and liquidity proxy observation also show a positively skewed leptokurtic distribution.

Trading volume adopts daily differential values as the model's observation. On the samples of observed countries, Japan has the largest trading volume, and its trading volume’s daily average change is also the greatest.

We used the method of formula (1) to calculate the daily liquidity and adopted the same method of taking log of first difference to observe the daily liquidity change. In view of numerical values, the lowest standard deviation of daily liquidity value is Japan's 1.5357; the highest liquidity change is Malaysia's 1.6109. It also reflects the larger trading volume, the smaller liquidity fluctuation in some way.

Table 2. Summary statistics

Variable		Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A : Return								
	$R_{j,t}$	0.0004	0.4566	-1.5598	2.1680	0.0899 **	1.6915 ***	384.3695 ***
	$R_{s,t}$	0.0006	0.5894	-5.8209	4.1717	-0.1221 ***	4.7864 ***	3051.1135 ***
	$R_{m,t}$	0.0009	0.6294	-2.6019	3.0565	0.1458 ***	3.5876 ***	1720.9546 ***
	$R_{y,t}$	0.0010	0.4796	-1.8556	1.8447	0.1684 ***	3.0404 ***	1242.9984 ***
	$R_{t,t}$	0.0011	0.4969	-2.1420	2.5401	0.3308 ***	5.3325 ***	3835.2866 ***
	$VIXR_{i,t}$	0.0002	0.0701	-0.3506	0.4960	0.6660 ***	3.8089 ***	1707.5646 ***
Panel B : Trading Volume								
	$\Delta Vol_{j,t}$	8252.13	15097173.10	-154971400	191112700	0.7988 ***	25.0795 ***	66232.1509 ***
	$\Delta Vol_{s,t}$	356.38	1706986.69	-16387000	22437200	0.8521 ***	24.2769 ***	62114.5882 ***
	$\Delta Vol_{m,t}$	1178.70	1481359.52	-10633500	13432500	0.6041 ***	15.2635 ***	24586.1473 ***
	$\Delta Vol_{y,t}$	1549.26	1384417.72	-10140200	11293700	0.1650 ***	7.5734 ***	6026.7455 ***
	$\Delta Vol_{t,t}$	3732.98	4708551.41	-50985100	68798300	1.1481 ***	32.3808 ***	110516.1079 ***
Panel C : Liquidity								
	$\Delta L_{j,t}$	-0.0013	1.5357	-6.9947	8.5645	0.0902 *	1.3345 ***	190.1725 ***
	$\Delta L_{s,t}$	-0.0006	1.5925	-8.6522	7.6716	0.1882 ***	1.7550 ***	337.8944 ***
	$\Delta L_{m,t}$	-0.0006	1.6109	-6.4789	7.7694	0.2671 ***	1.4484 ***	249.9580 ***
	$\Delta L_{y,t}$	-0.0011	1.6050	-6.1681	5.9597	0.1057 **	1.1889 ***	152.9343 ***
	$\Delta L_{t,t}$	-0.0014	1.5735	-7.5009	7.3019	0.0960 **	1.5876 ***	268.1988 ***

Note: Table2 shows the descriptive statistics of data sample, and contains Jarque-Bera Normal Distribution test results. In the ETF returns($R_{i,t}$) part, take log of first difference of daily closing price of each country's index ETS as its remuneration, in order to check the fluctuation of daily price remuneration; $\Delta Vol_{i,t} = (Vol_{i,t} - Vol_{i,t-1})$, $\Delta Vol_{i,t}$ represents the trading volume(Vol) changes on that day and the day before; $\Delta L_{i,t} = log\left(\frac{L_{i,t}}{L_{i,t-1}}\right)$, $\Delta L_{i,t}$ represents the liquidity ($L_{i,t}$) fluctuations, taking first difference of liquidity and then take log; For all *i=j, s, m, y, t* to be proxies as countries ETF, j=EWJ(Japan), s=EWS(Singapore), m=EWM(Malaysia), y=EWY(South Korea), t=EWT(Taiwan).

