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THE EFFECT OF INVESTOR SENTIMENT ON STOCK RETURNS IN OECD COUNTRIES[1]

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ABSTRACT

In this study, the effect of investor sentiment on stock returns in OECD countries was investigated. For this purpose, monthly data on the stock market indices, consumer confidence index, volatility index and trading volume of 17 OECD countries for the period February 2004-August 2021 were used. Interest rate was added to the model as a control variable. Panel data analysis results showed that there is a long-term relationship between investor sentiment and stock market index. It has been determined that consumer confidence index has positive and significant effects on stock market index in both long and short term, while fear index has negative and significant effects. It was seen that trading volume and interest rate had a significant and negative effect only in the long term. In addition, it has been concluded that all variables are the granger cause of the stock market index. The results of the study show that investor sentiment affects stock prices and more successful predictions can be made about the stock index returns of OECD countries by utilizing data on investor sentiment.

Keywords: *Behavioral Finance, Investor Sentiment, OECD Countries, Panel Data Analysis, ARDL.*

JEL Codes: *C33, G40, G41.*

1. INTRODUCTION

Traditional finance theories are based on the assumption that individuals make rational and correct investment decisions by taking into account all available information in order to maximize their returns. Traditional finance theories, which for a long time formed the basis of most financial research, have been criticized by many studies in the literature. The increasing number of these studies has shown that traditional finance theories cannot adequately explain the real market performance, and that individuals are not rational but normal and are affected by their prejudices based on their beliefs (Zouaoui et al., 2011: 724). Kahneman and Tversky's (1979) study examining the effects of psychology on investment decisions and asset prices, and the prospect theory put forward, led to the emergence of the field of

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behavioral finance. Following the prospect theory, other ideas that investigate the impacts of investor psychology on financial markets have been created. These include mental accounting, herd behavior, psychological biases, and investor sentiment.

Sensitivity, in a wide sense, relates to whether someone reacts to a situation with excessive optimism or pessimism for whatever cause. Numerous studies in the psychology literature have found that people's current emotions affect their judgments about future events (Antoniou et al., 2013: 246). Studies generally indicate that individuals who experience happy emotions make optimistic decisions whereas those experiencing negative emotions tend to make pessimistic ones. (Bower, 1981; Wright and Bower, 1992).

The importance of investor sentiment was first put forward by Keynes (1936). According to Keynes, consumer and producer sentiment plays a key role in explaining economic fluctuations (Van Aarle and Kappler, 2012: 44). According to Baker and Wurgler, investor sentiment is generally beliefs about future cash flows and investment risks that cannot be verified with existing facts (Baker and Wurgler, 2007, p. 129). Similarly, Investor sentiment was described by Shefrin as "aggregate errors of investors being manifest in security prices." (Shefrin, 2008: 216). Investor sentiment represents the mood of investors at any time (Livnat and Petrovits, 2009: 1). While some researchers define investor sentiment as the tendency to trade on noise rather than information, it is used among the public to express investor optimism or pessimism. The term sensitivity also has connotations about emotions, so it is expressed in the media as investor fear or risk aversion (Zhang, 2008: 8). According to Zhang, investor sentiment is the beliefs and expectations of market participants about fundamental value (Zhang, 2008: 1). Investor sentiment is considered as the situation in which investors' beliefs about future firm valuation deviate from basic information (Cui and Zhang, 2020: 564).

The basis of investor sentiment theory is the concept "noise" which was first used by Black (1986). This concept was later theorized by De Long et al (1990). Noises affect the expectations and sentiments of investors and cause them to over- or under-estimate expected returns. For this reason, behavioral finance advocates see investor sentiment as an additional source of systematic risk that should be priced in (Brown, 1999: 88; Statman et al., 2008: 20). Because the changes in noise traders' feelings cannot be predicted, these changes are likely to affect stock prices (Verma et al., 2008: 1303).

Investor sentiment has no place in the traditional finance approach. Price changes only reflect the arrival of news about future cash flows and interest rates. However, behavioral finance, which has emerged as an alternative approach, argues that investor sentiment can significantly affect the market and therefore the equilibrium asset prices. This approach resorts to behavioral explanations that loosen the rigid rationality requirement of traditional theories to explain market anomalies. Behavioral finance has become an increasingly productive branch of research, taking into account investor sentiment and deviations from perfect rationality, investigating how this might affect asset prices and investor behavior (Zhang, 2008: 4-6).

It is reasonable to assume that investor sentiment can affect the stock market because investor sentiment has a significant impact on economic activity levels. Investors worry that the stock market will decline and they will lose money when they have pessimistic forecasts for the economy. As a result, they sell their equities, which could lead to a decline in the market. (Chen, 2011: 225). Existing research shows that investor sentiment has a critical impact on stock prices and the activities of market participants (Cui and Zhang, 2020: 564). Numerous major publications focus on the impact of investor sentiment on future stock returns (Solt and Statman, 1988; Brown and Cliff, 2005; Baker and Wurgler, 2006). The study results show that individual investors are easily influenced by emotions. Huang et al. (2015) found that the return predictability of investor sentiment is due to investors' biased beliefs about their future cash flows.

Investor sentiment, which can also be defined as being optimistic or pessimistic about expected returns, is seen as a part of investors' psychological biases. Investors do not always react proportionally to new information. Investors can overreact by buying the winning stocks and selling the losing stocks under the influence of emotional factors and cognitive beliefs. In some cases, they may over- or under-react by dealing with rumors. These reactions move prices away from their true values and may cause anomalies in financial markets. Changes in the sensitiment level of investors affect their transactions in financial markets and often prevent them from making rational decisions. As a result, investor sentiment affects the asset prices in financial markets by determining the positions taken in the markets, how long they remain in these positions, and the short and long-term trading volume (Ergör, 2017: 2). In this direction, the need to investigate the effect of investor sentiment on stock returns has emerged.

Investor sentiment or belief is important in predicting future returns as it measures the expected economic conditions that change over time and the risk aversion level of investors over time (Charoenrook, 2003: 4). The addition of the fear index (VIX) and trade volume (TV) variables as well as the consumer confidence index (CCI) representing investor sentiment and the extension of the research to OECD countries make the study unique. In addition, the study has a unique structure in terms of investigating the asymmetric causality relationships between stock returns and investor sentiment in OECD countries and separating positive-negative shocks in investor sentiment.

Investor sentiment, which affects the future decisions of investors, cannot be observed directly because it is a behavioral situation. Studies examining the effect of investor sentiment on financial markets in the literature have used direct representatives such as surveys and confidence indices, as well as market-based representatives such as trading volume and trading rate. In this study, consumer confidence index and fear index, which directly represent investor sentiment, and transaction volume, which is indirect representative of investor sentiment, are used together.

