Special Issue on Business and Organization Research

Heterogeneity Analysis of the Stock Markets: The Case of Borsa Istanbul[1]

Hisse Senetleri Piyasalarında Heterojenlik Analizi: Borsa İstanbul Örneği

Sezer BOZKUŞ, Izmir Bakircay University, Turkey, sezer.bozkus@bakircay.edu.tr
Orcid No: 0000-0003-2865-3399
Hakan KAHYAOĞLU, Dokuz Eylul University, Turkey, hakan.kahyaoglu@deu.edu.tr
Orcid No: 0000-0002-6031-7494

Abstract: In this study, Borsa Istanbul's heterogeneity analysis is conducted based on the volatility within the framework of Heterogeneous Market Hypothesis (HMH) by considering the fact that this volatility is different in different time intervals. The diversity of decision-making units in the stock markets leads to differentiation of price movements at different time intervals. The issue, which underlies this differentiation, is the diversity of the decision-making units in terms of market, risk and related perception types. This diversity, which is defined as heterogeneity in terms of behavioral finance, is generally considered within the framework of HMH in financial literature. The essence of this hypothesis is that there is a difference between the behaviors of investors, i.e., those who trade on their behalf and those who trade in relation to a certain institution in the stock market. Therefore, when this process is not explained through standard volatility models, new techniques have been developed in the literature based on HMH. The technique used in this study, presents an empirical finding that demonstrates the validity of the hypothesis. The relationship between the heterogeneity of the market and the heterogeneity of decision-making units is demonstrated through the technique, which provides a volatility-based approach calculated from price movements in the market. Thus, this study, in addition to analyzing whether the Borsa Istanbul Stock Market has a heterogeneous market characteristic or not, also examines the impact of market participants on this formation. Accordingly, it is aimed to contribute to the literature by presenting policy recommendations within the framework of the empirical findings.

Keywords: Heterogeneous Market Hypothesis, HAR Model, Long Memory
JEL Classification: C58, G14, G17

Özet: Bu çalışmada amaç, Heterojen Piyasa Hipotezi (HPH) çerçevesinde oynaklık ve bu oynaklığın farklı zaman dilimlerinde farklı olmasına bağlı olarak, Borsa İstanbul Hisse Senetleri Piyasası'nın heterojenlik yapısının analizini yapmaktadır. Hisse senetleri piyasasında işlem yapan karar birimlerinin çeşitliliği, farklı zaman aralıklarında fiyat hareketlerinin farklılaşmasına neden olmaktadır. Bu farklılaşmanın temelinde ise, söz konusu karar birimlerinin piyasa, risk ve buna yönelik algılama biçimleri konusunda çeşitlilik göstermesidir. Davranışsal finans açısından heterojenlik olarak tanımlanan bu çeşitlilik, finans literatüründe genel olarak Heterojen Piyasa Hipotezi (HPH) çerçevesinde ele alınmaktadır. Bu hipotezin kaynağında özellikle hisse senetleri piyasasındaki kendi adına işlem yapanlar ile belirli bir kurumla ilişkili olarak işlem yapanların davranışları arasında farklılaşma olmasıdır. Bundan dolayı söz konusu süreç standart oynaklık modelleri aracılığıyla açıklanamadığından, literatürde heterojen piyasa hipotezini esas alan yeni teknikler geliştirilmiştir. Bu çalışmada kullanılan teknik, hipotezin geçerliliğini ortaya koyan bir bulgu sunmaktadır. Bununla birlikte, piyasadaki fiyat hareketlerinden hesaplanan oynaklığa dayalı bir yaklaşım sunan teknik yoluyla, piyasanın heterojenliği ile karar birimlerinin heterojenliği arasındaki ilişki de ortaya konmaktadır. Böylece Borsa Istanbul Hisse Senetleri Piyasası'nın heterojen bir piyasa özelliğine sahip olup olmadığını analiz etmenin yanında; bu çalışmada piyasa katılımcılarının söz konusu oluşum üzerindeki etkisi de incelenmektedir. Buna göre elde edilen ampirik bulgular çerçevesinde politika önerileri sunularak literatüre katkı sunulması hedeflenmektedir.

