

Investor Sentiment and ETF Liquidity

- Evidence from Asia Markets

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Abstract

This study aims to analyze the effect of investor sentiment on Exchange Traded Fund (ETF) liquidity, and to capture the variations in investor sentiment, mainly focusing on Asian ETF market data. We employ the Volatility Index and GARCH model to capture the volatility-clustering effect in the study. The empirical result shows that ETF has liquidity, and the degree of investor sentiment plays an important role in ETF liquidity within Asian countries. It indicates a volatility-clustering effect, dealing with the difference of trading systems, regulations in the market, and finds that the relationship between VIX and ETF liquidity is significantly different. Considering hedging against market risk and portfolio investment, this paper suggests that investors should take investor sentiment into their investment decisions, and re-adjust the investment weight of ETF product.

JEL classification numbers: C02, G11, G15

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

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1 Introduction

The global ETF Industry experienced its best growth ever pushing Asset Under Management, AUM) to \$2.6 trillion by the end of 2014 setting a new record. ETF trading activity was up by 13% in 2014 reaching \$18.7 trillion and will continue to rise, and ETF markets are advancing globally showing no signs of slowing down. According to ETF flows, the researcher finds that investors preferred less risky assets. Deutsche Bank expects global ETF assets to pass \$3 trillion in 2015. The rapid capital formation of ETF during recent years has made it one of the favorite investment products for retail investors, as it has lower investment costs especially compared to index funds. Gradually, ETF has also become one of the most important investment products in customer investment portfolios as compiled by Bank wealth management schemes; the lower trading cost makes ETF one of the most popular core assets for investors. Many policy holders will also choose ETF to accumulate their account value in life insurance and variable annuity products. The main reason why customer choose ETF is to be involved in market growth, especially in an era of low interest rates, while at the same time avoiding decreasing wealth due to the effects of inflation. When they are bullish about the market, they can be involved without spending time and effort to choose specific stocks or equality products. When they choose ETF as their investment product, they will consider the issuer, the trading platform, the value of the product, and liquidity, however they often ignore investment sentiment. Investor sentiment may cause price volatility, and therefore influence the liquidity of the investment product itself leading to a decrease in trading volume.

A review of the literature on research into ETF product features mainly focuses on capturing the behavior of the ETF product returns. Fujiwara (2006) finds that there is a correlation between the changes in discount rates and the small capital stock index, but these phenomena were not observed in an ETF. And Li et al. (2012) observed a U-shaped and an L-shaped intraday pattern for trading volume and return volatility. They found a significant increase in trading volume and turnover ratio for all ETFs both during and after the financial crisis. As there is a correlation between ETF and capital markets, a variety of ETF types in an investment portfolio can be means of hedging during a financial crisis. Boscaljon and Clark (2013) find that during a financial crisis, 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) observe that price discovery is influenced in a different manner by the temporal behavior of the exchange traded funds price discovery metric in the spot and futures markets across indexes. The market investor's transaction might be influenced by their individual sentiment, especially when there is high uncertainty in the market. Investor trading behavior will change significantly, i.e. feedback trading will cause wildly fluctuating prices. Recent researchers, 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 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 at different degrees of development, i.e. ETF product volatility in developed markets and significant variation in newly emerging Asian markets (Gutierrez et al., 2009). The difference in volatility might be caused by the speed that information spreads, the product features and investor's withholding information (Chiu et al., 2012). Levels of volatility will also cause changes in liquidity. In this article, 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 crisis, investors increased their demand for multiple financial products to reduce investment risk. In recent years, an increased emphasis on risk avoidance has meant that various countries have begun to diversify the types of financial derivatives available.

Generally speaking, investor behavior impacts their trading strategy. Investor sentiment will influence his or her trading behavior. So that when the market liquidity is measured by the trading volume, investor sentiment will of course become a critical factor. This paper aims to analyze whether the liquidity of ETF is influenced by investor sentiment.

