Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi • Cilt: 42 • Sayı: 2 • Aralık 2020, ISSN: 2587-2672, ss/pp. 340-360
DOI: 10.14780.muiibd.854509

ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

DAILY VOLATILITY ANALYSIS OF BIST 100 CONSTITUENTS BETWEEN 2018-2020

BIST 100 BİLEŞENLERİNİN 2018-2020 ARASI DÖNEM İÇİN OYNAKLIK ANALİZİ

Cavit PAKEL*
Kadir ÖZEN**

Özet

Geçtiğimiz dönemde Türkiye ekonomisi iki önemli şok geçirdi. Bunlardan ilki, Ağustos 2018'de yaşanan kur şokuydu. İkinci şok ise, ilk şoktan çok daha yüksek etkiye sahip olan ve 2020 yılı başında başlayıp bu makalenin yazımı esnasında devam etmekte olan COVID-19 pandemisi şokudur. Bu iki şokun gözlendiği dönemde önemli ekonomik ve finansal değişkenlerde kayda değer değişimlerin yaşanıp yaşanmadığı, hem politika yapıcılar hem de piyasa katılımcıları açısından önemli bir sorudur. Bu çalışmada bu soruya, yeni bir panel GARCH modelleme tekniği kullanılarak, BIST 100 endeksini oluşturan hisselerin günlük getirilerinin volatilite analizi açısından yaklaşılmaktadır. Sonuçlarımız, iki şok dönemi boyunca hisse senedi volatilitesinde önemli bir yükseliş olduğunu göstermektedir. Daha da önemlisi, bu yükselişin pandemi döneminde çok daha güçlü ve kalıcı olduğu görünmektedir. İlaveten, sektörler bazında gerçekleştirilen analiz sonuçlarına göre, sektörlerin ortalama volatilitelerinin şoklardan önceki periyoda göre ciddi oranda yükseldiği tespit edilmektedir.

Anahtar Kelimeler: BIST 100, COVID-19, GARCH, finansal volatilite
JEL Sınıflandırması: C01, C14, C23, C58

Abstract

The Turkish economy has experienced two important shocks in the recent past. The first is a currency shock which occurred in August 2018. A second, substantially more impactful, shock is the COVID-19 pandemic, which began in early 2020 and is still in progress. An interesting question from the perspectives of both policy makers and practitioners is whether significant changes in key economic and financial variables have been observed in the period marked by these two shocks. We investigate this question for the volatility of the daily returns on BIST 100 constituent equities, using a novel panel GARCH modelling approach. We find that during the periods associated with the two shocks, the stock market volatility has increased

* Cavit Pakel, Assistant Professor of Economics, Bilkent University, Department of Economics, 06800, Ankara. E-mail: cavit.pakel@bilkent.edu.tr

** Kadir Özen, MSc Candidate, Barcelona Graduate School of Economics, Ramon Trias Fargas, 25-27, 08005 Barcelona, Spain. Email: kadir.ozen@barcelonagse.eu

Makale Gönderim Tarihi: 04.09.2020
Yayına Kabul Tarihi: 16.11.2020

substantially. Importantly, this increase has been greater and more persistent during the pandemic period. Moreover, our analysis of sector-specific volatilities also reveals that this period of two shocks has witnessed a uniform increase in the average volatilities of all sectors, compared to the period before.
Keywords: BIST 100, COVID-19, GARCH, financial volatility
JEL Classification: C01, C14, C23, C58

1. Introduction

In the recent past, the Turkish economy has experienced two major shocks. Following a period of steady increase, between 13 and 14 August 2018 the TL/USD end-of-day exchange rate jumped from 5.94 to 6.88. After a period of increased volatility, the exchange rate became relatively more stable towards the end of 2018 (see Figure 1). Roughly 1.5 years after this currency shock, a global event of a much bigger proportion occurred: the COVID pandemic. On 30 January 2020, World Health Organization declared the outbreak a Public Health Emergency of International Concern. On 11 March 2020, Turkey announced its first confirmed coronavirus case. Shortly afterwards, the government started introducing widespread measures against COVID. More recently, many countries, including Turkey, have started to gradually relax these measures, while exercising a certain measure of caution (such as imposing social distancing rules and wearing of masks in public places). As things stand, it appears that the pandemic will have far reaching global economic and financial effects that will be felt for a long time.