Anahtar Kelimeler: Heterojen Piyasa Hipotezi, HAR Modeli, Uzun Hafiza
JEL Sınıflandırması: C58, G14, G17

1. Introduction

It is a fact that volatility is assumed to be a latent variable. For this reason, conditional mean and conditional variance models are used to examine the latent volatility. This assumption led to the introduction of ARCH and stochastic volatility approaches which are used mainly for financial market modeling and estimation. In relation to this situation, the behavior of financial market participants is analyzed based on their trading strategies to understand the logic behind the Efficient Market Hypothesis (EMH) (LeRoy, 1976; Fama, 1965, 1970, 1991, 1998). Along with the rapidly developing technological innovations, significant changes have been experienced in the functioning of the financial markets. Because of these changes, EMH has been questioned and alternative approaches have been emphasized. There are various approaches against EMH such as fractal market hypothesis (Peters, 1994), adaptive market hypothesis (Lo, 2005), chaos theory (Mandelbrot, 2005) and heterogeneous market hypothesis (Corsi, 2009). Compared to EMH approach, these opposing and novel approaches are based on frequency domain rather than time domain for analyzing the financial markets data and trading strategies. In addition, these approaches consider the asymmetric structure of the markets in various aspects. In this study, the validity of Heterogeneous Market Hypothesis (HMH) (Corsi, 2009) is examined. The

[1] This paper is orally presented at the International BOR Conference, 4-6 September 2019 in Izmir, Turkey and revised edition is prepared to publish.

Makale Geçmişi / Article History

Başvuru Tarihi / Date of Application : 19 Ekim / October 2019
Kabul Tarihi / Acceptance Date : 31 Ekim / October 2019

major reason why the heterogeneous structure of the financial markets is preferred for analysis is to provide a better understanding of the recent crises and to contribute to the decision-making units while forming an investment strategy.

In this paper, the heterogeneity of BIST is analyzed by using HAR approach. Firstly, the relevant literature review is presented in the following second section. Secondly, the data and methodology are explained by giving the underlying reasons of the application of Heterogeneous Autoregressive (HAR) model. In addition to the HAR Model, the related diagnostic tests are given with their interpretations to ensure the robustness of the Model estimation. Thirdly, the empirical findings of this study are presented and discussed based on the other results in the literature. Finally, policy recommendations are made based on the findings of BIST 100 index investor profile in Turkey.

2. Literature Review

There are new definitions complement to the EMH such as Chaos Theory (Mandelbrot, 2005), Behavioral Finance Theory (Shiller, 2003), Fractal Market Hypothesis (Peters, 1991, 1994), Adaptive Market Hypothesis (Lo, 2005) and last but not least, Heterogeneous Market Hypothesis (HMH) (Corsi, 2009) which are summarized at Figure 1. In this paper, the HMH is investigated and validity of the HMH is tested based on the BIST 100 index data. The major difference between the EMH and HMH approaches is arising from the way the analysis is conducted, i.e. EMH relies on time domain and, HMH rather depends upon frequency domain. In other words, the idea behind HMH is that participants with different time horizons perceive, react and cause different types of volatility components (Figure 2).

Figure 1. New approaches that complement the classic EMH
Source: Compiled by the authors.

There is a huge research on the analysis of stock market indices in the literature. These analyses are made mostly based on the performance, efficiency, co-movements and volatility of the stock market indices (Linton, 2019: 2-3). In this paper, literature review is prepared based on two topics, i.e. one is about the emergence of HMH and the second is about the methodology applied to measure the level of heterogeneity, i.e. HAR Model and related tests.

The analyses on HMH in the finance literature are summarized as follows: The variety of decision-making parts in the financial markets leads to differences of price fluctuations through different periods. Because of this difference, there is a diversity of the decision-making parts in terms of market, risk and related perception styles. This diversity, which is defined as “heterogeneity” in terms of behavioral finance, is generally considered within the framework of Heterogeneous Market Hypothesis (HMH) in financial literature. The essence of this hypothesis is that: “there is a difference between the behaviors of those who trade on their behalf and those who trade in relation to a certain institution in the stock market.” Therefore, new techniques have been proposed in the literature based on HMH for cases where the standard volatility models cannot provide a solution. The pioneering works are presented by Diebold and Mariano (1995), Muller et al (1997), Dacorogna et al. (1998), Lima (1998), Lux and Marchesi (1999), Malkiel (2003), Hansen et al. (2003), Barndorff-Nielsen and Shephard (2002), Lo (2004, 2005), Westerlund and Narayan (2012) and Patton and Sheppard (2015).

Theoretically, a financial market is composed of investors with various investment strategies ranging from short to long term durations. Therefore, the combinations of these various duration volatilities have produced the “long memory property” in financial markets. In the structure of heterogeneous markets, there are cascades that differ according to the preferences of investors. These cascades are expressed as short-term (daily), mid-term (weekly) and long-term (monthly) investments which are shown in Figure 3. The HMH, which states that the reactions of the investors with different time horizons realize, behave, and generate different types of volatility components, is the main motivation for the birth of HAR model (Khan, 2015: 83).

