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How can Google trends be used as a technical indicator for investor interest?

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ÖZET

Etkin piyasa hipotezinde, yatırımcıların karar alırken tüm pay senetlerinin tam geçmişine ulaşabildiği varsayılmaktadır. Piyasaya yeni bilgi gelmese bile yatırımcı ilgisinin piyasayı etkileyebileceği davranışsal finans alanında gerçekleştirilen çalışmalarda gözlemlenmiştir. Özellikle yatırımcıların yeterli bilgiye sahip olmadan yalnızca farkında oldukları hisse senetlerine yatırım yaptıklarının varsayılması yatırımcı tanınmışlık hipotezini ifade etmektedir. Doğrudan ölçülebilen bir kavram olmayan yatırımcı ilgisinin ölçümünde arama motoru ve sosyal medya verilerinden yararlanılabilmektedir. Literatürde yatırımcı ilgisinin incelendiği çalışmalar sıklıkla lineer modellerin uygulamalarıyla gerçekleştirilmiştir. Bu durum zaman serilerinde olası yapı değişikliklerinin dikkate alınmadığı ihtimalini düşündürmektedir. Nitekim literatüre bakıldığında doğrusal olmayan modellerin tahmin performansının doğrusal modellerden daha iyi olduğu gösterilmiştir. Bu doğrultuda, çalışmada yatırımcıların pay piyasasına ilişkin Google üzerinden araştırma yaparak bilgiyi ortaya çıkarmalarının işlem hacmi ile ilişkisi yatırımcı tanınmışlık hipotezi bağlamında doğrusal ve doğrusal olmayan ekonometrik teknikler aracılığıyla incelenmiştir. Çalışmada elde edilen bulgulardan hareketle, yatırımcıların araştırma yapmadan ve yeterince bilgiye sahip olmadan yalnızca farkında oldukları pay senetlerine yatırım yapmaları yatırımcı tanınmışlık hipotezinin desteklendiği göstermektedir. Bu kapsamda çalışmanın sonuçları 2020 yılı kapsamında yatırımcı tanınmışlık hipotezini destekler nitelikte gerçekleşmiştir. 2021 yılı kapsamında ise yatırımcı tanınmışlık hipotezini desteklemediği görülmektedir. Bu alanda gerçekleştirilecek olan sonraki çalışmalarda doğrusal olmayan regresyon tahminleri ile değişkenler arası ilişkilerin etki derecesinin belirlenmesi de mümkün gözükmektedir.

ANAHTAR KELİMELER

Yatırımcı tanınmışlık hipotezi, yatırımcı ilgisi, google trend aramaları, doğrusal olmayan nedensellik analizi.

Google trendler yatırımcı ilgisi için teknik gösterge olarak nasıl kullanılabilir?

ABSTRACT

In the efficient market hypothesis, it is assumed that investors can access the entire history of all stocks when making decisions. It has been observed in studies conducted in the field of behavioral finance that investor interest can affect the market even if new information is not available to the market. In particular, the assumption that investors invest only in stocks they are aware of without sufficient information expresses the investor reputation hypothesis. Search engine and social media data can be used to measure investor interest, which is not a directly measurable concept. Studies examining investor interest in the literature have often been carried out with the applications of linear models. This suggests that possible structural changes are not considered in the time series. When we look at the literature, it has been shown that the prediction performance of nonlinear models is better than linear models. In this direction, in the study, the relationship between the trade volume and the investor's discovery of information about the stock market by Google is examined through linear and nonlinear econometric techniques in the context of the investor reputation hypothesis. The study's findings show that the investor reputation hypothesis is supported by the fact that investors only invest in stocks of which they are aware

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without doing research and without having enough information. In this context, the study's results were realized in a way that supports the investor recognition hypothesis within the scope of 2020. In 2021, it was seen that it does not support the investor reputation hypothesis. In future studies to be carried out in this area, it seems possible to determine the degree of effect of nonlinear regression estimations and the relationship between variables.

KEYWORDS

Investor reputation hypothesis, ınvestor ınterest, google trend searches, nonlinear causality analysis.

Introduction

In the efficient market hypothesis, it is assumed that investors have access to whole information about all stocks when making their investment decisions. However, there may be situations where the price data is not accessible, and the required calculations cannot be performed in analyzing the data. Merton (1987) created a two-period capital market equilibrium model in an environment where each investor had information on the subset of available securities. He investigated the effects on the structure of equilibrium asset prices in a limited information situation. The primary behavioral assumption is that if an investor knows the equilibrium price, he will use it to build the optimal portfolio. Therefore, it is based on the assumption that if investors do not have enough information, they invest in stocks they are aware of. This model implies that firms can increase their investor bases without doing much about it. At the same time, the form of the information disclosed to the public did not arouse interest among investors; it is possible to raise investor awareness by changing the way the information is disclosed. According to the model, abnormal behavior is observed in markets dominated by rational investors.

According to behavioral finance, which brings a critical perspective to rational investor behavior, which is the assumption of the efficient market hypothesis, emotions have an important role in investors' financial decisions. Even if there is no new information on the financial market, it has been observed through studies in this area that investor interest will affect the market. The first research conducted to predict stock returns was based on the Random Walk Theory and Efficient Market Hypothesis. According to the Efficient Market Hypothesis, stock prices occur randomly. As a result, it cannot be predicted with a rate higher than 50% accuracy (Bollen et al., 2011:1). Fama, even states that the efficient market hypothesis must be false. While numerous studies provide evidence that stock prices are not entirely random, they all agree that the behavior of stock prices is approximately that of a random walk process (Qian and Rasheed, 2006:26).