An interesting question from the perspectives of both policy makers and practitioners is whether significant changes in key economic and financial variables have been observed in the period marked by these two shocks. In this article, we undertake an econometric analysis of stock market volatility during this period. In particular, we are interested in obtaining accurate estimates of the daily volatilities of BIST 100 index constituents throughout these two shock periods, at the level of both individual equities and sectors. Given the standard interpretation of volatility as a measure of risk, this analysis also allows us to understand the evolution of the risk structure in the stock market during this period.

Our econometric analysis is based on the generalised autoregressive conditional heteroskedasticity (GARCH) model.[1] Since its inception in 1982 in a seminal paper by Robert Engle[2], GARCH-type modelling has been one the most popular approaches for modelling the volatility of financial series, and especially that of stock market returns.[3] Accurate estimation of the GARCH model (and other GARCH-type models in general) requires very large datasets as it is difficult to capture GARCH effects with few observations. In many cases, this requirement for large datasets is not a problem as there are many interesting financial variables for which years of daily data are available. In our case, however,

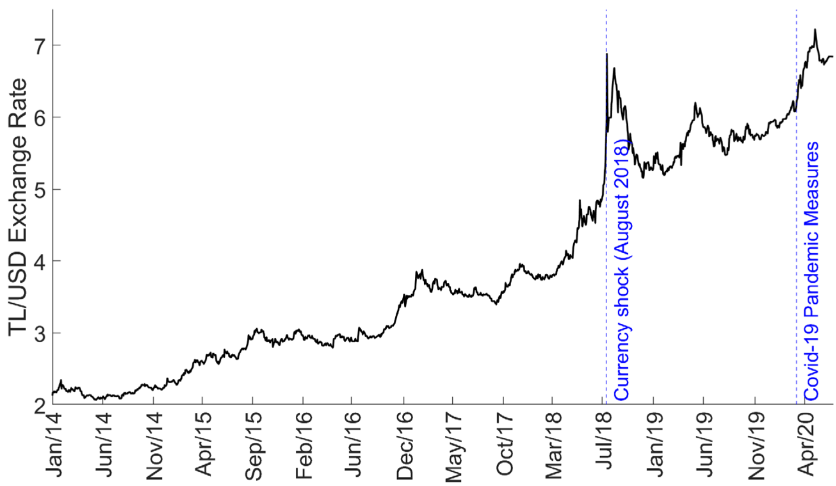
1 Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, Journal of Econometrics, 51: 307-327.

2 Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, Econometrica, 50: 987-1008.

3 Although the acronyms “ARCH” (autoregressive conditional heteroskedasticity) and “GARCH” refer to two particular models, it has become the convention to designate all the different models in this literature simply as GARCH-type models.

this is an important issue. The period we analyse has witnessed two shocks of diverse nature, and it is very likely that the volatility dynamics of the period we investigate is different from the dynamics of the preceding period. In other words, it is very unlikely that the model parameters remain fixed throughout our period of interest. Therefore, basing estimation on, say, 1000 observations is not desirable because the model parameters are unlikely to remain the same for such a long time period (about four years). Doing so would put unnecessary weight on data from the distant past which are uninformative and possibly misleading about the current volatility process. We would instead prefer to estimate the model parameters for every individual trading day, using a rolling window based on the most recent data.

Figure 1. TL/USD Daily End-of-Day Exchange Rate between 2 January 2014 and 2 July 2020.



Source: Central Bank of the Republic of Turkey.

To achieve this aim, we utilise a recently developed approach, which is specifically aimed at estimating the GARCH model with as little as 150 observations per equity.[4] As will be further explained in Section 2, this method is based on a panel data approach and uses insights from the panel data literature to obtain estimators that are corrected for the bias arising from using a short time dimension.

The main contribution of this paper is the volatility analysis of BIST 100 index constituents in the period between January 2018 and July 2020. In particular, we investigate the following questions: (i) Has there been any change in the volatility characteristics of BIST 100 constituents before and after May 2018? (ii) What are the relative magnitudes of stock market volatility during the currency and COVID shock periods? (iii) Has the relative risk ranking of different sectors (as measured by their average volatilities) changed during the currency and COVID shock periods? To the best of our

4 Pakel, C. (2019). Supplementary Appendix for Bias Reduction in Nonlinear and Dynamic Panels in the Presence of Cross-section Dependence, unpublished manuscript, 64-80.

knowledge, this paper is the first study to employ a panel approach in the GARCH-type volatility analysis of BIST 100 constituents. Moreover, it is also one of the few studies that investigate the daily volatility of BIST 100 equities during the currency shock and COVID shock periods. For other studies that analyse the effect of the COVID pandemic on the stock market see, among others, the works by Kayral and Tandoğan[5]; Keleş[6]; Kılıç[7]; Özdemir[8]; Özkan[9]; Öztürk, Şişman, Uslu and Çıtak[10].

