Empirical Linkages between Trading Volume and Stock Markets Shocks: When Sentiments Drive Investors' Behavior

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Abstract: *In this paper, we examine the impact of investor psychological state on their trading volume for the US stock market using a VECM model for the period from July 1987 to May 2014. We propose alternative specifications for investors' sentiment considering their optimistic and pessimistic states. We find that during pessimistic periods, investors' are extensively alerted. In optimistic and normal periods, they are less attentive.*

Introduction

The relation between stock price changes and trading volume has received great attention in the field of finance over the past two decades. Among others, Hou and Li (2014), Dhaoui (2013) Dhaoui and Khraief (2014), Chen (2012), Campbell et al. (1993), Chuang et al. (2009), Griffin et al. (2007), Karpoff (1987), Lee and Rui (2002), McMillan (2007) Al-Jafari and Tliti (2013) have focused on the nature of connections between trading volume and stock returns. However, even the importance of empirical findings, there is no consensus on empirical results of these studies, which show different causality directions. The diversity of nexus can be attributed to the fact that these studies have been conducted for different countries, and focused on different periods, and variables as well as they used different econometric methodologies. As discussed in Karpoff (1987), evidence on the return-volume relationship not only enhances the knowledge on the financial market structure, but also provides information to discriminate between competing theoretical models (Chen, 2012). In the same line, Campbell et al. (1993) document that the return-volume relation helps solve the identification problem for testing different models.

In this vein, it is generally believed that trading volume is positively associated with stock returns. However, empirical findings failed in several cases to confirm this though. For instance, an early empirical study by Granger and Morgenstern (1963) failed to find a correlation between the absolute value of daily price changes and the daily volume for the New York Stock Exchange (NYSE) over the period 1939-1961. Subsequent studies have found, however, more evidence of a positive correlation (Crouch, 1970; Epps and Epps, 1976).

During the last two decades, the focus has moved to examine what factors drive the trading volume-stock return relationship? In the real economy, investors react to the change in stock returns by increasing or decreasing their trading volume. What factors drive their trading behavior is a substantial question to explore. In this framework, studies have started to examine the trading volume – stock prices relation by asking questions such as, "do investors increase their trading when expecting a rise in stock price", or "does change in stock prices induce changes in investor's psychological state leading to high/less trading".

Although the few numbers of researches set in this framework, several explanations are proposed in previous studies. The investor sentiment has, however, attached the attention of researchers as a substantial component that can explain the evolution of economies and the market components summarized in trading volume and stock prices and returns. In this vein, "*there is now significant body of evidence from psychology and brain science that agents experience cognitive problems in understanding the world in which they live; they find it hard to process the information they face and to make sense of it. As a result, they use simple behavioral and informational rules. In a complex economic world agents do develop strong differences in beliefs about how the economy functions*" (De Grauwe and Kaltwasser, 2007). The sentiment is, thus, proposed as one of the factors that could seriously affect their trading strategies.

This paper seeks to investigate the role of investor sentiments and opinions summarized in optimistic and pessimistic beliefs about the future evolution of the stock market in determining their levels of trading. We propose new proxies to these psychological states of mind and develop a VECM model to supervise the long-term equilibrium and the short-term adjustment of trading volume to the change in the investor psychological state.

Using data for US stock market over the period 1991 to 2014, we find that investors trading volume is determined by their pessimistic state. Optimism and pessimism shocks exert asymmetrical impact on the investors' behavior. Over the pessimistic period, pessimistic sentiment drives the stock market. The optimistic state is without impact. In normal economic cycles, sentiments are without significant impact.

The remainder of this article is arranged as follows. In section 2, we present the literature overview on the sensitivity of stock market components to the investor's psychological state. The section 3 presents the methodology of the study. Subsequent sections describe the data, the variables' specifications and the econometric approach. The final section gives the policy implications and conclusions.

Literature Review

Beliefs and sentiments as part of the irrational world are important forces not only in everyday life, but also in the economic and financial field. There is convincing evidence in literature that investors are prone to exogenous sentiment waves, a fact that challenges the rationality hypothesis. Researchers in behavioral finance have provided a considerable impetus towards the psychological state of investors in making decisions (Barberis et al., 1998; Baker and Wurgler, 2007; Huisman et al., 2012). In this line, Baker and Wurgler (2007) argued that investors' sentiment predictive content regarding the future evolution of stock markets may act as an invaluable tool for the investors in developing successful trading strategies.

Generally, sentiments refer to the state of mind of the investors. They represent in terms of Baker and Stein (2004) the investors' propensity to speculate or investors' optimism/pessimism about a stock. Investor sentiment can be defined as investors' misevaluation on an asset (Baker and Stein, 2004) or also the component of investors' expectations about returns that are not justified by fundamentals (Lee et al., 1991). From a psychological viewpoint investors' trading behavior is not undertaken in isolation, they would be influenced by their emotions, feelings and psychological state at that point in time. In a positive state, investors become more optimistic, which decreases their attentiveness. They are, consequently, more likely to stick to their normal trading levels. In negative state they become, however, more alerted react by decreasing abnormally their trading levels.