2. LITERATURE REVIEW

The relationship between changes in investor sentiment and stock prices was first investigated by Otoo. Otoo (1999), in his study covering the period 1980: 6 - 1999: 6, aimed to explain whether the change in stock prices has a significant effect on consumer confidence or not. In the study, regression and simple VAR analysis were applied to monthly data of Michigan Investor Sentiment Index and Wilshire 5000 stock price index. The results of the analysis showed that the increase in stock prices has a positive effect on consumer confidence. It has been concluded that consumers may tend to use the movements in stock prices as a leading indicator for the future. Schmeling (2009), as a representative of investor sentiment, examined whether consumer confidence affects expected stock returns in 18 industrial countries for the period 1985: 1- 2005: 12. In the study, using the Granger causality test, it was determined that investor sentiment has a significant effect on total stock returns on average. Hsu et al. (2011) investigated the causality relationship between stock market index (SMI) and consumer confidence index using a panel data set consisting of 21 countries covering the period of January 1999-December 2007, using the Granger causality test and the CCMEG estimator. The analysis's findings demonstrated that the consumer confidence index and the stock market index are causally related in both directions. According to Hsu, the relationship between the consumer confidence index and the stock market index is that if consumers think that the economy will improve in the future, they will likely invest in the stock market. Chen (2011) looked into the asymmetric effects of consumer confidence in bear-bull markets as well as the relationship between low consumer confidence and stock returns during market fluctuations. Consumer confidence was measured in the study between January 1978 and May 2009 using monthly data from the SandP 500 index and monthly data from the University of Michigan Consumer Sentiment Index. The results of the study showed that consumer sentiment is important for stock returns. He found substantial and robust evidence that low confidence does, in fact, have an asymmetrical effect on stock returns. He concluded that greater market pessimism caused the market to remain in a bear regime for longer, while a higher lack of confidence had indeed pushed the stock market into bear territory. Pathiwasam (2011) examined the relationship between trading volume and stock returns. The sample of the research consists of 266 stocks traded on the Colombo Stock Exchange (CSE) between 2000 and 2008. The results of the analysis showed that stock returns are positively related to the simultaneous changes in trading volume. Furthermore, it has been found that changes in historical trading volume are inversely correlated with stock returns. It has been suggested that the illiquidity of low-volume stocks may be the reason for the negative relationship between trading volume and stock returns. As a result of the research, it is stated that the trading volume has the ability to anticipate stock returns and investors can make strategies based on the trading volume to make a profit. Kaya (2015) used daily data from January 2, 2009 to January 11, 2013 in his study, in which he examined the causal relationship between the fear index (VIX) and the BIST 100 index. In this direction, the Johansen-Juselius cointegration test was used to investigate the long-term relationship between the variables. The test result showed that there is a long-term relationship between the variables. This shows that the VIX index affects the BIST 100 index. As a result of the study, it is stated that investors can get an idea by following the fear index in determining their investment strategies. Sarı (2019) aimed to predict the BIST 100 return index with investor sentiment. For all models analyzed, monthly data covering the period 2007-2018 were used. According to the results of the study, CCI and VIX, which are direct variables representing investor sentiment, and trading volume and trading rate, which are indirect variables, were able to significantly predict BIST 100 stock returns. Conkir et al. (2021) aimed to determine the relationship between the VIX fear index and the stock market indices of developing countries (Turkey, Mexico, India, Russia, Indonesia). In this direction, the VAR Model and Granger Causality Analysis were applied to the study, which used monthly data from January 2015 to December 2019. It has been concluded that Turkish stock market indices are affected by the fear index. However, no causal relationship was found between the fear index and the stock market indices of Indonesia, India, Mexico and Russia.

3. SCOPE OF THE RESEARCH AND VARIABLES

This study aims to examine the effect of investor sentiment on stock returns within the scope of OECD countries. For this purpose, the monthly data of the 17 OECD members whose data is fully accessible for the period 2004:01-2021:08 were analyzed using the panel data analysis method.

Table 1. OECD Countries and Stock Market Indices in the Scope of the Study

	Country	**Stock Market Index**
1	USA	DOW 30
2	Germany	DAX
3	Australia	S&P ASX 200
4	Belgium	BEL 20
5	France	CAC 40
6	South Korea	KOSPI
7	Holland	AEX
8	England	FTSE 100
9	Ireland	ISEQ
10	Spain	IBEX 35
11	Sweden	OMXS 30
12	Switzerland	SMI
13	Italy	FTSE
14	Japan	NIKKEI 25
15	Mexican	S&P BMW
16	Portugal	PSI 20
17	Turkey	BIST 100

Source: http://www.oecd.org/

In the study, the consumer confidence index (CCI), trading volume (TV) and fear index (VIX) variables represent investor sentiment. In the light of the literature study, it is thought that these variables are among the indicators that best reflect investor sentiment both psychologically and financially. The interest rate is added to the model as a control variable. The study's limitations include the use of monthly data in the study, as the data is published monthly, and the data of all OECD countries is not fully accessible. The definitions of the variables used in the study and the sources from which they were obtained are shown in Table 2.

Table 2. Variables Used in the Study

Dependent Variable	**Değişken Tanımı**	**Source**
SMI	Logarithmic Value of Stock Market Index Closing Price	investing.com
Independent variables		
CCI	Logarithmic Value of Consumer Confidence Index	data.oecd.org
VIX	Logarithmic Value of Fear Index	investing.com
TV	Logarithmic Value of Market Trade Volume	investing.com
Control Variable		
IR	10-Year Government Bond Interest Rate	data.oecd.org

The main models used in the study are as follows:

Model 1: $$SMI_t = \beta_{0i} + \beta_1 CCI_{it} + \beta_2 VIX_{it} + \beta_3 TV_{it} + \beta_3 IR_{it} + e_{it} \quad (1)$$

Model 2: $$SMI_t = \beta_{0i} + \beta_1 CCI_{it} + e_{it} \quad (2)$$

Model 3: $$SMI_t = \beta_{0i} + \beta_1 VIX_{it} + e_{it} \quad (3)$$

Model 4: $$SMI_t = \beta_{0i} + \beta_1 TV_{it} + e_{it} \quad (4)$$

Model 5: $$SMI_t = \beta_{0i} + \beta_1 IR_{it} + e_{it} \quad (5)$$

Model 1 aims to investigate the effects of consumer confidence index (CCI), fear index (VIX), market trading volume (TV) and interest rate (IR) independent variables on stock market index price (SMI). Models 2, 3, 4 and 5 aim to investigate whether each independent variable is the cause of the index price. While building the model, the logarithm of each variable was taken. "β_0" represents the constant value, "$\beta_1, \beta_{2,} \beta_3$" represent the slope coefficients of the variables "ε" represents the error terms, "i" represents the country group, "t" represents the time dimension.

Consumer Confidence Index: The Consumer Confidence Index was first used by Fisher and Statman (2003) as a representative of investor sentiment. Consumer confidence index aims to measure consumers' personal economic conditions, their evaluations of national economic conditions, their expectations about the future economy, and their spending and saving trends in the short term. Consumers' expectations for the future can lead to various economic consequences. Positive expectations can lead consumers to spend more and use debt. On the other hand, Negative expectations enable consumers to reduce their spending, review their financial situation and increase their savings

(Kremer and Westermann, 2004: 3). The consumer confidence index is frequently used in the interpretation of many macroeconomic indicators and in measuring investor sentiment (Bremmer and Christ, 2003). Otoo (1999), Jansen and Nahuis (2003), Kandır (2006), Singal (2012), Sarwar (2012) and Lee (2019) stated that TGE was successful in estimating stock returns.

Fear Index: The high VIX index reflects the increasing fear of investors (Naifar, 2016: 32). The decrease in investor fear causes option prices to tend to decrease. Measured by the implied volatility of option prices, the VIX index represents the investor's beliefs about asset price volatility. The Wall Street Journal regularly reports VIX movements, while reporting on stock market or interest rate movements, it highlights the VIX index as a comment on investor sentiment (Bandopadhyaya and Jones, 2008, p. 28). Dash and Moran (2005), Banerjee et al. (2007), So and Lei (2015), Smales (2017) and Idnani et al. (2021) used the VIX index as an investor sentiment representative in their studies. Implied volatility, calculated based on option prices, is used as a measure of market risk. Therefore, implied volatility can be a criterion in estimating the change in expected returns (Konstantinidi et al., 2008: 2401). Numerous studies in the literature have shown that the VIX index is successful in predicting expected returns (Fleming, 1998; Becker et al., 2009; Blair et al., 2001).