We would like to underline at the outset that our analysis is not causal. In particular, we refrain from making any claims on the underlying mechanism between the shocks and stock market volatility, or the potential transmission links. While it may be tempting to reach quick conclusions about transmission mechanisms, this is not a straightforward task. To begin with, GARCH-type models are not causal, so they cannot yield any causal interpretations. Moreover, the dynamic nature of financial and macro variables requires appropriate macro-modelling approaches for a proper understanding of the complex links between them. For instance, in the case of the currency shock it is not immediately obvious whether currency volatility has a direct or indirect positive/negative effect on the stock market (or vice-versa). Therefore, while establishing causal links is certainly a very important research question, such an analysis is beyond the scope of our study.

Our study contributes to a sizeable literature on GARCH-type volatility analysis of Borsa Istanbul. One strand of this literature focusses on the comparison of different GARCH-type models on the basis of their out-of-sample predictive power; see, among others, the works by Sevütekin and Nargeleçekenler[11], Köksal[12], Alper et al.[13], and Gulay and Emec[14]. This literature suggests that, in general, the standard GARCH model has superior forecasting abilities. There is also a large literature which uses GARCH-type models to analyse various aspects of the BIST 100 (or the Istanbul Stock Exchange) index, focussing on objectives such as testing the presence of a relationship between stock

5 Kayral, İ. E., Tandoğan, N. Ş. (2020). BİST100, Döviz Kurları ve Altının Getiri ve Volatilitesinde COVID-19 Etkisi, Gaziantep University Journal of Social Sciences, 19: 687-701.

6 Keleş, E. (2020). COVID-19 ve BİST-30 Endeksi Üzerine Kısa Dönemli Etkileri, Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi, 42: 91-105.

7 Kılıç, Y. (2020). Borsa İstanbul'da COVID-19 (Koronavirüs) Etkisi, Journal of Emerging Economies and Policy, 5: 66-77.

8 Özdemir, L. (2020). COVID-19 Pandemisinin BIST Sektör Endeksleri Üzerine Asimetrik Etkisi, Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 5: 546-556.

9 Özkan, O. (2020). Volatility Jump: The Effect of COVID-19 on Turkey Stock Market, Gaziantep University Journal of Social Sciences, 19: 386-397.

10 Öztürk, Ö., Şişman, M. Y., Uslu, H., Çıtak, F. (2020). Effects of COVID-19 Outbreak on Turkish Stock Market: A Sectoral-Level Analysis, Hitit University Journal of Social Sciences Institute, 13: 56-68.

11 Sevütekin, M., Nargeleçekenler, M. (2004). İstanbul Menkul Kıymetler Borsasında Getiri Volatilitesinin Modellenmesi ve Önraporlanması, Ankara Üniversitesi SBF Dergisi, 61: 243-265.

12 Köksal, B. (2009). A Comparison of Conditional Volatility Estimators for the ISE National 100 Index Returns, Journal of Economic and Social Research, 11: 1-29.

13 Alper, C. E. et al. (2012). MIDAS Volatility Forecast Performance under Market Stress: Evidence from Emerging Stock Markets, Economics Letters, 117: 528-532.

14 Gulay, E., Emec, H. (2018). Comparison of Forecasting Performances: Does Normalization and Variance Stabilization Method Beat GARCH(1,1)-type Models? Empirical Evidence from the Stock Markets, Journal of Forecasting, 37: 133-150.

dividends and company value[15], uncovering the effects of price limits on daily equity volatilities[16], investigating the presence of a long memory property for index returns[17], investigating volatility spillovers[18], and analysing how emerging stock market volatilities are affected by US macro announcements[19].

The rest of the paper is organised as follows: in Section 2 we provide an overview of the GARCH methodology and, in particular, of the bias-corrected panel GARCH estimation method. The volatility analysis of BIST 100 equities is undertaken in Section 3, which is the main contribution of this paper. The last section concludes and discusses future research directions.

