ON THE RELATIONSHIP BETWEEN INVESTOR SENTIMENT, VIX AND TRADING VOLUME

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Abstract

As noise traders affect stock market by trading, sentiment, as a signal of noise, may have relationships with trading volume. This paper explores the effect of sentiment on the stock market's trading volume. Increase in Volatility Index (VIX) can explain the percentage increase in trading volume, but only in high VIX period. Besides, higher level of VIX is likely to be associated with greater variability of trading volume. The noise traders add liquidity to the market and provide more chances for investors to time their trade as the volatility of liquidity increases. These two kinds of impact lower rational investors' required return. The noise traders not only drive the price deviating from fundamental value, but also influence the liquidity dimensions.

JEL Classification: G12; G14

Keywords: Sentiment; Trading Volume; Volatility

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1. Introduction

In the area of modern finance, perfect market and rationality are usually assumed. Underlying logic is then carried out to give insight into how the market works. However, the facts in reality may not be consistent with the assumptions. One major assumption which is always challenged by behavioral finance researchers is rationality of investors. Investors are found to be irrational and subject to various biases (e.g. Kahneman and Tversky, 1979). Traditionally, mispricing from irrational investors is considered to be heterogeneous and can be offset. Even though there is mispricing, it disappears quickly due to arbitrage. However, Kumar and Lee (2006) show that some irrational investors' trades are systematically correlated. Besides, investors could motivate trade among each others, which is known as "herd effect". Gleason, Mathur and Peterson (2004) use intraday data and find that herd effect exists in the U.S. stock market. Furthermore, arbitrage can be costly and risky. Irrational investors, or noise traders, play an important role in financial market. De Long, Shleifer, Summers and Waldmann (1990) show that the unpredictability of noise traders' belief can create systematic risk and place limit to arbitrage. The magnitude of price deviation from fundamental value is affected by the proportion of noise traders and the level of mispricing. As the noise traders could have positive return from the trend they "created", they may become stronger and lengthen the mispricing period. Arbitrageurs may not be willing to compete with noise traders due to finite horizon because they could lose their wealth before the price goes back to the fundamental value. Shleifer and Summers (1990) have a detail discussion about the possibility and influence of noise traders. Introducing investor sentiment may help to explain various financial market anomalies.

There are a number of papers to investigate the impact of noise traders or investor sentiment on the stock market. Brown and Cliff (2005) find that sentiment can predict overall market return and the performance of both large and small firms. Neal and Wheatley (1998) compare few sentiment proxies according to their predictive power on return difference between large and small firms. Close-end funds discount and net mutual fund redemptions have such predictive power. Baker and Wurgler (2006) investigate the effect of sentiment on cross-sectional stock returns. They find that small stocks, young stocks and stocks with high volatility are more subject to sentiment than others. During high sentiment period, these stocks are overpriced and thus generate relatively low subsequent return. Glushkov (2006) develops a sentiment beta for individual stocks. It is defined as the change in stock return with respect to the change in sentiment. Consistent with Baker and Wurgler (2006), he finds that stocks with higher sentiment beta are likely to be young, small and comprised of more unique risks than those stocks with low sentiment beta. Cornelli, Goldreich and Ljungqvist (2006) and Dorn (2009) investigate the effect of sentiment on IPO performance. They use grey market price to capture investor sentiment. High grey market price indicates optimism. Stocks that are aggressively bought, or with high price in grey market have high first day return but poor long run performance. Yu and Yuan (2011) find that investors' sentiment affects the risk-return tradeoff. Mean-variance tradeoff is lower during high-sentiment period and becomes higher during low-sentiment period. Lee, Jiang and Indro (2002) find that volatility increases when investors become more bearish and vice versa.