In this vein, several studies recognized, however, the important role of investor sentiment in driving stock markets. For instance, Kim et al. (2014) examine the sensitivity of the relationship between disagreement among investors and future stock market returns

to the influences of the investor sentiment. They find that the degree of investor sentiment exerts significant influences on the relationship between disagreement and future stock market returns. Their results show also that the influence significantly varies with the sentiment periods. Higher disagreement, among investors' opinions, predicts significantly lower future stock market returns during high-sentiment periods. During low-sentiment periods findings show no significant effect.

Kim and Kim (2014) examined whether investor sentiment forecasts stock returns, volatility and trading volume. They used extensive data on 91 firms spanning the period from January 2005 till December 2010. Their findings show in intertemporal and cross-sectional regression analysis, no evidence that investor sentiment has predictive power for future stock returns either at the individual firm or at the aggregate level. They find, however, that prior stock price performance positively affects investor sentiment. On volatility and trading volume, results show also non significant impacts. For Brown and Cliff (2005) investor sentiment does not predict short-term market returns at weekly and monthly intervals, but it predicts long-term market returns at the next two to three years.

Investors trading behavior is driven to a large extent by expectations about the current and future state of the returns. Changes in expectations, therefore, directly impact their trading behavior. An expected increase and decrease in returns, for instance, will influence the agents' psychological state and induce them to adjust their levels of trading and investment decisions. Investor sentiment describes waves of optimism and pessimism (Baker and Wurgler, 2006). It represents the "*expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be*" (Brown and Cliff, 2004).

It is reported that optimism leads to a higher level of trading whereas pessimism is associated to a lower or even an absence of trading. The stock market reflects optimistic and pessimistic opinions. When investors become more optimistic, i.e., when they expect for good events, trading volume levels rise. Oppositely, when they become more pessimistic, i.e., when they expect for bad events, they decrease their trading levels. Excessive optimism leads to an increase in trading volume since optimistic investors over-evaluate the future stock returns. Optimistic investors tend to systematically overestimate the probability that good things will happen to them and, at the same time, to underestimate the probability that bad things will happen (Weinstein, 1980). They overestimate the precision of their knowledge and their judgment skills and react by making aggressive decisions, which increase significantly their trading volume (buy or sell). In opposition, the more pessimistic investors estimate a negative evolution of returns and decrease or postpone their trading. When results go against the former (the latter) forecasts a state of shock occurs and affect their sentiments and feelings that we can define as an optimism shock (pessimism shock). "Optimism and pessimism shocks" refer to changes in expectations due to a perceived change in fundamentals which eventually does not materialize.

The role of undue optimism and pessimism for investors' behavior fluctuations has long been recognized by economists in the past. Keynes (1936, p. 154), for example, wrote about "animal spirits" influencing reality and creating waves of optimism and pessimism. He documented that the "*market is subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legitimate where no solid basis exists for a sound calculation*". He added that about all of investors' decisions break with the foundation of rationality, and attributed the dysfunction of the economy to psychological components and non rational behavior. In this line, he argued that, "*most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the results of animal spirits* […] *and not at the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities*" (Keynes, 1936).

This challenge was being confirmed more recently when Akerlof and Shiller (2009) recognized the important role of investors' human psychologies in determining their investment behaviors. They have explained the way the economy works in terms of human psychology impacts. In the same framework, several authors such as Akerlof and Yellen (1985) argued that deviations from rationality do really matter, which confirms the significant dependence of investors' behavior to their psychological state.

King (2009) agreed with Akerlof and Shiller (2009) about the substantial role played the "animal spirits" behavior of investors in determining their investment strategies. He argued that an important part of economic fluctuations can be due to behavior biases. Moreover, many studies such as those of Azariadis (1981) and Woodford (1988) consider that thesefluctuationscan occureven in the situationwhere fundamentalconditions remain unchanged through the time. They attribute them, however, to the random wave of investors' beliefs often related to the optimistic and pessimistic state of thinking,.

Optimistic and pessimistic states of investors induce over and under-reactions in trading, respectively. For Ciccone (2003), investor sentiments and behaviors determine a substantial part of the stock market. Optimistic and pessimistic beliefs influence the extensively both the stock prices and trading volume and are reflected in them. Optimistic investors in the sense of Haruvy, et al. (1999) are "*those who tend to choose the strategy which can potentially give them the highest payoff*". These authors define optimistic investors as "*those who are motivated by worst-case scenarios and hence tend to choose a secure action*". According to Weinstein (1980, 1986, and 1989) and Otten (1989), optimistic investors overestimate the probability that positive events may happen to them than to others and similarly underestimate the probability that negative events may occur for them than for others. By extension, pessimistic investors attribute more probability of occurrence to negative events and less probability to positive events to which they are exposed. Accordingly, both optimistic and pessimistic investors adjust their trading strategies. The first react by trading aggressively, while the latter decrease (or postpone) their trading. In terms of trading strategies, Chen (2013) concludes that optimistic agents trade aggressively while pessimistic ones trade conservatively. These trading strategies are due to the fact that the optimistic investors (pessimistic investors)

tend to systematically overestimate (underestimate) the probability that good events will happen to them and, oppositely, underestimate (overestimate) the probability that bad things will happen. This can be understood in the sense that optimistic and pessimistic investors attribute dispersed probabilities to the risk perception.