2. Methodology

In this part, we provide a brief overview of the standard GARCH model (Section 2.1) and discuss the specific approach used in our empirical analysis, the bias-corrected panel GARCH estimator (Section 2.2). Let r_t be some variable of interest where $t = 1, \dots, T$ denotes time. In this study, r_t is the daily return on some equity (e.g. AKBANK, TURKCELL etc.) at time *t*. A standard generic structure for r_t is

$$r_t = \mu_t + \varepsilon_t,$$

where μ_t is the (potentially) time-varying conditional mean of daily returns and ε_t is a time-varying shock process. The standard assumption in the volatility literature is that $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma^2$ for some finite σ^2. We also note that daily stock returns typically fluctuate around zero, implying $\mu_t \approx 0$.[20] For that reason, we follow the standard convention and let $\mu_t = 0$ in what follows, which yields

$$r_t = \varepsilon_t.$$

15 Batchelor, R., Orakcioglu, I. (2003). Event-related GARCH: The Impact of Stock Dividends in Turkey, Applied Financial Economics, 13: 295-307.

16 Bildik, R., Elekdag, S. (2004). Effects of Price Limits on Volatility: Evidence from the Istanbul Stock Exchange, Emerging Markets Finance and Trade, 40: 5-34.

17 Kılıç, R. (2004). On the long Memory Properties of Emerging Capital Markets: Evidence from Istanbul Stock Exchange, Applied Financial Economics, 14: 915-922.

18 Erdem, C. et al. (2005). Effects of Macroeconomic Variables on Istanbul Stock Exchange Indexes, Applied Financial Economics, 15: 987-994.

19 Cakan, E. et al. (2015). Does U.S. Macroeconomic News Make Emerging Financial Markets Riskier? Borsa Istanbul Review, 15: 37-43.

20 While it is common to use $\mu_t = 0$ for daily equity returns, for other types of financial data a different approach for modelling μ_t may be appropriate. Two common options are to impose an AR structure (e.g. $\mu_t = \beta r_{t-1}$) or to employ a GARCH-in-means approach (e.g. $\mu_t = \mu + \delta\sigma_t^2$). For more information, see Chapter 7 of Kevin Sheppard's lecture notes: Sheppard, K. (2020). Financial Econometrics Notes, https://www.kevinsheppard.com/files/teaching/mfe/notes/financial-econometrics-2020-2021.pdf, (Last accessed: 16.11.2020).

2.1. The GARCH Model

Since their inception, GARCH-type models have proved to be very popular for modelling time-varying volatility. The GARCH(1,1) model[21] stands out in particular as the most popular and least complicated member of this large family of models.[22] In particular, let the shock process ε_t be such that $E(\varepsilon_t|F_{t-1}) = 0$ and $Var(\varepsilon_t|F_{t-1}) = \sigma_t^2$ where F_t is the information set at time t. Then, the GARCH(1,1) model is given by

$$\sigma_t^2 = \lambda(1 - \alpha - \beta) + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1,}^2 \tag{1}$$

where $\lambda > 0, \alpha \geq 0, \beta \geq 0$ and $\alpha + \beta < 1$. These standard parameter restrictions guarantee that the resulting variance process σ_t^2 will always be positive. Here α measures the effect of yesterday's shock on today's conditional variance, whereas the effect of yesterday's conditional variance is given by β. It can be shown by standard calculations that $\lambda = E(\varepsilon_t^2)$, and so λ is equal to the unconditional (or long-run) variance of ε_t.[23] The model is completed by specifying a conditional distribution for ε_t. A popular and analytically convenient option is the normal distribution[24]:

$$\varepsilon_t|F_{t-1} \sim N(0, \sigma_t^2). \tag{2}$$

Equations (1) and (2) together provide a complete structure which can be used to estimate the parameters (λ, α, β). Notice that the log-likelihood function for r_t is given by

$$\ell_t(\lambda, \alpha, \beta) = -\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma_t^2) - \frac{1}{2}\frac{r_t^2}{\sigma_t^2}.$$

Although one can estimate all parameters by maximising the joint log-likelihood function $\ell_T(\lambda, \alpha, \beta) = T^{-1}\sum_{t=2}^{T}\ell_t(\lambda, \alpha, \beta)$, a more convenient option is to estimate λ separately by the method of moments, using $\lambda = E(\varepsilon_t^2)$. This approach, known as variance-tracking[25], yields

$$\hat{\lambda} = \frac{1}{T}\sum\nolimits_{t=1}^{T} r_t^2 \quad and \quad (\hat{\alpha}, \hat{\beta}) = \arg max_{\alpha,\beta}\, \ell_T(\hat{\lambda}, \alpha, \beta). \tag{3}$$

21 Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, Journal of Econometrics, 51: 307-327.

22 Other well-known examples of models in this vein are the exponential GARCH, GJR-GARCH and Threshold-ARCH models, to name just of few. Different variants of the GARCH-family are too numerous to cite and interested readers are referred to the "glossary-type" survey of Bollerslev: Bollerslev, T. (2010). Glossary to ARCH (GARCH*). T. Bollerslev, J. Russell, and M. Watson (Eds.), Volatility and Time Series Econometrics: Essays in Honor of Robert Engle, Oxford University Press, 137-163.