The impact of noise traders leaks out in different way. Black (1986) has a detailed discuss about the noise: "Noise makes financial markets possible, but also makes them imperfect. If there is no noise trading, there will be very little trading in individual assets." As noise traders should affect the market by trading, the trading volume is expected to have relationship with the noise. According to the traditional CAPM, systematic risk is the only factor in determining price. As market cannot be perfect, some fashionable variables are found to have explanatory power on return. One of such variables is liquidity (e.g. Pástor and Stambaugh, 2003). Generally, stocks with higher level of liquidity should have lower return. Besides, the second moment of liquidity can also affect return. Chordia, Subrahmanyam and Anshuman (2001) find that there is negative relationship between return and variability of liquidity which is measured by dollar trading volume and share turnover. This surprising finding is explained by Pereira and Zhang (2008). Since higher variation of liquidity provides chance for investors to time their trade, required returns are relatively lower.

Odean (1999) demonstrates that investors with discount brokerage account are overconfident and have excessive trading volume. Brown (1999) shows that small investors would like to trade by using close-end fund data when sentiment is extreme. Furthermore, Baker and Stein (2004) argue that liquidity could serve as a sentiment indicator. Noise traders are likely to be retail investors who are subject to short-sales constraint. If noise traders are bullish about the market, they can simply buy shares and these trades thus facilitate liquidity. However, if noise traders are bearish about the market, short-sales constraint keeps them out of the market. Kurov (2008) finds that trend chasing strategy adopted by noise traders is more active during high sentiment period and this increases market liquidity.

As mentioned before, noise traders affect stock market by trading. Their trading activities, which affect liquidity, can also affect price. Therefore, it is worth to know the effect of noise traders on both level and variability of trading volume. This paper attempts to investigate this issue and aims to provide a better understanding about the relationship between sentiment and trading volume. Sentiment proxy is developed to capture the noise or irrationality of investors. It can serve as a noise signal which may have some relationships with trading activity. The better understanding on such relationships may help to assess the impact of noise traders. The realized price impact imposed by noise traders may be composed of various parts - price deviation from fundamental value, additional risk they introduce and additional liquidity and variability they provide. The first two parts may increase rational investors' required return whereas the last one could have a contrary impact. Furthermore, this paper uses daily volatility index to proxy sentiment. Sentiment proxies used in previous studies are usually monthly or yearly measures which may take time to be collected. In contrary, daily volatility index can be obtained publicly. It enables practitioners to assess the impact of noise traders more effortlessly and frequently. The following sections are data and methodology and then empirical results. Conclusion follows.

2. Data and methodology

Volatility Index (VIX) is used as the proxy to capture investor sentiment. VIX is firstly introduced by Whaley (1993) and the Chicago Board Options Exchange (CBOE) publishes VIX starting from 1993. The calculation method of VIX was changed in 2003. The original VIX represents the 30-day implied volatility of eight S&P 100 index options. In order to be closer to actual industry practices, since September 2003, VIX has been based on S&P 500 rather than S&P 100 index options because S&P 500 is the most widely used benchmark for the equity market in U.S. VIX used in this paper is downloaded from the CBOE website.[1] It measures the market's expectation of 30-day implied volatility and is often referred to as "investor fear gauge". The higher the VIX, the greater the fear is. Since noise traders are usually overconfident and over optimistic, they can be more aggressive than rational investors. Besides, noise traders are easily affected by various rumors or pseudo-signals. They may increase the volatility and the market expectation on future volatility, thus affect the performance of VIX. Therefore, VIX serves as the measure of noise signal in this paper.

Unlike asset pricing, there is no benchmark model for trading volume. Many factors are found to have influence on trading volume. Chordia, Roll and Subrahmanyam (2001) examine the determinants of daily change in trading activity. The determinants include market return related variables, short term interest rate, quality spread, term spread, weekday dummies, holiday dummy and GDP, unemployment rate and CPI announcement date dummies. These variables are included in our regression analysis to see if VIX has any additional explanatory power on trading volume. Trading volume of New York Stock Exchange (NYSE) is obtained from Datastream.