Specifically, optimistic investors' underestimate their exposure to risk and exaggerate their reaction since they expect only positive results and neglect the failure. In this vein, Shu (2010) argued that optimistic investors are less patient than those who are more pessimistic and react aggressively by underestimating their exposure to risk. Oppositely, the more pessimistic investors display a high-level of risk aversion. They become more and more receding when they make a decision like an investment in risky assets which leads to a decrease in trading volume.

Chuang et al. (2010) use weekly data during the period between January 1990 and December 2004 to supervise the change in investor sentiments in Taiwan Stock Market. They find that the change in trading volume can be used as a proxy for investor sentiments. They argued that a positive deviation of trading volume implies that investor sentiment jumps to become more optimistic and vice-versa.

In the French stock market framework, Rousseau et al. (2008) argued that pessimistic investors decrease their trading volume and avoid risky assets to prevent a loss. Psychological literature assimilates the pessimism to a statement of impotence or to an absurdity of human existence. In other side, the author's find that optimistic investors increase their trading volume and invest more in risky assets waiting for more performance in the future. As more risk adverse agents, pessimistic investors decrease or postpone their trading when they realize negative results. However, they maintain the same trading level once obtain abnormal profits. Optimistic investors trade aggressively after abnormal gain. They maintain normal trading when negative results are realized.

Carver, Scheier and Segerstrom (2010) suggest that optimism and pessimism sentiments focus on expectancies for the future and the way that the investors confront problems. The authors find that optimistic investor faces adversity differently than pessimistic one. They presume that optimistic investor uses more adaptive ways and "commit" himself to cope with the worst scenarios. In contrast to optimism, pessimism refers to fear, doubt and stress. Then, pessimistic investor tends to be hesitant and doubtful in the face of different challenges. Generally, the optimistic person assigns a low probability to the bad events that arrive to disturb his life. He assigns, in return, a high probability to the good events. The pessimistic person over-weights the probability of bad event and underestimates the probability of good events.

For Ali and Gurun (2009), individual behavior depends on both their psychological state and the characteristics of the period during which they are used to act. The authors echoed the view that optimism decreases the attentiveness of investors. To surmise, individuals are more alert during pessimistic periods and less attentive at optimistic times. In the same line, Chung et al. (2012, p. 219) suggest that "*when the*

economy is in expansion, investor optimism grow as reflected by the increase in sentiment. In contrast, investor sentiment tends to decrease when the economy is in contraction". As argued by Brown and Cliff (2005), when investor sentiment increases with the market price, the build-up of optimism leads to an extended period of market overvaluation. In contrast, investor's growing pessimistic beliefs in bad times may result in assets being underpriced.

Data and Methodology

In this section we initially describe the sample period and the variables. Then we analyze the time series properties of the relevant variables by means of conducting unit root and cointegration tests. Finally, we review previous specifications of investor sentiment indicators and we propose an alternative specification for optimism and pessimism shocks that we use in the empirical analysis.

Data

We use weekly data to analyze the impact of the stock market fluctuations on trading volume for the period 1987:07-2014:05. The starting date of the sample period is determined by the availability of weekly data on trading volume. The whole sample includes 1401 time series observations. We collect the data on the stock price index (P_t) and trading volume (V_t) from the Yahoo Finance pages. Following previous empirical studies on stock returns and trading volume, we include the following variables in the analysis: stock market returns, trading volume, investor sentiment indicators expressed in terms of optimism and pessimism. That is, we collect the following time series data.

- Stock prices. In this paper, we use the stock market returns expressed in percentages defined as the first logarithmic difference of the stock prices multiplied by 100: . This measure is already used by Chen (2012).

- Trading volume. The trading volume measures the volume of transaction. This variable is expressed in natural logarithm.

- The Market Trend (MT) expresses Bullish and bearish evolution of the stock market. Following previous studies the market trend is defined as the difference between the closing prices and the x-days lowest prices divided by the difference between the x-days highest prices and the x-days lowest prices. Based on the Schwarz Information Criterion (SC) lag length criteria we choose x=3 days. That is, the market trend is expressed following this relation:

$$MT = \frac{Closing\ Prices_t - Lowest\ Prices_{t,t-3}}{Highest\ Prices_{t,t-3} - Lowest\ Prices_{t,t-3}}.$$

Investors' sentiment specifications

Previous studies used two types of sentiment indicators that differ for daily and weekly returns due to data availability. The first family of indicators consists of the OEX put-call trading volume ratio, the OEX put-call open interest ratio and the NYSE ARMS index. The second family of indicators is compiled from surveys by the American Association for Individual Investors (AAII) and Investor Intelligence (II). These indicators are used for investigating individual stocks. Since we use aggregate stock market data, we propose alternative specifications for investors' sentiment, allowing supervising their optimistic and pessimistic expectation shocks. We define "optimism shocks" as an event that occurs when an investor expects the bullish market trend and react therefore expecting realizing a positive return however their expectations does not materialize. Similarly, a "pessimism shocks" occurs when investors expect a bearish market trend and react anticipating a decrease in returns and therefore reduce their trading volume (hold or postpone), however results indicate positive reaction of returns and investors miss consequently an opportunity.