Transaction Volume: According to some researchers (Odean, 1999; Glaser and Weber, 2007), the overall volume of transactions on global markets is too high to be adequately described by conventional financial theories that make the assumption of rationality. Instead, as stated by Glaser and Weber, "differences of opinion" and "overconfidence" are used to try and explain the large amount of transactions. Disagreements may occur because investors' prior opinions or methods of understanding information that is publicly available may vary (Glaser and Weber, 2007: 2). The opposite of overconfidence is overestimation of information or beliefs, which leads investors to tend to trade more. According to Baker and Stein (2004), trading volume can serve as a gauge of investor sentiment among investors. The market will be overvalued because irrational investors exaggerated expected returns, overvaluation will induce an overreaction, they will trade more, and the trading volume will rise when this happens. (Baker and Stein, 2004: 273).

Interest Rate: According to Malkiel (1982) and Modigliani and Cohn (1979), interest rates may be one of the key factors affecting stock values. Zhou (1996) showed that especially long-term bond yields have a significant effect on stock returns. Alam and Uddin (2009), in their study for developed and developing countries, stated that the interest rate has a significant negative relationship with the stock index price, and that a significant control of the interest rate in these countries will greatly benefit the stock market. In line with the literature, in this study, the interest rate was added to the model as a control variable and the interest rate of 10-year government bonds was used as a representative. This usage has grown more prevalent in the literature on the connection between interest rates and the stock market (Tangjitprom, 2012: 108; Moya-Martinez, 2015: 98). Stock prices tend to be more sensitive to movements in long-term interest rates, rather than short-term interest rates, due to the impact on the cost of debt and thus on firms' investment decisions (Bartram, 2002: 3; Ferrer et al., 2010: 437). Since the interest rate is an expense for companies, the increase (decrease) of long-term interest rates in particular has a decreasing (increasing) effect on operating profits. Changes in operating profits, on the other hand, affect stock prices.

4. EMPIRICAL FINDINGS

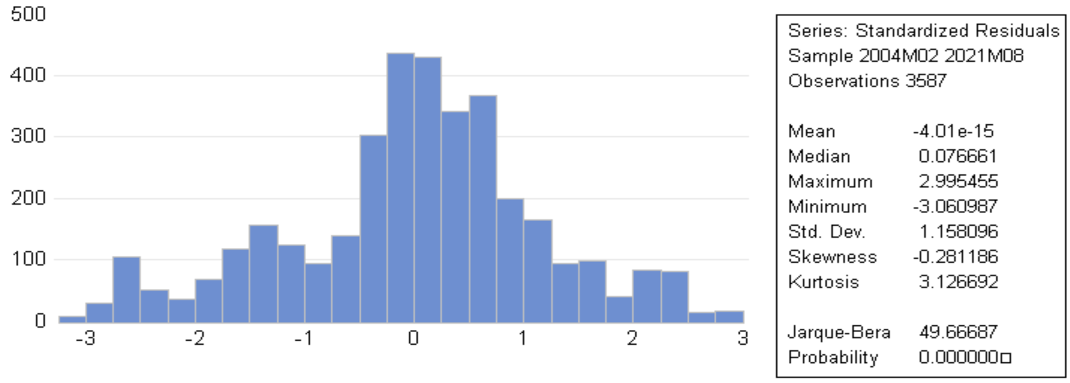
The effect of investor sentiment on stock returns was investigated by panel data analysis method. In this direction, first of all, descriptive statistics of the dependent and independent variables used in the analyzes are included.

Table 3. Descriptive Statistics

	SMI	CCI	VIX	TV	IR
Mean	9031.807	99.75906	19.07100	7514137650	3.477443
Median	5939.430	100.0272	16.31000	3540000000	3.032000
Maximum	53304.74	109.0984	59.89000	121230000000	24.48000
Minimum	170.8100	91.75481	9.510000	1280000	-0.975000
Std. Deviation	9848.122	2.022459	8.478512	9638691970	3.374213
Skewness	2.065718	-0.616342	2.071296	3.289046	2.330678
Kurtosis	7.301692	4.462072	8.153347	23.14000	11.31610
Jargue-Bera	5316.729	546.5937	6534.026	67090.48	13583.64
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observation	3587	3587	3587	3587	3587

The descriptive statistics given in Table 3 cover the period 2004:02-2021:08 for 17 countries in the data set. When the descriptive statistical results of the variables are evaluated, the average value for the stock market index price is 9031. It shows that when the CCI is above 100, consumers are optimistic, and when it is below, they are pessimistic. The VIX index fluctuates between 10 and 20 basis points in periods when risk perception is low (Berglöf et al., 2009: 9). In terms of standard deviation values, it can be said that there are high deviations from the average value only in the series related to the trading volume variable, while there are no high deviations in the series related to the index price, consumer confidence index, fear index and interest rate variables. According to the kurtosis, skewness and Jargue-Bera values, which show whether the series comply with the normal distribution, it can be said that the series belonging to the variables do not comply with the normal distribution.

Figure 1. Histogram Chart for the Model



When the histogram graph created on the basis of the model with the assumption of normal distribution is examined, the Jargue-Bera probability value shows that there is no normal distribution. In this case, the results of the normal distribution analysis made on the basis of the model and the variable support each other. Therefore, it is assumed that there is no normal distribution in the correlation analysis performed to test the multicollinearity problem. The total number of observations used in the study is 3587.

In order to be able to make analyzes suitable for the data set and to reach consistent and unbiased results, it was first investigated whether there was a multicollinearity in the model. Multicollinearity refers to the linear relationship between two or more variables (Paul, 2006: 2). High-level relationships between explanatory variables may cause multicollinearity problems and distort the analysis results. The higher the multicollinearity, the less reliable the estimates (Alin, 2010: 370). The relationship between independent factors and dependent variables is disrupted when two or more explanatory variables have a high correlation. This might result in unreliable coefficients that may differ from one sample to another. (Daoud, 2017: 1). This situation causes the relationships between variables to be misinterpreted. Whether there is a multicollinearity problem or not can be determined by correlation analysis, VIF (variance inflation factor) and tolerance tests and observed with scatter diagrams.

Table 4. Spearman Correlation Analysis Results

Correlation t-statistics Possibility	SMI	CCI	VIX	TV	IR
SMI	1.000000 ….. …..				
CCI	-0.001058 -0.063347 0.9495	1.000000 ….. …..			
VIX	-0.057412 -3.443215 0.0006	-0.392577 -25.55723 0.0000	1.000000 ….. …..		
TV	0.121839 7.349836 0.0000	-0.146776 -8.884387 0.0000	0.095449 5.741219 0.0000	1.000000 ….. …..	
IR	-0.101686 -6.120142 0.0000	-0.126466 -7.633407 0.0000	0.055380 3.320991 0.0009	0.247738 15.31053 0.0000	1.000000 ….. …..

The multicollinearity problem is addressed by examining the correlations between the explanatory variables (Tay, 2017: 2006). High correlation between explanatory variables means multiple linear connections (Alin, 2010: 370). This value should not be over 60% to 80% (Tay, 2017: 2006). The series of the variables used in the study do not conform to the normal distribution. For this reason, Spearman correlation analysis, which is used in the absence of normal distribution, was performed to determine the correlation coefficients between the variables. When the correlation analysis results in Table 4 are examined, it is seen that the highest level of correlation between the variables is 39.25%. Therefore, there is no multicollinearity problem in the model.

Table 5. VIF Values

Variable	Coefficient of Variance	Decentralized VIF Value	Central VIF Value
CCI	1.108137	62712.94	1.233588
VIX	0.003402	76.26770	1.206283
TV	0.000190	246.1203	1.070383
IR	3.49E-05	2.191353	1.062516
C	24.52233	65511.83	NA

Another test used to test the multicollinearity problem is the inflation factor analysis of variance. In case of correlation between explanatory variables, the standard error of the coefficients of the estimators will increase and as a result the variance of the coefficients of the explanatory variables will inflate. VIF is a tool used to measure how inflated the variance is (Daoud, 2017: 4). A VIF value greater than 5 indicates a multicollinearity problem (Heiberger and Holland, 2015: 291; Daoud, 2017: 4). When the VIF analysis results given in Table 5 are examined, it is seen that the central VIF value is at most 1.233588. In this case, there is no VIF value greater than 5. As a result, VIF analysis results show that there is no multicollinearity problem, which is consistent with the correlation analysis results.