Researchers have discussed stock markets from different perspectives, from the efficient market hypothesis to the emergence of behavioral finance. Various theories have been proposed for predicting market behavior. Behavioral finance theory was developed basically to eliminate the defects of the efficient market hypothesis (Shiller, 1999: 1307). Measuring investor sentiment is difficult due to unobservable and heterogeneous behavior. Due to data availability, especially in recent years, Google search volume has become a popular investor sentiment index (Bozkurt, 2022: 47). It allows timely control of investor interest as it can be compared with passive interest criteria. At the same time, the searches made by individual investors about the related stocks on Google indicate that the stocks attract attention (Topaloğlu and Ege, 2020: 194). Da et al. (2011) is the first study to measure investor interest using data from Google trend searches. The study determined companies traded in the US capital market as keywords, and the relationship between investor interest, transaction volume, and advertising expenditures. It has been stated by Dzielinski (2012) that there are two essential advantages of using Google trend search data. The first is the possibility of obtaining higher frequency data than survey data. The second is related to its spontaneous emergence, independent of the developments in the financial markets. This eliminates the problem of internality, which causes the biggest problem in estimation in econometric analyses. However, compared to the survey data, it generates almost instantaneous data for the near future, which is essential, especially for predicting the future. Several studies show a significant correlation between stock variables (return, volume, and volatility) and related Google searches. Google search data predicts future stock prices (Bijl et al., 2016; Kim et al., 2019; Preis et al., 2010). Nonlinear Granger causality tests seem to be another alternative (Hiemstra & Jones, 1994; Diks & Panchenko, 2006; Tank et al., 2021). However, it should be noted that most previous studies have been limited to applications of linear models. This suggests that possible structural changes and/or changes in the time series should be considered. Nonlinear causality testing was proposed by Baek and Brock (1992) to deal with nonlinearity. It has been determined by Monte Carlo simulation that the prediction performance of linear models decreases in nonlinear cases. Therefore, the test is widely used in many fields, such as macroeconomics and finance (Hiemstra & Jones, 1994). Following Keynes (1936), Kaldor (1940) and Hicks (1950) established nonlinear mathematical models. However, it took a long time before any nonlinearity of the kind implied by these models was tested in the context of time series. Because linearity assumption has been dominant in time series analysis for a long time (Van Dijk & Franses, 2000). Even in cases where it is theoretically accepted that the data creation processes followed by the variables or the relationship between the variables are not linear, linear time series models have generally been used in the application phase. With the decrease in the difficulties in the estimation phase, there has been an increase in the field of nonlinear time series, especially in practice-oriented studies since the early 1990s. In order for individual investors to determine the right strategies in portfolio management and corporate firms in asset pricing, it is of great importance to determine the form of the relationship correctly.

Analyzing the relationship between investor interest and equity markets in Turkey, Akgün (2016), Bilgiç (2017), Korkmaz et al. (2017), and Erten and Korkmaz (2018) are available. However, the study measured the relationship between stock returns, trading volume, and limited investor interest. However, it is necessary to reveal whether the findings support the efficient market hypothesis or behavioral finance theory. In this context, even if there is no new information coming to the market, the effect of revealing the information on the trading volume by researching the share market on Google will be investigated. Looking at the literature, it has been shown that the prediction performance of nonlinear models is better than linear models. In this direction, in the study, the relationship between the trade volume and the investor's discovery of information about the stock market by Google is examined through linear and nonlinear econometric techniques in the context of the investor reputation hypothesis.

Literature Review

There are studies in which Google trend search data is used in different areas in the economics literature. The first study to examine investor interest using data from Google trend searches is Da et al. (2011). The study discusses the share market codes of companies traded in the US capital market and the frequency of Google searches to measure investor interest. As a result, a relationship was determined between the frequency of searches and the transaction volume. In addition, it has been stated that the words searched in the search engine are also an indicator of emerging interest. The first study in finance is by Mondria et al. (2010). In the study, the validity of the hypothesis (home bias) that investors tend to invest only in shares in their own countries has been empirically examined. Additionally, the use of search data has proven very useful in many areas of finance, such as corporate areas. Monitoring financial news (Drake et al. 2012) or investor bias in stocks (Mondria et al. 2010) can be analyzed with the help of this data tool to predict the behavior of investors. Identifying the way data affects asset prices, volume, and volatility (Joseph et al., 2011; Padungsaksawasdi et al. 2019) and, accordingly, macroeconomic policies (Poutachidou and Papadamou 2021) on stock market dynamics are provided.

Google search volume data has the potential to help customers, investors, and policymakers make better decisions. When seeking information to make investment decisions, investors consider Google trends as they provide news about changes in prices (Salisu et al., 2021). It is seen that the techniques of causality analysis, portfolio analysis, panel data analysis, correlation analysis, and vector autoregression models are frequently used in studies examining investor interest in equity markets trading volume (Beer et al., 2012; Vlastakis & Markellos, 2012; Dzielinski, 2012; Zhang et al., 2013). Recent studies in which equity markets were analyzed through Google trend search data are given in Table 1.