23 For a detailed textbook treatment of GARCH models and their theoretical background, see: Francq, C., Zakoïan, J. M. (2010). GARCH Models: Structure, Statistical Inference and Financial Applications, Wiley.

24 Other typical options are the *t* and skewed-*t* distributions. However, the well-known work of Bollerslev and Wooldridge shows that, as long as the conditional mean and variance are correctly specified, parameter estimators will remain consistent even if the normality assumption is violated: Bollerslev, T., Wooldridge, J. M. (1992). Quasi-maximum Likelihood Estimation and Inference in Dynamic Models with Time-varying Covariances, Econometric Reviews, 11: 143-172.

25 Francq, C. et al. (2011). Merits and Drawbacks of Variance Targeting in GARCH Models, Journal of Financial Econometrics, 9: 619-656.

An important limitation, which applies to any GARCH-type model, is that accurate parameter estimation requires a large dataset, typically around 1000 daily observations, if not more, as it is difficult to capture GARCH effects with few observations. This is because of two key factors: first, these models are highly nonlinear and have a recursive structure, requiring numerical estimation methods and, therefore, a large number of observations for convergence to a solution. Second, macro and financial variables are typically characterised by serial dependence, which means that individual observations carry less information (compared to independently distributed variables) and therefore a larger dataset is required for asymptotic convergence to take effect. For standard financial variables, data are available in abundance. However, in cases (such as ours) where one wants to base estimation on a shorter history of data, the small-sample bias will be substantial enough to make standard GARCH estimation methods unreliable.

2.2. Bias-corrected Panel GARCH Method

In order to make the GARCH model operational with a limited number of observations, Pakel et al. propose a panel GARCH approach which utilises both cross-sectional and time-series information.[26] In particular, let r_{it} be the return on asset i (i=1,...,N) at time t, and let F_{it} be the information set for asset i at time t. Then, their panel GARCH model for , $\sigma_{it}^2 = Var(r_{it}|F_{it-1})$ the conditional variance of asset i, is given by

$$\sigma_{it}^2 = \lambda_i(1-\alpha-\beta) + \alpha\varepsilon_{it-1}^2 + \beta\sigma_{it-1}^2, \qquad \varepsilon_{it}|F_{it-1} \sim N(0,\sigma_{it}^2), \tag{4}$$

where we again assume that the shock process ε_{it} is conditionally normal. Estimation is again based on the standard restrictions $\lambda_i > 0, \alpha \geq 0, \beta \geq 0$ and $\alpha + \beta < 1$, , as for the GARCH(1,1) model. The model in (4) imposes that (α,β) be the same across all assets while leaving λ_i to be heterogenous across assets. This is motivated by the general observation that, for equity returns, estimates of α and β tend to cluster around similar values[27] (for α this is around 0 whereas β is usually around 1). Leaving λ_i to be asset-specific allows each asset to have a different long-run variance, and provides flexibility.

The main insight in this approach is that when (α,β) is the same across assets, the econometrician can use the bigger information pool provided by the time and cross-section dimensions (as opposed to using the information in a single time-series to estimate (α,β) separately for each asset). The motivation here is to dampen the effect of the small-T bias by using the extra information coming from the cross-section dimension.

The original estimation approach used by Pakel et al.[28] is the natural extension of the estimator in (3):

$$\hat{\lambda}_i = \frac{1}{T}\sum_{t=1}^{T} r_{it}^2 \quad and \quad (\hat{\alpha},\hat{\beta}) = \arg max_{\alpha,\beta} \frac{1}{N}\sum_{i=1}^{N} \ell_{iT}(\hat{\lambda}_i,\alpha,\beta), \tag{5}$$

26 Pakel, C. et al. (2011). Nuisance Parameters, Composite Likelihoods and a Panel of GARCH Models, Statistica Sinica, 21: 307-329.

