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Market Sentiment and Stock Market Volatility: Evidence from Tehran Stock Exchange

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Abstract
This study aimed to evaluate the significance and severity of the relationship between market sentiment and the volatility of the Tehran Stock Exchange Price Index (TEPIX). We drew on the principal component analysis (PCA) to provide a composite sentiment index using a set of proxies. In addition, ARIMA-E-GARCH hybrid models were applied to model the volatility of the TEPIX and other control variables. Subsequently, GLS regression was used to measure the impact of market sentiment and the control variables variation on the volatility of the TEPIX. The findings showed that the influences of optimistic and pessimistic sentiment on the volatility of TEPIX were both statistically significant and respectively, negative and positive. However, the severity of these negative and positive effects was slight. Furthermore, we found that the stock exchange volatility was highly affected by the volatility of the inflation and the liquidity much more than the other variables such as optimistic and pessimistic sentiment.

Keywords: market sentiment, noise trading, stock volatility, behavioral finance, Tehran Stock Exchange Price Index.

JEL Classification: C10, G12, G40, G41.

1. Introduction

Perfect market and rationality are usually considered as the main assumptions of modern finance. According to the efficient market hypothesis (Fama, 1970), all information is immediately reflected in stock prices, and traders are expected to behave rationally. However, the real facts may not be compatible with these presumptions. The rationality of investors is an important presumption that is often questioned by behavioral finance studies. It is observed that investors are irrational and exposed to different biases (e.g., Kahneman & Tversky, 1979). In classical finance, the effect of sentiment on the market is ignored, and it is claimed that in highly competitive markets, irrational trading activities such as attention to signals that are not related to the economic fundamentals will be quickly eliminated through arbitrageurs (Barbris Barberis & Thaler, 2003; Shleifer & Vishny, 1997).

Over the past few decades, the existence of anomalies, excessive volatilities, and bubbles have raised doubts about the efficient market hypothesis. Some behavioral financial scholars have proved the existence of irrational traders in the financial markets, causing the market's deviation from efficiency. These irrational traders are known as noise traders (Herve et al., 2019). This approach is based on two primary presumptions. First, all traders are not

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completely rational and their financial decisions are affected by opinions or sentiments that may not be completely consistent with fundamental data and these cognitive biases and sentiments affect their preferences for choosing some stocks (Dimic et al., 2018; Kapoor & Prosad, 2017; Shefrin & Statman, 1984). As such, these noise traders may base their trades on sentiment instead of information, but their perception is that they have valuable information to make a profit in the market (Black, 1986). Second, there may be restrictions on arbitrage (Chu et al., 2017; Lin et al., 2019 2018; Shleifer & Summers, 1990). DeLong et al. (1990) explained that the unpredictability of noise traders' behavior could cause restrictions for arbitrage. In the behavioral finance literature, the presence of more volatility may indicate more noise traders in the market and less willing or able arbitrageurs to position against them, leading to a decrease in the efficiency of the market pricing system.

Shleifer and Summers (1990) discussed the effects and consequences of noise traders in the financial markets in detail and stated that investor sentiment plays a major role in understanding various anomalies in financial markets. Brown (1999) believed that the trading behavior of noise traders is connected to the market-wide sentiment. Noise traders are more likely to participate in financial markets during periods of high sentiment and optimism because they consider noise and sentiment instead of fundamental information and trade (Shen et al., 2017)

There are several ways to define investor sentiment. Sentiment is characterized as an investor's general attitude toward specific financial assets or financial markets that is not really based on the fundamental facts (Antoniou et al., 2015). Market sentiment is additionally known as 'investor sentiment,' and it is not necessarily predicated based on the fundamentals. Baker and Wurgler (2006) interpreted it as the tendency to speculate on an asset or the overall optimistic or pessimistic attitude that traders have about the asset. Furthermore, Baker and Wurgler (2007) explained investor sentiment as an opinion and an attitude, usually affected by feelings about future cash flows and risks that are not in accordance with realities and fundamental data. In addition, Yung-Chou Lei (2005) stated that investor sentiment is defined as the appetite of irrational traders (compared to rational traders) to an asset.

The relationship between sentiment-based noise trading activities and stock market volatilities may have implications for traders and policymakers. In standard asset pricing models, it's presumed that the risk is only attributed to the fundamental components. Nevertheless, the excessive volatility of financial markets led by increased sentiment-based noise trading can create movements in risk that are not justifiable with movements in the fundamental factors (Nasiri et al., 2021; Rupande et al., 2019).

This study investigates the connection between investor sentiment and volatility on the Tehran Stock Exchange Price Index (TEPIX). It is hypothesized that noise trader behavior driven by investor sentiment enhances the price volatility on Tehran Stock Exchange.

This study contributes to the empirical literature in three dimensions. First, this study examines the relationship between investor sentiment and volatility in a new financial market (Tehran Stock Exchange). Second, it measures the effect of investor sentiment categories (optimistic and pessimistic) on the volatility of the TSE separately. Third, new sentiment proxies (both individual and institutional) are introduced to derive the sentiment index.

The remainder of this paper is structured as follows. Section 2 provides a literature review on market sentiment and its relationship with volatility. Section 3 illustrates the research hypotheses, variables, and research models. Section 4 explains the empirical results and the robustness checks. Section 5 discusses the findings and draws conclusions.

2. Literature Review

2. 1. Market Sentiment Measure

In extensive studies on measuring market sentiment and its effect on financial markets, a variety of sentiment measures and indices have been used, and there does not exist a single comprehensive investor sentiment measure. Measures related to sentiment can be classified into two common categories, namely direct and indirect. Direct indicators explore expectations and feelings of traders in a particular group such as individual traders or newspaper and newsletter writers about the market. These direct or survey sentiment indicators seek to gain insights into the future of irrational traders by asking investors about their optimism. The USB/Gallup Index and the Investor Sentiment Intelligence Index are survey indicators that are designed, respectively, based on a survey of individual investors and financial newsletter writers. Brown and Cliff (2004, 2005) used the “bull-bear” spread, defined as the percentage of stock investment newsletters known to be bullish minus the percentage considered by Investors’ Intelligence as bearish.