Table 1 Stock markets and google search data summary literature

Author/s	Aim	Method	Result
Vozlyublennaia (2014)	Relationship between Dow Jones, NASDAQ, S&P 500, Gold Index, West Texas Oil Index returns and investor interest	Causality Analysis	Investor interest has been found to increase market efficiency.
Takeda & Wakao (2014)	The relationship between the stock returns and trading volume of companies traded on the Japanese stock exchange and investor interest	Panel Data Analysis	A positive relationship was found between stock returns, trading volume and investor interest.
Fink & Johann (2014)	Examining the relationship between investor interest and liquidity volatility and return in the DAX index	Panel Data Analysis	No relationship was found between liquidity and return. A relationship was found between Google trend searches and days with high investor interest.
Nurazi Et al. (2015)	Examining the relationship between Indonesian stock exchange liquidity and investor interest	Panel Data Analysis	A positive relationship was found between liquidity and investor interest.
Akgün (2016)	Examining the relationship between IPO returns and investor interest of 145 companies in Turkey	Generalized Moments Method	A positive relationship has been found between returns and Google trend searches.
Tantaopas et al. (2016)	Examining the relationship between Asia-Pacific stock markets and investor interest	Causality Analysis	A relationship was found between transaction volume and volatility and Google trend searches.
Bijl et al. (2016)	Examining the relationship between the share returns of 431 companies in the S&P 500 index and investor interest	Panel Data Analysis	A negative relationship was found between returns and Google trend searches.
Chen (2017)	Examination of the relationship between stock returns of 67 countries and investor interest in Bloomberg	Vector Autoregressi on Model	A negative relationship was found between returns and Google trend searches.
Adachi et al. (2017)	Examination of the relationship between the stock prices of companies in the JASDAQ and Mothers market in Japan and investor interest	Panel Data Analysis	A positive relationship was found between liquidity and prices and Google trend searches.
Yung & Nafar (2017)	Examining the effect of investor interest on the expected returns of UK real estate investment trusts.	CAPM & AFT	It has been determined that real estate investment trusts that receive greater attention from investors provide higher returns than those that do not.
Korkmaz et al. (2017)	Examining the effect of investor interest on BIST-100 return and trading volume	Causality Analysis	A one-way causality relationship has been determined from investor interest to index return.
Bozanta et al. (2017)	Examining the relationship between adjusted closing prices of 12 stock market indices and investor interest	Correlation Analysis	A negative correlation was found between Google trend searches and prices in the LSE.L, TMX Group Limited, and Nikkei225 indices. A positive relationship was observed in other groups. A one-way causality relationship has been determined from investor interest to index return.
Bilgiç (2017)	Examining the relationship between investor interest and demand for Borsa Istanbul	Regression Analysis	A positive relationship was found between the trading volume and investor interest.

Wang et al. (2018)	Examining the effects of investor interest on liquidity and returns in four sectors (real estate, automobile, health and finance) among the Shenzhen CSI 300 index.	Principal Component Analysis	A relationship was found between liquidity and return and investor interest. There was a negative relationship between adverse investor interest and a positive relationship with positive investor interest.
Ahluwalia (2018)	Examining the relationship between the returns of 500 stocks in the S&P 500 and investor interest	Panel Data Analysis	A statistically significant relationship was found between returns and Google trend searches.
Kim et al. (2019)	Examining the relationship between the trading volumes of the largest companies in the Oslo Stock Exchange and Google searches	Panel Data Analysis	The effect of increasing Google trend searches in predicting increased volatility and trading volume has been identified. A statistically significant relationship was found between returns and Google trend searches.
Jain & Biswal (2019)	Examining the relationship between gold searches on Google, gold spot prices, stock prices, and the US Dollar-Indian Rupee exchange rate	Nonlinear Causality Analysis	A significant relationship was found between gold prices and investor interest, and it was seen that the interest increased as the prices decreased.
Topaloğlu & Ege (2020)	Examining the effect of investor interest on the trading volume and return of banks listed on Borsa Istanbul.	Panel Data Analysis	A positive relationship was found between stock returns and Google trend searches.
Liu et al. (2021)	Investigation of the effect of the main products of the 5 big technology companies operating in the USA on the financial performance of the search volume in the Google search	Regression Analysis	Negative relationship between company name search volume and companies' return on equity, return on assets and Tobin q ratio; There is a positive relationship between the search volume of the company's main products and the equity and return on assets.
Nur (2021)	Examining the impact of social media on the financial performance of 9 oil and gas companies listed on the Indonesian Stock Exchange.	Panel Data Analysis	The positive effect of the number of social media accounts of the companies and the comments made on various platforms about the companies on the value of the company.

It is seen that the studies conducted to investigate the relationship between the return of the equity markets and the trading volume and the investor interest are frequently included in the international literature, while the studies are limited in the national literature. In addition, it is seen that the analytical approaches used in research are often linear.

Method

In this section, first Dickey and Fuller(1979): DF(1979), Phillips and Perron(1988): PP(1988), Kapetanios, Shin and Snell(2003): CSR(2003) stationarity/unit root tests, and Broock, Dechert and Scheinkman(1987): BDS linearity test is briefly mentioned. Then, due to its use in the study Granger causality and Dicks and Panchenko nonlinear causality test are given.

Unit root tests

DF(1979) Test

It is a test used to determine whether linear series have a unit root. It is known that the test power and the reliability of the results decrease in case of structural changes or breaks in the series and non-linearity of the series (Akgül & Özdemir, 2018). In the test introduced by Dickey and Fuller (1979), the existence of a unit root is determined in the series. The presence of the unit root in the formation processes of the time series is tested under the null hypothesis.

$$Y_t = \rho Y_{t-1} + \varepsilon_t \qquad (3)$$

Since the test statistic $\left(\tau = \frac{\hat{\rho}-1}{se(\hat{\rho})}\right)$ calculated under the first-order autoregressive process H_0 hypothesis ($H_0: \rho = 1$) does not fit the standard t-distribution, it is decided by comparing it with the τ table. If the test statistic is more negative than the table critical value, the H_0 hypothesis is rejected. The H_0 hypothesis states that the studied series is stationary and does not contain a unit root. In this test, the least squares estimators lose their efficiency in case of autocorrelation between the error terms. Therefore, it is recommended to use the Extended Dickey-Fuller test (ADF) in this case.

$$\Delta Y_t = \rho Y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta Y_{t-i}\, \varepsilon_t \qquad (4)$$

In the ADF test, the decision stage proceeds the same as in the DF test. Various information criteria are used to determine the optimum number of delays to be included in the equation (Dickey and Fuller, 1979: 427-431).

PP(1988) Test

In this test, which uses non-parametric statistical methods without adding the autocorrelation lagged difference values in the error term, new assumptions are added to the error term.

$$\Delta Y_t = \alpha Y_{t-1} + X_t' \delta + \varepsilon_t \qquad (5)$$

With the addition of constant or constant and deterministic components (X_t) that express the trend, it expresses $\alpha = \rho - 1$. Test statistic obtained as a result of non-parametric corrections $\left(\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{-1/2} - \frac{T(f_0-\gamma_0)(s_e(\hat{\alpha}))}{\alpha f_0^{1/2} s}\right)$ tests the existence of unit root $(H_0: \alpha = 0)$ under the H_0 hypothesis by comparing it with Mackinnon critical values. The f_0 estimation can be made with the AR Spectral Density Estimation Method (Phillips & Perron, 1988:337-338).

