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International Investors, Volatility, and Herd Behavior: Borsa İstanbul, 2001-2016

Araştırma Makalesi /Research Article

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ABSTRACT: *We study herding in Borsa Istanbul between 2001 and 2016, focusing on the effects of international investors and market volatility. Herding explains 31% of total variability in the cross sectional standard deviation of beta values, controlling for market fundamentals. We perform time-series analysis of a herding index and find that herding increases following increased trading by international investors, but falls with overall trading volume on the market. Herding rises in response to increased volatility, rather than leading to it, against previous arguments. Investors do not herd during economic crises, but following important events that raise political tension in the country.*

Keywords: Herd behavior; Borsa İstanbul; Volatility; International investors.

JEL Codes: G11, G12, G14, G15, G4; C32, C58.

Uluslararası Yatırımcılar, Volatilite ve Sürü Davranışı: Borsa İstanbul, 2001-2016

ÖZ: *Bu çalışmada Borsa İstanbul'da 2001 ve 2016 yılları arasında sürü davranışı çalışılmış, ve özellikle uluslararası yatırımcı ve volatilite etkilerine odaklanılmıştır. Sürü davranışı, temel pazar göstergeleri kontrol edildiği durumda, yatay-kesitsel beta değerlerindeki hareketliliğin %31'ini açıklamaktadır. Elde ettiğimiz sürü davranışı endeksinin zaman serisi analizi, sürü davranışının uluslararası yatırımcıların ticaret hacmi ile arttığını, ancak toplam ticaret hacmi ile azaldığını göstermektedir. Sürü davranışı, artan pazar volatilitesi ile artmakta, ancak -yazındaki kimi iddiaların aksine- pazarda bir volatilite artışına neden olmamaktadır. Sürü davranışının ekonomik kriz dönemlerinde artmadığı, ancak ülkede politik gerilimi artıran önemli olaylar sonucunda yükseliş gösterdiği bulunmuştur.*

Anahtar Kelimeler: Sürü davranışı, Borsa İstanbul, Volatilite, Uluslararası yatırımcılar.

JEL Kodları: G11, G12, G14, G15, G4; C32, C58

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1.Introduction

Herding in financial markets has been the subject of a large empirical literature, due to its behavioral relevance and its potential effect on market outcomes. Evidence for herding is claimed through an examination of the cross-sectional dispersion of absolute stock returns, usually called the CSAD method (Christie and Huang, 1995; Chang, Cheng and Khorana, 2000), or individual beta values in the market in a state-space framework (Hwang and Salmon, 2004). The literature produced mixed results, but provided ample evidence for the prevalence of herding in developed and emerging economies (Caparrelli, D'Arcangelis and Cassuto, 2004; Saastamoinen, 2008; Chiang, Li and Tan, 2010; Economou, Kostakis and Philippas, 2011; Chiang et al., 2013; Messis and Zapranis, 2014; among many others).

However, studies on the causes and consequences of herding are still relatively rare. We study herding behavior by investors in Borsa Istanbul (BIST), in order to investigate herding behavior in relation to international investments and market volatility. There is evidence against a conventional understanding that large, international players invest rationally, while local investors in developing countries tend to exhibit herding (Choe, Kho and Stulz, 1999; Froot, O'Connell and Seasholes, 2001; Yao, Ma and He, 2014; Gonçalves and Eid, 2017; Chattopadhyay, Garg and Mitra, 2018). We contribute to this literature by providing a similar result for Borsa İstanbul. We find that herding increases with the volume of international transactions, but falls with overall transaction volume on the market. This may seem puzzling since international investors are larger players and have adequate resources for portfolio management. However, international investors are more risk-averse (Pop, 2012), and have informational disadvantages compared to locals. We argue that this renders herding a viable option, especially for those that invest in a diverse set of markets. Hence, herding by international investors is likely a consequence of international portfolio diversification in emerging markets.