Indirect indices interpret the expectations of traders in a particular group by analyzing market data that reflect that group’s behavior. The Principal Component Analysis (PCA) is the most common method to provide an indirect measure of investor sentiment from several indirect indicators utilized in the studies of Glushkov (20052006), Baker and Wurgler (2006), Ling et al. (2010), Beer and Zouaoui (2013), Chen et al. (2013), Doojin et al. (2017) and Pei-En (2019). The first principal component, which provides maximum common variation, is used as a single measure of sentiment.

Many studies have used indirect methods to calculate the sentiment index. Some have measured the sentiment index for a single stock (Doojin et al., 2017), while many other studies have tried to calculate the sentiment index for the whole market (Baker & Wugler, 2006, 2007; Chuangxia et al., 2014; Ling et al., 2010; Mazviona, 2015; Pei-En, 2019).

The range of indirect proxies used to measure the sentiment index is extensive. In this regard, Baker and Wurgler (2006) extracted a sentiment index through a linear combination of six indirect proxies, including the closed-end fund discount, the NYSE share turnover ratio logarithm, the number of IPOs, the average first-day return on IPOs, the ratio of equity issues to total issues, and the dividend premium defined as the log difference of the average market-to-book ratios between corporations that pay dividend and do not pay it. In addition, Chuangxia et al., (2014) selected indirect proxies of CEFD, RIPO, NIPO, the number of new investor accounts for shares (NIA), and Shanghai share turnover (TURN). Furthermore, Chowdhury et al. (2014) used five proxies, including TRIN index (TRading INdex, also known as Arms Index), trade volume, number of IPOs per month, number of BOs (Beneficiary Owners) account changes, and moving average. In addition, considering conditions and constraints of the Korean market, Doojin et al. (2017) used four sentiment measures including Relative Strength Index (RSI), Psychological Line Index (PLI), the logarithm of Trading Volume (LTV), and Adjusted Turnover Rate (ATR).

Some studies have also used a combination of direct and indirect methods to calculate the sentiment index. For example, Beer and Zouaoui (2013) focused on two direct sentiment proxies and four indirect sentiment proxies. Therefore, they constructed a composite index using principal component analysis from six sentiment proxies, including the Investors’ Intelligence spread Bull-Bear (II), University of Michigan’s Consumer Confidence Index (UMI), the net new cash flows of the US equity mutual funds (FLOW), the closed-end fund discount (CEFD), first-day returns on IPOs (RIPO), and the number of IPOs in every month (NIPO). Aziz Khan and Ahmad (2018) also used a direct sentiment index called

Google Search Volume Index (GSVI) and nine indirect proxies, including NIPO, CEFD, Advance–Decline Ratio (AVDC), Dividend Premium, Interest Rate, Price–Earnings Ratio (PE), Turnover, Money Flow Index (MFI), and Relative Strength Index (RSI).

Trading volume is one of the most common proxies employed in sentiment studies of Baker and Wurgler (2006, 2007), Chowdhury et al. and Rahman (2014), and Mazviona (2015). By analyzing trading data of individual investors, Barber et al. (2006) found that individual investors purchase and sell stocks in a regular manner, which is compatible with the systematic sentiment. In addition, Black (1986) stated that noise traders, regardless of their adverse impact on the price discovery mechanism, are a necessary factor for increasing market liquidity. He discussed in more detail that because of noise, trading in financial markets becomes possible; thus, if we stop noise trading, the trading volume is significantly reduced. On the other hand, he stated that the noise is a reason for the imperfection of financial markets. Likewise, Wang (2009) found that speculative noise trading increases liquidity, but it makes prices less efficient. As buying and selling of noise traders influence stock markets, the trading volume is expected to be linked with the noise in the financial market. Furthermore, Baker and Stein (2004) believed that a high level of liquidity is a sign of the extensive presence of irrational traders in the market. In other words, a rise in trading volume represents an increase in investor sentiment. In addition, Simon and Violet (2015) and Liu (2015) claimed that sentiment, as a symptom of noise, has a relationship with trading volume. Thus, an increase in liquidity triggers an increase in sentiment. On the other hand, Dunham and Garcia (2021) concluded that the direction of the sentiment-liquidity relationship depends on the sentiment measure they use. They showed that an increase (a decrease) in investor sentiment measured by Twitter content results in a decrease (an increase) in the average firm's share liquidity, but an increase (a decrease) in news sentiment results in an increase (a decrease) in the average firm's share liquidity.

2.2. Market Sentiment and Volatility

There is a large body of literature describing the impact of noise traders or investor sentiment on the stock markets, and the results of these studies show that the excess volatility of stock markets can be explained by the sentiment. Authors such as Podolski et al. (2009), Chuang et al. (2010), Uygur and Taş (2012), Bahloul and Bouri (2016), and Ya'Cob (2019) investigated the relationship between investor sentiment and stock return volatility in different countries. Some studies concluded that sentiment-motivated investors are ineffective (Black, 1986), some showed their positive effect (Tetlock, 2007), and results of other studies illustrated their negative effects on financial markets (Da et al., 2015; DeLong et al., 1990).