Table 6. Endogeneity Test

Correlation /t-statistics /Probability	CCI	VIX	TV	IR
Error Term	0.041058 2.460400 0.0139	0.000933 0.055840 0.9555	0.070684 4.242822 0.0000	0.045664 2.737001 0.0062

The case of a high correlation between the error term of the model and the explanatory variables is called the 'endogeneity problem' (Ünlü et al., 2011: 206). The existence of the endogeneity problem poses a significant threat to the consistency of the analysis results. Although a coefficient seems to adequately explain the assumed relationship, the results will be inconsistent in the presence of endogeneity. In this case, the observed correlation may be far from the real relationship (Antonakis et al, 2014: 4). For this reason, testing whether there is an endogeneity problem is important for the consistency and reliability of the research. The results of the endogeneity test are given in Table 6. When the results are examined, it is seen that the correlation between the explanatory variables and the error term is quite low (up to 7.06%). Accordingly, it can be stated that there is no endogeneity problem in the model.

Table 7. Peseran and Yamagata (2008) Homogeneity Delta Test Results

	Delta Tilde	Probability	Delta Tilde Adj	Probability
Model	122.244	0.000	124.012	0.000
SMI	1.137	0.128	1.145	0.126
CCI	-1.717	0.957	-1.729	0.958
VIX	-2.914	0.998	-2.935	0.998
TV	35.667	0.000	35.923	0.000
IR	5.767	0.000	5.809	0.000
H0: There is homogeneity. H1: There is no homogeneity.				

Swamy (1970) developed the homogeneity test, which investigates whether the slope coefficients are homogeneous in cross-section units and can be applied to panel data models whose cross-section size (N) is larger than the time series dimension (T) (Peseran and Yamagata, 2008: 50). Peseran and Yamagata (2008) developed and standardized Swamy's homogeneity test in order to test homogeneity in large panels (Inglesi-Lotz et al, 2015: 171). The homogeneity of the slope coefficients is important for the selection of unit root, cointegration and causality tests. Pesaran and Yamagata (2008) homogeneity delta test was used to investigate homogeneity in this study. When the test results given in Table 7 are examined, it is seen that the calculated delta probability values of the model and the TV and IR variables are below the critical value of 0.05. Therefore, the null hypothesis of 'there is homogeneity' of the delta test for the model and these variables was rejected and they were found to be heterogeneous. It is seen that the delta probability values of the SMI, CCI and VIX variables are greater than the critical value of 0.05. In this case, the null hypothesis of 'there is homogeneity' of the delta test for these variables cannot be rejected. Therefore, it was determined that the SMI, CCI and VIX variables were homogeneous.

In panel data analysis, it can be mentioned that there is a cross-section dependency when a shock occurring in any of the cross-sections affects the other sections. Many panel data models assume that the observations of the cross-sections are independent of each other. However, there may be common shocks affecting all sections. Economic theories suggest that cross-sections often engage in actions that lead to interdependence. In the case of cross-sectional dependence, the results obtained from estimators that assume cross-section independence may be inconsistent (Hsiao et al., 2007: 2). For this reason, it is necessary to test whether there is a cross-section dependency and to decide which tests will be appropriate for unit root and cointegration analyzes. Whether there is a cross-sectional dependence between the series can be tested with the Breusch and Pagan (1980) LM test, Peseran (2004) CDlm, Peseran (2004) CD and Peseran, Ullah, Yamagata (PUY) (2008) LMadj test. This study is based on the results of the Peseran, Ullah, and Yamagata (2008) LMadj test. The reason for this is that the time dimension (211) is larger than the cross-section dimension (17) of the panel data model used and the PUY (2008) test eliminates the possibility of the deviations in the LM test and the correlation sum of the Pesaran CD test being zero (Topaloğlu, 2018: 22).

Table 8. Cross Section Dependency Test Results

	LM (Breusch & Pagan,1980)		CDlm (Peseran, 2004)		CD (Peseran, 2004)		LMadj (PUY, 2008)	
	Statistics	Probability	Statistics	Probability	Statistics	Probability	Statistics	Probability
Model	9962.48	0.000	595.818	0.000	92.934	0.000	643.680	0.000
SMI	12872.4	0.000	772.261	0.000	84.181	0.000	772.221	0.000
CCI	6774.71	0.000	402.530	0.000	71.590	0.000	402.490	0.000
VIX	28696.0	0.000	1731.70	0.000	169.398	0.000	1731.66	0.000
TV	4814.87	0.000	283.65	0.000	29.242	0.000	283.658	0.000
IR	3502.22	0.000	204.108	0.000	18.467	0.000	54.534	0.000
H0: There is no cross-section dependency. H1: There is a cross-section dependency.								

When the cross-section dependency test results given in Table 8 are examined, the probability values calculated for both the model and each variable are consistently below the critical value of 0.05 in all tests. Therefore, the null hypothesis of 'no cross-section dependence' was rejected. Thus, it has been determined that there is a cross-sectional dependence in all variables and in the model. This result shows that the shock experienced in one of the OECD countries also affected the others. In the unit root and cointegration tests to be carried out in the next stages of the study, tests that take into account the cross-section dependency will be preferred.

If there is a correlation between the horizontal sections in the panel series, the asymptotic properties of the tests may be affected. For this reason, different unit root tests have been developed depending on whether there is a dependency between the sections (Şak, 2018: 261). While first-generation unit root tests are used in panel data without cross-sectional dependence, second-generation unit root tests are used in panel data with cross-sectional dependence (Hurlin and Mignon, 2007: 2). In this direction, the PANIC unit root test, which takes into account the existence of cross-sectional dependence, was used to test the stationarity of the variables.

Table 9. PANIC Panel Unit Root Test Results

		Constant		Constant and Trend	
Level		t-Statistic	Probability Value	t-Statistic	Probability Value
SMI	*PCe_Choi*	-2.2250	0.9870	-2.4973	0.9937
	PCe_MW	15.6524	0.9970	13.4070	0.9994
CCI	*PCe_Choi*	0.4643	0.3212	-1.1868	0.8823
	PCe_MW	37.8285	0.2987	24.2135	0.8928
VIX	*PCe_Choi*	0.2931	0.3847	4.2426	0.0000***
	PCe_MW	4.8291	0.3053	16.0000	0.0030***
TV	*PCe_Choi*	0.2401	0.4051	2.2284	0.0129**
	PCe_MW	35.9801	0.3759	52.3759	0.0229**
IR	*PCe_Choi*	-2.2951	0.9891	-2.9976	0.9986
	PCe_MW	15.0741	0.9979	9.2815	1.000
First Difference					
SMI	*PCe_Choi*	12.3693	0.0000***	12.3693	0.0000***
	PCe_MW	136.0000	0.0000***	136.0000	0.0000***
CCI	*PCe_Choi*	12.3693	0.0000***	11.9145	0.0000***
	PCe_MW	136.0000	0.0000***	132.2499	0.0000***
IR	*PCe_Choi*	12.3693	0.0000***	12.3693	0.0000***
	PCe_MW	136.0000	0.0000***	136.0000	0.0000***

H0: There is a unit root.
H1: There is no unit root.
Note: ***,** and * indicate 1%, 5% and 10% significance levels, respectively.