Herding is argued to be a significant cause of volatility (Froot, Scharfstein and Stein, 1992; Hirshleifer and Teoh, 2003; Blasco, Corredor and Ferreruela, 2012). While authors have detected herding during times of uncertainty (Chiang and Zheng, 2010; Galariotis, Rong and Spyrou, 2015; Indārs, Savin and Lublóy, 2019), the causal relationship between volatility and herding has not been studied. A novelty of our approach is that we study the time series behavior of a herding index in detail. We use Granger causality analysis to show that past herding does not help predict future volatility, finding that herding is a *consequence* of increased volatility rather than its *cause*. Hence, herding appears as a response to increased volatility in the market, which renders it difficult to read market signals, rather than being a key source of uncertainty or frenzy itself.

Another common argument is that herding occurs during times of economic crisis or stress (Demirer, Kutan and Zhang, 2014). However, evidence for negative relationships between herding and crises has been accumulating as well. Hwang and Salmon (2004) find herding to fall during crisis periods in the U.S. and South Korea. Pop (2012) reports a similar finding for Romania, while Choe, Kho and Stulz (1999) report herding to decline during economic crisis in Korea.[4] We report results that support this thesis for BIST. During crises, investors have a tendency to fall back to market fundamentals rather than herd. However, our analysis indicate that herding rose in BIST during times of political tension. Few studies have examined herding in relation to political events (Chiang and Zheng, 2010; Indārs, Savin, and Lublóy, 2019). We add to this evidence, suggesting that herding may primarily be a political phenomenon, rather than following underlying market fundamentals.

Previous studies on BIST established the presence of herding during various time periods. While studies based on the CSAD methodology provide mixed results (Altay, 2008; Dogukanlı and Ergün, 2011; Çelik, 2013; Cakan and Balagyozgan, 2014; Balcılar and Demirer, 2015), studies employing the state-space method invariable agree on the presence of herding (Demir, Mahmud and Solakoglu, 2014; Solakoglu and Demir, 2014; Özsu, 2015; Durukan, Özsu and Ergun, 2017). However, these studies have not sufficiently studied causes and consequences of herding. Demir, Mahmud and Solakoglu (2014) discuss shares of foreign investment in BIST but do not provide an analysis in relation to herding. Durukan, Özsu and Ergun (2017) show that international investors herd less during crisis periods, but do not provide a link between herding in BIST and international trading. Our econometric analysis show that herding rises in BIST as a result of higher international investments.

2.Empirical Method

We take our empirical methodology from Hwang and Salmon (2004). We begin with a modified CAPM equation

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{it}^b = \beta_{it} - h_t(\beta_{it} - 1) \tag{1}$$

where $E_t^b(r_{it})$ and β_{it}^b denote the short-run expectation of the excess return and beta for asset *i* at time *t*, $E_t(r_{mt})$ is market excess return at time *t* and $h_t \leq 1$ is a herding parameter. The idea is that herding by investors lead to observed beta

[4] There is a large related literature on increased trading in futures causing volatility in the underlying market. Cheng, Kirilenko and Xiong (2014) note that during the 2008 financial crisis futures traders reduced their holdings which would suggest they are speculatorsi also implying reduced volatility in the financial markets due to reduced futures trading. Similar results are reported by include Adrangi and Chatruth (1998), Wang (2002), Chatrath and Song (1999) and Chang, Chou and Nelling (2000). There is also large evidence for the link between volatility and trading volume. Ezzat and Kirkulak-Uludag (2017) argue that number of trades is a better predictor of volatility than trading volume for Saudi Arabia.

values that deviate from real underlying betas. The case $h_t = 0$ represents the absence of herding. If $h_t = 1$ then $\beta_{it}^b = 1$ and there is perfect herding towards the market portfolio, and the stock imitates the market index. Various degrees of herding lie in between these extremes. The case $h_t < 0$ represents adverse herding, for which high-beta stocks ($\beta_{it} > 1$) appear to obtain even higher beta values and low-beta stocks ($\beta_{it} < 1$) even lower. Mean reversion towards the long-term equilibrium dictates that periods of adverse herding will eventually follow periods of herding.