***, **, and * indicate statistical significance at the 1%, 5%, and.10% levels,

Table 3. Parameter estaimate results

	$\Delta L_{j,t}$		$\Delta L_{s,t}$		$\Delta L_{m,t}$		$\Delta L_{y,t}$		$\Delta L_{t,t}$	
	Coefficient (Std. Error)		Coefficient (Std. Error)		Coefficient (Std. Error)		Coefficient (Std. Error)		Coefficient (Std. Error)	
Variable	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Panel A : Mean Equation										
Constant	-0.0206	-0.0280	-0.0345	-0.0396	-0.0127	-0.0129	-0.0362	-0.0368	-0.0361	-0.0385
	(0.0264)	(0.0255)	(0.0254)	(0.0253)	(0.0266)	(0.0263)	(0.0267)	(0.0263)	(0.0262)	(263.0000)
$\Delta Vol_{i,t-1}$	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$VIXR_{i,t-1}$	-0.9450 ***	-0.9740 **	-1.1426 ***	-1.1746 ***	-1.5941 ***	-1.5962 ***	-1.5911 ***	-1.5860 ***	-0.7719 *	-0.7980 **
	(0.3507)	(0.4051)	(0.3980)	(0.4044)	(0.3948)	(0.3709)	(0.3992)	(0.4195)	(0.4110)	(0.4021)
$VIXR_{i,t-1}$ X $Dum_{i,t-1}$		-0.3328 ***		-0.3472 ***		-0.0086		-0.0497		-0.1321 ***
		(0.0634)		(0.0586)		(0.0474)		(0.0518)		(0.0432)
Panel A : Variance Equation										
C	1.6428 ***	1.5411 ***	1.7571 ***	1.6981 ***	1.3913 ***	1.3895 ***	1.4168 ***	1.4095 ***	1.7253 ***	1.6754 ***
	(0.1484)	(0.1540)	(0.1342)	(0.1347)	(0.1240)	(0.1362)	(0.1526)	(0.1518)	(0.1379)	(0.1429)
A	0.2495 ***	0.2291 ***	0.2991 ***	0.2839 ***	0.3059 ***	0.3062 ***	0.2919 ***	0.2917 ***	0.2792 ***	0.2834 ***
	(0.0296)	(0.0274)	(0.0308)	(0.0312)	(0.0341)	(0.0337)	(0.0315)	(0.0321)	(0.0300)	(0.0301)
B	0.0293	0.0825	-0.0202	0.0047	0.1424 ***	0.1430 **	0.1540 **	0.1570 **	0.0025	0.0191
	(0.0653)	(0.0681)	(0.0494)	(0.0527)	(0.0529)	(0.0572)	(0.0615)	(0.0610)	(0.0521)	(0.0536)
Log Likelihood Value	-4535.6339	-4521.7675	-4588.5858	-4570.9220	-4612.1449	-4612.1307	-4638.0107	-4637.5312	-4583.8608	-4580.1354
LR		27.73 ***		35.33 ***		0.03		0.96		7.45 ***

Note: Model 1: $\Delta L_{i,t} = a_0 + a_1 \Delta\, Vol_{i,t-1} + a_2 VIXR_{i,t-1} + \varepsilon_{i,t}$; Model 2: $\Delta L_{i,t} = a_0 + a_1 \Delta\, Vol_{i,t-1} + a_2 VIXR_{i,t-1} + a_3 VIXR_{i,t-1} \times PESS - Dummy_{i,t-1} + \varepsilon_{i,t}$; For all *i=j, s, m, y, t* to be proxies as countries ETF, j=EWJ(Japan), s=EWS(Singapore), m=EWM(Malaysia), y=EWY(South Korea), t=EWT(Taiwan). LR = $-2\ (L_R - L_U) \sim \chi 2(m)$, L_R = Model 1 L_U = Model 2, m=1

***, **, and * indicate statistical significance at the 1%, 5%, and.10% levels,,

4.2 Empirical results analysis

In consideration of each country's ETF and individual time effect, Table 3 lists the regression results of Model 1 and Model 2.

A. In Model 1, the previous period's trading volume ($\Delta Vol_{i,t}$) and investor sentiment ($VIXR_{i,t}$) was used to observe the effect of each country's ETF liquidity, ($\Delta L_{i,t}$), and Model's coefficients of variation were adopted to detect if each country's ETF liquidity possesses the volatility-clustering phenomenon.

From the empirical results of Model 1, we can see these five countries' daily trading volume and liquidity change show significant positive results. Although its coefficient is very small, it also shows the increase (decrease) of previous period's trading volume will make the liquidity increase (decrease).