Sentiment drives volatility by affecting the noise trading behavior on financial markets. Models in behavioral finance show the link between stock market volatilities and sentiment-motivated noise trading activities (Black, 1986; Campbell & Kyle, 1993; DeLong et al., 1990). These models explain that the return volatility of financial markets will be widely affected by noise traders. Delong et al. (1990) believed that the existence of noise traders and arbitrage restrictions would cause excess volatility of stock prices (i.e., prices will shift more than changes justified by fundamental values). This result is compatible with the hypothesis previously proposed by Black (1986) that a rise in noise trading levels causes a rise in short-term volatility. Campbell and Kyle (1993) proposed a theoretical model for the price discovery mechanism that shows noise trading activities will result in overreacting to fundamental factors and accordingly excess volatility. Moreover, Danthine and Moresi (1993) argued that further facts and information will reduce volatility in financial markets because high information will put rational traders in a better position to interact with each other, resulting in reducing losses from noise trading. However, similar to other models, the authors believed that higher levels of noise will raise the amount of short-term volatility in the lack of new information. Similarly, Podolski et al. (2009) evaluated the link between noise trading and volatilities in daily prices. Based on Black’s (1986) study, these authors investigated whether increasing the volatility caused by the activities of noise traders creates further risk into stock prices. The results indicated that the noise traders’ activities have a significant positive effect on the volatility of daily stock prices. Furthermore, it is shown that small-cap shares are more affected by noise traders, as there are more arbitrage restrictions in these stocks. Maitra and Dash (2017) also achieved the same result that small size stocks are more prone to the impact of sentiment in the Indian stock market. Furthermore, Naik and Padhi (2016) and Kumari and Mahakud (2016) showed that investor sentiment affects the conditional volatility of the Indian market. Kumari and Mahakud (2016) further argued that the link between the volatility of stock return and investor sentiment is permanent, suggesting that investor sentiment in the Indian stock market has a major effect in determining the level of the stock market volatility. On the other hand, Abdelhédi-Zouch et al. (2015) found the significant effect of investor sentiment in the enhancement of volatility during the 2007-2008 U.S financial crisis. This was a time with major sentiment as a result of the positive perspective on the future of financial markets. Besides, Bahloul and Bouri (2016) showed that sentiment is positively correlated with price volatility of important futures markets in the U.S. and that sentiment destabilizes these markets. By examining the behavior of the Malaysian Stock Exchange volatility during the 2008 U.S crisis, Ya’Cob (2019) found that the excess volatility of the stock market may be explained by the irrational behavior of traders.

Some studies specifically examined the effect of daily traders (as noise traders) on the volatility of financial markets. Campbell et al. (2001) argued that day trading activities may be an important factor to increase volatility, especially during the technology stocks boom. Applying an indirect indicator of sentiment based on stock message board activity, Koski et al. (2004) provided evidence to support the viewpoint that noise traders in the guise of day traders increase volatility in the NASDAQ stock market. Kyrolainen (2007) also showed a strong positive link between the trading volume of day traders and intraday volatility in stocks traded heavily on a daily basis. Furthermore, by assessing different bivariate VAR models with intraday data, Chung et al. (2009) found that more trading by day traders leads to more return volatility.

The major question of which groups – individual traders (Frazzini & Lamont, 2005; Schmeling, 2007), institutional traders (Devault et al., 2019; Hong & Stein, 2007) or both of them (Nofsinger & Sias, 1999; Verma & Soydemir, 2009) – tend to make sentiment-based decisions has not been clarified yet. Considering individual traders as noise traders, Foucault et al. (2011) discussed the relationship between noise traders and volatilities. Their research demonstrated that when short selling or purchasing on margin becomes more expensive for individual traders compared to institutional traders because of reform, the volatility of the stocks that are influenced by this reform decreases compared to the volatility of other stocks. This result proves a positive correlation between noise trading and volatility. On the other hand, Beaumont et al. (2005) suggested an extensive model that simultaneously measures the effects of individual and institutional sentiments on stock return and volatility. Utilizing indirect sentiment variables for the German stock market, the results of their study indicated that institutional sentiment has only a minor effect on conditional volatility of big-cap stocks, but individual sentiment influences conditional volatility of both big and small-cap stocks. Furthermore, Verma and Verma (2006) recognized a negative connection between noise traders and volatility. The authors applied the AAII investor sentiment index, a revised version of Brown and Cliff’s (2005) indicator, for noise trading in the shape of investor sentiment. As such, they employed the EGARCH model to test the asymmetric effects of sentiment. Verma and Verma (2006) discerned a relationship between rational and irrational sentiments of both individuals and institutions. The researchers argued that individual investor sentiment responds to institutional investor sentiment but not vice versa. Furthermore, they concluded that irrational sentiment has a highly negative connection with volatility. Based on Brown and Cliff's (2005) study, Kurov (2008) also stated that strong investor sentiment negatively affects the monthly and weekly volatility of the futures market. Noise traders may have the most significant impact on financial markets' volatilities in the short term, while the liquidity they provide will mitigate any influence on volatility in a longer period.

In many studies, the GARCH family models were utilized to measure the relationship between sentiment and volatility. Lee et al. (2002) used a GARCH-in-mean model to measure the influence of sentiment on return and volatility. It was found that shifts in the sentiment level are adversely related to the market conditional volatility, which indicates if traders have become more pessimistic (or optimistic) and volatility has increased (or decreases). Moreover, Chuang et al. (2010) utilized a generalized autoregressive conditional Heteroskedasticity in the mean (GARCH-M) model and showed that changes in trading volume, as an indicator of market sentiment, have a considerable effect on the volatility of the Taiwan Stock Exchange. Periods of optimistic sentiment have enhanced trading volume and market volatility, indicating the wider presence of noise traders in financial markets during high sentiment periods. Further, Uygur and Taş (2012) presented a structure to model conditional volatility in which the impact of noise trader demand shocks on the volatility of stock exchange indices of the different countries was measured. Some GARCH family models – namely, GARCH, the exponential GARCH (EGARCH), and the threshold GARCH (TGARCH) – were employed to investigate whether earning shocks affect more the conditional volatility during high sentiment times. The investor sentiment measure applied in this study uses short-term data of trading volume, and notable evidence showed that volatility in market indices is asymmetric, indicating earning shocks have more effect on conditional volatility when increasing the sentiment. Rahman et al. (2013) similarly tested the effect of noise trading motivated by sentiment on expected returns and volatility of the stock exchange of Bangladesh. Empirical outputs based on a GARCH-in-mean model indicated that changes in investor sentiment affect the stock returns and volatility. Yu et al. (2014) used GARCH-M and TARCH-M models to investigate the impact of sentiment on the risk-return relationship in the stock market of Taiwan. Employing Consumer Confidence Index as a measure of sentiment, they provided evidence of a positive connection between the mean and the variance in low sentiment times.