From (1) we can write the cross sectional standard deviation of beta values as $Std_c(\beta_{it}^b) = Std_c(\beta_{it})(1 - h_t)$. Some manipulation gives

$$log\, Std_c(\beta_{it}^b) = \mu + H_t + v_t \tag{2}$$

where $\mu = E([Std_c(\beta_{it})]]$, $H_t = \log(1 - h_t)$, and $v_t \sim iid(0, \sigma_v^2)$. Allowing H_t to be AR(1), the model can be characterized as a standard state-space model and can be estimated using the Kalman filter. In order to obtain a measure of herding that is above and beyond the effects of important market fundamentals (overall market volatility and returns), we introduce these as additional independent variables in (Std). We write our preferred state-space specification as

$$\begin{aligned} &log\, Std_c(\beta_{it}^b) = \mu + H_t + c_1 \log \sigma_{mt} + c_2 \log r_{mt} + v_t \\ &H_t = \varphi H_{t-1} + \eta_t \\ &\eta_t \sim iid(0, \sigma_\eta^2);\ v_t \sim iid(0, \sigma_v^2) \end{aligned} \tag{3}$$

where σ_{mt} and r_{mt} are measures of the aggregate volatility and returns in the market. Critical parameters in (SS1) are φ and σ_η whose non-zero values indicate herding.

3.Data

Our raw data consists of daily stock prices on the BIST between January 2nd, 2001 and April 30th, 2016. We obtained daily stock prices for all 499 firms listed on the BIST during the said time period. The data on individual daily stock prices, including the price of the BIST 100 index have been obtained from the Matriks Data Terminal. Data on total trading volume and trading volume by investor types (international or domestic) have been obtained from the Finnet 2000 data service. International investors comprise 0.92% of investors on BIST, but hold 62.36% percent of free-floating shares traded on Borsa İstanbul as of the end of 2015 (Borsa İstanbul Annual Report, 2015).

All returns that are referred to in the paper are compounded returns calculated using daily closing prices. Monthly market volatility is calculated by using square daily returns as in Schwert (1989). Table 1 reports key descriptive statistics for our raw data, i.e., stock returns for all stock-day pairs in the sample and the BIST 100 market index. Table 2 reports descriptive statistics for monthly variables that are used in the estimation of the state-space system (SS1). The Jarque-Bera statistic rejects the normality of $\log Std_c(\beta_{it}^b)$ for the whole sample (*JB*=42.014), but does not reject normality when three extreme data points are excluded (*JB*=1.534). Instead of losing these observations, we use Huber-White robust standard errors as suggested by Drukker and Gates (2011).

Table 1: Descriptive statistics: Daily returns of stocks and BIST 100

Variable	Sample Size	Mean	Median	St.Dev.	Min	Max
Stock Returns	1,326,848	3.7x10-4	0.0000	0.0336	-0.938	0.839
BIST 100 Returns	3849	7.9x10-4	0.0010	0.0207	-0.181	0.135

Table 2: Descriptive statistics for variables in state-space analysis monthly statistics

Variable	Mean	Median	St.Dev.	Min	Max
Market Return	.0009	.0023	.0117	-.1056	.0406
Volatility	.6645	.4175	1.2041	.1712	14.53
log (Volatility)	-.7449	-.8735	.6462	-1.7652	2.6763
Std. of Betas	.3558	.3424	.1231	.0687	.7699
log (Std. of Betas)	-1.0968	-1.0717	.3717	-2.6773	-.2616
Growth (Trade volume)	-.0009	-.0099	.2640	-.7708	.9942
Growth (Foreign trade)	.0125	-.0003	.3021	-1.014	.8799

4.Analysis and Results

In order to estimate the state-space model, we begin by estimating characteristic equations for each stock in our dataset, using daily data over monthly intervals. This gives estimates of beta values (β_{it}^b) for each stock-month (*it*), hence a monthly panel (184 months) of beta values. Then $\log Std_c(\beta_{it}^b)$ are computed from these estimates for each month in our sample. We then estimate the state-space specification (SS1) using monthly data from January 2001 through April 2016. Estimated parameters are reported in Table 3. In Column 1 (Model 1), we estimate the model without including $\log \sigma_{mt}$ (market volatility) and r_{mt} (market return). Column 2 (Model 2) reports estimates of the full specification in (3).

In both specifications, estimates of herding parameters, $\hat{\varphi}$ and $\hat{\sigma}_{\eta}$are statistically significant, implying the presence of herding towards the market portfolio. The large estimated values for $\hat{\varphi}$ (0.79 and 0.68) indicate that herding is a quite persistent process. The herding series in BIST is less persistent than that of the U.S., but has a similar coefficient to that of South Korea (Hwang and Salmon, 2004). Herding explains 31% of the total variability in $Std_c(\beta_{it}^b)$ controlling for market fundamentals.