In the coefficients of investor sentiment ($VIXR_{i,t}$), each country's numerical values are at the 10% significance level and above, all showing negative results, which is consistent with our general understanding.When the financial market is full of uncertainty, and the change of investor sentiment volatility is large, it will affect the liquidity of investment subject matter; i.e. when the investor sentiment volatility is large, the ETF subject matter liquidity will deteriorate, in which Japan is -0.945, Singapore of -1.1426, Malaysia of -1.5941, South Korea of -1.5911, Taiwan of -0.7719.From each country's empirical values, we can find that when the change of investor sentiment volatility becomes larger, the ETF liquidity of Malaysia and South Korea is worse than the other three countries. It seems can be inferred that these two countries' financial markets react to messages is more delayed than the other three countries; its liquidity is easy to be affected by international situation and investor sentiment.

In terms of conditional variance equations in Model 1, the estimated coefficients of each country's ETF ARCH effect (A) and GARCH effect (B) are: Japan: 0.2495 & 0.0293, Singapore: 0.2991 & -0.0202, Malaysia: 0.3059& 0.1424, South Korea: 0.2919 & 0.1540, Taiwan: 0.2792 & 0.0025 respectively. At the 1% significance level, only the coefficients of ARCH effect show significant results. However, at the 5% significance level and above, the coefficients of Malaysia and South Korea GARCH effect show significant results, and these two countries' estimated coefficients are non-negative real numbers, meeting the positive defined condition assumption. Inaddition, the volatility-clustering estimated coefficients (A+ B) are namely Malaysia 0.4483, South Korea 0.4459, both less than 1; also meet the GARCH model's condition for stability.Therefore, it shows that Malaysia and South Korea ETF liquidity existsa liquidity-volatility-clustering phenomenon, namely Malaysia and South Korea ETF liquidity has a significant GARCH effect.Empirical result seems can infer the financial market's ETF product development level is more mature such as Japan, Singapore, Taiwan, and then the GARCH effect will be less significant, i.e. the country of more mature financial market's ETF product development level can react to the financial market's messages quickly and completely.

B. In Model 2, add the cross-multiplying term ($VIXR_{i,t} \times PESS - Dummy_{i,t}$) of pessimistic dummy variable and investor sentiment under the framework foundation of Model 1.When investor sentiment ($VIXR_{i,t}$) fluctuation is over a standard deviation (7.01%), we define the dummy variable of pessimistic sentiment as 1, on the contrary as 0. This study uses the setting of cross-multiplying term of pessimistic dummy variable and investor sentiment to magnify the effect of investor sentiment on liquidity, in order to observe the influence degree of the pessimistic market-investment atmosphere on each country's ETF liquidity.Through Table 3, we can find the likelihood estimates of Model 2 are all larger than model 1, so the fit of model 2 is better than model 1.

The data of empirical results in Model 2 show these five countries' ETF daily trading volume and liquidity change are consistent with Model showing significant positive results, its coefficient is very small. In the pessimistic sentiment period, the increase (decrease) of previous period's trading volume will still make the liquidity increase (decrease).

In the coefficients of investor sentiment ($VIXR_{i,t}$), each country's numerical values are at the 5% significance level and above, all showing negative results.The variables in the added cross-multiplying term of pessimistic dummy variable and investor sentiment, we find coefficients of the variables all show negative results. Of course, it is consistent with our general understanding. When the financial market is full of uncertainty, the volatility of investor sentiment change will be bigger; also, the effect on the liquidity of investment subject matter will be deeper. It is worthwhile to note that the variables in the cross-multiplying term, in which Japan is -0.3328, Singapore of -0.3472, Taiwan of -0.1321, show the 1% significance level. However, Malaysia and South Korea negative coefficients do not show a significant level.This shows that the increasing uncertainty of financial market will cause more intense investor sentiment volatility. Especially, when the market is facing a pull-up panic index, ETF liquidity in Japan, Singapore and Taiwan will quickly react, showing a negative correlation, i.e. in the panic period, these three countries' ETF liquidity will fall significantly, while Malaysia and South Korea will not have significantly increased change of liquidity. The results of the empirical model show that the liquidity difference of the various countries during the panic period is easily affected by the characteristics of the world's financial markets, such as the differences of markup-markdown restriction and short sales constraints; therefore, it shows an inconsistent characteristic.