In this paper, and taking into account that investors' levels of trading are driven by their psychological state and that the disparity between forecasts and results determines the sentiment shock we propose the following approach to specify the optimism and pessimism shocks. We start by presenting preliminary specifications describing the analysis strategy of investors to finish by presenting new proxies for optimism and pessimism shocks.

- Percentage changes in Stock market prices. This variable is defined as the first difference of stock market prices reported to the market price at time t-1 and is computed as $\Delta P_t = (P_t - P_{t-1}) / P_{t-1}$ x 100, where P_t is the Stock market price at time t. Stock market return variation allows to supervise both stock market returns increases and stock market returns decreases. The changes in stock market returns give a substantial illustration of the stock market specific shocks. The specific shock includes positive and negative shocks.

- Positive specific shock. This variable only considers increases in stock market returns, that is . This relation specifies the positive stock market specific shock.

- Negative specific shock. This variable only considers decreases in stock market returns, that is . This relation specifies the negative stock market specific shock.

The expectation of stock market returns increases and decreases and the expected market trend drive the investors' behavior expressed in terms of their trading intensity. Investors increase (decrease) their trading volume when expecting a bullish (bearish) market trend and positive (negative) changes in stock prices. If results go against their expectations the investors support an optimism (pessimism) shock since the loss they realize are due to unrealistic expectation and are not determined by the intrinsic unfavorable evolution of supply and demand orders (supply-demand law).

Thus, based on their expectations of the market trend and the evolution of the stock market returns (increases and decreases) investors express optimistic and/or pessimistic feelings and modify their trading volume accordingly. The analysis of the changes in expected market trend and the aggregate stock market returns allows distinguishing between the two types of shocks affecting investors' sentiment: optimism and pessimism shocks. The optimism shocks (OS_t) specification is described as follows:

$$OS_t = \Delta P_t, \quad if \quad sign(\Delta P_t) \neq sign(\Delta MT_t) \tag{1}$$

and   0 ,   otherwise

and pessimism shocks (PS_t) is,

$$PS_t = \Delta P_t, \quad if \quad sign(\Delta P_t) = sign(\Delta MT_t) \tag{2}$$

and   0 ,   otherwise

where ΔP_t and MT are the growth rate of stock market prices and the market trend, respectively, at the time t. that is, a stock market price change is defined as an optimism shock if the sign of the stock market price variation is different from the sign of the market trend variation, while it is identified as a pessimism shock if these signs are equal. For example, a stock market price increase (decrease) together with a market trend increase (decrease) will be identified as a pessimism shock, while a stock price increase (decrease) associated with a market trend decrease (increase) will be identified as an optimism shock. Figure 1 shows the temporal evolution of trading volume, stock prices (specific shock) and optimism and pessimism shocks and justifies the new specification we propose in this paper. For example, we observe that the increase in trading volume in Mars 2000 corresponds to significant specific shock price (global shock in prices), optimism shock and pessimism shock, together. For the period spanning the end of 2000 to recent date we observe that while optimism shocks remain nonsignificant, the stock price and pessimism shocks indicator follow a similar path and determine the trading volume evolution. Since pessimism shocks describe the investors' expectation of negative evolution of stock markets in terms of prices and returns, and the last selected period corresponds to a series of financial scandals and recessions, this evolution observed in Fig. 1 provides a real illustration of the investors' behavior following their optimistic and pessimistic expectation of the stock market evolution.

Figure 1. Temporal Evolution of Trading Volume, Specific Shocks, Optimism Shocks and Pessimism Shocks
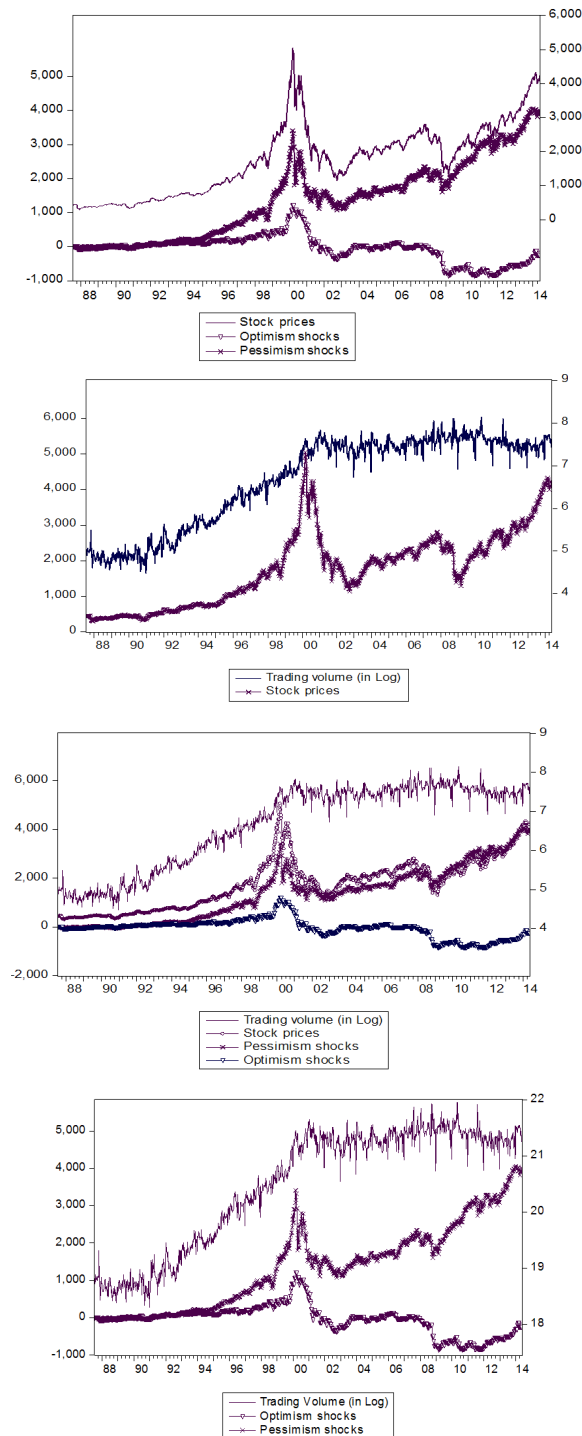
We observe also a break point in the first half of the year 2000 characterized by tremendous bull followed by a period of high fluctuation of prices and trading volume. The sentiment indicators move extensively over the period 2000 to now with a strong degradation in optimistic state and at fast speed.