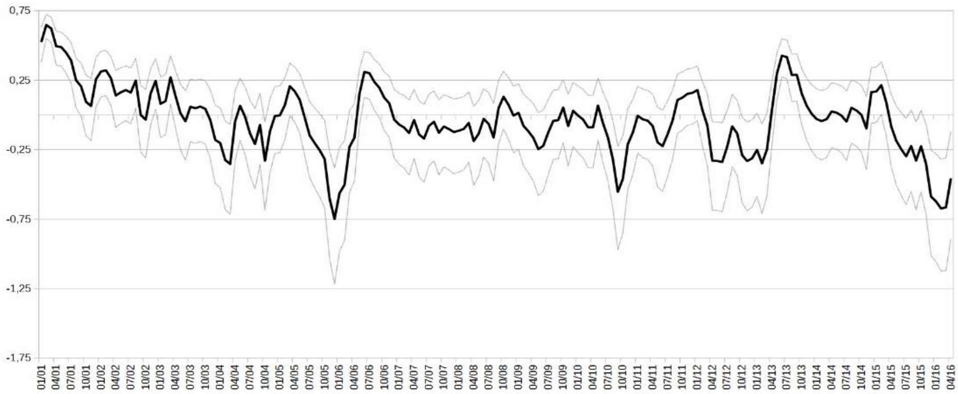
Table 3: State-Space Model Estimates

Variable	Model 1	Model 2
μ	-1.104**	-1.419**
	(-15.53)	(-37.25)
φ	0.791**	0.683**
	(6.65)	(7.30)
σ_v	0.230**	0.312**
	(3.45)	(4.95)
σ_η	0.184*	0.116**
	(2.04)	(2.83)
log σ_{mt}		-0.433**
		(-13.52)
r_{mt}		1.419
		(1.07)
Proportion of signal	0.495	0.313
Log-likelihood	-51.47	14.10
AIC	110.9	-16.2
SBIC	123.8	3.1
N	184	184

Notes: AIC: Akaike Information Criterion; SBIC: Schwartz Information Criterion. ** and * denote statistical significance at 1 and 5 percent respectively. t-statistics are in parenthesis.

The method gives a prediction for the state variable, i.e., a prediction ($\widehat{H_t}$) for H_t. These predictions are used to derive a time-varying index for herding, $\widehat{h_t} = 1 - \exp(\widehat{H_t})$.

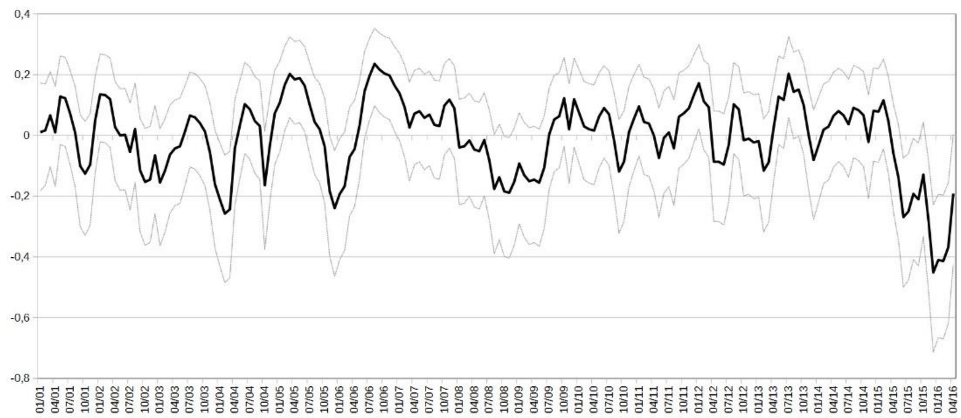
Figure 1: Monthly series for the herding index, $\widehat{h_t^1}$, predicted by Model 1. Dotted lines give the 95% confidence interval



Figures 1 and 2 display this herding measure obtained from model 1 (which we call $\widehat{h_t^1}$) and model 2 (which we call $\widehat{h_t^2}$), respectively. Controlling for market fundamentals reduces the magnitude of the herding parameter significantly, even though the patterns of innovations are similar. Figures also provide 95%

confidence intervals for h_t^i, which allow us to see that the index is significantly different from zero during various time periods. According to $\widehat{h_t^1}$, the herding index is significantly different from zero for a total of 50 months (24 months of herding, 26 months of adverse herding). For model 2 ($\widehat{h_t^2}$), we get a statistically significant herding measure for a total of 30 (13 months of herding, 17 months of adverse herding). Model 2 clears $\widehat{h_t}$ of any correlation with market volatility and return, hence this series has a smaller magnitude and standard deviation.