KSS(2003) Test

Kapetanios, Shin, and Snell(2003) proposed an approach that would separate the nonstationary linear process from the stationary but nonlinear process. While this test expresses the unit-rooted null hypothesis of the nonlinear Exponential Soft Transition Autoregressive (ESTAR) process, the alternative hypothesis represents stationarity.

$$\Delta Y_t = \gamma Y_{t-1}[1 - exp(-\theta Y_{t-1}^2)] + \varepsilon_t \qquad (\theta \geq 0)$$
(6)

The exponential pass function $[1 - exp(-\theta Y_{t-1}^2)]$ is adapted for nonlinear tuning. Under the H_0 hypothesis, the linear process ($H_0: \theta = 0$), while the alternative hypothesis is nonlinear but globally stationary, the process is tested. Since H_0 will not be tested directly, the auxiliary regression equation is obtained. In case of serial correlation, the equation is expanded.

$$\Delta Y_t = \delta Y_{t-1}^3 + \varepsilon_t \qquad (7)$$

$$\Delta Y_t = \sum_{j=1}^{p} p_j \Delta Y_{t-j} + \delta Y_{t-1}^3 + \varepsilon_t \qquad (8)$$

The calculated test statistic $\left(t_{NL} = \frac{\hat{\delta}}{se(\hat{\rho})}\right)$ is obtained by t_NL asymptotic critical values simulations (Kapetonis et al., 2003; 363-364).

BDS test

The non-parametric test developed by Broock, Hsieh and LeBaron (1991) after its introduction by Broock, Dechert and Scheinkman (1987) examines the autocorrelation between the current and past values of time series. Its difference from other linearity tests is that it is based on the cointegration integral of the theory of chaotic processes. A chaotic process is defined as a process that is created by a deterministic process but has the appearance of a stochastic process and exhibits similar autocorrelation features (Granger and Teräsvirta, 1993: 90). The test, which detects only non-linearity and does not reveal the type of dependency, is applied after de-trending or first difference by fitting an appropriate linear model to eliminate the linear structure. The test statistic $C_m(l)$ is the cointegration integral corresponding to various *m* chaotic process dimensions, *l* is the distance $W_m(l) = \frac{\sqrt{T}[C_m(l)-(C_l(l))^m]}{\sigma_m(l)}$ is calculated and compared with the critical value (critical value for α=0.05 = ±1.96) and the nonlinear structure is examined (Broock et al., 1996:203-205).

Granger causality test

In the test in which the definition of *"If the prediction of variable Y is more successful when the past values of X are used than when the past values of X are not used, then X is the Granger cause of Y"* is tested, causality inference is made, not prediction. Therefore, the variables should be stationary beforehand (Granger, 1988:554).

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \varepsilon_{1t} \quad (9)$$

$$X_t = \sum_{j=1}^{m} \alpha_j Y_{t-j} + \sum_{j=1}^{m} \beta_j X_{t-j} + \varepsilon_{2t} \quad (10)$$

However, in the absence of linearity in the series, the standard Granger causality test is not suitable for revealing the existence of a nonlinear causality relationship between the series. Because linear Granger causality analysis does not consider nonlinear causal relationships between variables.

Diks and panchenko nonlinear causality test

In the presence of nonlinearity, Monte Carlo experiments have shown that the prediction success of nonlinear approaches is more successful than linear models (Baek & Brock, 1992). However, the non-parametric Baek and Brock(1992) test has been difficult to implement because of its rigid assumptions. The basic hypothesis of the nonlinear Granger causality test was tested by Diks and Panchenko (2006) with a non-parametric test. In the test, which was developed against the problem of frequently rejecting the null hypothesis, it was suggested to apply the test to the residuals of the model by estimating the Vector Autoregression Model (VAR) first in order to eliminate the linear dependence. In this way, the residuals are used to extract the nonlinear structure of the original data.

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i \left(\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)\right) \quad (11)$$

The test statistic expressing the composite density functions converges to the normal ($\overset{d}{\rightarrow}$ converges) with the distribution $\sqrt{n}\frac{(T_n(\varepsilon_n)-q)}{S_n} \overset{d}{\rightarrow} N(0,1)$

$\left(\left(\varepsilon_n = Cn^{-\beta}\right),\ (C > 0),\ \left(\frac{1}{4} < \beta < \frac{1}{3}\right)\right)$. Diks and Panchenko recommend one-sided application of the test. In addition, since the filtering process is a linear VAR model, the assumption of independent, identical and Normal distribution of residuals should be provided in the definition of the model $\varepsilon_t \sim N.i.i.d(0, \sigma^2)$ (Diks & Panchenko, 2006:1656-57).

Findings

Investor interest cannot be measured directly, surveys and news analysis were used in the first studies to measure it. In later studies, data from social media platforms and search engines have been begun to measure active investors' interest. Since 2004, the frequency of the data scanned by the Google company in the search engine is accessed through Google trend searches. Normalization is performed in order to facilitate the comparison of the data. In the normalization of the data, the volume index of the day of the week indexed according to the highest volume of the month (RWW), the sum of this index (RDV), the volume index of the week taken from the trends (WV) and the volume indexed according to the highest week search volume in the data date are used.

$$RWW_w = {}_{i=7}^{7}RDV_{wi} \qquad \{i = 1,2,3,4,5,6,7\}$$
(12)

$$DV_t = \frac{WV_w}{DV_t} \times RDV_{wi}$$
(13)

The normalization process is performed according to any word's full search and current search numbers. The normalized search numbers are rescaled according to the highest online search level. As a result of scaling, the searched word varies between 0 and 100. At the same time, it is possible to obtain weekly statistics on how often any word is searched through this platform.