According to Chiu et al. (2012) research indicates that with an increase in funding illiquidity during the subprime crisis period, a corresponding increase in the bid-ask spread and a decrease in market depth was found, indicating a general reduction in equity liquidity,

According to the related introduction on ETF liquidity change (Chiu et al., 2012), previous findings demonstrate that ETF liquidity will be influenced by volatility value, which is seldom discussed in current literature. They mentioned and believed, with clear evidence, that shocks to liquidity and a continuous flow of poor market information will put pressure on ETF redemption and therefore change financial liquidity, which will influence the liquidity of the ETF itself. However, they did not explain the reason why investor sentiment might be the cause of this type of liquidity change. Investors are influenced by market information, which will impact the fluctuation of investor sentiment, and possibly further influences the liquidity of ETF. This paper extends the research on ETF liquidity, by considering the sentiment factor. Chau et al. (2011) found statistically significant evidence suggesting that a negative relationship between autocorrelation and volatility, sentiment influence seems to be stronger during a bullish market. They find evidence of a 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 behavior. They focus on the evidence from research of a relationship between investor sentiment and trading behavior. Although there is a significantly negative correlation between autocorrelation and volatility, which they recognize, according to the statistical data measuring investor sentiment, there is evidence that investor sentiment will influence volatility and therefore alter trading behavior. However, there is no further explanation or discussion about the relationship between investor sentiment and volatility change.

The key point in the above two articles is that investor sentiment is an abstract qualitative factor, which influences ETF volatility to indicate its liquidity. In addition, our paper contributes to their discussion on investor sentiment.

Gutierrez et al. (2009) finds 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 findings demonstrate that local market information can be used to explain ETF volatility and returns in Asia, but the discussion on the source of volatility is not discussed in detail. On the other hand, they find that 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 reviews the interaction between the findings of these three papers to observe how investor sentiment can influence ETF returns and ETF volatility using volatility.

This paper analyses the ETF samples from five main countries in the Asia-Pacific region, including Japan, South Korea, Taiwan, Malaysia and Singapore, from January 31st 2005 to January 30th 2015. This includes the period of the global financial crisis period, to provide evidence of the effect of the financial crisis on liquidity. The empirical data indicates that trading volume and investment sentiment have a significant impact on the ETF liquidity of the sample countries. We review previous data, and find liquidity features volatility clusters, which means that liquidity will perform high or low in specified period. We adopt the GARCH model to analyze the sample data, and the empirical results prove that investor sentiment has a significant impact on overall ETF volume. The empirical results will be significantly different during a time of crisis, and we believe that this is caused by the different financial environment, system or investment sentiment in these countries, which is also proved by our results. We found that the ETF liquidity volatility cluster phenomenon apparently exists in Malaysia and South Korea, but it becomes less apparent in financial markets such as Japan, Singapore, and Taiwan, where there is a greater maturity in ETF products. For countries with inconsistent ETF liquidity, we infer that it is based on the countries

financial environment; changes in transaction systems, maturity of ETF products and investment sentiment.

The remainder of the paper is organized as follows. Section 2 briefly reviews the related literature and Section 3 describes the variables and empirical research models used in our investigation. The data and descriptive statistics are provided in Section 4 where the basic statistics applied to variables in the research are presented and which then discusses the main empirical results and robustness checks. Finally, Section 5 concludes the paper.

2 Literature review

2.1 Sentiment and trading behavior

After the 2008 financial crisis, investors increased their demand for multiple financial products to reduce risk, causing various countries to diversify their financial derivatives. ETF being one of the biggest. The recent research into ETF volatility points out that investor sentiment, which might be influenced by certain exceptional events, impacting investor trading behavior, depending on the investor's positive or negative expectation. What is more, this will further affect the trading volume proportionally. In past literatures, Edelen et al, (2010) regarded sentiment fluctuation in terms of risk tolerance, or overly optimistic or pessimistic cash flow forecast investment environment. In each case, the impact of the influence of sentiment on asset pricing should be obvious from fundamentals. The research into investor sentiment usually focuses on a discussion about target returns, investor sentiment and trading. Glabadanidis (2014), has proven that abnormal returns are generated by a moving average (MA) trading strategy, but investor sentiment cannot fully explain its anomalies. This research shows that it is impossible to use investor sentiment to explain abnormal returns generated by trading policies, as one empirical research shows that abnormal returns generated from using trading strategies might exclude the influence on target price performance caused by investor sentiment. However, another researcher 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.