Table 1 contains summary statistics of our selected variables. Results display excess kurtosis (with the exception of the trading volume), negative skewness. As regards to the standard deviation we notice a quite small standard deviation for the stock return and the trading volume, which indicates that these variables are close together. Oppositely for the sentiment shock indicators (optimism and pessimism), we notice a large standard deviation which indicates that these variables are more spread out.

Table 1. Descriptive Statistics

	Stock Return	Trading volume	Optimism shock	Pessimism shock
Mean	0.163660	20.48683	-0.138087	2.856517
Median	0.350174	21.08096	0.000000	0.000000
Maximum	17.37695	21.96302	201.9800	608.2700
Minimum	-29.17528	18.29180	-297.8800	-1,125.160
Std. Dev.	3.129302	1.060491	27.84315	68.70475
Skewness	-1.137603	-0.637576	-2.306248	-3.133827
Kurtosis	12.43302	1.836465	32.06180	64.23620
Jarque-Bera	5,492.580	173.9472	50,544.76	221,192.0
Probability	0.000000	0.000000	0.000000	0.000000
Observations	1,400	1,401	1,401	1,401

Note: this table shows summary statistics. Column 1 reports the results for the stock returns, column 2 reports the results for the trading volume (in log), column 3 and 4 report the results for optimism and pessimism shock indicators.

Results and discussion

Traditionally, correlation coefficients are used as the main analytical tool for describing the relations among a group of variables. However, under certain conditions using cointegration instead of correlation may have important advantages, because cointegration allows us to find and identify possible common trends, if they exist (Baxa, 2007). Before running cointegration tests we are used to run unit root tests to identify if the series are cointegrated and if yes to determine the order of cointegration. Unit root tests are conducted to investigate whether the selected series are stationary. The results of the Augmented Dickey Fuller, (ADF) test, the Phillips-Perron (pp) test

and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSSS) tests are reported in Table 2. Results of the unit root tests confirm the presence of a unit root in level for each selected series. The hypothesis of the presence of a unit root is rejected in the first difference. All selected series are, consequently, cointegrated in order one I(1).

Table 2. Unit Root Tests (variables: Stock price, Trading volume, Bias of Optimism, Bias of pessimism)

Variable	ADF	PP	KPSS
In level			
Stock Price	-2.029854	-1.993181	0.248917***
Trading Volume	-2.570678	-1.059624	0.575137***
Optimism shock	-1.700311	-1.883497	0.651798***
Pessimism Shock	-2.466497	-2.483773	0.231078***
1st Difference			
Stock Price	-38.54587***	-38.54504***	0.069230
Trading Volume	-17.58161***	-114.3456***	0.062912
Optimism shock	-35.23835***	-35.39480***	0.089760
Pessimism Shock	-44.83261***	-45.84355***	0.048352

*Note: ADF, PP and KPSS are Augmented Dickey Fuller, Phillips-Perron and Kwiatkowski, Phillips, Schmidt, and Shin test statistics, respectively. In ADF and PP, the null hypothesis is that the series has a unit root. In KPSS the null hypothesis is that the series is stationary. *** denotes 1% significance level. Lags in ADF test are chosen by Schwarz Information Criterion (SC). For all Unit Root tests, the test equation includes trend and intercept.*

Once the order of integration of each variable is established, we then evaluate whether the variables under consideration are cointegrated. According to Engle and Granger (1987), a linear combination of two or more nonstationary series having a same integrating order may be stationary. If such a stationary linear combination exists, the series is considered to be cointegrated and long-run equilibrium relationships exist. Cointegration implies that causality exists between the two variables, but it does not indicate the direction of the causal relationship. The Johansen cointegration test based on the autoregressive representation discussed by Johansen (1988) and Johansen and Juselius (1990) constitutes the most commonly used method. The results for the Johansen and Juselius cointegration tests are reported in Table 3.