Figure 2: Monthly series for the herding index, $\widehat{h_t^2}$, predicted by Model 2. Dotted lines give the 95% confidence interval.



The magnitude and significance of the herding index in Figure 2 leads to a number of observations. Herding is relatively low and is not statistically significant during the period following the 2008 economic crisis. The period during the global financial crisis and its aftermath is not a time of herding, but one of adverse herding. The same can be said about the 2001 crisis, for which we see that the large cross sectional standard deviation of betas is explained away by market volatility. This suggests that herding is not associated with periods of economic crisis in Turkey. Investors seem to turn to market fundamentals in periods of turmoil rather than herd, as also noted by Hwang and Salmon (2004) for the U.S. and South Korea.

There are findings suggesting that herding is related more intimately to political events rather than market fundamentals (Chiang and Zheng, 2010; Indārs, Savin, and Lublóy, 2019). While periods of economic crises are not associated with herding, we observe significant herding during times of political tension or unrest. Herding index reaches its highest level since 2006 during Gezi Park Protests of late May 2013. The herding measure at this time point survives controlling for market fundamentals, hence it is visible in both $\widehat{h_t^1}$ and $\widehat{h_t^2}$. The peak at 2006 is likewise difficult to attribute to economic fundamentals, but it immediately follows an important assassination in the Council of State (Danştay), which led to heightened political tension in the country for some time.

4.1.VAR analysis and Granger Causality

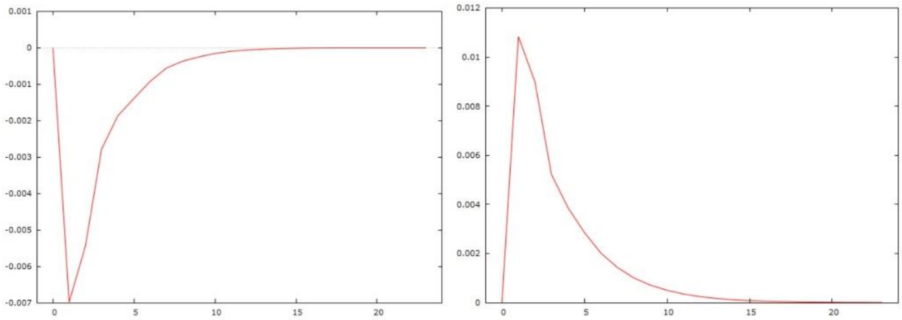
We then study the relationship between herding and market volatility, market return, trading by international investors and total trading volume and in a VAR setting. Note that Model 2 already controls for the component of the cross-sectional standard deviation of betas that can be attributed to market volatility and return, hence, $\widehat{h_t^2}$ is clear of any direct effects of these variables. However, $\widehat{h_t^1}$can help understand the direction of (Granger) causality between herding and market fundamentals.

Both herding series, as well as market volatility and return are stationary at 5% significance according to the Augmented-Dickey Fuller test. Total trading volume (in logs) is $I(1)$ and needs first-differencing in order to obtain a stationary series. Trading volume by international investors (in logs) is trend-stationary. We choose to use the first-difference of this series as well in order to keep a growth interpretation for the two variables, i.e., total and international trading volume. Using this variable after detrending does not change our results.

We use VAR(2) specifications for both $\widehat{h_t^1}$ and $\widehat{h_t^2}$. Akaike and Schwartz information criteria exhibit disagreement regarding the preferred lag order, but the optimal choice is never larger than two, and does not affect our results. Instead of reporting VAR coefficients, we plot the impulse response of $\widehat{h_t^2}$ to both trading volume series in Figure 3. Herding falls following an increase in the growth of overall trading volume (left panel), but increases following an increase in the growth of international trading volume (right panel). The response of herding to these variables is such that the effect of a one-time impulse lasts for a period of about 13 to 15 months. The corresponding VAR coefficients of both these variables are statistically significant. VAR analysis for $\widehat{h_t^1}$ produces similar results.