Recent research points out that Investor sentiment will affect the trading behavior of the average investor or institutional 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 periods where investor sentiment is high. There are normally three types of investor sentiment, and the degree of each type will have an impact on the target price, the

trading volume, or product selection. In the case of a positive sentiment, Chau et al. (2011) finds that there is significant positive feedback trading in the U.S. ETF markets, and the intensity of which tends to increase when investors are optimistic consistent with the view that the market is less rational and inefficient during high-sentiment periods due to a higher participation by noise traders in such periods. In the case of negative sentiment, Chiu et al. (2014) shows that when the fear-based market sentiment increases when there is a bearish institutional investor expectation, there will be a significant decrease in net buying volume and market liquidity than in normal times in response to the interaction between fear-based sentiment and institutional investor expectation. Therefore, the variation in Investor sentiment will impact investment products and trading volume. This will especially impact product selection and therefore the investment portfolio. ETF can meet the investor requirement of reduced risk, and expected return. From the above discussion it is clear from previous literature that factors which impact trading such as sentiment should not be ignored, especially the risk-averse investor. A positive sentiment in the market will increase the volatility risk and affect ETF returns. The implication is that as market trading volume is influenced, then so is liquidity.

Investor sentiment does not only affect trading behavior, but there is also a correlation with volatility, which further impacts returns from investment products. A contemporaneous relation between changes in investor sentiment and U.S. stock market returns is introduced by Brown and Cliff (2004). Even if investor sentiment can be used to predict stock returns, Lemmon and Portniaguina (2006) find the returns on small size stocks can be predicted by investor sentiment. In recent years, research on the correlation between investor sentiment and volatility is expanding. The relation between the expected returns and volatility in the U.S. stock market hinges on investor sentiment were first proposed 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 a negative correlation with sentiment during periods of high market volatility. This empirical research shows that investor sentiment is obviously correlated with volatility and return in a variety of ways. Such as, the asymmetry found 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. This is captured by Chung et al. (2012). Furthermore, Baker and Wurgler (2006) prove that investor sentiment is related to the expected returns and risks in the market. Undervalued stocks are likely to be undervalued more strongly when investor sentiment is low and vice versa when investor sentiment is high. 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. According to Ho and Hung (2009), the explanatory power

of asset pricing models for stock returns are enhanced by incorporating investor sentiment in modeling the dynamics of risk exposure. In these studies, they found that although there are variations in correlation between investor sentiment and volatility, investor sentiment still provides a powerful tool for explaining investment returns. Chiu et al. (2012) recently proposed that as far as ETF liquidity is concerned the fund flow and liquidity will change in correlation when big events occur. The trading volume of ETF has increased significantly in recent years causing research into ETF financial products to attract more attention.

2.2 Trading behavior and volatility

In order to discuss the correlation between investor sentiment and trading behavior, trading behavior and volatility also needs to be included. The difference in time zones or trading hours will cause product price volatility leading to dramatic increases or decreases. Masahiro (2008) proposes a hump-shaped relation between trading volume and information precision, and a positive correlation between trading volume and absolute price changes. The volatility and correlation of stock returns in the highly volatile and strongly correlated equilibrium will increase when there is accurate information. Besides, many papers discuss 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 into the momentum effect has discovered that behavior in the financial field may provide evidence of the existence of a long-term memory. Rossi and Magistris (2013) find that in most cases, volume and volatility are characterized by a long memory but not fractionally cointegrated. They also find right tail dependence, which is indicative of the behavior of volatility and volume when surprising news impacts the market. Almost all of this research demonstrates that the correlation between trading behavior and volatility are significant.

2.3 Volatility and liquidity

As the expansion of the scale of the fund market increases and the maturity of the institutional investor continues to grow, the requirement of the institutional investor for market liquidity is increasing, and the risk management of this liquidity receives increasing amounts of attention. If the trading volume of the financial product is not large, or the liquidity is poor, it will cause concern for both the institutional investors and the government financial regulation department, so that liquidity becomes an important research topic. In order to improve the trading diversity in the fund market, governments need to pay more attention to the liquidity of newly promoted products. Past research has compared results where there is 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 has mainly focused on

the pricing mechanism problem, i.e. excessive differences, opaque pricing, and a lack of market makers. However, it is also very important to understand the effect of changes in liquidity on financial products, because a lack of liquidity will lower trading will which will result in a sharp fall in institutional investor profit and hinder the government's ability to promote new financial products. In their initial research into liquidity, Pastor and Stambaugh (2003) first reported on finding return sensitivity in market liquidity. This highlighted this area of investment which led to more studies on liquidity and volatility, Chordia et al. (2005) also found that innovations in the stock and bond market are strongly correlated to liquidity and volatility. From these the common elements which drive liquidity and volatility in stock and bond markets may be inferred. Consequently, correlation between volatility and liquidity are receiving increasing attention. In research by 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 have focused on developing measurement tools for volatility and other factors. He et al. (2014) proposed that all liquidity measures of SEO (Seasoned Equity Offering) firms show significant improvements after SEO events. The relative offer size, the change in stock price and volatility with corresponding signals are greatly associated with the magnitudes of reduction in transaction cost measures for illiquidity. This research has revealed the importance of liquidity issues, which are not only faced by government financial supervision departments, but are also an important global risk management topic after the 2008 financial crisis.