[1] http://www.cboe.com

Datastream's market return index is used to proxy the market return which defined as the percentage change of the return index. Interest rate related variables are downloaded from Federal Reserve website.[2] The announcement date of GDP and the announcement date of CPI and unemployment rate are obtained from Bureau of Economic Analysis and Bureau of Labor Statistics respectively.[3] All variables are on daily basis. To be included in the sample, data should be available for all variables in a specific trading day with positive trading volume.

The dependent variable of the first time series regression test is the daily percentage change of trading volume (**%ΔVO**) and the explanatory variables are:

ΔVIX : daily change in VIX

MKT+ : market return at time t and equals to 0 if return is negative

MKT– : market return at time t and equals to 0 if return is positive

MA5MKT+ : average return during t-1 to t-5 and equal to 0 if negative

MA5MKT– : average return during t-1 to t-5 and equal to 0 if positive

MA5|MKT| : average absolute return during t-1 to t-5

ShortRate : difference between Federal Fund Rate at t and t-1

TermSpread : daily change in the difference between the yield on 10-year Treasury bond and Federal Fund Rate

QualitySpread : daily change in the difference between the yield on Moody's Baa corporate bond and yield on 10-year Treasury bond

Holiday : 1 if a specific trading satisfies (1) if Independence Day, Christmas, or New Year's Day falls on a Friday, then the previous Thursday, (2) if any holiday falls on a weekend or on a Monday, then the following Tuesday, (3) if any holiday falls on another weekday, then the preceding and following days, and 0 otherwise.

MON, TUE, WED, THU : 1 if trading day is a Monday, Tuesday, Wednesday or Thursday respectively, and 0 otherwise.

GDP(1-2), UNP(1-2), CPI(1-2) : 1 on the two trading days prior to a GDP, unemployment or CPI announcement respectively, and 0 otherwise.

GDP(0), UNP(0), CPI(0) : 1 on the day of a GDP, unemployment , CPI announcement respectively, and 0 otherwise.

Except those dummy variables, all other six variables have been examined for stationarity before running time series regression.[4] Stationarity matters since regression using non-stationary time series could result spurious relationship and misleading result. In this paper, both parametric test, augmented Dickey-Fuller (ADF) test, and non-parametric test, Phillips-Perron (PP) test, are employed to test the null hypothesis of unit root. In Table 1, the p-values are all less than 0.01 and thus all the six variables are stationary at the 1% significance level. The percentage change of trading volume, daily change in VIX, average absolute return, spreads in short term as well as long term interest rate and daily difference of yield between corporate bond and Treasury bond do not deviate from the mean persistently.

In addition to the level of trading volume, this paper also examines the effect of sentiment on its second moment - the variability of trading volume. In literature, there is lack of study to investigate the determinants of the variability in trading volume. In our second test, the explanatory variables are modified based on the assumption that variables that can affect the level of trading volume can also affect the variability of trading volume. Thus, the dependent variable of the second test is the coefficient of variation (**CV(VO)**) which is calculated from trading volumes during t to t-4.[5] The explanatory variables are:

AVG(VIX) : average VIX during t to t-4

AVG(MKT+) : average market return during t to t-4 and equal to 0 if negative

AVG(MKT–) : average market return during t to t-4 and equal to 0 if positive

AVG(ShortRate) : average ShortRate during t to t-4

AVG(TermSpread) : average TermSpread during t to t-4

AVG(QualitySpread) : average QualitySpread during t to t-4

Holiday' : 1 if there is holiday during t to t-4 and 0 otherwise

GDP, UNP, CPI : 1 if there is GDP, unemployment or CPI announcement during t to t-4, respectively

Similar to the first regression test, except those dummy variables, all other five variables have been examined for stationarity by using both ADF test and PP test. The statistical results are given in Table 2. The null hypothesis of unit root has been rejected at the 1% significance level for all the variables and thus they are stationary.

[2]http://www.federalreserve.gov/econresdata/releases/statisticsdata.htm
[3]http://www.bea.gov and http://www.bls.gov respectively
[4]Stationarity implies that the time series have constant mean and variance over time and they will exhibit mean reversion and never "go too far away".