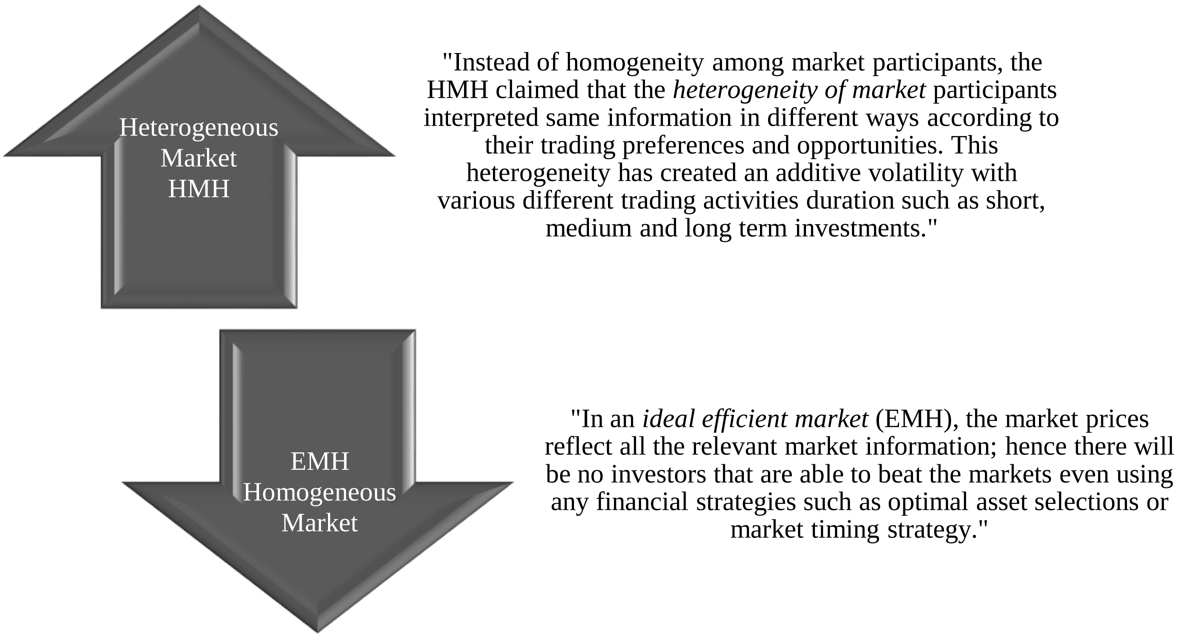

Figure 2. Comparison of EMH vs. HMH
Source: Fama, 1998 and Corsi, 2009.

The literature review on the HAR Model is summarized as follows: Current finance literature is mostly interested in analyzing intraday high frequency data by using time varying return volatility models. Among these models, the HAR Model that is proposed by Corsi (2009) has been widely accepted. This is because the HAR Model is relatively simple and has a consistent forecasting performance in applications for high frequency financial market data. Corsi (2009) proposes the HAR model to estimate the “volatility cascades” with a simple and parsimonious way. Corsi (2009) states that the investors have different risk appetite in different time horizons and such investors recognize and respond to different volatility components which are categorized as daily, weekly, and monthly.

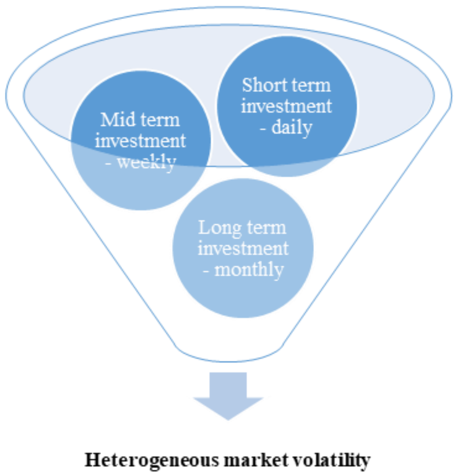

Figure 3. Heterogeneous Market Structure
Source: Corsi, 2009.

The formulation of a typical HAR Model is an extension of ARCH Models and it is introduced by the joint work of Muller et. al (1997). The new HAR modeling approach is mostly estimated by using Realized Volatility (RV) and the ordinary least squares (OLS) simultaneously. The estimation process consisting of five major steps, is defined in the next section. According to Westerlund and Narayan (2012), the critical success factor for achieving the accurate HAR model is related to the way the estimator is chosen. Hence, it is accepted that HAR model gives out better empirical results in the predictability of return volatility. There are various empirical works for predicting stock market volatility and heterogeneous markets in the finance literature such as Morris,1994; Osier, 1995; Patton, 2011; Choi and Varian, 2012; Vozlyublennaia, 2014; Romano and Wolf, 2017; Buccheri and Corsi, 2017; Taylor, 2017; Cipollini et al. 2017; Clements and Preve, 2019.