There is extensive research into investor sentiment and trading behavior, trading behavior and volatility, past volatility and liquidity, however the correlation between investor sentiment and liquidity are seldom examined. This paper will try to make deductions based on past theoretical foundations, and analyze research data using related models, to prove a correlation between investor sentiment and liquidity.

3 Variables, information and research methods

This study explores whether there is a significant correlation between investor sentiment and ETF liquidity, a dummy variable is added to represent periods of pessimistic investor sentiment. In addition, a second model is used to perform a paired observation on the influence on change of fluidity during a period of panic. We also use the GARCH model to capture whether the liquidity exhibits the volatility cluster effect. In terms of information, we use the American panic index to represent investor sentiment, and for the ETF information, iShares by Black Rock (the world's largest ETF issuing platform) is used. We selected 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

3.1.1 ETF liquidity ratio

We selected the ETF in Japan, Korea, Taiwan, Malaysia and Singapore from the iShare platform, and we used Karolyi et al. (2012) to calculate ETF liquidity, this paper calculates the liquidity ratio as follows:

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

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

3.1.2 Volume

This paper uses trading volume in shares as found 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.

3.1.3 Investor sentiment-VIX index measures

Market Volatility Index ("VIX") is a measure of the implied volatility S&P 100 index option. Often referred to as the "investor fear index" (Whaley, 2000), we use this index as a proxy variable for investor sentiment. The VIX index was introduced by CBOE (Chicago Board Options Exchange) in 1993, it is an index obtained after weighting the average of index options implying volatility. The index reflects the costs investors are willing to pay and 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 investors are more anxious about the stock market status; when the index is lower, it indicates the stock index change for the market will tend to slow down. The calculation of VIX is done by selecting a total of eight sequences from the previous-month and the following-month put and call options of S&P 100 index option that are closest to the at-the-money, and respectively calculates its weighted average of implied volatility to obtain the index. Later, the index was amended in 2003. The selected

subject was changed from S&P 100 to S&P 500, and changes were made to the closest at-the-money put and call options sequences to all of the sequences. The broader subject matter basis provides market participants with an indicator that can better reflect the overall broader market trend. The empirical period for this paper will use the new VIX index amended in 2003 for the estimate. .

3.1.4 Dummy variable ($PESS - Dummy_{i,t}$)

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, as opposed to 0. This study will be able to, through the setting of a cross-multiplying term as a pessimistic dummy variable and investor sentiment ($VIXR_{i,t} \times PESS - Dummy_{i,t}$), observe the influence of investor sentiment on liquidity in the panic period. This will allow us to observe the degree of influence of the pessimistic market-investment atmosphere on each country's ETF liquidity.

3.2 Model specification

3.2.1 Generalized autoregressive conditional heteroscedasticity (GARCH)

In order to identify whether the liquidity exhibits volatility clusters and other characteristics, we added the detection of the GARCH model to the model. The traditional econometric model and time sequence model both assume the variances of error terms are fixed in order to conduct related deduction and research. However, the rationality of this assumption has been challenged by many scholars, because information the general financial time sequence does not obey this assumption, i.e. the presentation of variances vary over time. Therefore, Engle (1982) proposed the Autoregressive Conditional Heteroskedasticity (ARCH) Model. Bollerslev (1986) amended the ARCH model and proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, he thought that 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 the GARCH(p, q) model is as follows:

$$Y_t = X_t \beta + \varepsilon_t \quad (2)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t) \quad (3)$$

$$\sigma_t = C + A \varepsilon_{t-1}^2 + B \sigma_{t-1} \quad (4)$$

In the above expression (3), Ω_{t-1} means all the information set can be obtained in the 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-estimated parameter vector. The parameters C , A and B are non-negative real numbers, to ensure the variances is positive, and meets the $A+B < 1$ condition of the stationary state. Meanwhile, it adopts the maximum likelihood estimation method to obtain the estimates of parameters C , A and B :

$$\underset{C,A,B}{Max} L = \prod_{t=1}^T \frac{1}{\sqrt{2\pi\sigma_t^2}} \text{Exp}\left\{-\frac{x_t^2}{2\sigma_t^2}\right\} \quad (5)$$