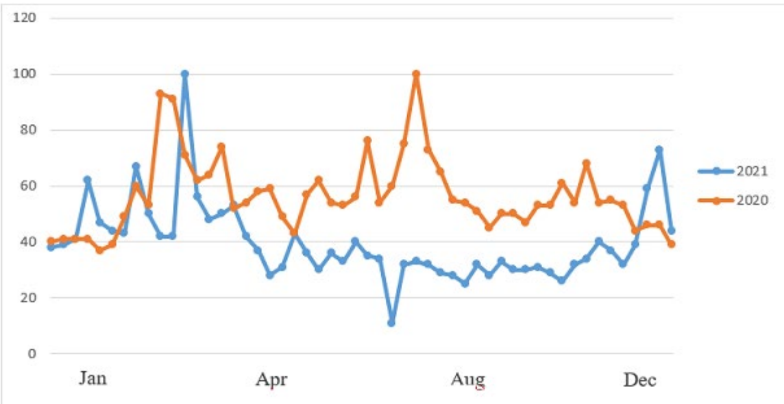

Figure 1 Search query result for the word “BIST” on Google Trends (2020 & 2021).

Changes in investor interest over time can be seen in the chart. According to the calculations, a hot money inflow exceeding 500 million dollars was experienced in the share market only in August 2020. The 5-year Credit Default Swap value in Turkey declined to 360. In the same period of 2021, it is observed that the interest of investors decreased. It is thought that this is due to the price drops in the crypto money markets, which are alternative investment tools. As a result of the increasing popularity of cryptocurrencies, especially in recent years, the relationship with the share markets has also been investigated. When evaluated in general, it is seen that the search results obtained from the Google search engine are a suitable variable in measuring investor interest.

Borsa İstanbul stock prices, which are among the data analyzed within the scope of this study, were obtained from the Thomson Reuters database. Google Trend search volumes of Borsa İstanbul were obtained manually via the Google Trends website. The variables were handled between 13/05/2020-30/09/2020 and 13/05/2021-30/09/2021, and comparisons were made in the analyses. The analysis techniques used were carried out through the RStudio program. Descriptive statistics of the variables with logarithmic transformation are given in Table 1. In the study, Borsa İstanbul stock prices are given as "BIST," and Google Trend search volumes are given as "GT_BIST."

Table 1 Descriptive statistics

Statistics \ Variables	GT_BIST (2020)	BIST (2020)	GT_BIST (2021)	BIST (2021)
Mean	7.482635	7.011268	7.255791	7.620370
Median	7.473637	7.009671	7.259862	7.573531
Maximum	8.968651	7.086462	7.299203	9.132271
Minimum	5.958425	6.899653	7.205516	6.548219
Std. Dev.	0.476866	0.043841	0.025918	0.374897
Skewness	-0.054064	-0.332459	-0.346783	0.993004
Kurtosis	4.726739	2.880355	1.956734	6.287730
Jarque-Bera	12.59689	1.920811	6.604714	62.08723
Probability	0.0001839	0.382738	0.036796	0.000000

When the normal distribution feature of the variables is examined, it has been determined that only the BIST variable conforms to the normal distribution for 2020.

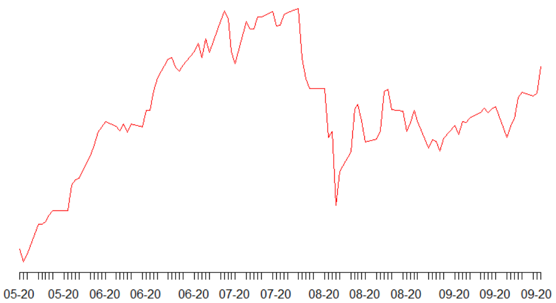

Figure 2. Logarithmic BIST Graph (2020).

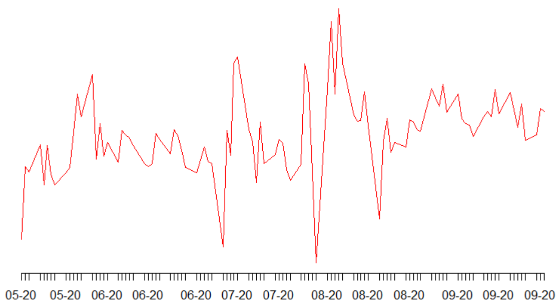

Figure 3 Logarithmic Google Trend Graph (2020).

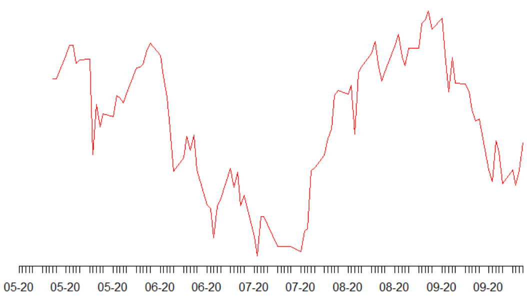

Figure 4. Logarithmic BIST Graph (2021).

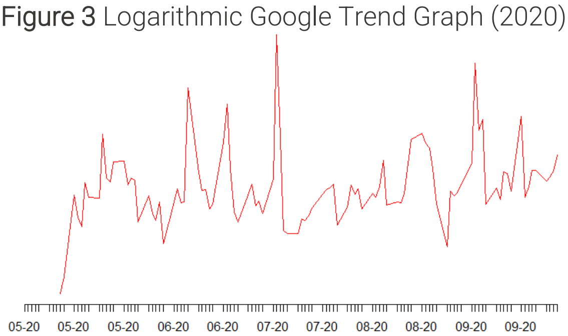

Figure 5 Logarithmic Google Trend Graph (2021).

When the BIST variable is analyzed for 2020, it is seen that the highest stock prices occurred in July and the lowest in May. In 2021, it was determined that the period with the highest stock prices in September, and the lowest period was July. Looking at the Google trend search volume for BIST for 2020, it is seen that both the highest and lowest volumes were in July. In 2021, it was determined that the volume was highest in July and lowest in May.

Before proceeding to the causality analysis, the BDS test was applied to determine the process followed by the variables to be included in the analysis, and the results are given in Table 2.