3. Research Method

The HAR Model is applied in this study and the underlying reason of the application of this research method is explained briefly as follows: Firstly, realized volatility[2] (RV) is calculated in logarithmic form in Equation 1. Although RV is not a directly observable variable, it is possible to estimate realized variance consistently and then further calculate the RV simultaneously (Clements and Preve, 2019: 3-4).

$$\log \mathrm{RV}_t^{(n)} = \frac{1}{n}\left(\log \mathrm{RV}_t + \ldots + \log \mathrm{RV}_{t-n+1}\right) \tag{1}$$

Based on Corsi (2009) approach, the time horizon is defined with three different cascades, i.e. daily in short-term, weekly in mid-term and monthly in long-term. These cascades mean that the HAR Model is established as a linear function of realized volatility on a daily, weekly and monthly return series[3] (Clements and Preve, 2019: 5-6).

$$\log \sigma_{t+1d}^{(d)} = \log \mathrm{RV}_{t+1d}^{(d)} + \tilde{\epsilon}_{t+1d} \tag{2}$$

Hence, substituting the formulas in equation 2 to equation 3 and equation 4; the HAR Model is established to estimate the *beta* coefficients for each cascade. Considering equation 2, $\tilde{\epsilon}_t$ is the measurement error of the model.

$$\log \mathrm{RV}_{t+1d}^{(d)} = c + \beta^{(d)} \log \mathrm{RV}_t^{(d)} + \beta^{(w)} \log \mathrm{RV}_t^{(w)} + \beta^{(m)} \log \mathrm{RV}_t^{(m)} + \epsilon_{t+1d} \tag{3}$$

In this way, new time series are generated with different time intervals to estimate the heterogeneity of the market in the following section.

$$\begin{aligned} r_t &= \tilde{\sigma}_t^{(d)} z_t \\ \log \tilde{\sigma}_{t+m}^{(m)} &= c^{(m)} + \phi^{(m)} \log \mathrm{RV}_t^{(m)} + \tilde{\omega}_{t+m}^{(m)} \\ \log \tilde{\sigma}_{t+w}^{(w)} &= c^{(w)} + \phi^{(w)} \log \mathrm{RV}_t^{(w)} + \gamma^{(w)} E_t[\log \tilde{\sigma}_{t+m}^{(m)}] + \tilde{\omega}_{t+w}^{(w)} \\ \log \tilde{\sigma}_{t+d}^{(d)} &= c^{(d)} + \phi^{(d)} \log \mathrm{RV}_t^{(d)} + \gamma^{(d)} E_t[\log \tilde{\sigma}_{t+w}^{(w)}] + \tilde{\omega}_{t+d}^{(d)} \\ &\text{daily } d = 1, \text{ weekly } w = 5, \text{ monthly } m = 22 \end{aligned} \tag{4}$$

After generating the three time series as shown in Equation 4, the HAR Model estimation is exercised considering the investor time preferences on daily, weekly and/or monthly intervals. The HAR Model is applied in the five major steps as shown in Figure 4. In the first step, the volatility of time series data is defined. In the second step, the index vector *h* based on the lagged values of the time series for the daily, weekly and monthly components is constructed. In the third step, the three volatility components for daily, weekly and monthly are calculated as averages of lagged values for each step *t*. In the fourth step, we consider these time series as new time series with different frequencies. Finally, in the fifth step, the values of the three volatility components are regressed by using OLS. In this way, we obtain the *beta* coefficients for the daily, weekly and monthly components to forecast ahead.

[2] The RV is defined in the finance literature as sum of the squared returns within day *t*. Hence, the logarithmic daily trading data from BIST 100 index are taken and used for the model estimation process.

[3] These cascades are colored to make follow-up easier for the readers in equation 2, 3 and 4 such that red is d=daily; green is w=weekly; blue is m=monthly in color.