Take log of the above expression:

$$LL = -\frac{\tau}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{\tau} \ln \sigma_t^2 - \frac{1}{2} \sum_{t=1}^T \frac{x_t^2}{\sigma_t^2} \quad (6)$$

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

3.2.2 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 ($PESS - Dummy_{i,t}$) from model 1 and combined with investor sentiment to form a cross-multiplying term ($VIXR_{i,t} \times PESS - Dummy_{i,t}$). This cross-multiplying term was used to represent the market panic period in order to observe when the market was presenting a pessimistic investment atmosphere. This allowed us to observe whether there was any difference in each country's ETF liquidity influence. Therefore, the model settings of this study are described as follows:

$$\text{Model 1 : } \Delta L_{i,t} = a_0 + a_1 \Delta Vol_{i,t-1} + a_2 VIXR_{i,t-1} + \varepsilon_{i,t} \quad (7)$$

Model 2:

$$\Delta L_{i,t} = a_0 + a_1 \Delta Vol_{i,t-1} + a_3 VIXR_{i,t-1} \times PESS - Dummy_{i,t-1} + \varepsilon_{i,t} \quad (8)$$

$$\varepsilon_{i,t} \sim N(0, h_{i,t}) \quad (9)$$

$$h_{i,t} = C + A\varepsilon_{i,t-1}^2 + Bh_{i,t-1} \quad (10)$$

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 ETF i on Day t , taking the log of the first difference in investor sentiment ($VIX_{i,t}$). This model setting mainly observes each country's current-period ETF liquidity change, and therefore, at the right side of the equation, no matter whether it is $\Delta Vol_{i,t}$ or $VIX_{i,t}$, we take both of 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), we add the ($PESS - Dummy_{i,t}$), which is a dummy variable. When the investor sentiment fluctuation of ETF i on day t is over a standard deviation, it means that the pessimistic sentiment has increased. This is then deemed the panic period, and the dummy variable is expressed on the contrary as 0. Through forming a cross-multiplying term ($VIXR_{i,t} \times PESS - Dummy_{i,t}$) with investor sentiment, when the market presents a pessimistic investment atmosphere, to observe any differences between each country's influence on ETF liquidity. Equations (9) and (10) are the conditional variance equations. They are mainly to estimate the coefficients of each country's ETF ARCH 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 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 is obtained from the Data stream International database.

Table 1: Data Source 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 was a major financial crisis affects markets around the world. The countries included in this research were Japan, South Korea, Taiwan, Malaysia and Singapore were covering several major countries in East Asia. A total of 2518 samples were taken from trading-days, due to the model adopting the estimation from previous-day change; therefore, there were 2517 observation samples. The fluctuation in the American panic index was used as the proxy variable for investor sentiment. In order to detect whether the liquidity exhibits volatility clusters and other characteristics, we included the GARCH in the model. Furthermore, variable sequence data must take the unit root test prior to each model estimation, to detect whether each variable obeys the assumption of stationary sequence. This is necessary in order to avoid the problem of spurious regression. In the test, the ADF (Said and Dickey, 1984) and PP (Phillips and Perron, 1988) of the traditional linear unit root test method were adopted to conduct the detection. The results shows that all the empirical variables taking the linear unit root test were at the 1% significance level. They all reject the null hypothesis of the 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 the data sample, and contains Jarque-Bera Normal Distribution test results. In the ETF returns part, we take the log of the first difference in the daily closing price for each country's ETS index as its remuneration, in order to check the fluctuation of daily price remuneration. From the value of the 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 used the taking the log

of the 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.