Results in Table 3 show that there are cointegration vectors. The Table includes the ranks given in the first line, the number of cointegration vectors in line 2 and eigenvalues and trace statistics. The critical value is mentioned using asterisks.

Table 3. Johansen and Joelius Cointegration Tests (variables Trading volume, Stock Market Returns, Supply shocks, Demand shocks)

	r = 0		r ≤ 1		r ≤ 2		r ≤ 3	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Trace statistic	353.2420***	376.5302***	22.99796	45.15492**	5.713970	19.09174	0.087136	5.626271
Max-Eigen stat	330.2440***	331.3753***	17.28399	26.06318**	6.626834	13.46547	0.087136	5.626271

Note: (1) model with an intercept. (2) model with an intercept and a linear trend. R: number of cointegration vectors. *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% levels of significance, respectively. In column 2 (r=0) we test the null hypothesis of no cointegration against the alternative of cointegration. In column 3 we test the null hypothesis of 0 or 1 cointegrating vector against the alternative of r=2. The lag length in all the tests has been selected according to the Schwarz Information Criterion (SC).

The null hypothesis is that the number of cointegrating relationships is equal to r, which is given in the "maximum rank" observed in the first line of the Table 4. The alternative is that there are more than r cointegrating relationships. We reject the null if the trace statistic is greater than the critical value. We start by testing H_0: r=0. If this null hypothesis is rejected, we repeat for H_0: r=1. The process continues for r=2, r =3, etc. The process stops when a test is not rejected. In our case, results from cointegration tests with an intercept and a linear trend show that we can reject H_0: r=0 since the trace statistics are greater than the critical values. Results show also the rejection of the H_0: r=1 based on the cointegration tests with an intercept and a linear trend. Finally, for r more than the aforementioned rank results indicate to stop to reject the null hypothesis because the trace statistics become less than their critical values. Consequently, we can conclude that there are 2 cointegration vectors. The existence of one or more cointegration vectors explains that the variables have a long run relationship and we should continue to use VECM (Vector Error Correction Model).

Based on these findings, the long-run equilibrium relationship is given by the following relation (results for long-run cointegrating equation):

$$V_t = -16.55593 - 10.98560\ R_{t-1} - 0.000692\ OS_{t-1} - 0.001610\ PS_{t-1} + \varepsilon_t \qquad (3)$$

$$(-19.2067) \qquad (-0.51491) \qquad (-3.48351)$$

t-statistics are given in ( ). Since the selected series are cointegrated, a VECM is set up for investigating short-run and long-run causality. In the VECM, the first difference of the endogenous variable (trading volume in log) is regressed on a 3 period lags of the cointegration equation. The VECM contains the cointegration relation built into the specification so that it restricts the long-run behavior of the endogenous variable to converge to its cointagrating relationship while allowing for short-run adjustment dynamics. The error correction model can be written by the following equations:

$$\Delta V_t = \beta_{10} + \sum_{i=1}^{k11} \beta_{11i} \Delta V_{t-i} + \sum_{i=1}^{k12} \beta_{12j} \Delta R_{t-j} + \sum_{i=1}^{k13} \beta_{13m} \Delta OS_{t-m}$$
$$+ \sum_{i=1}^{k14} \beta_{14n} \Delta PS_{t-n} + \beta_{15} ECT_{t-1} + \mu_{1t}$$

$$(4)$$

$$\Delta R_t = \beta_{10} + \sum_{i=1}^{k21} \beta_{21i} \Delta R_{t-i} + \sum_{i=1}^{k22} \beta_{22j} \Delta V_{t-j} + \sum_{i=1}^{k23} \beta_{23m} \Delta OS_{t-m}$$
$$+ \sum_{i=1}^{k24} \beta_{24n} \Delta PS_{t-n} + \beta_{25} ECT_{t-1} + \mu_{2t}$$

$$(5)$$

$$\Delta OS_t = \beta_{30} + \sum_{i=1}^{k31} \beta_{31i} \Delta V_{t-i} + \sum_{i=1}^{k32} \beta_{32j} \Delta R_{t-j} + \sum_{i=1}^{k33} \beta_{33m} \Delta OS_{t-m}$$
$$+ \sum_{i=1}^{k34} \beta_{34n} \Delta PS_{t-n} + \beta_{35} ECT_{t-1} + \mu_{3t}$$

$$(6)$$

$$\Delta PS_t = \beta_{40} + \sum_{i=1}^{k41} \beta_{41i} \Delta V_{t-i} + \sum_{i=1}^{k42} \beta_{42j} \Delta R_{t-j} + \sum_{i=1}^{k43} \beta_{43m} \Delta OS_{t-m}$$
$$+ \sum_{i=1}^{k44} \beta_{44n} \Delta PS_{t-n} + \beta_{45} ECT_{t-1} + \mu_{4t} \qquad (7)$$

where V_t, R_t, OS_t, OP_t, and μ_t denote respectively the trading volume, the US stock market return, the optimism shock, the pessimism shock and the error term that follows a Gaussian white noise. Δ and ECT denote respectively the difference operator and the error correction term. The significance of coefficients (β_i) of the explanatory variables is mentioned as the presence of causality in the short-run.