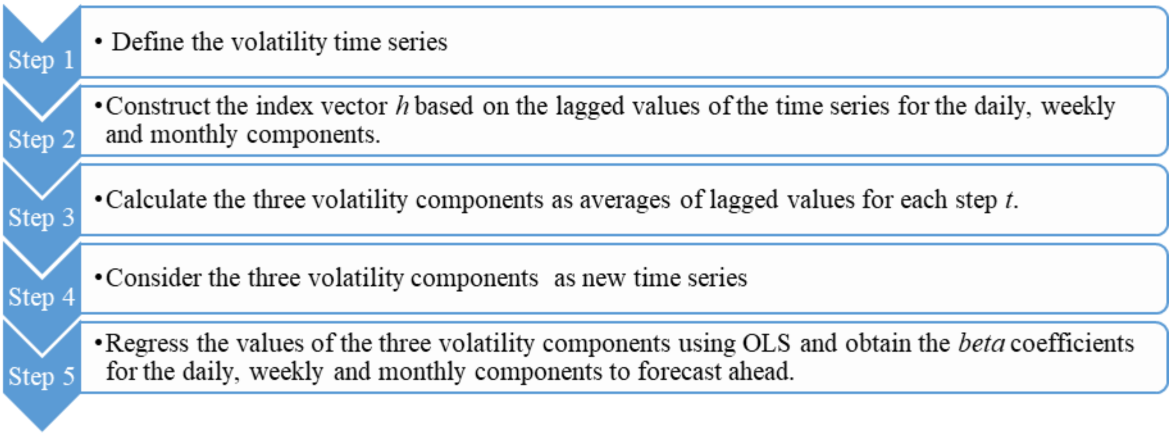

Figure 4. HAR Model Implementation Process
Source: Corsi, 2009.

There are three components used with the length of $n_1 = 22$ (monthly), $n_2 = 5$ (weekly), $n_3 = 1$ (daily) respectively. It is a fact that the volatility at long time perspectives has an impact on the volatility at short time perspectives, and for this reason, the auto-correlation function of the model will increase. This further leads to an increase in its memory persistence. In other words, even if the HAR model is not considered long memory process, it still contains the properties of financial data similar to the long memory models (Corsi and Reno, 2009: 3-4).

It is a fact that high frequency integrated volatility estimation is widely used to measure the latent financial volatility which cannot be directly observed from the raw data. The high frequency data consist of more trading information as compared to daily closed data. In addition, such data have significant impact on the accuracy in portfolio analysis and risk management.

4. Empirical Findings

In this paper, BIST 100 index data are used in the empirical analysis and firstly, the descriptive statistics are given and secondly the HAR Model estimation is presented with the interpretation of three time cascades respectively. The R program and codes are applied for the HAR Model estimation process.

4.1. Descriptive Statistics

In this case, the data are taken from Borsa Istanbul. BIST 100 index -high frequency time series 5-minute interval data is used for the analysis for the period between February 5th, 2015 and July 31st, 2019. The total number of data is 98,392. Log return series are generated before starting the estimation process as shown in Figure 5. The descriptive statistics are calculated for the RV time series data in order to capture the type of distribution before starting any empirical analysis. Jarque - Bera Normality (JB) test results of RV is equal to 0.375 with the p- value of 0.829. This means that the RV series for three time intervals are normally distributed. In addition, the classical ADF unit root test (Dickey and Fuller, 1979) is applied to the RV series and the results indicate that the series is stationary. In our case, the number of sample data is huge, i.e. 98,392 that may lead to some biased estimations due to size distortions. In order to overcome size distortion problem, there are some additional tests proposed in the literature namely, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test (Kwiatkowski et al., 1992). According to KPSS test results, the RV series is not stationary. This contradictory test result with ADF test is arising from the size distortions as it is usually experienced in the literature. When ADF test and KPSS test results are not giving the similar findings, then this could be a sign of a fractal characteristic in the observed series. In such cases, Hansen and Racine (2018) propose to adopt a novel unit root test which is defined as an "averaging procedure to deal with model uncertainty" during the testing process. This test is called the Hansen-Racine Bootstrap Test. Monte Carlo simulations are applied for this test to achieve the lowest size distortions among its peers. In this way, the superior power of test is generated by decreasing the variance of estimation meanwhile controlling misspecification bias for the series (Hansen and Racine, 2018: 8-10).

The above-mentioned tests are all applied and the test results are shown in Table 1. According to the unit root test results, ADF test and Hansen-Racine test are providing the same finding, i.e. the observed series is stationary, but KPSS test result is indicating that the series is not stationary.

Table 1. Unit Root Test Results

ADF	KPSS	Hansen-Racine
-49.3977**	1.4378,	-31.62183**

Signif. codes: 0 '***' 0.01 '**' 0.05

We adopt Hansen-Racine Bootstrap test results since this test is more superior than the other tests. On the other hand, KPSS test result may be seen as a leading indicator of the investors' varying trading strategies in a heterogeneous market. Thus, it is possible to proceed on the next steps to estimate the HAR Model.