When the PANIC unit root test results given in Table 9 are examined, it is seen that the probability values calculated for the VIX and TV variables are below the critical value. Therefore, the null hypothesis of 'there is a unit root' for these variables is rejected. Therefore, it has been determined that these variables do not contain a unit root and are stationary at the level. It is seen that the probability values calculated for the SMI, CCI and IR variables are above the critical value. Therefore, the hypothesis of 'there is a unit root' for these variables cannot be rejected. Therefore, it has been determined that these variables contain a unit root and are not stationary at the level. In case the data is not stationary, it is necessary to make it stationary by taking the first difference (Gujarati and Porter, 2012: 760). In this direction, the unit root test was performed again by taking the first differences of the SMI, CCI and IR variables. As a result of the test, it was seen that the probability values of the variables were below the critical value. Therefore, the degree of stationarity of these variables was determined to be I (1). Cointegration tests were conducted to determine the degree of stationarity of the variables and to investigate whether there is a long-term relationship between the series after they have the same level of stationarity. If there is a long-term relationship between the variables, these variables will be cointegrated (Gujarati and Porter, 2012: 762).

Table 10. Results of Cointegration Tests

Pedroni Panel Cointegration Test Results				
	t-Statistic	Probability Value	Weighted t-Statistic	Probability Value
Within-dimension				
Panel v-Statistic	10.47348	0.0000***	1.395788	0.0814*
Panel rho-Statistic	-77.83638	0.0000***	-80.89647	0.0000***
Panel PP-Statistic	-49.60982	0.0000***	-51.40752	0.0000***
Panel ADF-Statistic	-48.88691	0.0000***	-50.91907	0.0000***
Between-dimension				
Group rho-Statistic	-84.20261	0.0000***		
Group PP-Statistic	-59.57573	0.0000***		
Group ADF-Statistic	-58.48709	0.0000***		
Kao Panel Cointegration Test Results				
	t-Statistic	Probability Value		
ADF	-2.532559	0.0057***		
Residual Variance	0.003424			
HAC Variance	0.000158			
H0: There is no cointegration between the series. H1: There is cointegration between the series. Note: ***,** and * indicate 1%, 5% and 10% significance level, respectively.				

The cointegration relationship between the variables was examined with two different analysis methods, namely the Pedroni Cointegration test and the Kao Cointegration test. The Pedroni test has positive features such as allowing more than one explanatory variable, variability of the cointegration vector between different parts of the panel, and heterogeneity of errors in cross-section units (Asteriou and Hall, 2007: 374). The Pedroni cointegration test includes seven different tests that test whether the panel data is cointegrated. Four of these tests make *within-dimension* and three of these tests make *between-dimesion* estimation (Pedroni, 1999: 657). When the Pedroni Panel Cointegration test results given in Table 10 are examined, it is seen that the probability values for all seven tests are below the critical values. Therefore, the null hypothesis of no cointegration between the series is rejected. In this direction, it has been determined that there is a cointegration relationship between the series.

Another test applied in the study in order to examine the cointegration relationship between the variables is the Kao (1999) Panel cointegration test. Kao presented a cointegration test for panel data analysis by using DF and ADF tests (Baltagi, 2005: 252). When the Kao cointegration test results given in Table 10 are examined, the null hypothesis that there is no cointegration between the series is rejected because the ADF probability value is below the critical value. In this direction, similar to Pedroni (1999) panel cointegration test results, it was determined that there was a high-significance cointegration relationship between the series.

After determining that there is a long-term relationship between the variables, the long-term relationship between the variables was examined with the ARDL method. The Panel-ARDL method developed by Pesaran and Smith (1995) and Pesaran, Shin and Smith (1999) is a suitable method for estimating non-stationary heterogeneous panels (Ersin and Süt, 2021: 305). It can also be applied if the explanatory variables are stationary at different levels (I(0) and I(1)), provided that they are not I(2). ARDL method allows to examine short-term relationships as well as long-term relationships between variables.

Table 11. Panel ARDL Model Estimation Results

Variable	Coefficient	Standard Deviation	t-Statistics	Probability
Long Term				
CCI	6.300447	1.766009	3.567619	0.0004
VIX	-0.756716	0.024972	-6.678112	0.0000
TV	-0.110180	0.043266	-2546568	0.0109
IR	-0.080038	0.024972	-3.205088	0.0014
Long Term				
CCI	3.733355	0.478281	7.805785	0.0000
CCI (-1)	-1.586583	0.336801	-4.710745	0.0000
VIX	-0.110977	0.003518	-31.54755	0.0000
VIX (-1)	-0.038501	0.003007	-12.80328	0.0000
TV	-0.002240	0.005091	-0.439941	0.6600
TV (-1)	0.007247	0.002508	2.889839	0.0039
IR	0.004265	0.011381	0.374775	0.7079
IR (-1)	0.004932	0.004669	-1.056228	0.2909
C	-0.413471	0.038179	-10.82973	0.0000
TREND	1.36E-05	2.53E-05	0.537248	0.5911

The panel ARDL Pooled Mean Group (PMG) analysis findings were evaluated according to the Akaike information criterion and the ARDL (1,2,2,2,2) model was obtained by determining the optimum lag lengths. Accordingly, the relationship between the variables was analyzed and given in Table 11. When the results of the analysis are examined, it is seen that there are statistically significant relationships between the variables of CCI, VIX, TV and IR and the SMI variable in the long term. Against the 1% unit increase in the CCI, the SMI increases by 6.30% in the long run. In the long run, the SMI decreases by 0.7%, 0.11% and 0.08%, respectively, in the face of a 1% unit increase in the VIX, TV and IR variables. When the short-term relationships are examined, it is seen that there are statistically significant relationships between the CCI and VIX variables and the SMI variable. Against the 1% unit increase in the CCI, the SMI increases by 3.73% in the short term. In the face of a 1% unit increase in the VIX, it decreases by 0.75%. No statistically significant relationship was found between the TV and IR variables and the SMI variable in the short term. A significant and positive relationship was observed only in the first lag of the TV variable. In this context, for the period 2004:02- 2021:08 of 17 OECD countries, it has been determined that the CCI has a significant and positive effect on the SMI in both the long and short term, and the VIX has a significant and negative effect in both the long and short term. While it was determined that the TV and IR variables had a significant and negative effect on the index price in the long term, no significant relationship was observed in the short term.

Table 12. Bootstrap Causality Test Results 1

	CCI=>SMI		VIX=>SMI		TV=>SMI		IR=>SMI	
Countries	**W_i**	**P_i**	**W_i**	**P_i**	**W_i**	**P_i**	**W_i**	**P_i**
USA	3.802	0.703	2.590	0.274	1.175	0.556	6.673	0.083**
Germany	15.116	0.004***	5.950	0.051*	4.336	0.227	20.425	0.000***
Australia	20.086	0.003***	4.744	0.093*	19.14	0.085*	10.248	0.017**
Belgium	9.967	0.041**	0.810	0.667	5.947	0.311	12.063	0.007***
France	9.405	0.052*	1.105	0.576	8.556	0.036**	9.922	0.019**
S. Korea	29.991	0.000***	7.223	0.027**	6.002	0.050**	21.284	0.046**
Holland	7.783	0.100*	1.987	0.370	11.75	0.038**	12.507	0.006***
England	6.405	0.171	6.210	0.045**	11.85	0.018**	11.075	0.011**
Ireland	4737	0.315	2.468	0.291	2.085	0.353	3.662	0.160
Spain	12.745	0.013***	1.646	0.439	3.927	0.416	0.492	0.782
Sweden	8.780	0.067**	2.769	0.251	6.081	0.298	12.231	0.007***
Switzerland	11.607	0.114	0.552	0.759	8.010	0.046**	5.492	0.019**
Italy	10.988	0.027**	1.179	0.277	4.266	0.371	0.990	0.610
Japan	8.715	0.648	5.448	0.066*	0.429	0.513	8.685	0.122
Mexican	10.112	0.039**	3.635	0.162	11.51	0.118	7.489	0.187
Portugal	5.455	0.363	2.133	0.344	5.205	0.157	7.927	0.160
Turkey	11.326	0.023***	0.015	0.902	5.096	0.078*	0.546	0.460
Panel Fisher	105.734	0.000***	52.038	0.025**	67.382	0.001***	109.977	0.000*

Note: *,**,*** indicate 10%, 5% and 1% significance level, respectively.