Tables 4.1 through 4.6 report results from Granger Causality analysis. Analysis of $\widehat{h_t^1}$ and $\widehat{h_t^2}$ (Tables 4.1 and 4.2) imply that international trading volume Granger-causes the herding measure, while the opposite is not true (Tables 4.3 and 4.4). Hence, our results find evidence of herding *by* these investors and not *toward* their choices. We find this to be plausible since international investors are positioned at an information disadvantage against locals regarding the real economic, social, and corporate environment in question. Tzu-Yi Yang and Yu-Tai Yang (2015) show international institutional investors' responses to news to be quite different than that of domestic institutional investors. International investors may also exhibit higher degrees of risk aversion (Pop, 2012), which may contribute to the same outcome.

Figure 3: Impulse response of $\widehat{h_t^2}$ to the growth of trading volume (left), and to the growth of trading volume by foreign investors (right)



The relationship between $\widehat{h_t^1}$ and market volatility is that volatility causes herding (Table 4.1), but not vice-versa (Table 4.5). The herding index does not affect market volatility. As expected, neither market volatility or return has a direct effect on $\widehat{h_t^2}$ (Table 4.2), as this variable is constructed by already controlling for these variables.

Table 4.1: Granger-causes of $\widehat{h_t^1}$

Model 1	**Wald χ^2**	**p-value**
$\widehat{h_t^1}$	140.6	0.000
Market return	3.064	0.216
log (Market volatility)	104.7	0.000
Gr (Trading volume)	6.428	0.040
Gr (Int. Trading)	6.311	0.043

Table 4.2: Granger-causes of $\widehat{h_t^2}$

Model 2	**Wald χ^2**	**p-value**
$\widehat{h_t^2}$	180.8	0.000
Market return	2.581	0.275
log (Market volatility)	2.097	0.350
Gr (Trading volume)	9.607	0.008
Gr (Int. Trading)	7.316	0.026

Table 4.3: Granger-causes of International Trades

Model 1	**Wald χ^2**	**p-value**
$\widehat{h_t^1}$	.9890	0.610
Market return	11.63	0.003
log (Market volatility)	6.617	0.037
Gr (Trading volume)	8.301	0.016
Gr (Int. Trading)	35.51	0.000%

Table 4.4: Granger-causes of International Trades

Model 2	**Wald χ^2**	**p-value**
$\widehat{h_t^2}$	.3106	0.865
Market return	12.54	0.002
log (Market volatility)	7.384	0.024
Gr (Trading volume)	8.398	0.015
Gr (Int. Trading)	34.70	0.000

Table 4.5: Granger-causes of Volatility

Model 1	**Wald χ^2**	**p-value**
$\widehat{h_t^1}$	3.910	0.142
Market return	.9735	0.615
log (Market volatility)	11.48	0.176
Gr (Trading volume)	5.345	0.069
Gr (Int. Trading)	.4163	0.812

Table 4.6: Granger-causes of Volatility

Model 2	**Wald χ^2**	**p-value**
$\widehat{h_t^2}$	1.799	0.407
Market return	.8685	0.648
log (Market volatility)	9.282	0.319
Gr (Trading volume)	5.161	0.076
Gr (Int. Trading)	.5427	0.762

5. Conclusion

This article provides an analysis of herding behavior in Borsa İstanbul (BIST), using market data between January 2001 and April 2016. We use the methodology proposed by Hwang and Salmon (2004), and obtain a herding index and study the time series properties herding, focusing on its relation to aggregate market volatility, market return, as well as overall trading volume and trading by international investors.

We find that an increase in the volume of international transactions lead to an increase in herding. This is not due to the increased trading volume, as this latter leads to a fall in the herding index. We argue that the informational disadvantages and a higher degree of risk aversion render them prone to herding. We show that investors do not herd in BIST during economic crises, but herding can be linked to periods of political unrest in the country. Granger causality analysis indicates that herding is a consequence of high market volatility, but it is not among its causes, in the sense that past values of the herding index does not help the prediction of future volatility on BIST.

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