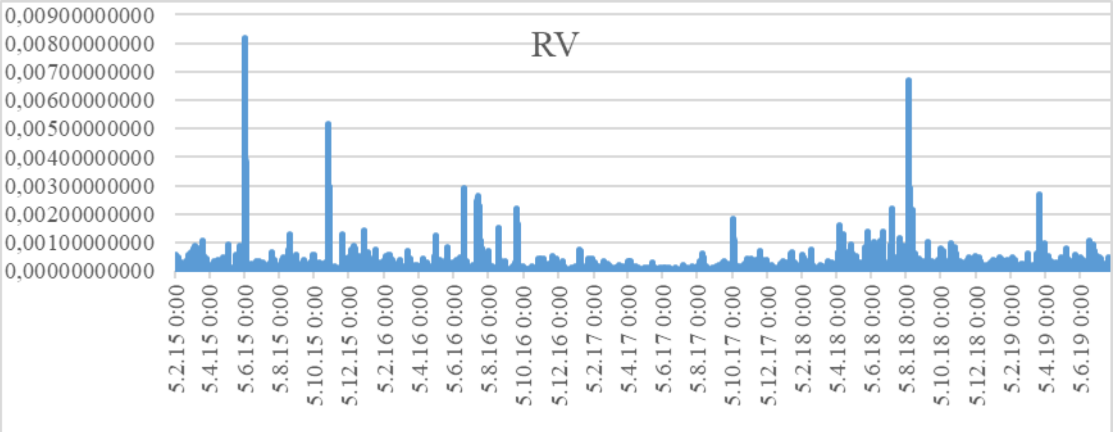

Figure 5. RV for BIST 100 index (2015-2019)

4.2. HAR Model Estimation

The HAR Model is based on the following assumption for the hypothesis testing:

When the $RV^{(d)} > RV^{(m)}$, the HAR model estimation gives information about the investment strategy such that the estimates rapidly return to its long term average level. In this case, the price elasticity of demand in the market is greater than the price elasticity of supply. The market tends to stabilize continuously. On the other hand, when the $RV^{(d)} < RV^{(m)}$, the HAR model let the estimates slowly return to its long term average level. In this case, the market conditions, which have a characteristic that the slopes of the supply curve and the demand curve converge, apply.

The HAR Model is estimated in three cascades and the first cascade is defined as HAR Model with horizon 1 on a daily basis. In this respect, the model estimation is generated by using the formula as:

RV1 = beta0 + beta1 * RV1 + beta2 * RV5 + beta3 * RV22 (5)

Table 2. HAR Model with horizon 1 (Daily)

Coefficients	Estimate (RV)	t value Pr(>|t|)
Beta0 (Average)	-1.45242	-45.89 < 2e-16 ***
Beta1 (Daily)	0.55819	154.24 < 2e-16 ***
Beta2 (Weekly)	0.28900	57.09 < 2e-16 ***
Beta3 (Monthly)	0.02512	6.06 1.4e-09 ***
Residual standard error: 1.45 on 98366 degrees of freedom Multiple R-squared: 0.632, Adjusted R-squared: 0.632 F-statistic: 5.62e+04 on 3, 98366 DF, p-value: <2e-16		

Signif. codes: 0 '***' 0.01 '**' 0.05

The second cascade of HAR Model estimation is based on the mid-term time intervals on a weekly basis by using the formula as:

RV5 = beta0 + beta1 * RV1 + beta2 * RV5 + beta3 * RV22

Table 3. HAR Model with horizon 5 (weekly)

Coefficients	Estimate (RV)	t value Pr(>|t|)
Beta0 (Average)	9.07e-06	35.1 <2e-16 ***
Beta1 (Daily)	7.82e-01	188.9 <2e-16 ***
Beta2 (Weekly)	1.19e-01	22.9 <2e-16 ***
Beta3 (Monthly)	-4.73e-02	-16.3 <2e-16 **
Residual standard error: 7.46e-05 on 98362 degrees of freedom Multiple R-squared: 0.804, Adjusted R-squared: 0.804 F-statistic: 1.35e+05 on 3 and 98362 DF, p-value: <2e-16		

Signif. codes: 0 '***' 0.01 '**' 0.05

The third cascade of HAR Model estimation is based on the long time intervals on a monthly basis by using the formula as:

RV22 = beta0 + beta1 * RV1 + beta2 * RV5 + beta3 * RV22

Table 4. HAR Model with horizon 22 (Monthly)

Coefficients	Estimate (RV)	t value Pr(>|t|)
Beta0 (Average)	2.82e-05	76.7 <2e-16 ***
Beta1 (Daily)	5.51e-01	93.6 <2e-16 ***
Beta2 (Weekly)	1.48e-01	20.1 <2e-16 ***
Beta3 (Monthly)	-1.55e-01	-37.4 <2e-16 ***
Residual standard error: 0.000106 on 98345 degrees of freedom Multiple R-squared: 0.492, Adjusted R-squared: 0.492 F-statistic: 3.17e+04 on 3 and 98345 DF, p-value: <2e-16		