However, it seems that the effect of investor sentiment on the volatility depends on whether investor sentiment is optimistic or pessimistic, indicating that sentiment-volatility relationship is asymmetric (Aydogan, 2017; Kumari & Mahakud, 2016 2015; Piccoli et al., 2018; Schneller et al., 2018; Smales Lee, 2016). Some scholars such as Lee et al. (2002), Chi and Zhuang (2011), Lu and Lai (2012) and Chuangxia et al. (2014) classified investor sentiment into two categories of optimistic and pessimistic sentiment to examine the effect of each of them on the return or volatility of stock market. Optimistic sentiment periods lead to lower volatility, whereas in pessimistic sentiment periods, there is more uncertainty and, thus, more volatility (DeLong et al., 1990). Moreover, the inefficiency of financial markets and arbitrage limitations permit variables related to uncertainties to form more volatile markets, and when sentiment is pessimistic, the volatility intensifies (Aydogan, 2017; Lee et al., 2002; SmalesLee, 2016; Yu & Yuan, 2011).

Based on the theoretical and experimental literature, the purpose of this research was to examine the linkage between market sentiment (both optimistic and pessimistic) and the volatility in Iran Equity Market with a broader sentiment index. Accordingly, it aimed to verify the following hypotheses in Tehran Stock Exchange:

H1: There is a positive and significant relationship between optimistic sentiment and volatility of Tehran Stock Exchange Price Index.

H2: There is a positive and significant relationship between pessimistic sentiment and volatility of Tehran Stock Exchange Price Index.

3. Data Description and Methodology

In this research, monthly related and available data from the Tehran Stock Exchange website[1] and Economic Trends of Central Bank[2] of the Islamic Republic of Iran from March 2011 to February 2017 were used.

3.1. Variables

In the following sections, the main variables of this study are described.

3.1.1. Sentiment Proxies and Variables

Seven indicators, considering the limitations to access market data and conditions of Iran stock market were adopted to indirectly measure a composite sentiment index in Tehran Stock Exchange based on the principal component analysis (PCA) method. Some studies, such as Chakravarty (2001) and Kurov and Lasser (2004), have suggested that individual traders fall into noise traders, while institutional investors are informed traders. However, other studies such as Willman et al. (2006) and Podolski et al. (2009) have found that institutional traders, such as fund managers and portfolio managers, do not always act rationally and are often involved in noise trading activities. Therefore, in this research, five proxies related to individual traders and two proxies related to institutional traders were applied. Sentiment proxies related to individual traders were: (1) individual trading volume (Vs), (2) online trading volume (Vo), (3) the number of active investor accounts for shares (NAC), (4) average first-week returns on IPOs (RIPO), and (5) new cash flows inputs of equity mutual funds (NIPO). Sentiment proxies, used as institutional sentiment proxies, were: (1) the proportion of shares in the portfolio of mutual funds and ETFs (Sf) and (2) trading volume of mutual funds, ETFs, and portfolio management companies (Vf).

3.1.2. Control Variables

Each sentiment proxy would likely include a sentiment (noise) portion and a fundamental portion that is not related to sentiment (Baker & Wugler, 2006). Several control variables were selected to eliminate these fundamental effects in measuring sentiment. These control variables were also used in this study to measure volatility. These variables included inflation, Brent oil price, gold coin price (Iranian Bahar Azadi Gold Coin), liquidity, and Iranian Rials (IRR) exchange rate (Rials/dollars Rate).

3.1.3. Tehran Stock Exchange Price index (TEPIX)

Since March 1990, the TEPIX index has been published. It includes all companies of the Tehran Stock Exchange. TEPIX represents the general trend of the prices among the stock exchange companies, and it is affected by the price changes. Note that TEPIX does not

1. https://www.tse.ir
2. https://www.cbi.ir/category/EconomicTrends_en.aspx

indicate the amount of dividends paid to shareholders. However, this index is comprehensive, balanced, and accessible. As can be seen in Figure 1, the stock market price index has experienced ups and downs during 2011-2017.

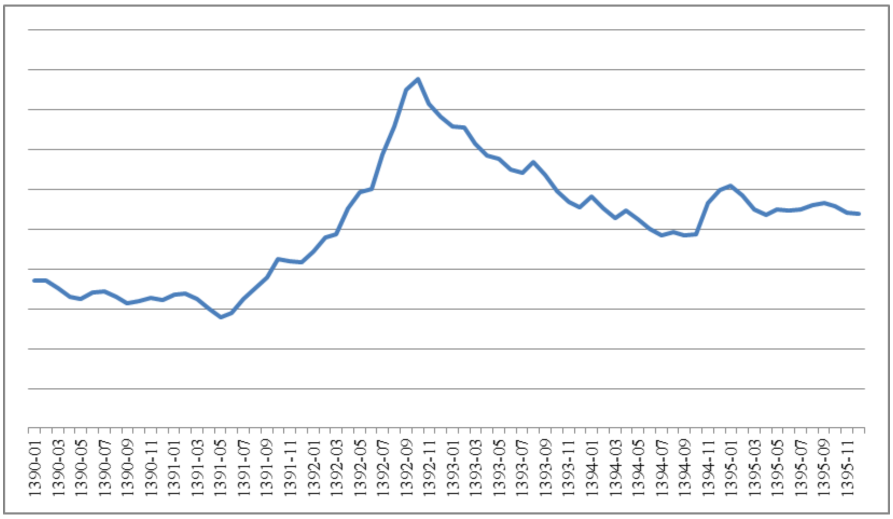

Figure 1. the Tehran Stock Exchange Price Index During the Period 2011 to 2017;t6

3.2. Methodology

Similar to some previous studies (e.g., Beaumont et al., 2005; Podolski et al., 2009; Wang, 2009), this study investigated the effect of noise traders on excess volatility of the stock prices in the Tehran Stock Exchange. This section also contains several steps that will be described below.

3.2.1. Principal Component Analysis (PCA)

In this study, the market sentiment index was indirectly measured based on market data by the method of Principal Component Analysis (PCA), which has been widely applied in the sentiment studies, including Glushkov (20062005), Baker and Wurgler (2006), Ling et al. (2010), Beer and Zouaoui (2013), Chen et al. (2013), Doojin et al. (2017) and Pei-En (2019). In this method, a group of correlated variables is transformed into a smaller group of uncorrelated variables named principal components. The first principal component (PC), which provides maximum variance, is used as a measure of sentiment.