Table 2 BDS linearity test

		BIST				GT_BIST			
	Dimension	BDS Test Statistic	Std. Error	Z-Statistic	p-value	BDS Test Statistic	Std. Error 0.0094	Z-Statistic	p-value
2020	2	0.16256	0.0072	22.414	0.0000	0.04006		4.2485	0.0000
	3	0.27362	0.0115	23.629	0.0000	0.08111	0.0150	5.3835	0.0000
	4	0.35041	0.0135	25.298	0.0000	0.11203	0.0180	6.2096	0.0000
	5	0.39855	0.0145	27.484	0.0000	0.12726	0.0189	6.7288	0.0000
	6	0.42520	0.0140	30.271	0.0000	0.12469	0.0183	6.7966	0.0000
	Dimension	BDS Test Statistic	Std. Error	Z-Statistic	p-value	BDS Test Statistic	Std. Error	Z-Statistic	p-value
2021	2	0.147816	0.0044613	32.04280	0.0000	0.050627	0.010485	4.828522	0.0000
	3	0.248831	0.007350	33.85446	0.0000	0.074822	0.016821	4.448045	0.0000
	4	0.311734	0.008770	35.54547	0.0000	0.080304	0.020229	3.969819	0.0000
	5	0.348420	0.009157	38.04887	0.0000	0.068669	0.021296	3.224469	0.0000
	6	0.363915	0.008846	41.14052	0.0000	0.052685	0.020747	2.539334	0.0000

It has been determined that the variables examined within the scope of 2020 and 2021 are not linear in all dimensions; in other words, the null hypothesis expressing linearity was rejected at all significance levels. Based on this fundamental finding, nonlinear unit root tests should be used to control the stationarity of the series. Kapetanios et al. (2003), in the nonlinear unit root test, the Taylor approach is frequently used by simplifying it. However, to examine how the results will be affected if nonlinearity is ignored in the study, both linear and nonlinear unit root tests are applied, and the results are given in Table 3.

Table 3 Unit root tests results

	Test	ADF (Sabit & Trend)			PP (Sabit & Trend)			KSS (Trendden Arındırılmış Model)		
	Variable	%1	%5	%10	%1	%5	%10	%1	%5	%10
		-4.02	-3.44	-3.14	-5.34	-4.85	-4.60	-3.93	-3.40	-3.13
2020	LBIST		-2.180028			-4.607938			0.980524	
2020	ΔLBIST		-9.848811			-10.40443			-7.463942	
		ADF (Sabit)			PP (Sabit)			KSS (Sabitten Arındırılmış Model)		
		%1	%5	%10	%1	%5	%10	%1	%5	%10
		-2.58	-1.94	-1.61	-4.94	-4.44	-4.19	-3.48	-2.93	-2.66
2020	LTREND		-6.697265			-8.608908			-0.704886	
2020	ΔLTREND		-			-			-5.147162	
2021	LBIST		-1.851131			-2.359753			-0.283223	
2021	ΔLBIST		-11.38143			-12.25619			-7.261766	
2021	LTREND		-6.590298			-7.417266			-0.506126	
2021	ΔLTREND		-			-			-9.692326	

Note: According to the Schwarz information criterion of optimal delay length in the ADF test, the Newey-West Bandwith criterion was used to determine the bandwidth for the PP test. The critical values for the CSR test were obtained from the CSR (2003) study.

For the BIST variable, it is seen that the linear unit root tests ADF and PP tests give the same results as the CSR test in both 2020 and 2021. It is determined that the BIST variable is not stationary in its level state; in other words, the existence of the unit root, which is the primary hypothesis, cannot be rejected, and the variable becomes stationary when the first difference is taken. However, when we look at the Google trend search volume for BIST, it is seen that linear unit root tests are stationary at both levels in 2020 and 2021. However, in the CSR test, which considers its nonlinear structure, it is determined that the first difference of the variable is stationary. The results of linear Granger causality analysis estimated by the results of linear unit root tests are given in Table 4.

Table 4 Linear granger causality analysis

	Statistic / Aspect of Relationship	$L_x = L_y$	F-Statistics	*p*-value
2020	BIST → GT_BIST	5	2.40235	0.0436
	GT_BIST → BIST	5	2.44647	0.0404
2021	BIST → GT_BIST	1	0.07231	0.7886
	GT_BIST → BIST	1	7.23187	0.0084

Note: Lx=Ly denotes optimal delay values for causality.

$$\Delta LBIST_t = \alpha_1 + \sum_{p=1}^{k} \beta_{1p} \Delta LBIST_{t-p} + \sum_{p=1}^{k} \delta_{1p} LGT\_BIST_{t-p} + \varepsilon_{1t} \quad (14)$$

$$LGT\_BIST_t = \alpha_2 + \sum_{p=1}^{k} \beta_{1p} LGIT\_bIST_{t-p} + \sum_{p=1}^{k} \delta_{1p} \Delta LBIST_{t-p} + \varepsilon_{2t} \quad (15)$$

Looking at the results of the linear causality analysis for 2020, it is seen that there is a bidirectional causality relationship between BIST stock prices and Google trend search volume. In 2020, it was determined that there is only a one-way causality relationship from Google trend search volume to BIST stock prices. In order to make comparisons, Diks and Panchenko's (2006) test was applied for nonlinear causality analysis by the result of the CSR test, in which the nonlinear structure of the variables was taken into account. When the Kurtosis values of the stationary series are examined, it is seen that there is a varying variance structure in the data set. A nonlinear causality test is supported (Diks & Panchenko, 2006). Before the test, the VAR model was estimated to eliminate the linear dependency structure. Nonlinear causality analysis was also applied to the residual terms of the predicted model. The validity of the VAR models built on this was tested. It was seen that the residuals are normally distributed with zero mean and constant variance (N.i.i.d). Diks and Panchenko's nonlinear causality tests are applied for different delays such as bandwidth ε=1.5 with residuals and Lx=Ly=1,2,3,4,5, and the results are given in Table 5.