In terms of conditional variance equations in Model 2, the estimated coefficients of each country's ETF ARCH effect (A)and GARCH effect (B)are Japan 0.2291 & 0.0825, Singapore 0.2839 & 0.0047, Malaysia 0.3062 & 0.1430, South Korea 0.2917 & 0.1570, Taiwan 0.2834 & 0.0191 respectively. It is consistent with Model 1. At the 1% significance level, only the coefficients of ARCH effect show significant results. Similarly, at the 5% significance level and above, the coefficients of Malaysia and South Korea GARCH effect show significant results, and these two countries' estimated coefficients are non-negative real numbers, meeting the positive defined condition assumption.In addition, the volatility-clustering estimated coefficients (A+B), are namely Malaysia 0.4492, South Korea 0.4487, both less than 1; also meet the GARCH model's condition for stability. It shows that in the panic period, Malaysia and South Korea ETF liquidity still has the liquidity-volatility-clustering phenomenon.

Summarization above results, trading volume and investor sentiment has significant influence on sample countries' ETF liquidity. When trading volume increases (decreases), the liquidity of subject matter also increases (decreases), when investor sentiment volatility ($VIXR_{i,t}$) increases (decreases), the liquidity shows a worse (better) performance. It shows that the investor sentiment does affect the ETF liquidity; especially in the panic period, Malaysia and South Korea ETF does not have significant evidence to show the investor sentiment will be intensely performed on poor liquidity. In addition, we found that in the empirical, whether it is in the panic period or not, Malaysia and South Korea ETF liquidity has a liquidity-volatility-clustering phenomenon, while this phenomenon in the country of more mature financial market's ETF product development level, such as Japan, Singapore, Taiwan, becomes not significant.

5. CONCLUSION

In the past, there was literature in which the investor sentiment about transaction behavior, the correlation analysis between liquidity and returns volatility, or the relationship between investor sentiment and returns were frequently explored and discussed, while the relationship between investor sentiment and liquidity was rarely discussed. The effect of investor Sentiment on each country's ETF liquidity was explored in this study.

Through trading data of each country's ETF financial products, the liquidity models were established to represent capital market's liquidity of various countries in order to be adopted to analyze and research the changes between investor sentiment and liquidity. In addition, a dummy variable was added in the empirical model for to the effect of the panic period on liquidity to be observed.

The study period was from Jan 31, 2005 to Jan 30, 2015. The observation period was 10 years long, and the sample period covered the financial tsunami period, which helped us to detect the effect of financial tsunami period on liquidity. In addition, the ETFs of five main countries in Asia-Pacific region were used in the study as research samples, including the ones of Japan, South Korea, Taiwan, Malaysia and Singapore. Information results of empirical data indicated that trading volume and investor sentiment have significantly effect on the liquidity of the ETFs of the countries. The increase (decrease) in previous period's trading volume would also make the ETF subject matter liquidity increase (decrease). In the panic period, the ETFs of Malaysia and South Korea does not have significant evidence to show that investor sentiment would intensely reflect in the performance of liquidity.

We reviewed historical data and found that liquidity has a Volatility-clustering characteristic, that is, in a specific period, the liquidity has the better or worse phenomenon, so we adopted GARCH model to capture it. The empirical results show that the overall trading volume of ETFs are siginificantly correlated to the sentiments of investors. However, in the panic period, such results will produce much more significant differences. We believe that it is caused by the differences of different countries' financial environments, systems or investor sentiments. Such results are also confirmed in our empirical results. In particular, we found that whether it is in the panic period or not, the liquidity of the ETFs in Malaysia and South Korea has a significant Liquidity-volatility-clustering phenomenon. However, this phenomenon in the countries with ETF products of higher development level in financial markets, such as in Japan, Singapore, Taiwan, becomes not significant. For the inconsistencies in market liquidity, it was inferred in this paper that it is caused by the financial environment, trading system changes, maturity of the development of ETF financial products and investor's trading restrictions in a country. For example, in the financial tsunami period, Taiwan implemented a comprehensive shrinkage limit on short sales trading, and so will this kind of restriction cause a significant effect on liquidity.

With the empirical results in this paper, we indeed confirmed that investor sentiment has a significant effect on the liquidity of ETF. The financial environmental differences among different countries include trading systems, the maturity of ETF financial commodity developmental level, and the specific supporting policies implemented by governments when investors face specific major market messages, such as the restrictions on short sales. However, we did not in-depth discussed what are the related effects between the said differences and liquidity are. We also recommend researchers to detect and do research on the liquidity about price limit, trading volume restrictions, etc. in the future.

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