3.2.2. Hybrid Model of ARIMA- E-GARCH

To measure the volatility of the stock price index and other control variables, the hybrid model of ARIMA and E-GARCH with a two-phase procedure was used. This hybrid model, integrating an ARIMA model with GARCH error items, is used to evaluate the univariate series and to estimate the values of approximation series (see Bollerslev & Wooldridge, 1992; Chen et al., 2011; Liu & Shi, 2013; Tan et al., 2010; Zhou et al., 2006). In the first step, the most fitting ARIMA model is employed to model the linear data of time series. ARIMA model is estimated by determining the order of the model using the Box-Jenkins method (1976), which is a repetitious method involving four stages of identification, estimation, diagnostic checking, and forecasting. In the second phase, the EGARCH conditional variance heterogeneity model is used to model the nonlinear patterns of the residuals of ARIMA models and derive volatility of stock price index and other control variables. In this procedure, the error term ε_t of the ARIMA model follows a GARCH process of orders p and q. Because financial data is highly marked by high volatility, the ARCH impact of each model, i.e., the existence of conditional heteroscedasticity, must be checked (Mahesh, 2005). The EGARCH model (p, q) is calculated as Equation (1):

$$log\left(\sigma_t^2\right)=\omega+\sum_{j=1}^{q}\beta_j\ log\left(\sigma_{t-j}^2\right)+\sum_{k=1}^{r}\gamma_j\ \frac{\varepsilon_{t-1}}{\sigma_{t-1}}+\sum_{i=1}^{p}\alpha_j\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|+v_t \quad (1)$$

Three interesting characteristics of the EGARCH model are:

1. The conditional variance equation has a logarithmic-linear form. Although $\log(\sigma_t^2)$ is large, the amount of σ_t^2 cannot be negative. Hence, the coefficients are allowed to be negative.
2. As an alternative to utilize the amount of $\varepsilon^2{}_{t-1}$, this model uses the standardized amounts ε_{t-1} (ε_{t-1} divided by σ_{t-1}). Nelson (1991) showed that this standardization enables a better interpretation of the amount and persistence of the shocks.
3. The EGARCH receives the leverage effect. If $\varepsilon_{t-1}/\sigma_{t-1}$is positive, the shock's effect on the conditional variance logarithm will be equal to $\alpha_1 + \lambda_1$. If $\varepsilon_{t-1}/\sigma_{t-1}$ is negative, the shock's effect on the conditional variance logarithm will be equal to $-\alpha_1 + \lambda_1$.

The methodology of this hybrid approach is demonstrated in Figure 2

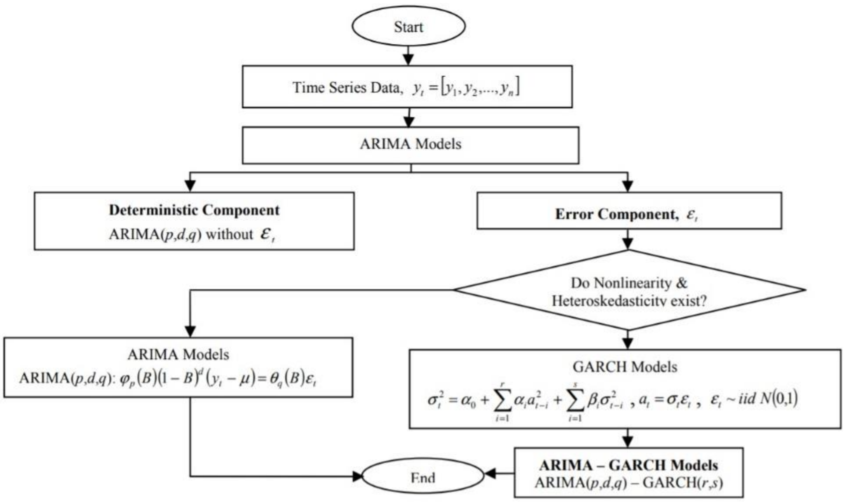

Figure 2. Flowchart of Hybridization Protocol for Box-Jenkins and GARCH Models Adapted From Yaziz et al. (2013)

3.2.3. Generalized Least Square (GLS) Regression

Finally, to measure the effect of sentiment index and control variables volatility on the volatility of the Tehran Stock Exchange price index, Generalized Least Square (GLS) regression was applied. Generalized or weighted least squares regression is a modification of the ordinary least squares, which takes into account the inequality of variance in the observations.

4. Empirical Results

To determine the stationarity of the data, the KPSS unit root test was applied. The null hypothesis of this test indicated the absence of a unit root, showing that the variables were stationary. The results of this test presented in Table 1 show that all variables have been stationary. In addition, the descriptive statistics of the variables are shown in Table 2.

Table 1. Results of KPSS Unit Root Test (Data Source: Author's Calculations)

Variable	Test statistic	Critical values		
		1% Level	5% Level	10% Level
Log (VO)	0.4622	0.7390	0.4630	0.3470
Log (VS)	0.1077	0.2160	0.1460	0.1190
Log (VF)	0.0896	0.2160	0.1460	0.1190
Log (P)	0.443	0.74	0.46	0.35
Log (CPI)	0.5385	0.7390	0.4630	0.3470
Log (EXR)	0.3754	0.7390	0.4630	0.3470
Log (PGOLD)	0.3305	0.7390	0.4630	0.3470
Log (LIQ)	0.1350	0.2160	0.1460	0.1190
Log (POILB)	0.4413	0.7390	0.4630	0.3470
OPTNEW	0.1295	0.7390	0.4630	0.3470
PESSNEW	0.1208	0.7390	0.4630	0.3470
OPTEM	0.1481	0.7390	0.4630	0.3470
PESSEM	0.1126	0.7390	0.4630	0.3470
GCPI*	0.2372	0.7390	0.4630	0.3470
GLIQ*	0.2497	0.7390	0.4630	0.3470
GGOLDOLD *	0.3438	0.7390	0.4630	0.3470
GPOILB*	0.1088	0.2160	0.1460	0.1190
GEXR*	0.2671	0.7390	0.4630	0.3470

Note:*" "shows GARCH model of control variables.