Table 5 Nonlinear causality analysis

	Statistic / Aspect of Relationship	$L_x = L_y$	*t*-statistics	*p*-value
2020	GT_BIST → BIST	4	2.81492	0.0300
2021	BIST → GT_BIST	2	3.94593	0.0226

Note: The values of ε are given as ε=1.5 for N=100 (Diks and Panchenko, 2006: Table 1, 1658). Only statistically significant lags, t-statistics and p-values are tabulated.

Looking at the nonlinear causality analysis results for 2020, it is seen that there is a one-way relationship from Google trend search volume to BIST stock prices. In 2021, it was determined that there is a one-way relationship that is precisely the opposite. When two different analyzes are compared, it is seen that the emerging relationships are in different patterns. In the absence of linearity, the standard Granger causality test approach is not suitable for revealing the existence of a nonlinear causality relationship between the series. This is because nonlinear causal relationships between the variables are not taken into account (Akgül and Özdemir, 2018).

Conclusion

With the studies in behavioral finance, it has been observed that investor interest will affect the market even if there is no new information on the market. Since investor interest is not a directly measurable concept, search engine and social media data can be used to measure active investor interest. In the study, the relationship between the investor's discovery of information on the stock market by researching on Google and the transaction volume was examined through linear and non-linear econometric techniques in the investor reputation hypothesis. As a result of the findings supporting the investor reputation hypothesis and the correct determination of the shape of the relationship, the possibilities of guiding investment decisions were examined.

When the results are evaluated for 2020, In linear causality analysis, it was seen that there is a bidirectional causality relationship between Google trend searches and transaction volume. When nonlinear estimation is made with the same variables, it has been determined that the relationship is one-way for the transaction volume from Google trend searches. Accordingly, it is possible to say that Borsa Istanbul is frequently followed by curiosity among the public in Turkey, and this situation increases the interest when there is activity. It also reveals that similar movements have been observed in prices following increased internet searches. It can be inferred that the popularity of a financial asset can affect its price. When the results are evaluated for 2021, In the linear causality analysis, it was seen that there is a one-way relationship between Google trend searches to transaction volume. When nonlinear estimation is made with the same variables, it has been determined that there is a one-way relationship between transaction volume to Google trend searches. Accordingly, it was concluded that the increase in the trading volume in the stock market is an essential factor affecting the frequency of searches on the internet. Considering that the trading volume is a leading indicator showing the direction of the market, it is concluded that investors in BIST demand information about the market according to the changes in the market. Empirical results for 2020 in nonlinear causality analysis Korkmaz et al. (2017), Vozlyublennaia (2014), and for 2021 Jain & Biswal (2019) study. However, causality analysis studies in Turkey are carried out under the assumption of linearity for various periods. Since there is no similar study in which the nonlinear relationship is taken into account, it was not possible to compare the findings obtained. It is an essential resource for individual and institutional investors who can interpret the effect of investor interest in increasing the transaction volume and use it as a strategy. It has several advantages over classical variables used in macroeconomic forecasting. According to officially published statistics, it is real-time rather than delayed, geo-restrictions are possible, and the estimator panel is expanded. For this reason, it can be suggested that search engine data should be a source of motivation for potential research. However, in line with the results obtained from the study, a preferably nonlinear combination of the Google trends series can significantly increase the predictive power by outperforming any benchmark (Borup et al., 2020). Otherwise, when the data is used to predict econometric models, it may affect parameter estimates, leading to incorrect economic or political decisions.

According to the investor reputation hypothesis, investors only invest in stocks they are aware of without adequate research and knowledge. In this context, the study results were realized in a way that supports the investor recognition hypothesis within the scope of 2020. In line with the theory, investors generally actively research the stock that attracts their attention, which causes an increase in price and returns for the stock that attracts the investor's attention. In this case, it can be said that investors can obtain above-normal returns by directing their investment strategies with the information they obtain by using Google search engine data. It is thought that the awareness to be created about the fact that the price of each financial asset may fluctuate from time to time and that an investment decision should not be taken with panic will be beneficial in order to prevent this situation. It is seen that the results of the study do not support the investor reputation hypothesis within the scope of 2021. In some studies in the literature, a temporary increase in stock returns was observed after the increase in Google searches. This situation, which individual investors cause, can create price pressure. Some studies have also shown that the increase in Google search results in a temporary increase in returns. If internet searches have risen before returns, it indicates price pressure.

In the study, the importance of the information in the theoretical theories about finance was investigated in terms of Borsa İstanbul. In this context, it helps to understand how the pricing mechanism in the market changes when the demand for information on the stock market increases. Search data, which indicates investor interest and is freely available, enables small investors to determine their investment preferences by checking them. At the same time, it provides a more timely control of investor interest as it compares it with passive interest criteria. In future studies to be carried out in this area, it seems possible to determine the degree of effect of nonlinear regression estimations and the relationship between variables. In addition, to examine situations such as price pressure, it is recommended to examine on which days of the week the calls increase and on which days the returns increase.

Yazar Katkı Oranları başlığı

Çalışmaya 1. Yazar: %100 oranında katkı sağlamıştır.

Çıkar Çatışması Beyanı

"How Can Google Trends Be Used as a Technical Indicator for Investor Interest?" başlıklı makalemin herhangi bir kurum, kuruluş, kişi ile mali çıkar çatışması yoktur. Yazarlar arasında da herhangi bir çıkar çatışması bulunmamaktadır.