[5]Coefficient of variation (CV) is the ratio of the standard deviation to the mean or says the ratio of the risk assumed to the expected return.

Table 1. Unit Root Tests for Percentage Change of Trading Volume and Other Explanatory Variables

%ΔVO. is the dependent variable of daily percentage change of trading volume. The non-dummy explanatory variables are: **ΔVIX** : daily change in VIX; **MA5|MKT| :** average absolute return during t-1 to t-5; **ShortRate** : difference between Federal Fund Rate at t and t-1; **TermSpread** : daily change in the difference between the yield on 10-year Treasury bond and Federal Fund Rate; and **QualitySpread** : daily change in the difference between the yield on Moody's Baa corporate bond and yield on 10-year Treasury bond.

	$H_0 : \rho = 1$ (unit root) vs. $H_a : \rho < 1$ (stationary)			
	Augmented Dickey-Fuller (ADF)		Phillips Perron (PP)	
Variables	*t*-statistic	*p*-value	adj. *t*-statistic	*p*-value
%ΔVO	–40.03685	0.0000	–103.0135	0.0001
ΔVIX	–27.09572	0.0000	–73.99451	0.0001
MA5|MKT|	–4.974289	0.0000	–9.714263	0.0000
ShortRate	–29.84085	0.0000	–73.67275	0.0001
TermSpread	–22.57799	0.0000	–82.81058	0.0001
QualitySpread	–23.33128	0.0000	–61.80139	0.0001

Table 2. Unit Root Tests for Coefficient of Variation of Trading Volume and Other Explanatory Variables

CV(VO) is the dependent variable of the coefficient of variation calculating from trading volumes during t to t-4. The explanatory variables are: **AVG(VIX)** : average VIX during t to t-4; **AVG(ShortRate)** : average ShortRate during t to t-4; **AVG(TermSpread)** : average TermSpread during t to t-4; and **AVG(QualitySpread)** : average QualitySpread during t to t-4.

	$H_0 : \rho = 1$ (unit root) vs. $H_a : \rho < 1$ (stationary)			
	Augmented Dickey-Fuller (ADF)		Phillips Perron (PP)	
Variables	*t*-statistic	*p*-value	adj. *t*-statistic	*p*-value
CV(VO)	–16.56809	0.0000	–18.41725	0.0000
AVG(VIX)	–4.265633	0.0005	–3.681708	0.0044
AVG(ShortRate)	–9.247656	0.0000	–35.39464	0.0000
AVG(TermSpread)	–10.69019	0.0000	–23.56933	0.0000
AVG(QualitySpread)	–7.546654	0.0000	–15.42974	0.0000

Figure 1 is the time series plot of VIX. VIX is consistently low throughout the period from 1997 to 2007, which includes the Asian crisis, the dot-com bubble and the SARS event. However, VIX around the 2008 financial crisis is extremely high. The result may be due to the development of online trading in the past few years. Most noise traders are likely to be small traders and retail traders. The popularity of online trading helps them to trade easily and frequently. Thus they are easier to assess the stock market and have greater influence (add higher volatility) on the market comparing to the past years.

In order to test whether there exists asymmetric effect of sentiment on the trading volume, two sub-samples, namely low and high sentiment period are drawn from the whole sample period from January 1997 to December 2010. January 2005 to December 2005 is defined as low VIX period whereas July 2008 to June 2009 is defined as high VIX period.

3. Empirical results

Figure 2 is the time series plot of change in VIX and percentage change in trading volume. Both series exhibit some extreme large changes during the sample period. Change in VIX is relatively small during low sentiment period and large during high sentiment period. On the other hand, the swing of percentage change in trading volume does not vary much across time. The change in VIX has almost zero average, meaning that changes in VIX from time to time offset each other. The investor sentiment cannot persistently increase in the market. It may appear in the market temporarily. The realized VIX may be the sum of general level of VIX which is caused by market fundamental issues and the additional VIX imposed by noise traders. It is hard to observe any relationship between the two variables by simply observing the graph. The coefficient of correlation in Table 3 may highlight some ideas. The three coefficients of correlation are all positive. There is positive relationship between VIX and trading volume. Besides, the coefficient of correlation using high VIX period data (+0.2019) is higher than the other two. The positive relationship between VIX and trading volume is stronger during high VIX period.