Table 2. Summary on the Descriptive Statistics of the Selected Variables (Data Source: Author's Calculations)

Variable		Mean	Std. Dev.	Min	Max	Kurtosis	Skewness
LOG(P)	TEPIX	10.110	0.306	9.588	10.647	1.784	-0.152
LOG (VS)	Trading volume (Vs)	-0.797	0.293	-1.687	-0.203	3.443	-0.710
LOG(VO)	Online trading volume	-1.739	0.598	-3.102	-0.957	2.069	-0.632
LOG(VF)	Trading volume of mutual funds, ETFs, and portfolio management companies	-4.184	0.485	-5.210	-2.991	2.847	0.169
LOG (CPI)	Consumer Price Index	5.125	0.321	4.531	5.523	1.868	-0.550
LOG (LIQ)	Liquidity	15.558	0.421	14.896	16.274	1.765	0.075
LOG (EXR)	Iranian Rials (IRR) exchange rate	10.207	0.374	9.319	10.519	3.120	-1.296
LOG (PGOLD)	Iranian gold coin price	9.103	0.285	8.280	9.520	3.866	-1.075
LOG (POIB)	Brent Oil price	4.393	0.416	3.503	4.846	1.874	-0.717

4.1. Measuring Sentiment

It is noted that sometimes sentiment may be due to some changes in fundamental components (Baker & Wurgler, 2006, 2007). Therefore, to purify the sentiment and eliminate the effects of fundamental and non-sentiment-related components, the ARIMA time series model for each of the extracted sentiment proxies was run, albeit after seasonal adjustment and eliminating the seasonal calendar effects (Table 3 shows ARIMA models of selected variables). Error term (ε_t) of each ARIMA model was considered as pure sentiment proxy. The logarithm of variables was used for time series models of sentiment indicators – excluding RIPO – which have positive and negative values. Box–Jenkins method was used to find the best fit of an ARIMA time-series model to historical values of a time series. Next, the error terms of the ARIMA model of sentiment proxies were applied to measure principal component analysis, and the first component was considered as composite sentiment index (Figure 1). The criterion for determining the first component as Sentiment Index was the eigenvalue (percentage of the variance of the first component) and the factor loadings (coefficients) of the variables in the first component. Seven variables were entered into the model. Then, after analyzing the model based on the above criteria, three variables, including Vo, Vs, and $V_{f,}$ remained in the final composite sentiment index.

Table 4 shows the percentage of total variance explained by the extracted components. According to the data in this table, the eigenvalue of PCA1 as the composite sentiment index would explain 71.37% of the total variance, which is a desirable value.

As Table 5 shows, all factor loadings (coefficients) of the first component are above 0.6.

Table 3. Results of Estimating ARIMA Models for Final Sentiment Proxies Through PCA Model (Data Source: Author's Calculations)

Variable	Coefficient	Standard deviation	T-student	Probability
Estimation of ARIMA model for VO				
C	-2.0142	0.6639	-3.0337	0.0034
AR(1)	0.9886	0.0234	42.301	0.000
MA(1)	-0.4854	0.1095	-4.4314	0.000
SIGMASQ	0.0499	0.0087	5.7380	0.000
Estimation of ARIMA model for VS				
C	-0.8053	0.1549	-5.1990	0.000
AR(1)	0.9348	0.0620	15.0766	0.000
MA(1)	-0.6039	0.1417	-4.2620	0.0001
SIGMASQ	0.0423	0.0061	6.9252	0.000
Estimation of ARIMA model for VF				
C	-4.161	0.118	-35.248	0.000
AR(1)	0.597	0.077	7.779	0.000
SIGMASQ	0.146	0.023	6.47	0.000

Table 4. Total Variance Explained (Data Source: Author's Calculations)

Component	Eigenvalues		
	Variance	% of Variance	Cumulative % of variance
1	2.141	71.366	71.366
2	0.708	23.610	94.976
3	0.151	5.024	100.00

Table 5. Coefficients (Factor Loading) of Variables in the First Component (Data Source: Author's Calculations)

Variables/ indicators	EVF	EVO	EVS
Factor loading of the first component	0.66	0.916	0.661

Thus, the final composite sentiment index through the Principal Component Analysis (PCA) is as follows:

$$SENT_i = 0.916EVO + 0.929EVS + 0.661EVF \quad (2)$$

Some scholars such as Lee et al. (2002), Chi and Zhuang (2011), Lu and Lai (2012) and Chuangxia et al. (2014) have classified investor sentiment into two categories of optimistic and pessimistic sentiment to examine the effect of each of them on the return or volatility of stock market. In this step, the sentiment index was classified into two modes: optimistic (OPTNEW) and pessimistic (PESSNEW) sentiments and in the following, the effect of these two modes of sentiments on volatility of the price index of Tehran Stock Exchange would be measured separately. The separation method was based on the positive or negative sign of monthly values of sentiment index, where positive values indicated optimistic sentiments and negative values indicated pessimistic sentiments.

4.2. Modeling the Volatility of Tehran Price Index (TEPIX) and other Control Variables

After making sure that the time series were stationary, to estimate the EGARCH model for each of the mentioned variables, the conditional mean of each time series needed to be estimated. The fit pattern for the time series of each variable was estimated using Box-Jenkins method (1976). Analyzing predicted autocorrelation and partial autocorrelation function (ACF, PACF) determined the model of the conditional mean value. The ARMA (p, q) models validation was dependent on the minimization of the parameters for AIC (Akaik's information criterion) and BIC (Schwarz's information criterion). The EGARCH model runs on the residual of each ARIMA model. Table 6 shows the conditional mean and variance equations of price index of Tehran Stock Exchange, inflation, Brent oil price, gold coin price (Iranian Bahar Azadi Gold Coin), liquidity, and Iranian Rials (IRR) exchange rate (Rials/Dollars Rate), respectively. All EGARCH coefficients are significant at the assumed probability levels. In addition, the results of ARCH Autoregressive Conditional Heteroskedasticity test on EGARCH models residuals showed the absence of ARCH effect on the residuals of the models, which are presented in Table 7.