The sources of causality can be identified from the significance test of the coefficients of the independent variables in the VECM. Regarding the causality of the short-run, we can test the nullity of the parameters associated with independent variables in each equation of the VECM using the χ^2-Wald statistics. The causality in the long-run can be tested by the significance of the speed of adjustment. We use the t-statistics of the coefficients of the ECT, which indicate if there are long-run causal effects. The VECM is estimated by the maximum likelihood method. The lag length is selected based on the Schwarz Information Criterion (SC). Table 4 reports the estimation results of the error correction model.

Table 4. Estimation Results of the Error Correction Model

		ΔV_t	ΔR_t	ΔOS_t	ΔPS_t
Long-Run	ECT_{t-1}	-0.001365*** (-3.59991)	0.065754*** (7.09957)	-0.224868** (-2.98751)	0.039604 (0.19696)
Short–Run	ΔV_{t-1}	-0.408973*** (-15.4225)	-0.695147 (-1.07359)	0.871704* (0.16565)	-9.116828 (-0.64854)
	ΔV_{t-2}	-0.263721*** (-9.47188)	-0.270062 (-0.39725)	9.833475* (1.77981)	-22.31821 (-1.51212)
	ΔV_{t-3}	-0.169219*** (-6.39327)	0.510835 (0.79042)	1.389072 (0.26447)	5.530460 (0.39416)
	ΔR_{t-1}	-0.009825** (-2.70055)	-0.064034 (-0.72084)	0.447755 (0.62022)	-0.243761 (-0.12639)
	ΔR_{t-2}	-0.005755** (-2.01192)	-0.039960 (-0.57218)	0.477611 (0.84149)	-1.638778 (-1.08082)
	ΔR_{t-3}	-0.000710 (-0.58483)	-0.003274 (-0.11048)	0.057854 (0.24022)	-0.029865 (-0.04642)
	ΔOS_{t-1}	-0.000217 (-1.18422)	-0.018694*** (-4.17484)	-0.143152*** (-3.93382)	-0.057933 (-0.59594)
	ΔOS_{t-2}	-0.000215 (-1.15896)	0.005500 (1.21632)	0.032880 (0.89473)	0.194400** (1.98023)
	ΔOS_{t-3}	-0.000153 (-0.83521)	-0.004993 (-1.11262)	0.041295 (1.13230)	-0.151832 (-1.55845)
	ΔPS_{t-1}	-0.000265** (-2.58276)	-0.006534** (-2.60411)	0.058286** (2.85838)	-0.153062** (-2.80984)
	ΔPS_{t-2}	-0.000019 (-0.18324)	0.002094 (0.82501)	0.056732** (2.75085)	0.034117 (0.61925)
	ΔPS_{t-3}	-0.000081 (-0.78388)	-0.001451 (-0.57287)	0.025596 (1.24320)	-0.097307* (-1.76920)
	Intercept	0.004230 (1.22578)	0.014572 (0.17295)	-0.576218 (-0.84154)	3.512770* (1.92043)
	R-squared F-statistic	0.169733 21.73266	0.497593 105.2891	0.182855 23.78877	0.042325 4.698309

*Note: this table shows the results for the VECM model. The first line reports the results for the long run equilibrium. Lines 2 to 13 reports results for the short term run. The first column reports results for the trading volume, column 2 reports results for the stock returns, column 3 and 4 report results for optimistic and pessimistic shock indicators. *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% levels of significance, respectively. The lag length in all the tests has been selected according to the Schwarz Information Criterion (SC).*

Results in Table 4 shows a negative sign of the cointegration equation coefficient for the Trading Volume and the optimism shocks equations at 1% and 5% level of significance, respectively. This result confirms the existence of long-run equilibrium relationships. We notice however that the endogenous variable converge to its cointagrating relationship with a lower adjustment speed for the trading volume equation and a speedy adjustment for the optimism shocks equation. As regards the short-run causality, results show significant sensitivity of the changes in trading volume to its historical variations, to the stock market specific shocks and to the pessimism shocks with a negative sign and a high sensitivity to their experiences in trading and a less sensitivity to their feelings and psychological perception of the market evolution. This result is confirmed by the impulse response functions of the trading volume to the different types of shocks (specific shock, optimism and pessimism shocks).

Figure 2 shows the generalized impulse response functions of trading volume to a shock affecting the following variables: (i) stock market returns (specific shocks); (ii) optimism; (iii) pessimism. We find that the response of the trading volume of the US market shocks may differ depending on the nature of the impulse variables. The main results can be summarized as follows.

First, we find nonsignificant effects of the stock market returns (specific shocks) and the optimism shock in the short-term (about the first two weeks). Starting in the third week the trading volume reacts significantly and positively to the stock market returns. The response to the optimism shock is negative and remains quite smoothed. We find also a significant and negative response of trading volume to pessimism shocks. The speed of response is very faster than that observed in the stock market returns and the optimism shocks (after 1 week for the pessimism vs. after about 2 to 3 weeks for the stock returns and the optimism). The high sensitivity of trading volume to the pessimism component is due to the effect of the series of negative events that characterized the economic system in the US during the selected period and that exerted significant impact on the psychological state of investors.