Table 13. Bootstrap Causality Test Results 2

	SMI=>CCI		SMI=>VIX		SMI=>TV		SMI=>IR	
Countries	**W_i**	**P_i**	**W_i**	**P_i**	**W_i**	**P_i**	**W_i**	**P_i**
USA	16.670	0.011**	0.224	0.894	2.444	0.295	19.289	0.000***
Germany	10.841	0.028**	0.235	0.889	15.017	0.002***	10.921	0.012**
Australia	24.393	0.000***	1.589	0.452	8.657	0.732	7.742	0.052*
Belgium	8.117	0.087*	0.372	0.830	15.885	0.007***	5.642	0.130
France	10.530	0.032**	1.602	0.449	6.979	0.073**	8.211	0.042**
S. Korea	17.908	0.022**	0.487	0.784	3.495	0.174	52.604	0.000***
Holland	15.725	0.003***	0.784	0.676	4.795	0.441	10.511	0.015**
England	7.698	0.103	0.133	0.936	2.594	0.628	17.330	0.001***
Ireland	21.237	0.000***	1.798	0.407	1.105	0.576	0.314	0.855
Spain	21.677	0.000***	3.142	0.208	6.688	0.153	3.406	0.182
Sweden	10.041	0.040**	0.319	0.853	2.366	0.797	9.326	0.025**
Switzerland	11.018	0.138	0.479	0.787	9.947	0.019**	0.974	0.324
Italy	1.226	0.874	0.542	0.462	1.769	0.778	2.570	0.277
Japan	16.753	0.115	0.181	0.913	0.081	0.776	8.376	0.137
Mexican	5.107	0.276	0.276	0.871	5.117	0.646	11.550	0.041**
Portugal	10.907	0.053*	1.859	0.395	0.918	0.821	4.841	0.436
Turkey	3.298	0.509	0.033	0.857	6.125	0.047**	1.727	0.189
Panel Fisher	124.802	0.000***	15.335	0.998	58.523	0.006***	125.441	0.000***

Note: *,**,*** indicate 10%, 5% and 1% significance level, respectively.

Another preferred test in the study to determine the effect of variables on predicting the index price is the panel causality test developed by Emirmahmutoğlu and Köse (2011) to reveal the causality relationships between variables. The reason why this test is preferred is that in heterogeneous panel data sets, country-specific test statistics can be obtained by making separate time-dimensional estimations for the sections (countries) in the panel, and then a general result can be obtained by combining the test statistics of the countries. Thus, a conclusion can be reached both for each country separately and for all countries. When the results of the countries in Table 12 and Table 13 are evaluated separately, the null hypothesis of "CCI is not the cause of SMI" rejected for Germany, Australia, Belgium, France, S. Korea, Netherlands, Spain, Sweden, Italy, Mexico and Turkey. Accordingly, it has been concluded that the consumer confidence index is the reason for the changes in the index price in these countries. For the USA, England, Ireland, Switzerland, Japan and Portugal, the null hypothesis of 'TGE is not the cause of EF' could not be rejected. Therefore, it has been concluded that the consumer confidence index is not the reason for the index price for these countries. While the causality relationship is bidirectional for Germany, Australia, Belgium, France, S. Korea, Netherlands, Spain and Sweden; It has been determined that there is a one-way trend from the consumer confidence index to the index price for Italy, Mexico and Turkey. The null hypothesis of 'VIX is not the cause of SMI' was rejected for Germany, Australia, S. Korea and Japan. In these countries, a one-way causality relationship has been determined from the fear index to the index price. The null hypothesis 'TV is not the cause of SMI' was rejected for Australia, France, S. Korea, Netherlands, UK, Switzerland and Turkey. Therefore, it has been concluded that the transaction volume for these countries is the reason for the index price. It has been determined that the causality relationship between the trading volume and the stock market index in France, Switzerland and Turkey is bidirectional. The null hypothesis 'IR is not the cause of SMI' was rejected for the USA, Germany, Australia, Belgium, France, S. Korea, Netherlands, UK, Sweden and Switzerland. Therefore, it has been concluded that the interest rate is the cause of the index price for these countries. While the causality relationship is bidirectional for the USA, Germany, Australia, France, S. Korea, Netherlands, England and Sweden; It has been determined that there is a one-way causality relationship from consumer confidence index to index price for Belgium and Switzerland.

Table 14. Hatemi-J (2012) Asymmetric Causality Test Results

Causality	Statistic	Probability	Causality	Statistic	Probability
CCI^{+}=>SMI^{+}	98.793	0.000***	EF^{+}=>TGE^{+}	114.152	0.000***
CCI^{+}=>SMI^{-}	36.310	0.361	EF^{+}=>TGE^{-}	45.334	0.093
CCI^{-}=> SMI^{+}	43.601	0.125	EF^{-}=>TGE^{+}	78.785	0.000***
CCI^{-}=> SMI^{-}	112.331	0.000***	EF^{-}=>TGE^{-}	80.951	0.000***
VIX^{+}=> SMI^{+}	26.841	0.804	EF^{+}=>$VİX^{+}$	15.342	0.998
VIX^{+}=> SMI^{-}	16.880	0.994	EF^{+}=>$VİX^{-}$	147.498	0.000***
VIX^{-}=> SMI^{+}	22.702	0.930	EF^{-}=>$VİX^{+}$	33.202	0.507
VIX^{-}=> SMI^{-}	37.464	0.313	EF^{-}=>$VİX^{-}$	104.552	0.000***
TV^{+}=> SMI^{+}	28.215	0.747	EF^{+}=>$İH^{+}$	50.055	0.037**
TV^{+}=> SMI^{-}	38.526	0.272	EF^{+}=>$İH^{-}$	86.917	0.000***
TV^{-}=> SMI^{+}	46.346	0.077	EF^{-}=>$İH^{+}$	50.142	0.037**
TV^{-}=> SMI^{-}	122.698	0.000***	EF^{-}=>$İH^{-}$	92.742	0.000***
IR^{+}=> SMI^{+}	60.712	0.003***	EF^{+}=>$FAİZ^{+}$	67.526	0.001***
IR^{+}=> SMI^{-}	78.305	0.000***	EF^{+}=>$FAİZ^{-}$	64.592	0.001***
IR^{-}=> SMI^{+}	50.876	0.031**	EF^{-}=>$FAİZ^{+}$	85.605	0.000***
IR^{-}=> SMI^{-}	42.865	0.142	EF^{-}=>$FAİZ^{-}$	196.008	0.000***

The '=>' notation expresses the null hypothesis of no causality. **,*** indicate 5% and 1% significance level, respectively.

Traditional causality approaches based on Granger (1969) accept that the effect of positive and negative shocks in variables is the same. However, the results obtained from these tests can be misleading due to the presence of asymmetric information in financial markets and different reactions to positive and negative shocks of the same magnitude in case of heterogeneity of market participants (Yılancı and Bozoklu, 2014: 214). In this context, the Hatemi-J (2012) asymmetric causality test, which is an approach based on the difference between the effects of positive and negative shocks in the variables, was also carried out in the study. The results of the Hatemi-J asymmetric causality test showing the causality relationship between the variables separately according to the positive and negative shock situations are given in Table 14. When the test results are examined, it is seen that there is a bidirectional causality relationship at the 1% significance level from the positive shocks in the consumer confidence index to the positive shocks in the stock market index and from the negative shocks in the consumer confidence index to the negative shocks in the stock market index. In other words, in case of a positive (negative) shock in the consumer confidence index, the index price reacts positively (negatively). An asymmetric causality relationship from the positive or negative shocks occurring in the fear index to the index price could not be determined. While there is no asymmetric causality relationship from positive shocks in trading volume to positive or negative shocks in index price, bidirectional asymmetric causality relationship from negative shocks in trading volume to both positive shocks and negative shocks in index price has been determined. A bidirectional asymmetric causality relationship has been determined from the positive shocks in the interest rate to the positive or negative shocks in the index price. In addition, it was concluded that there is a bidirectional asymmetric causality relationship from the negative shocks in the interest rate to the positive shocks in the stock market index.