Table 6. Estimation of the ARMA–GARCH Model of TEPIX & Control Variables (Data Source: Author's Calculations)

	Variable	$\boldsymbol{\alpha_0}$	**AR(1)**	**MA(1)**	**MA(2)**
Conditional mean equation of log (P)	Coefficient	9.5925*	0.9676*	0.5834*	0.1996*
	Std. Dev.	0.000000067	0.02222	0.03224	0.05363
Conditional variance equation of log (P)	Variable	β_0	$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	$\varepsilon_{t-1}/\sigma_{t-1}$	$\log(\sigma_{t-1}^2)$
	Coefficient	-1.1464*	-0.8899*	0.2003*	0.7098*
	Std. Dev.	0.0031	0.02	0.0697	0.0005
Conditional mean equation of log (CPI)	Variable	α_0	*AR(1)*	*AR(2)*	*MA(1)*
	Coefficient	6.8607	1.7721*	-0.7738*	-0.4163*
	Std. Dev.	0.2090	0.000	0.000	0.0773
Conditional variance equation of log (CPI)	Variable	β_0	$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	$\varepsilon_{t-1}/\sigma_{t-1}$	$log(\sigma_{t-1}^2)$
	Coefficient	-1.6616	-0.4984 **	0.5732 *	0.8066*
	Std. Dev.	0.6896	0.1959	0.1449	0.0637
Conditional mean equation of log (EXR)	Variable	α_0	*AR(1)*	*MA(1)*	
	Coefficient	10.8077*	0.98050*	0.3716**	
	Std. Dev.	0.4332	0.0056	0.1472	
Conditional variance equation of log (EXR)	Variable	β_0	$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	$\varepsilon_{t-1}/\sigma_{t-1}$	$log(\sigma_{t-1}^2)$
	Coefficient	-1.9439	0.7229**	0.2802	0.7841*
	Std. Dev.	0.4043	0.3617	0.1799	0.0577
Conditional mean equation of log (PGOLD)	Variable	α_0	*AR(1)*	*MA(1)*	*@Trend*
	Coefficient	8.5088	0.9670*	0.2302**	0.0124*
	Std. Dev.	0.0679	0.0251	0.1004	0.0018
Conditional variance equation of log (PGOLD)	Variable	β_0	$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	$\varepsilon_{t-1}/\sigma_{t-1}$	$log(\sigma_{t-1}^2)$
	Coefficient	0.0351	-0.3412*	0.1953***	0.9643*
	Std. Dev.	0.1101	0.1172	0.1043	0.000
Conditional mean equation of log (LIQ)	Variable	α_0	*AR(1)*	*MA(1)*	*@Trend*
	Coefficient	14.8489	0.8659*	-0.1567*	0.0211*
	Std. Dev.	0.0020	0.0246	0.0467	0.0018
Conditional variance equation of log (LIQ)	Variable	β_0	$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	$\varepsilon_{t-1}/\sigma_{t-1}$	$log(\sigma_{t-1}^2)$
	Coefficient	-2.1625	-0.5875***	-0.6317*	0.7380*
	Std. Dev.	0.9412	0.3325	0.1832	0.1078
Conditional mean equation of log (POILB)	Variable	α_0	*AR(1)*	*AR(2)*	*MA(1)*
	Coefficient	4.4689	0.1564*	0.7854*	0.9857*
	Std. Dev.	0.1965	0.0344	0.0252	0.0045
Conditional variance equation of log (POILB)	Variable	β_0	$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	$\varepsilon_{t-1}/\sigma_{t-1}$	$log(\sigma_{t-1}^2)$
	Coefficient	-3.2349	-0.5565**	-1.2478*	0.3669*
	Std. Dev.	0.6272	0.2619	0.1849	0.1369

Note: *, **, *** show significance at 1%, 5%, and 10% probability level, respectively.

Table 7. Results of ARCH Test for E-GARCH Models (Data Source: Author's Calculations)

E-GARCH models	nR^2 statistic	F statistic
GP	0.2930 (0.5883)	0.2858 (0.5947)
GCPI	0.011097 (0.9161)	0.010772 (0.9177)
GLIQ	0.1186 (0.731)	0.1153 (0.7353)
GEXR	0.112709 (0.7371)	0.109576 (0.7417)
GPGOLD	0.1964 (0.6576)	0.19116 (0.6634)
GPOIL	0.001 (0.9746)	0.000 (0.9751)

Note: The numbers in the parentheses indicate the probability level.

4.3. The Effect of the Investor Sentiment on Volatility of the Tehran Stock Exchange Price Index

To measure the effect of traders' optimistic and pessimistic sentiments on the volatility of the Tehran Stock Exchange Price Index, a generalized least squares method was used. Table 8 shows regression results, where the dependent variable in each model is the volatility of the price index of Tehran Stock Exchange and independent variables include the volatility of competing markets as control variables and sentiment index. The results show that the effect of optimistic sentiment on the volatility of the Tehran Stock Exchange Price Index (TEPIX) is negative and it is significant at 1% level. This finding indicates that the optimistic sentiment decreases the volatility of the stock price index, although the severity of this negative effect is slight. In addition, the volatility of inflation and liquidity has a positive and significant effect on the volatility of the stock market. The amount of inflation and liquidity coefficients show that the effect of these two variables on the volatility of the stock price index is considerable. In general, the above model explains that the volatility of the stock market is more influenced by the volatility of other markets than by optimistic sentiment.

The effect of pessimistic sentiment on the volatility of the stock price index is positive and significant, that is, the increase in pessimistic sentiment leads to an increase in the stock market volatility, although the coefficient value shows a slight effect. In addition, the effect of inflation and liquidity volatility on stock market volatility is positive and significant. The coefficients indicate that the stock market volatility is highly influenced by inflation and liquidity volatility. This influence is higher than the effect of other variables, including pessimistic sentiment.