Signif. codes: 0 '***' 0.01 '**' 0.05

These empirical findings, which are shown in daily horizon Table 2, weekly horizon Table 3 and monthly horizon Table 4 respectively, are indicating the sign of an asymmetric propagation of volatility. These findings are supporting the results in the literature (Muller et al., 1997; Arneodo et al., 1998; Lynch, 2000; Lynch and Zumbach, 2003), i.e. volatility upon long time horizons have more durable influence on those at short time horizons than otherwise. Accordingly, the behavior of BIST 100 index market participants shows that decision-making units make quick decisions and act more individually rather than in an institutional context. Corporates are expected to make long-term investment decisions and portfolio management strategies based on their corporate strategies.

5. Conclusion

As a conclusion, this study adds to the literature of HMH using high frequency data under the heterogeneous market hypothesis framework. The empirical findings are supporting the heterogeneous market hypothesis where market participants with different investment time horizons have different ways to interpret market information differently. In our case, Hansen-Racine Bootstrap Test, which is proposed as a novel approach to unit root testing with superior power achieved by Monte Carlo simulations, is applied to the observed high frequency financial time series data.

Using the additive components of various volatilities framework, the real structure of the stock market Borsa Istanbul can be better explained by the long memory volatility behavior. This significant finding supports the difference between ADF and KPSS test results. This statistical element is an important outcome in portfolio strategy planning and further explores the heterogeneous market hypothesis. The consequences of this study also provide better forecasts and market risk determinations for the financial industries that involve with risk management and investment portfolio analysis.

Finally, yet importantly, investor behavior in Borsa Istanbul varies over time. Short-term investors have higher risk appetite and higher volatility of returns. However, this situation does not affect the long-term investor profile for BIST 100 index. The potential trading strategy and investor behavior justification could be that the long-term volatility is important for short-term traders while short-term volatility is not necessarily affecting the long-term trading strategies in BIST 100 index. If this finding is also valid for the other markets, it is necessary for financial markets to interpret the short term as an indicator of the behavior of prices in Turkey.

REFERENCES

Arneodo, A., J. Muzy, and D. Sornette (1998), "Casual cascade in stock market from the"infrared" to the "ultraviolet". European Physical Journal B 2, 277.

Barndorff-Nielsen E. and N. Shephard (2002), "Econometric analysis of realized volatility and its use in estimating stochastic volatility models". Journal of Royal Statistical Society, Series B, 64:253–280.

Buccheri and F. Corsi (2017), "HARK the SHARK: Realized volatility modelling with measurement errors and nonlinear dependencies". SSRN Electronic Journal, 2017

Clements Adam and Preve Daniel P. A. (2019), "A Practical Guide to Harnessing the HAR Volatility Model", National Centre for Econometrics Research, Australia, NCER Working Paper: 120, http://www.ncer.edu.au/papers/documents/WP120.pdf , (Access date: 15.06.2019)

Cipollini, G.M. Gallo, and E. Otranto (2017), "On heteroskedasticity and regimes in volatility forecasting". SSRN Electronic Journal, 2017.

Choi, H. and Varian, H. (2012), "Predicting the present with google trends", Economic Record 88(s1), 2–9.

Corsi F. (2009), "A simple approximate long-memory model of realized volatility", Journal of Financial Econometrics, 7(2):174–196, 2009.

Corsi F. and Reno R. (2009), "HAR volatility modelling with heterogeneous leverage and jumps", https://web.stanford.edu/group/SITE/archive/SITE_2009/segment_1/s1_papers/corsi.pdf, (Access date: 15.06.2019)

Dacorogna, M., Muller, U., Dav, R., Olsen, R. and Pictet, O. (1998), "Modelling short-term volatility with garch and harch models", Nonlinear Modelling of High Frequency Financial Time Series, pp. 161–76. Edited by C. Dunis and B. Zhou, John Wiley, Chichester.

De Lima, P.J.F., (1998), "Nonlinearities and Nonstationarities in Stock Returns", Journal of Business & Economics Statistics 16, pp. 227 – 236.

Diebold and R.S. Mariano (1995), "Comparing predictive accuracy", Journal of Business and Economics Statistics, 13:253–263.

Dickey, D. A. and Fuller, W. A. (1979), "Distribution of the estimators for autoregressive time series with a unit root", Journal of the American Statistical Association 74(366), 427–431.

Hansen, A. Lunde, and J. Nason (2003), "Choosing the best volatility models: the model confidence set approach". Oxford Bulletin of Economics and Statistics, 65:839–861, 2003.