Figure 1. Time Series Plot of Volatility Index (VIX), 1997 – 2010

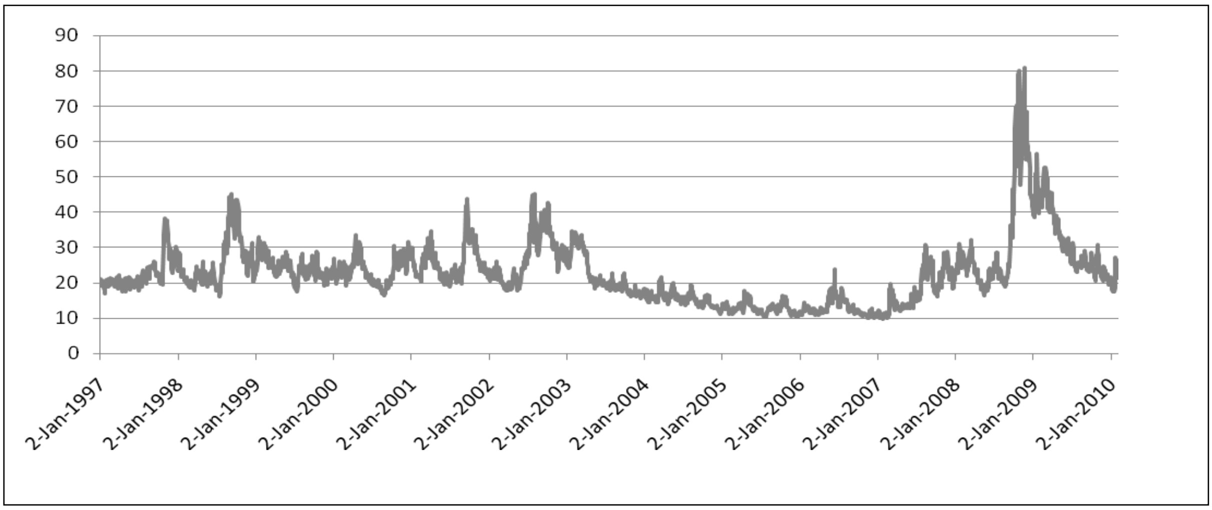

Figure 2. Time Series Plot of Change in VIX and Percentage Change of Trading Volume, 1997 - 2010