27 Brownlees, C. T. (2019). Hierarchical GARCH, Journal of Empirical Finance, 51, p.17.

28 Pakel et al., 2011, 311.

where

$$\ell_{iT}(\lambda_i,\alpha,\beta)=\frac{1}{T}\sum\nolimits_{t=2}^{T}\left(-\frac{1}{2}\ln(2\pi)-\frac{1}{2}\ln(\sigma_{it}^2)-\frac{1}{2}\frac{r_{it}^2}{\sigma_{it}^2}\right).$$

However, a more interesting estimation approach has recently been suggested, based on the observation that the model in (4) is essentially a member of the general class of nonlinear and dynamic panel models with individual-specific parameters. This class of models is the subject of a substantial literature in panel data econometrics — however, the focus of this literature is almost exclusively confined to microeconometric applications and volatility modelling has not been a subject of interest. Importantly for our purposes, methods for removing the small-T bias of (α,β) have already been proposed in that literature.[29] Using this insight, in recent work Pakel proposes a bias-corrected version of the panel GARCH estimator.[30] Let, for brevity, $\theta=(\alpha,\beta)$. The proposed estimator is an integrated likelihood estimator given by

$$\hat{\theta}_{IL}=\arg max_{\theta}\frac{1}{NT}\sum_{i=1}^{N}\ln\int_{\Lambda}\exp\big(T\ell_{iT}(\lambda_i,\theta)\big)\,\pi_i(\lambda_i)d\lambda_i, \tag{6}$$

where

$$\pi_i(\lambda_i)=\{E[-\partial^2\ell_{iT}(\lambda_i,\theta)/\partial\lambda_i^2]\}^{1/2}\exp\left(\frac{T}{2}\frac{E[(\partial\ell_{iT}(\lambda_i,\theta)/\partial\lambda_i)^2]}{E[\partial^2\ell_{iT}(\lambda_i,\theta)/\partial\lambda_i^2]}\right), \tag{7}$$

and Λ is the set of possible values for λ_i. This particular choice of $\pi_i(\lambda_i)$ guarantees that the small-sample bias of $\hat{\theta}_{IL}$ will be of order $1/T^2$, as opposed to the estimator in (5) which is not bias-corrected and so has a small-sample bias of order $1/T$. In other words, the integrated likelihood estimator has a diminished small-sample bias, making it accurate even when T is very small.[31] We underline that the bias-corrected estimator of equation (6) is not a different volatility model, but an alternative method (which is robust to small sample sizes) for estimating the parameters of the panel GARCH model in (4). In connection with this point, this approach also imposes the parameter restrictions $\alpha\geq 0,\beta\geq 0$ and $\alpha+\beta<1$.

29 For a comprehensive survey of this literature along with the standard correction methods, see: Fernández-Val, I., Weidner, M. (2018). Fixed Effects Estimation of Large-T Panel Data Models, Annual Review of Economics, 10: 109-138.

30 Pakel, 2019, 64-80.

31 For the original use of the integrated likelihood method in the panel data literature and the derivation of the bias correcting weight function $\pi_i(\lambda_i)$ see: Arellano, M., Bonhomme, S. (2009). Robust Priors in Nonlinear Panel Data Models, Econometrica, 77: 489-536.

Even though $\hat{\theta}_{IL}$ is an accurate estimator, one still has to estimate λ_i in order to fully model σ_{it}^2. Unfortunately, a bias-corrected estimator for λ_i does not exist. However, Pakel[32] proposes

$$\tilde{\lambda}_i = \arg max_{\lambda_i} \ell_{iT}(\lambda_i, \hat{\theta}_{IL}), \tag{8}$$

under the restriction λ_i>0. The intuition here is that, the likelihood function $\ell_{iT}(\lambda_i, \hat{\theta}_{IL})$ will be more informative about λ_i since it is based on the bias-corrected $\hat{\theta}_{IL}$, with the consequence that λ_i is a more accurate estimator compared to λ_i.

Importantly, the simulation analysis in Section S4.1 of Pakel's work reveals that $\hat{\theta}_{IL}$ provides an accurate estimator of $\hat{\theta}$ even with 150-200 time-series observations[33]. Moreover, the analysis of predictive ability in Section S4.2 of the same work also confirms that the estimator in (8) leads to superior predictive ability compared to other methods[34]. In light of this information, the bias-corrected panel GARCH estimator stands out as the appropriate method for our purposes. Our empirical analysis will, therefore, be based on this method.