Hansen B. and J. Racine (2018), "Bootstrap Model Averaging Unit Root Inference", McMaster University - Department of Economics Working Paper No. 2018-09 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3156028 (Access date: 15.06.2019)

Fama, E. (1965), "Random walks in stock market prices". Financial Analysts Journal 21(5), 55–59.

Fama, E. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work". Journal of Finance 25, 383–417.

Fama, E. (1991), "Efficient Capital Markets: II." Journal of Finance 46(5), 1575–1617.

Fama E. F. (1998), "Market efficiency, long-term returns, and behavioral finance", Journal of Financial Economics 49 (1998) 283—306, http://www.e-m-h.org/Fama98.pdf , (Access date: 05.06.2019)

Khan Muhammad Yousaf (2015), Advances In Applied Nonlinear Time Series Modeling, Dissertation an der Fakultät für Mathematik, Informatik und Statistik der Ludwig–Maximilians–Universität München, https://core.ac.uk/download/pdf/79055317.pdf , (Access date: 05.06.2019)

Kwiatkowski, D., P.C.B. Phillips, P. Schmidt and Y. Shin (1992), "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root," Journal of Econometrics, 54, 159-178.

LeRoy, S. (1976), "Efficient capital markets: Comment". Journal of Finance 31, 139–141.

Linton, Oliver (2019), "Comparison between Chinese, US, and European Stock Markets", Cambridge University, July 2019, https://obl20.com/wp-content/uploads/2019/07/Chinesestock2.pdf , (Access date: 05.06.2019)

Lo, Andrew W. (2004). "The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective". Journal of Portfolio Management 30: 15–29.

Lo, Andrew W. (2005), "Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis". Journal of Investment Consulting 7: 21–44.

Lynch, P. E. (2000), Adaptive models for speculative turbulence, PhD thesis, Department of Electrical and Electronic Engineering, University of Manchester Institute of Science and Technology. Manchester, M60. UK.

Lynch, P. and G. Zumbach (2003), "Market heterogeneities and the causal structure of volatility". Quantitative Finance 3(4), 320–331.

Lux, T. and M. Marchesi, (1999), “Scaling and Criticality in a Stochastic Multi-Agent Model of a Financial Market”, Nature, 397, pp. 498 - 500.

Mandelbrot, Benoit B. (2005), "The inescapable need for fractal tools in finance," Annals of Finance, Springer, vol. 1(2), pages 193-195, October.

Malkiel, B. (2003), “The efficient market hypothesis and its critics”. Journal of Economic Perspectives 17(1), 5982.

Morris, S., (1994), “Trade with heterogeneous prior beliefs and asymmetric information”. Econometrica. 62 (6), 1327-1347

Muller, U. , M. Dacorogna, R. Dave, R. Olsen, O. Pictet, and J. Weizsacker (1997), “Volatilities of different time resolutions – analyzing the dynamics of market components”, Journal of Empirical Finance, 4:213–239, 1997.

Osier, C.L., (1995), “Exchange rate dynamics and speculator horizons”. Journal of International Money and Finance 14 (5), 695-719.

Patton, A. J. (2011), “Volatility forecast comparison using imperfect volatility proxies”, Journal of Econometrics 160(1), 246–256.

Patton A. J. and K. Sheppard (2015), “Good volatility, bad volatility: Signed jumps and the persistence of volatility”. Review of Economics and Statistics, 97:683–697.

Peters, E. (1991), Chaos and Order in the Capital Markets - A New View of Cycles, Prices, and Market Volatility. John Wiley & Sons, Inc.

Peters, E. (1994). Fractal Market Analysis – Applying Chaos Theory to Investment and Analysis. New York: John Wiley & Sons, Inc.

Romano and M. Wolf, (2017), “Resurrecting weighted least squares”. Journal of Econometrics, 197:1–19, 2017.

Shiller, R.J. (2003), “From Efficient Market Theory to Behavioral Finance”, Journal of Economic Perspectives—Volume 17, Number 1—Winter 2003—Pages 83–104. https://pubs.aeaweb.org/doi/pdfplus/10.1257/089533003321164967 , (Access date: 25.06.2019)

Vozlyublennaia, N. (2014), “Investor attention, index performance, and return predictability”, Journal of Banking & Finance 41, 17–35.

Taylor (2017), “Realised variance forecasting under Box-Cox transformations”. International Journal of Forecasting, 33:770–785, 2017.

Westerlund J. and P.K. Narayan (2012), “Does the choice of estimator matter when forecasting returns?” Journal of Banking and Finance, 36:2632–2640, 2012.