The model observes that the trading volume adopts daily differential values. 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 the log of first difference to observe the daily liquidity change. In view of the 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, mean in smaller liquidity fluctuation

Table 2: Summary statistics

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A : Return							
$R_{i,t}$	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
$R_{v,t}$	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							
$\Delta Vol_{i,t}$	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
$\Delta Vol_{v,t}$	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							
$\Delta L_{i,t}$	-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
$\Delta L_{v,t}$	-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: Table 2 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 estimate results

Variable	$\Delta L_{j,t}$		$\Delta L_{s,t}$		$\Delta L_{m,t}$		$\Delta L_{y,t}$		$\Delta L_{t,t}$	
	Coefficient (Std. Error)		Coefficient (Std. Error)		Coefficient (Std. Error)		Coefficient (Std. Error)		Coefficient (Std. Error)	
	Model 1	Model 2								
Panel A : Mean Equation										
Constant	-0.0206 (0.0264)	-0.0280 (0.0255)	-0.0345 (0.0254)	-0.0396 (0.0253)	-0.0127 (0.0266)	-0.0129 (0.0263)	-0.0362 (0.0267)	-0.0368 (0.0263)	-0.0361 (0.0262)	-0.0385 (263.0000)
$\Delta Vol_{i,t-1}$	0.0000 *** (0.0000)	0.0000 *** (0.0000)								
$VIXR_{i,t-1}$	-0.9450 *** (0.3507)	-0.9740 ** (0.4051)	-1.1426 *** (0.3980)	-1.1746 *** (0.4044)	-1.5941 *** (0.3948)	-1.5962 *** (0.3709)	-1.5911 *** (0.3992)	-1.5860 *** (0.4195)	-0.7719 * (0.4110)	-0.7980 ** (0.4021)
$VIXR_{i,t-1} \times Dum_{i,t-1}$		-0.3328 *** (0.0634)		-0.3472 *** (0.0586)		-0.0086 (0.0474)		-0.0497 (0.0518)		-0.1321 *** (0.0432)
Panel A : Variance Equation										
C	1.6428 *** (0.1484)	1.5411 *** (0.1540)	1.7571 *** (0.1342)	1.6981 *** (0.1347)	1.3913 *** (0.1240)	1.3895 *** (0.1362)	1.4168 *** (0.1526)	1.4095 *** (0.1518)	1.7253 *** (0.1379)	1.6754 *** (0.1429)
A	0.2495 *** (0.0296)	0.2291 *** (0.0274)	0.2991 *** (0.0308)	0.2839 *** (0.0312)	0.3059 *** (0.0341)	0.3062 *** (0.0337)	0.2919 *** (0.0315)	0.2917 *** (0.0321)	0.2792 *** (0.0300)	0.2834 *** (0.0301)
B	0.0293 (0.0653)	0.0825 (0.0681)	-0.0202 (0.0494)	0.0047 (0.0527)	0.1424 *** (0.0529)	0.1430 ** (0.0572)	0.1540 ** (0.0615)	0.1570 ** (0.0610)	0.0025 (0.0521)	0.0191 (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: $\Delta L_{i,t} = a_0 + a_1 \Delta Vol_{i,t-1} + a_3 VIXR_{i,t-1} \times PESS - Dummy_{i,t-1} + \varepsilon_{i,t}$; 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 = $-2(L_R - L_U) \sim \chi^2(m)$, $L_R = \text{Model 1}$ $L_U = \text{Model 2}$, $m=1$

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

4.2 Empirical results analysis

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

4.2.1 The regression results of Model 1

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 the Model's coefficients of variation were adopted to detect if each country's ETF liquidity possesses volatility-clustering.

From the empirical results from Model 1, we can see that these five countries' daily trading volume and liquidity changes show significant positive results. Although the coefficient is very small, it also shows an increase (decrease) of the previous period's trading volume which 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 the 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 there is a change in investor sentiment then volatility becomes larger. The ETF liquidity of Malaysia and South Korea is worse than the other three countries. It can be inferred from this that these two countries' financial markets have a much bigger delayed reaction to messages when compared to the other three countries; the liquidity is easily affected by international situations and investor sentiment.

In terms of the conditional variance equations in Model 1, the estimated coefficients for each country's ETF ARCH effect (A) and GARCH effect (B) are: Japan: 0.2495 and 0.0293, Singapore: 0.2991 and -0.0202, Malaysia: 0.3059 and 0.1424, South Korea: 0.2919 and 0.1540, Taiwan: 0.2792 and 0.0025 respectively. At the 1% significance level, only the coefficients of the ARCH effect show significant results. However, at the 5% significance level and above, the coefficients of Malaysia and South Korea, the 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) namely Malaysia 0.4483, South Korea 0.4459, are both less than 1; these also meet the GARCH model's condition for stability. Therefore, it shows that in Malaysia and South Korea ETF liquidity they exhibit the liquidity-volatility-clustering phenomenon, namely Malaysia and

South Korea ETF liquidity has a significant GARCH effect. From these results it seems we can infer that if the financial market's ETF product development level is more mature in countries such as Japan, Singapore, Taiwan, then the GARCH effect will be less significant, i.e. the country with a more mature financial market's ETF product development level can react to the financial market information quickly and completely.