2.3. Details of Estimation

In obtaining $\hat{\theta}_{IL}$, we follow the same recipe outlined in Section S4.4 of Pakel's paper, and full details of estimation can be found there.[35] The first-step consists of estimation of (α, β) by maximising the integrated likelihood function in equation (6). This integral is quite complicated and does not yield a closed-form solution. As such, the econometrician first has to calculate the integral numerically and then optimise the resulting integrated likelihood function by numerical methods. Notice that $\pi_i(\lambda_i)$ is a population quantity, so it has to be replaced by its sample counterpart; this is obtained by replacing the population moments by their consistent estimators. The integral in (6) is then calculated via a simple quadrature method. Theoretically, the integral has to be evaluated over Λ, the whole set of possible values for λ_i, which is computationally not feasible. Instead, we focus on a grid of 15 equally-spaced values for λ_i; the upper/lower bounds of this grid are chosen to be 1.20/0.80 times the maximum/minimum squared return across the sample used for estimation. The resulting integrated likelihood function is then optimised numerically with respect to (α, β) which yields $\hat{\theta}_{IL}$. In the next stage, $\hat{\theta}_{IL}$ is used to construct the likelihood function in (8). As is well known, maximisation of GARCH likelihood functions (such as the one in (8)) does not yield closed-form solutions due to the recursive structure of GARCH. Hence, λ_i is also obtained by numerical optimisation. All computations were done on MATLAB.

32 Pakel, 2019, 69.

33 Pakel, 2019, 66-67.

34 Pakel, 2019, 68-69.

35 Pakel, 2019, 71-72.

3. Volatility Analysis of BIST 100 Index Constituents

Our dataset consists of the daily returns on all BIST 100 index constituents that were continuously traded between 27 May 2013 and 2 July 2020, which corresponds to 1783 observations per equity.[36] This corresponds to 90 firms. We also consider a sector-level analysis of BIST 100 constituents where we focus on the sectors industrials, financials and services which consist of 43, 30 and 13 equities, respectively.[37] These are the sectors with the largest number of firms in them, and together they cover 86 of the 90 equities analysed here (we note that each firm belongs to a single sector only). The remaining four firms belong to the sector technology; however, we omit this sector from our analysis, since the panel approach would be unreliable with only four firms. A full list of all the firms considered in this study is provided in Table 1.

Table 1. BIST 100 Constituent Equities Considered in the Empirical Analysis, and Their Sector Information.

BIST 100 Const.	Company Name	Sector	BIST 100 Const.	Company Name	Sector
AEFES	ANADOLU EFES	INDUSTRIALS	KARSN	KARSAN OTOMOTIV	INDUSTRIALS
AGHOL	ANADOLU GRUBU HOLDING	FINANCIALS	KARTN	KARTONSAN	INDUSTRIALS
AKBNK	AKBANK	FINANCIALS	KCHOL	KOC HOLDING	FINANCIALS
AKCNS	AKCANSA	INDUSTRIALS	KERVT	KEREVITAS GIDA	INDUSTRIALS
AKGRT	AKSIGORTA	FINANCIALS	KLMSN	KLIMASAN KLIMA	INDUSTRIALS
AKSA	AKSA	INDUSTRIALS	KORDS	KORDSA TEKNIK TEKSTIL	INDUSTRIALS
AKSEN	AKSA ENERJI	SERVICES	KOZAA	KOZA MADENCILIK	INDUSTRIALS
ALARK	ALARKO HOLDING	FINANCIALS	KOZAL	KOZA ALTIN	INDUSTRIALS
ALBRK	ALBARAKA TURK	FINANCIALS	KRDMD	KARDEMIR (D)	INDUSTRIALS
ALGYO	ALARKO GMYO	FINANCIALS	LOGO	LOGO YAZILIM	TECHNOLOGY
ALKIM	ALKIM KIMYA	INDUSTRIALS	MGROS	MIGROS TICARET	SERVICES
ANACM	ANADOLU CAM	INDUSTRIALS	NETAS	NETAS TELEKOM.	TECHNOLOGY
ARCLK	ARCELIK	INDUSTRIALS	NTHOL	NET HOLDING	FINANCIALS
ASELS	ASELSAN	TECHNOLOGY	OTKAR	OTOKAR	INDUSTRIALS
AYGAZ	AYGAZ	INDUSTRIALS	OYAKC	OYAK CIMENTO	INDUSTRIALS
BAGFS	BAGFAS	INDUSTRIALS	PETKM	PETKIM	INDUSTRIALS
BIMAS	BIM MAGAZALAR	SERVICES	SAHOL	SABANCI HOLDING	FINANCIALS
BIZIM	BIZIM MAGAZALARI	SERVICES	SASA	SASA POLYESTER	INDUSTRIALS
BRISA	BRISA	INDUSTRIALS	SELEC	SELCUK ECZA DEPOSU	SERVICES
BRSAN	BORUSAN MANNESMANN	INDUSTRIALS	SISE	SISE CAM	FINANCIALS

36 Our analysis spans the period between 2 January 2014 and 2 July 2020. However, since estimation for each day requires 150 observations, our estimation sample starts from 27 May 2013.