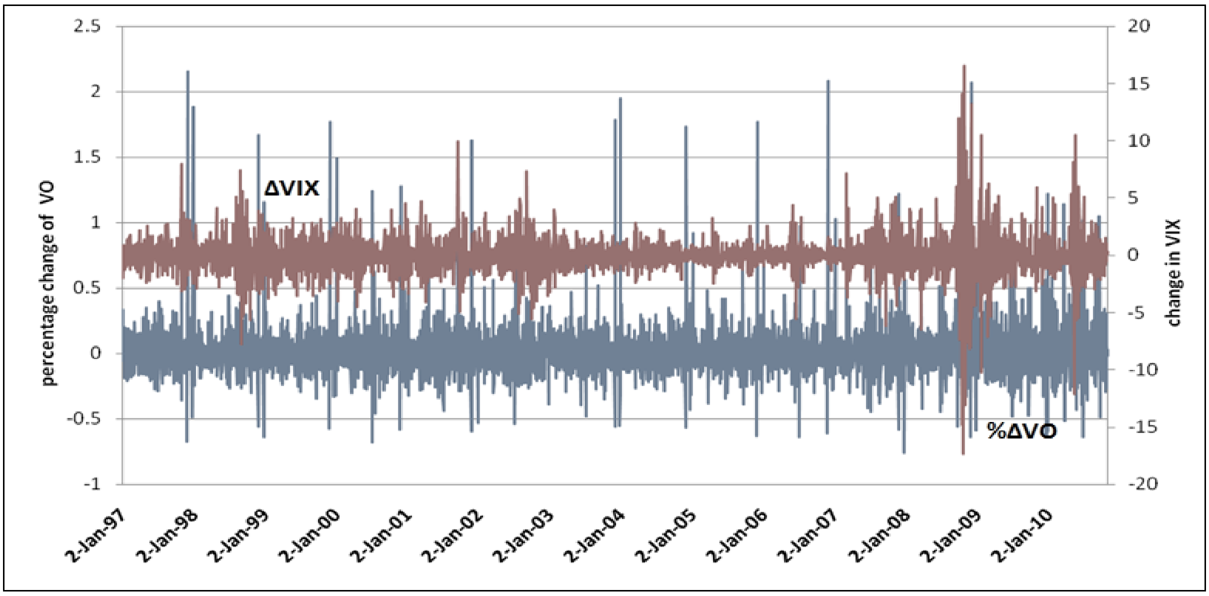

Table 3. Summary Statistics of %ΔVO and ΔVIX

Summary statistics of the percentage change in trading volume and the change in VIX. Coefficient of correlation between them during the whole sample period, high VIX period and low VIX period.

	Mean	Median	Maximum	Minimum	Standard Deviation
%ΔVO	0.0185	0.0005	2.1552	–0.7604	0.2081
ΔVIX	0.0001	–0.0800	16.5400	–17.3600	1.7080
Coefficient of Correlation (ΔVIX & %ΔVO)					
Whole Period (1997/01 - 2010/12)		High VIX Period (2008/07 - 2009/06)		Low VIX Period (2005/01 - 2005/12)	
0.1107		0.2019		0.1263	

Table 4 shows the first regression results for percentage change in trading volume as the dependent variable. In panel A, the coefficients of MKT+, MKT–, MA5MKT+, MA5MKT– and MA5|MKT| are in expected sign. MA5|MKT| is used to investigate the impact of market volatility on the trading activity. Indeed, it is significant in all the three panels. Volatility is the factor that can significantly affect trading volume regardless the presence of controlled variables. In panel B, MKT+ is positively significant whereas the MKT– is not significant. Thus it indicates that during high VIX period, the trading volume reacts fast only to the most recent positive market movement. However, the reaction to the negative market movement is relatively slow and reluctant, which is reflected by the significance of MA5MKT–. When there is a downward trend in the market return, the trading volume starts to decrease. Since noise traders are generally optimistic, they may react fast to the positive market movement and buy shares aggressively. On the other hand, they are reluctant when the market has negative return. They may sell stocks and realize the loss after the market exhibits an obvious decreasing trend. In panel C, both MKT+ and MKT– are significant while both MA5MKT+ and MA5MKT– are not significant. As the noise trader becomes the minority during low VIX period, the trading volume reacts fast to the recent market movement.

Comparing panels A and B, the weekday dummies, which are used to capture the systematic seasonal pattern in trading activity (see Chordia, Roll and Subrahmanyam, 2001), become not significant during high VIX period. As the noise traders play a significant role in the high VIX period, VIX is able to capture the trading pattern measured by the week day dummies. Besides, the macroeconomic announcement date dummies also become not significant in panel B. One potential explanation is that the effect of the macroeconomic announcement is grabbed by VIX.

After adding those explanatory variables that used in Chordia, Roll and Subrahmanyam (2001), VIX is still significant in panels A and B. If VIX increases, the percentage change in trading volume also increases. The result implies that more trades are associated with higher VIX. In the two sub-samples, the effect of VIX only exists during high sentiment period. As VIX can be viewed as the signal of noise, the result may imply that noise traders increase trading volume. When VIX is low, the noise traders are out of the market, or their role is not significant, VIX has less power in explaining the changing pattern of trading volume.