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Genişletilmiş Özet

Etkin piyasa hipotezinde, yatırımcıların karar alırken tüm pay senetlerinin tam geçmişine ulaşabildiği varsayılmaktadır. Davranışsal finans alanındaki çalışmalar ile birlikte piyasaya yeni bir bilgi gelmese dahi yatırımcı ilgisinin piyasayı etkileyeceği gözlemlenmiştir. Özellikle yatırımcıların yeterince bilgi sahibi olmadan sadece farkında oldukları hisse senetlerine yatırım yaptıklarının varsayılması yatırımcı tanınmışlık hipotezi olarak adlandırılmaktadır. Yatırımcı ilgisi doğrudan ölçülebilen bir kavram olmadığı için aktif yatırımcı ilgisinin ölçümünde arama motoru ve sosyal medya verilerinden yararlanılabilmektedir. Google arama hacmi verileri, müşterilere, yatırımcılara ve politika yapıcılara daha iyi kararlar verme konusunda yardımcı olma potansiyeline sahiptir. Yatırım kararları almak için bilgi ararken, yatırımcılar fiyatlardaki değişikliklerle ilgili haberler sağladıkları için Google trendlerini dikkate almaktadırlar. Literatürde yatırımcı ilgisinin incelendiği çalışmalar sıklıkla lineer modellerin uygulamalarıyla gerçekleştirilmiştir. Bu durum zaman serilerinde olası yapı değişikliklerinin dikkate alınmadığı ihtimalini düşündürmektedir. Nitekim literatüre bakıldığında doğrusal olmayan modellerin tahmin performansının doğrusal modellerden daha iyi olduğu gösterilmiştir. Ayrıca pay piyasaları getirisi ve işlem hacminin yatırımcı ilgisiyle olan ilişkisini araştırmaya yönelik yapılan çalışmaların uluslararası yazında sıkça yer aldığı, ulusal yazında ise çalışmaların sınırlı kaldığı görülmektedir. Bu doğrultuda, çalışmada yatırımcıların pay piyasasına ilişkin Google üzerinden araştırma yaparak bilgiyi ortaya çıkarmalarının işlem hacmi ile ilişkisi yatırımcı tanınmışlık hipotezi bağlamında doğrusal ve doğrusal olmayan ekonometrik teknikler aracılığıyla incelenmiştir. Yatırımcı tanınmışlık hipotezine göre yatırımcılar yeterince araştırma yapmadan ve bilgi sahibi olmadan sadece farkında oldukları pay senetlerine yatırım yapmaktadırlar.

Bu kapsamda çalışmada incelenen değişkenler hem doğrusal hem de doğrusal olmayan nedensellik analizi teknikleri aracılığıyla ele alınmıştır. Elde edilen bulgular 2020 yılı için değerlendirildiğinde; doğrusal nedensellik analizinde Google trend aramaları ile işlem hacmi arasında çift yönlü nedensellik ilişkisi olduğu görülmüştür. Aynı değişkenlerle doğrusal olmayan tahmin yapıldığında ilişkinin tek yönlü ve Google trend aramalarından işlem hacmine yönelik olduğu tespit edilmiştir. Sonuçlar 2021 yılı için değerlendirildiğinde ise doğrusal nedensellik analizinde Google trend aramalarından işlem hacmine tek yönlü ilişki olduğu görülmüştür. Aynı değişkenlerle doğrusal olmayan tahmin yapıldığında ise işlem hacminden Google trend aramalarına tek yönlü ilişki olduğu tespit edilmiştir. Buradan hareketle, Türkiye'de Borsa İstanbul'un halk arasında sıkça merak ve takip edildiği, hareketlilik oldukça da bu durumun ilgiyi artırdığını söylemek mümkündür. Ayrıca internet aramalarında yaşanan artışı takiben fiyatlarda da benzer hareketler görüldüğünü ortaya koymaktadır. Aynı zamanda pay piyasasında işlem hacminin artması piyasasının internette aranma sıklığını etkileyen önemli bir faktör olduğu sonucuna varılmıştır. İşlem hacminin piyasasının yönünü gösteren öncü bir gösterge olduğu dikkate alındığında, BİST'teki yatırımcıların piyasadaki değişimlere göre piyasaya yönelik bilgi talebinde bulunduğu sonucu ortaya çıkmaktadır. İnceleme yapılan dönemler bazında değerlendirme yapıldığında; 2020 yılı kapsamında yatırımcı tanınmışlık hipotezinin desteklendiği, 2021 yılı kapsamında ise yatırımcı tanınmışlık hipotezini desteklemediği sonucuna ulaşılmıştır.

Yatırımcı ilgisinin işlem hacmini arttırıcı etkisini yorumlayabilen, strateji olarak kullanabilen bireysel ve kurumsal yatırımcılar açısından önemli bir kaynaktır. Makroekonomik tahminlerde kullanılan klasik değişkenlere göre çeşitli avantajlara sahiptir. Resmi olarak yayınlanan istatistiklere göre gecikmeli değil gerçek zamanlı olması, coğrafi sınırlandırmaların mümkün olması ve tahmin edici panelinin genişletilmesi imkânları tanımaktadır. Bu nedenle arama motoru verilerinin potansiyel araştırmalara motivasyon kaynağı olması önerilebilmektedir. Ancak çalışmadan da elde edilen sonuçlara paralel olarak, Google trendler serisinin tercihen doğrusal olmayan bir şekilde birleştirilmesi, herhangi bir kıyaslamadan daha iyi performans göstererek tahmin gücünü önemli ölçüde artırabilmektedir. Aksi halde veriler ekonometrik modelleri tahmin etmek için kullanıldığında, sonunda yanlış ekonomik veya politik kararlar alınmasına yol açacak parametre tahminlerini etkileyebilecektir. Çalışmada finans ile ilgili kuramsal teorilerde yer alan bilginin önemi Borsa İstanbul açısından araştırılmıştır. Bu bağlamda pay piyasasına yönelik bilgi talebinin artması durumunda piyasadaki fiyatlama mekanizmasının ne şekilde değiştiğinin anlaşılmasına yardımcı olmaktadır. Yatırımcı ilgisini belirten ve ücretsiz bir şekilde eşanlı temin edilebilen arama verileri özellikle küçük yatırımcıların kontrol ederek yatırım tercihlerini belirlenmesine imkân tanımaktadır. Aynı zamanda yatırımcı ilgisini pasif ilgi ölçütleriyle karşılaştırdığı için daha zamanında kontrol edilmesini sağlamaktadır. Bu alanda gerçekleştirilecek olan sonraki çalışmalarda doğrusal olmayan regresyon tahminleri ile değişkenler arası ilişkilerin etki derecesinin belirlenmesi de mümkün gözükmektedir.