The vector autoregressive model system (VAR), proposed by Sims (1980), is used to examine the interactions of variables that are thought to be in a relationship with each other (Güriş, 2018: 397). It is very important to determine the optimal lag length when estimating the VAR model. Because in VAR Analysis, when the lag length is chosen longer than it should be, the variables can take higher values than their actual values, thus excessive parameterization problems may arise (Seddighi, 2000: 300).

Table 15. Delay Length Test Results

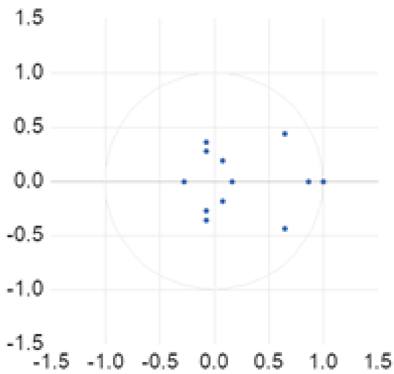
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4543.467	NA	9.73e-06	2.649078	2.658020	2.652273
1	5354.590	19761.53	3.10e-08	-3.101101	-3.047448	-3.081934
2	6445.199	2174.230	1.66e-08	-3.721723	-3.623360	-3.686585
3	6680.773	468.9525	1.47e-08	-3.844364	-3.701289*	-3.793253
4	6743.317	124.3241	1.44e-08	-3.866230	-3.678445	-3.799147
5	6781.122	75.03735	1.43e-08	-3.873688	-3.641192	-3.790633
6	6830.938	98.73193	1.41e-08	-3.888141	-3.610934	-3.789113
7	6862.392	62.24933	1.40e-08	-3.891900	-3.569982	-3.776900
8	6964.764	202.2989*	1.34e-08*	-3.936962*	-3.570333	-3.805990*

*Indicates the optimal lag length determined by the relevant criteria.
LR: LR Test Statistic
FPE: Final Prediction Error

AIC: Akaike Information Criterion **SIC:** Schwarz İnformation Criterion **HQ:** Hannan and Quinn Criterion

In Table 15, the test results of the most common information criteria used to determine the lag length suitable for the Var Model are given. The lag lengths that minimize these criteria are considered optimal. In this study, the lag length was taken as '3' according to the Schwarz information criterion. The Schwarz information criterion is widely preferred in research (Tsai, 2017; Zheng, 2020).

Figure 2. Inverse Roots of AR Characteristic Polynomial



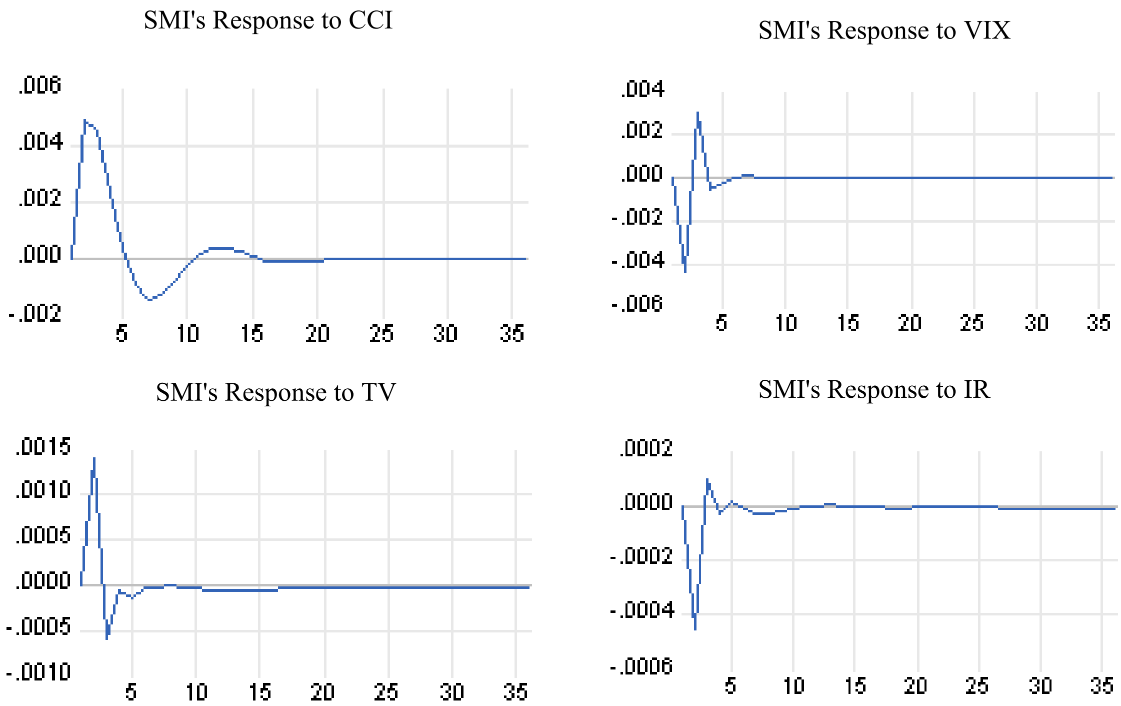
In order to ensure the stationarity of the estimated VAR model, AR characteristic roots must be located within the unit circle. When the inverse roots of the AR characteristic polynomial given in Figure 2 are examined, it is seen that no AR root is outside the circle. This shows that the established VAR model is stable.

Table 16. Variance Decomposition Analysis Results

Period	Std. Error	SMI	CCI	VIX	TV	IR
1	0.050957	100.0000	0.000000	0.000000	0.000000	0.000000
4	0.054798	90.42299	5.073467	1.205257	0.133207	3.265080
8	0.059385	81.93650	9.703825	1.478455	0.131008	6.750208
12	0.063488	75.85092	12.75612	1.644990	0.131822	9.616143
16	0.067423	70.98216	15.28235	1.775091	0.131747	11.82865
20	0.071130	67.12009	17.27733	1.879439	0.131665	13.59148
24	0.074651	63.97357	18.89995	1.964439	0.131617	15.03043
28	0.078014	61.35624	20.25082	2.035081	0.131580	16.22628
32	0.081238	59.14632	21.39132	2.094742	0.131547	17.23607
36	0.084339	57.25548	22.36709	2.145789	0.131520	18.10011

Variance decompositions and impulse response analysis are typically used in a VAR model to solve the relationships between variables (Lütkepohl, 2009: 281). Variance decomposition analysis was performed in order to determine which variable or variables were most effective on the dependent variable. According to the variance decomposition results of the index price given in Table 16, it is seen that 100% of the variance of the EF variable is explained by itself in the first period. From the second period, the degree to which the variables explain the changes in the index price increases. According to the variance decomposition analysis results, the most effective variable on the variance of the index price is the consumer confidence index. The second effective variable in explaining the changes in the index price is the interest rate. As of the end of the 36th period, 57% of the change in the Index price is due to itself, 22% to the consumer confidence index, and 18% to the interest rate. While the degree to which the fear index explains the index price is 2%, the degree to which the trading volume variable explains the index price is insignificant.