Table 5 shows the second regression results for coefficient of variation of trading volume as the dependent variable. The level of market return appears to be a determinant of the variability of trading volume. Better market performance is associated with larger variation in trading volume. The coefficient of AVG(VIX) is positive and significant as well. If the level of VIX over the successive trading days is higher, the variability of trading volume over the successive trading days also tends to be larger. Noise traders are usually uninformed. Their trade is based on noise or sentimental belief and is likely to be affected by various news or rumors. During high VIX period, the noise traders share a significant portion of investors. The induced trades are noise trading. The volatility of trading activity is likely to be induced by those noise trading. Their variable trading behavior may also affect the volatility in stock returns. Lee et al. (2002) find that stock market return volatility increases when investors become more bearish.

Table 4. Time Series Regression for Percentage Change in Trading Volume

Dependent Variable : %ΔVO						
	Panel A Whole Period[a] (1997/01 - 2010/12) 3443 Observations		Panel B High VIX Period[b] (2008/07 - 2009/06) 250 Observations		Panel C Low VIX Period[c] (2005/01 - 2005/12) 250 Observations	
Explanatory Variables	Coefficients	*p*-value	Coefficients	*p*-value	Coefficients	*p*-value
ΔVIX	0.0279***	0.0000	0.0269***	0.0007	– 0.0199	0.5123
MKT+	6.9513***	0.0000	5.7601***	0.0012	11.0057**	0.0023
MKT–	– 1.9560*	0.0516	– 0.0525	0.9799	–20.9593**	0.0188
MA5MKT+	1.4763	0.3999	8.8393	0.1460	3.4678	0.7138
MA5MKT–	– 0.8218	0.4282	– 6.5810***	0.0015	6.7781	0.2811
MA5|MKT|	– 4.9120***	0.0000	– 5.6677***	0.0001	–13.9890**	0.0147
MON	– 0.0419**	0.0124	– 0.1141	0.1681	0.0068	0.9208
TUE	0.1056***	0.0000	– 0.0465	0.4614	0.1040***	0.0093
WED	0.0376***	0.0004	– 0.0707	0.2902	0.0294	0.4065
THU	– 0.0021	0.8473	– 0.0536	0.3425	– 0.0104	0.7814
Holiday	– 0.1214***	0.0000	– 0.1287	0.1433	– 0.0664	0.3772
ShortRate	0.0031	0.9721	– 0.6226***	0.0016	0.2305	0.4662
TermSpread	– 0.0968	0.1802	– 0.6039***	0.0004	– 0.0926	0.6763
QualitySpread	0.1780	0.2408	0.0371	0.8812	0.4923	0.3754
GDP(1-2)	0.0163	0.2148	0.0161	0.6830	0.0905	0.2736
GDP(0)	0.0087	0.5289	0.0409	0.5237	– 0.0471	0.1965
UNP(1-2)	0.0054	0.5636	– 0.0334	0.3543	0.0162	0.4750
UNP(0)	– 0.0371***	0.0060	– 0.1084	0.1055	– 0.0680*	0.0877
CPI(1-2)	– 0.0086	0.2423	– 0.0410	0.3447	– 0.0363	0.2486
CPI(0)	0.0603***	0.0000	0.0043	0.9227	0.0074	0.8444
Intercept	– 0.0009	0.9401	0.0989	0.1452	– 0.0197	0.6675
F-statistic	26.0096***	0.0000	3.3657***	0.0000	3.1180***	0.0000
R-squared	0.1320		0.2272		0.2140	
Adj. *R*-squared	0.1269		0.1597		0.1454	