Figure 2. Generalized Impulse Functions of Trading Volume to Stock Market Returns and Shocks of Optimism and Pessimism

Response of Trading Volume to Stock Market Return Innovation

Response of Trading Volume to Optimistic Innovation

Response of Trading Volume to Pessimistic Innovation
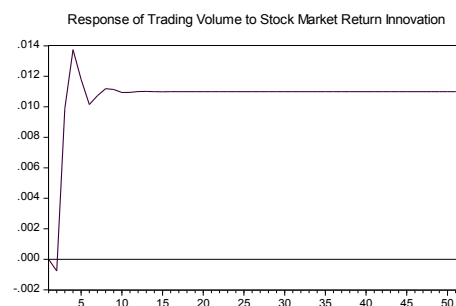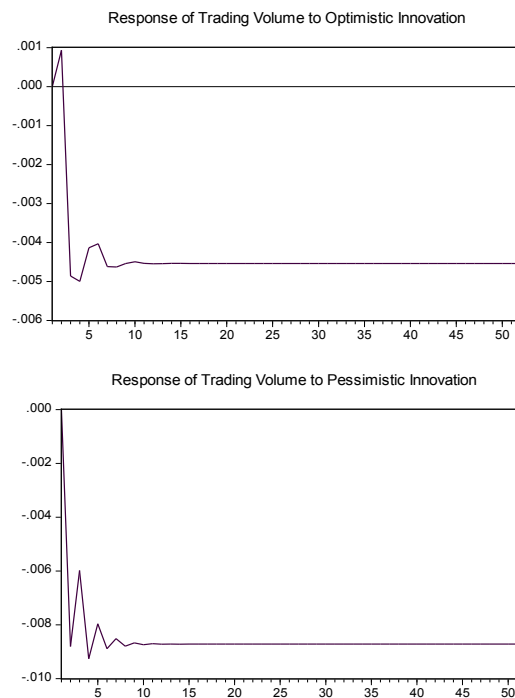
Conclusion

The relation between trading volume and stock price changes has received considerable attention over the past two decades in the field of finance. Several authors attribute, however, the disparity in results to exogenous effects associated in part to the change in the psychological state of investors. This paper analyzes the response of trading volume to the change in investors' psychological state. Waiting for good or bad results, investors express optimistic and pessimistic states of mind. Investors who wait for a positive evolution of stock market react aggressively and increase their trading volume. Once the stock market moves in the opposite sense and their expectations don't materialize, they loss of confidence and assume an optimism shock. When they wait for bad results and decrease, therefore, their trading, however the state of returns be a success, they assume a pessimism shock. The sample includes 1401 time series observations over the period 1987:07-2014:05. The results we obtained based on the Johansen and Joelius cointegration tests and the VECM model show a higher sensitivity of investor's trading behavior to their pessimistic forecasts than to their optimistic forecasts. The US stock market reacts more significantly following a pessimism shock than to an optimism shock. This result suggests that investors overweight the probability of bad event and underestimate the probability of good events and is in line with previous predictions in literature (see, for example, Carver et al. 2010; Weinstein, 1980; Chen, 2013). The extensive sensitivity of investors trading levels to pessimism shocks can be due to a series of pessimistic events that happened in the US over the selected period, which

push the US market to become more pessimistic and significantly sensitive to all events able to affect directly or indirectly the US economy. Psychological viewpoint confirms the American investors' psychological state. In fact, optimistic sentiment can be built across the time, but is broken after a simple shock.

In regard to the validity of the results we found the pessimistic state of the US stock market is due to the series of events the US has sustained over the last two decades. In major, these events have occurred inside the US country. In fact, the US has experienced a long period of turbulence starting with the first war in Irak of 1991 known as the "*Operation Desert Storm*" (17 January 1991 to 28 February 1991) to the bursting of the Internet bubble in Mars 2000, the attack of 11 September, the war in Afghanistan (07 October 2001), the series of failures and scandals that affect the telecommunication and technology giants (World-com failure in 2001-2002, the Enron failure in 2001 and the Tycho-electronics failure in 2002), …), the second war in Irak (20 Mars 2003 to 15 December 2011), the subprime crisis. These events have influenced sensitively the psychological state of the population and in particular of the investors. This period has been one of the most pessimistic period that knows the US. This has induced a substantial change in the investors' psychological state. Rational expectation losses of popularity and the investors expressed irrational behaviors. They have expressed heterogeneous psychological states moving from optimistic to pessimistic feelings and sentiments. Their decisions have been driven by their state of sentiment varying from optimism to pessimism. The intensity of negative events has feed in the investors a sense of pessimism and determined their trading strategies which explain the aforementioned results we find in this study. This behavior expressed by the investors over the aforementioned pessimistic period is in line with the findings of Ali and Gurun (2009) who document that investors are more alert during pessimistic periods and less attentive at optimistic times.

One of the important contributions of this paper is to introduce the first specifications of optimistic and pessimistic shocks. However, although this contribution one of the limitation is to incorporate observations describing the individual investor sentiments such as those issued from the AAII and II indicator weekly published by the American Association of Individual Investor.

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