Figure 3. Impact Response Analysis



The impulse-response analysis results showing the response of SMI to a standard deviation shock that may occur in the SMI, VIX, TV and IR variables are shown in Figure 3. The first reaction of the index price to a shock in the consumer confidence index is positive. This reaction turns negative as of the second month and returns to positive as of the seventh month and approaches the long-term equilibrium value as of the 15th month. The first reaction of the index price to a shock in the fear index is negative. The direction of this reaction changes and turns positive as of the second month, and by the fourth month, the reaction turns negative and approaches the long-term equilibrium value. In the face of a standard deviation shock in the trading volume, the index price first responds positively. As of the second month, it gives a negative and then a positive reaction and approaches the long-term equilibrium value as of the sixth period. Against a standard deviation shock in the interest rates, the index price initially reacts negatively, then this reaction turns positive and reaches the long-term equilibrium value as of the tenth month with small fluctuations.

5. CONCLUSION

This study aims to examine the effect of investor sentiment on stock returns within the scope of OECD countries. For this purpose, monthly stock market index, consumer confidence index, fear index, market transaction volume and interest rate data for the period 2004:02- 2021:08 of 17 countries that are members of the OECD and whose data can be fully accessed were obtained. The obtained data were analyzed by panel data analysis method.

The analysis results, in line with the literature, showed that there is a significant and positive relationship between the consumer confidence index and the index price in both the long and short run (Otoo, 1999; Jansen and Nahuis, 2003; Kremer and Westermann, 2004; Charoenrook, 2005; Görmüş and Güneş, 2010; Usul et al., 2017; Eyüboğlu and Eyüboğlu, 2018). Causality test results showed that TGE was the granger cause of the index price. This result implies that changes in consumer beliefs have causal effects on investment behavior. Hsu et al., (2011) and Wong and Lievano (2009) reached similar results in their studies. When consumers believe that the future economic conditions will be good and have stronger confidence and optimistic attitude towards the economic situation, they will tend to invest more in the stock market, which will cause the stock market index to rise.

In addition, according to estimates made separately for countries, it has been determined that TGE is the reason for the changes in the stock market index price for Germany, Australia, Belgium, France, S. Korea, Netherlands, England, Spain, Sweden, Italy, Mexico and Turkey. However, it seems that TGE is not the cause of the stock market index price in the USA, UK, Ireland, Switzerland, Japan and Portugal. This situation can be attributed to the cultural characteristics of the countries. Geert Hoftsede examined countries in four different cultural dimensions, namely individualism-collectivism, power distance, femininity-masculinity and uncertainty avoidance, in his study in 1984 to investigate intercultural differences. Uncertainty avoidance can be defined as the degree to which members of a culture are threatened by uncertain or unknown situations. This feeling is expressed by the need for predictability. Uncertainty avoidance is related to the extent to which individuals can adapt to uncertain situations and their tendency to take risks. In cultures with low uncertainty avoidance, individuals tend to take risks because their anxiety levels are relatively low (Hofstede et al., 2010: 196). According to the indicators published by Hofstede, the cultural dimension of uncertainty avoidance is higher in Germany, Australia, Belgium, France, S. Korea, Spain, Italy, Mexico and Turkey than in the USA, England and Ireland. In this context, it is thought that the reason for the effect of CCI on stock markets for these countries may be investor sensitivity stemming from the loss aversion bias in these countries.

It is seen that the causality relationship between consumer confidence index and stock returns is bidirectional. The causality from stock returns to consumer confidence index can be explained by the fact that the stock market is a leading indicator of future income and economic status. Korkmaz and

Çevik (2007), Bremmer (2008), Olgaç and Temizel (2008), Topuz (2011), Eyüboğlu and Eyüboğlu (2018) reached similar results in their studies.

It has been determined that the relationship between the fear index and the index price is significant and negative both in the long and short term in line with the literature (Fleming et al., 1995; Sarwar, 2012; Shaikh and Padhi, 2014; Esqueda et al., 2015; Sadeghzadeh, 2018). The increase in the VIX index is a situation that requires caution for investors. When investors have negative expectations about the economy, they fear that the stock market will drop and they will lose money. As a result, they sell their stock, which can cause the market to decline. In addition, test results showed that the stock market index price of VIX is the granger cause. Kaya (2015) and Smales (2017) reached similar results in their study. High VIX levels reflect pessimism and cause stock prices to fall. It is concluded that VIX is the cause of the stock market index price in Germany, Australia, S. Korea, England and Japan. For these countries, it can be said that the VIX index creates sensitivity for investors.

It has been determined that the TV variable has a significant and negative effect on the SMI in the long run. According to the available literature, high trading volume indicates the existence of rumored investors. If the investors are optimistic, it is expected that the trading volume will affect the stock returns positively, and if there are overconfident investors, it is expected to affect it negatively. Accordingly, it can be said that the transaction volume in OECD countries is due to overconfidence. In addition, according to estimates made separately for countries; In Australia, France, S. Korea, the Netherlands, England, Switzerland and Turkey, it was concluded that IH was the cause of SMI. Stankov and Lee (2014), in their study for 33 countries, concluded that there is overconfidence in all countries (France and Switzerland were not included in the study) in which we found a causal relationship. In this context, it is thought that the reason for the effect of TV on stock markets for these countries may be investor sentiment arising from overconfidence in these countries.

It has been determined that the IR variable has a significant and negative effect on the index in the long run, and that the interest rate is the cause of the index price. According to the available literature, there are two reasons for this relationship. First, because the interest rate is an expense, an increase in interest rates has a reducing effect on operating profits. Changes in operating profits affect stock prices. Secondly, if interest rates rise too high, investors tend to tend to the bond market by selling their stocks, thinking that they can get more returns by buying bonds. This situation has a decreasing effect on stock prices. Samitas and Kenourgios (2007), Alam and Uddin (2009), Hsing (2011) and Amarasinghe (2015) reached similar results in their studies.

In addition, it is seen that all investor sentiment representatives used in the study are the cause of stock returns in Australia and S. Korea. This causality relationship can be explained by the fact that mostly individual investors trade in these stock markets. Individual investors can make more noise-based transactions than institutional investors. The share of individual investors in total transactions may differ from country to country. As a matter of fact, the Australian stock market is known to have a high level of direct stocks by individual investors, which increases the influence of individual investors on the index (Henker and Henker, 2010: 281). Similarly, individual investors have a larger trading volume than institutional investors in the Korean equity market. While the Korean stock market is known for the dominant role of individual investors, institutional investors have a larger share than individual investors in the US stock market (Jang, 2017: 142-143). The results of the analysis show that for the USA, no representative of investor sentiment is the cause of stock returns.

According to the results of the asymmetric causality test, in case of a positive (negative) shock in the consumer confidence index, the index price reacts positively (negatively). An asymmetric causality relationship from the positive or negative shocks occurring in the fear index to the index price could not be determined. Another asymmetric causality relationship is seen in the event of a negative shock in the trading volume, in which case the index price reacts negatively. Low volume indicates that the market is illiquid and has high price volatility. The risk perception caused by high price volatility may cause investors to sell their stocks and decrease the index price.

Analysis results show that investor sentiment is successful in predicting stock returns. According to the results of the analysis, the most effective variable on the variance of the index price is the consumer confidence index. According to the impulse response analysis results, it is seen that one standard deviation shocks that may occur in the CCI, VIX, TV variables have a two-month effect on the EF, fluctuating in the following months and reaching the long-term equilibrium value.

The results of the study show that investor sentiment affects stock prices and more successful predictions can be made about the stock index returns of OECD countries by utilizing data on investor sentiment. It can be stated that it would be beneficial to carry out economic policies in OECD countries not only based on past data, but also by giving importance to the psychology of investors and their expectations and concerns about the future. In future studies, analyzes can be made on a sectoral basis to test whether investor sentiment differs by sector. In a sectoral study, investor sentiment can be represented by different variables. By focusing on events such as the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic, it is possible to analyze how investor sentiment was affected during these crisis periods.

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