Table 8. Results of GLS Model to Test the Effect of the Market Sentiment and Other Control Variables Volatility on TEPIX Volatility (Data Source: Author's calculations)

Variable	CC	OPTNEW	GCPI	GLIQ	GP(-1)
Coefficient	0.0003	-0.00022*	5.2448*	0.8437*	0.6166*
Std. Dev.	0.00003	0.00003	0.3295	0.1272	0.0440
T-statistic	9.3317	-6.5588	15.9168	6.6315	14.0012
Weighted model	R-squared	0.887	**Unweighted model**	R-squared	0.406
	Durbin–Watson statistic	1.91		Durbin–Watson statistic	2.04
Variable	CC	PESSNEW	GCPI	GLIQ	GP(-1)
Coefficient	0.0003	0.00016*	5.7937*	0.7216**	0.6273*
Std. Dev.	0.00004	0.00004	0.6511	0.3469	0.0471
T-statistic	7.3371	3.9621	8.8982	2.0799	13.3112
Weighted model	R-squared	0.8612	**Unweighted model**	R-squared	0.403
	Durbin–Watson statistic	2.04		Durbin–Watson statistic	2.01

Note: *, **, *** show significance at 1%, 5%, and 10% probability level, respectively.

5. Discussion and Conclusions

This paper provided a complementary interpretation of the noise trader approach by inspecting the effects of noise traders on the conditional volatility of the price index of Tehran Stock Exchange using the ARIMA-EGARCH model over the period 2011–2017. Similar to many previous studies (Baker & Wurgler, 2006; Chen et al., 2013; Doowon & Heejin et al., 2017; Mazviona, 2015; Pei-En, 2019), in this study, a composite sentiment index was constructed based on the market data using the method of Principal Component Analysis. Furthermore, in this study, seven sentiment variables were applied into the PCA model. After analyzing the data based on the eigenvalue (percentage of the variance of the first component) and the factor loadings (coefficients) of the variables, three variables remained in the final composite sentiment index. These variables were related to the trading volume of individual and institutional traders. Therefore, the final constructed sentiment index was consistent with the results of previous studies, and sentiment – as a signal of noise – has a relationship with trading volume (Baker & Stein, 2002; Liu, 2015; Simon & Violet, 2015). In this study, five control variables related to the other markets including inflation, liquidity, Brent oil price, gold price, and exchange rate were applied. To model the volatility of the stock price index and other control variables, the hybrid model of ARIMA and E-GARCH with a two-phase procedure was also used. Finally, to measure the effect of traders' optimistic and pessimistic sentiments on the volatility of the Tehran Stock Exchange Price Index, a generalized least squares method was applied.

The results showed that the effects of optimistic and pessimistic sentiment on the volatility of the Tehran Stock Exchange Price Index (TEPIX) are negative and positive, respectively, and both of them are statistically significant. It is confirmed that the volatility of Tehran Stock Exchange is explained by investor sentiment, but the sentiment-volatility relationship showed an asymmetric behavior. In other words, the increase in optimistic sentiment decreases the volatility of the stock price index, but the increase in pessimistic sentiment leads to an increase in the stock market volatility. These results are consistent with the findings of Lin (2009), Yang and Copeland (2014), Gang He et al. (2020), and Ferreira et al. (2021). Nevertheless, the severity of these negative and positive effects is slight. This finding is consistent with the results obtained by Haritha and Rishad's (2020) and Audrino et al. (20212020). On the other hand, the effects of inflation and liquidity volatility on stock market volatility were found to be positive and significant. In addition, the coefficients indicated that the stock market volatility is highly influenced by inflation and liquidity volatility much more than other variables, including optimistic and pessimistic sentiment. Based on the results of this research, the first main hypothesis is rejected but the second main hypothesis is confirmed.

5.1. Practical Implication

In practice, this research helps understand the role of sentiment (non-fundamental) factors and macroeconomic (fundamental) factors such as liquidity and inflation on the volatility of Iran' Equity Market Indices. In this study, there was no evidence of a significant effect of investor sentiment on the volatility of the stock price index. This result can indicate that the level of knowledge and awareness of stock market actors is appropriate and the amount of noise in transactions is low. In addition, it may show that the regulatory body has used its policy tools, such as price limits, trading halts, etc., appropriately to control volatility. Additionally, the expansion of mutual funds, ETFs, and portfolio management companies might have led to some liquidity being injected into the capital market by these financial institutions, which are affected less by sentiment. At the same time, regulators should not ignore the significant effect of the liquidity and inflation volatility on stock market volatility. They should try to firstly, control liquidity and inflation fluctuations with the right policy, and secondly, direct this liquidity towards productive markets. The accurate measurement of the effects of market sentiment helps traders, fund managers, and portfolio managers make better investment decisions. For policymakers, volatility caused by sentiment can have a negative effect on the performance of markets and the asset pricing. If the presence of sentiment-driven traders in the stock markets expands and the negative effect of sentiment is strengthened, we will witness capital outflows from the market and market instability. Therefore, policymakers have to control stock market volatility to protect investors and boost investors' confidence in the capital markets.

5. 2. Limitations and Further Research Directions

This research has also faced some limitations. First, there were restrictions on access to some data and information on selected sentiment variables. This problem was solved by a direct request from the Securities and Exchange Organization of Iran, Central Securities Depository of Iran, and Iranian Data Processing Companies, although this process was very time-consuming. Second, considering the conditions and limitations of the Iranian capital market, the use of some common sentiment variables was not appropriate for Tehran Stock Exchange. Therefore, in consultation with experts, instead of the number of new stock accounts and the return of the first day of the initial public offerings, the number of active accounts and the average return of the first week of the initial public offerings were used, respectively.

Further research is needed to measure survey sentiment index by direct method or other indirect methods and then examine its effect on the excess volatility of different stock market indices. In addition, measuring the effect of noise trading activities or market sentiment on the emergence of bubbles in financial markets is another important issue that is suggested to be addressed in the future.

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