4.2.2 The regression results of Model 2

In Model 2, we added the cross-multiplying term ($VIXR_{i,t} \times PESS - Dummy_{i,t}$) as the pessimistic dummy variable for 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 pessimistic sentiment as 1, otherwise it would be 0. This study uses the setting of cross-multiplying terms for the pessimistic dummy variable and investor sentiment to magnify the effect of investor sentiment on liquidity, in order to observe the degree of influence of the pessimistic market-investment atmosphere on each country's ETF liquidity. Through Table 3, we can see that the likelihood estimates for Model 2 are all larger than model 1, so Model 2 is a better fit than model 1.

The results from Model 2 show these five countries' ETF daily trading volume and liquidity changes are consistent with the model showing significant positive results, its coefficient is very small. In the pessimistic sentiment period, the increase (decrease) of the 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 terms of the pessimistic dummy variable and investor sentiment, we find that the coefficients of the variables all show negative results. This is consistent with our general understanding. When the financial market is full of uncertainty, the volatility in 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, all 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 in markup-markdown restrictions and short sale constraints; therefore, it shows these characteristics are inconsistent.

In terms of the conditional variance equations in Model 2, the estimated coefficients for each country's ETF ARCH effect (A) and GARCH effect (B) are Japan 0.2291 and 0.0825, Singapore 0.2839 and 0.0047, Malaysia 0.3062 and 0.1430, South Korea 0.2917 and 0.1570, Taiwan 0.2834 and 0.0191 respectively. It is consistent with Model 1. At the 1% significance level, only the coefficients of the 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 are less than 1; they 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.

To summarize the above results, trading volume and investor sentiment has a significant influence on the sample countries ETF liquidity. When trading volume increases (decreases), the liquidity of the 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. In Malaysia and South Korea ETF, there is no significant evidence to show a strong relationship between investor sentiments and will be intensely performed on poor liquidity. In addition, we found that whether during the panic period or not, Malaysia and South Korea ETF liquidity has a liquidity-volatility-clustering phenomenon, while this phenomenon is not significant in countries with more mature financial market ETF product development level, such as Japan, Singapore, and Taiwan.

5 Conclusion

In the past, literature investigated investor sentiment and transaction behavior, analysis into the correlation between liquidity and returns volatility, as well as the relationship between investor sentiment and returns. However, despite all this research, 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 about each country's ETF financial products, liquidity models were established to represent capital market liquidity for various countries in order to analyze and research the changes in investor sentiment and liquidity. In addition, a dummy variable was added in the empirical model to reflect the panic period in which the liquidity was observed.

The study period was from Jan 31, 2005 to Jan 30, 2015. The observation period was 10 years, and the sample period covered the financial tsunami period. This helped us to detect the effect of the crisis on liquidity. In addition, the ETFs of five main countries in the Asia-Pacific region were used in the study as research samples. These included Japan, South Korea, Taiwan, Malaysia and Singapore. Results from the empirical data indicated that trading volume and investor sentiment have a significant effect on the liquidity of the ETFs in these countries. The increase (decrease) in the previous period's trading volume would also make the ETF liquidity increase (decrease). In the panic period, there is no significant evidence that the ETFs of Malaysia and South Korea investor sentiment would be reflected in the liquidity performance.

We reviewed historical data and found that liquidity exhibits Volatility-clustering characteristics, that is, in a specific period, liquidity has better or worse volatility-clustering, so we adopted the GARCH model to capture it. The empirical results show that the overall trading volume of ETFs show a significant correlation with investor sentiment. However, during the panic period, the results showed much more significant differences. We believe that this is caused by the differences in financial environments, systems or investor sentiments within individual countries. Such results are also confirmed by our 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 have a significant Liquidity-volatility-clustering phenomenon. However, this phenomenon in the countries with ETF products with a higher development level in financial markets, such as in Japan, Singapore, Taiwan, then it becomes insignificant. 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 this kind of restriction will have 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 carry out an in-depth discussion about what the related effects between the said

differences and liquidity are. We also recommend that researchers should analyze and research into some of the other characteristics that impact liquidity such as price limits and trading volume restrictions in the future.

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