The dependent variable is the daily percentage change of trading volume, **%ΔVO**. The explanatory variables are: **ΔVIX** : daily change in VIX; **MKT+** : market return at time t and equals to 0 if return is negative; **MKT–** : market return at time t and equals to 0 if return is positive; **MA5MKT+** : average return during t-1 to t-5 and equal to 0 if negative; **MA5MKT–** : average return during t-1 to t-5 and equal to 0 if positive; **MA5|MKT| :** average absolute return during t-1 to t-5; **ShortRate** :

difference between Federal Fund Rate at t and t-1; **TermSpread** : daily change in the difference between the yield on 10-year Treasury bond and Federal Fund Rate; **QualitySpread** : daily change in the difference between the yield on Moody's Baa corporate bond and yield on 10-year Treasury bond; **Holiday** : 1 if a specific trading satisfies (1) if Independence Day, Christmas, or New Year's Day falls on a Friday, then the previous Thursday, (2) if any holiday falls on a weekend or on a Monday, then the following Tuesday, (3) if any holiday falls on another weekday, then the preceding and following days, and 0 otherwise; **MON, TUE, WED, THU** : 1 if trading day is a Monday, Tuesday, Wednesday or Thursday respectively, and 0 otherwise; **GDP(1-2), UNP(1-2), CPI(1-2)** : 1 on the two trading days prior to a GDP, unemployment or CPI announcement respectively, and 0 otherwise; **GDP(0), UNP(0), CPI(0)** : 1 on the day of a GDP, unemployment , CPI announcement respectively, and 0 otherwise.

***, ** & * denote coefficients significantly different from zero at 1%, 5% & 10%, respectively.

(a), (b) & (c) use 8-lag, 4-lag & 4-lag Newey-West standard errors, respectively.

Table 5. Time Series Regression for Coefficient of Variation of Trading Volume

Dependent variables : CV(VO)[d]		
Explanatory variables	Coefficient	*p*-value
VG(VIX)	0.0010***	0.0048
AVG(MKT+)	1.2671**	0.0370
AVG(MKT–)	– 1.0086*	0.0753
Holiday'	0.0556***	0.0000
AVG(ShortRate)	– 0.2264**	0.0170
AVG(TermSpread)	0.1286	0.1725
AVG(QualitySpred)	0.1469	0.3197
GDP	0.0111**	0.0317
UNP	– 0.0166***	0.0000
CPI	– 0.0059	0.2108
Intercept	0.0885***	0.0000
F-statistic	44.0587***	0.0000
R-squared	0.1138	
Adj. *R*-squared	0.1112	

The dependent variable is the coefficient of variation calculated using trading volume during t to t-4, **CV(VO)**. The explanatory variables are : **AVG(VIX)** : average VIX during t to t-4; **AVG(MKT+)** : average market return during t to t-4 and equal to 0 if negative; **AVG(MKT–)** : average market return during t to t-4 and equal to 0 if positive; **AVG(ShortRate)** : average ShortRate during t to t-4; **AVG(TermSpread)** : average TermSpread during t to t-4; **AVG(QualitySpread)** : average QualitySpread during t to t-4; **Holiday'** : 1 if there is holiday during t to t-4 and 0 otherwise; **GDP, UNP, CPI** : 1 if there is GDP, unemployment or CPI announcement during t to t-4, respectively.

***, ** & * denote coefficients significantly different from zero at 1%, 5% & 10%, respectively.

(d) uses 8-lag Newey-West standard errors.

4. Conclusion

Level and variability of liquidity are found to significantly affect market return. Trading volume, as a proxy of liquidity, may be worth to be investigated. Noise traders could impose risks on price by deriving it from the fundamental value. Besides, as noise traders should affect price by trading, their trading behavior, captured by level and variability of trading volume, may also have effect on return. The change in VIX significantly explains the percentage change in trading volume, but such effect only exists in high sentiment period. Their correlation coefficient is positive, meaning that when VIX increases, trading volume also increases. The volatility of trading volume is also found to be positively related to the level of VIX. When the level of VIX during successive trading days is higher, the variability of trading volume during the same period is also higher.

On one hand, noise traders drive price deviation from fundamental value. Arbitrageurs or rational investors may require higher return for compensating the mispricing risk. On the other hand, noise traders also add liquidity and induce the variability of liquidity. Previous researches show that the increase in the level and/or variability in liquidity lower the required return. Therefore, the realized price impact of noise trader may be a combination of different kinds of impact. This consideration may help in explaining different findings among researches and provide an alternative approach to assess the impact of noise traders.

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