37 Sector information for BIST 100 constituents, as of the third quarter of 2020, is obtained from https://www.borsaistanbul.com/en/sayfa/3542/bist-stock-indices (last accessed on 7 August 2020). This list also contains weights of each equity in their sector index.

BUCIM	BURSA CIMENTO	INDUSTRIALS	SKBNK	SEKERBANK	FINANCIALS
CCOLA	COCA COLA ICECEK	INDUSTRIALS	SODA	SODA SANAYII	INDUSTRIALS
CEMTS	CEMTAS	INDUSTRIALS	TATGD	TAT GIDA	INDUSTRIALS
CIMSA	CIMSA	INDUSTRIALS	TAVHL	TAV HAVALIMANLARI	FINANCIALS
CLEBI	CELEBI	SERVICES	TCELL	TURKCELL	SERVICES
DEVA	DEVA HOLDING	INDUSTRIALS	THYAO	TURK HAVA YOLLARI	SERVICES
DOAS	DOGUS OTOMOTIV	SERVICES	TKFEN	TEKFEN HOLDING	FINANCIALS
DOCO	DO-CO	SERVICES	TOASO	TOFAS OTO. FAB.	INDUSTRIALS
DOHOL	DOGAN HOLDING	FINANCIALS	TRGYO	TORUNLAR GMYO	FINANCIALS
ECILC	ECZACIBASI ILAC	FINANCIALS	TRKCM	TRAKYA CAM	INDUSTRIALS
EGEEN	EGE ENDUSTRI	INDUSTRIALS	TSKB	T.S.K.B.	FINANCIALS
EKGYO	EMLAK KONUT GMYO	FINANCIALS	TTKOM	TURK TELEKOM	SERVICES
ENKAI	ENKA INSAAT	SERVICES	TTRAK	TURK TRAKTOR	INDUSTRIALS
EREGL	EREGLI DEMIR CELIK	INDUSTRIALS	TUPRS	TUPRAS	INDUSTRIALS
FROTO	FORD OTOSAN	INDUSTRIALS	ULKER	ULKER BISKUVI	INDUSTRIALS
GARAN	GARANTI BANKASI	FINANCIALS	VAKBN	VAKIFLAR BANKASI	FINANCIALS
GLYHO	GLOBAL YAT. HOLDING	FINANCIALS	VESTL	VESTEL	INDUSTRIALS
GOODY	GOOD-YEAR	INDUSTRIALS	YATAS	YATAS	INDUSTRIALS
GOZDE	GOZDE GIRISIM	FINANCIALS	YKBNK	YAPI VE KREDI BANK.	FINANCIALS
GSDHO	GSD HOLDING	FINANCIALS	ZOREN	ZORLU ENERJI	SERVICES
GUBRF	GUBRE FABRIK.	INDUSTRIALS			
GUSGR	GUNES SIGORTA	FINANCIALS			
HALKB	T. HALK BANKASI	FINANCIALS			
HEKTS	HEKTAS	INDUSTRIALS			
IPEKE	IPEK DOGAL ENERJI	INDUSTRIALS			
ISCTR	IS BANKASI	FINANCIALS			
ISFIN	IS FIN.KIR.	FINANCIALS			
ISGYO	IS GMYO	FINANCIALS			
ISMEN	IS Y. MEN. DEG.	FINANCIALS			
KAREL	KAREL ELEKTRONIK	TECHNOLOGY			

Table 2. Cross-Section Dependence and Panel Unit Root Test Results

Panel Cross-Section Dependence Test Result		
Test Type	*Test Statistic*	*p-Value*
Pesaran	843.607	0.00
Friedman	50938.228	0.00
Frees	9.356	0.00
CADF Panel Unit Root Test Results		
Test statistic	*Approximate critical values*	

	1%	5%	10%
-6.42	-2.65	-2.57	-2.52

Note: Results of the panel cross-section dependence and panel unit root tests for the panel of returns used in this paper, which contains 1783 time observations on 90 equities. The top panel reports the cross-section dependence test results for Pesaran's, Friedman's and Frees' tests. The bottom panel reports the results for the panel unit root test of Pesaran[38]. Critical values have been obtained from Table II(c) of Pesaran's original paper for the case T=200 and N=100.

In generating the returns series for each equity, we follow the standard practice and use $r_{it} = 100 * \ln(P_{it}/P_{it-1})$where P_{it} is the closing price of equity *i* at date *t*. Before starting our main analysis, we investigate our dataset for the presence of cross-section dependence and non-stationarity. To test the former, we employ the diagnostic test for cross-sectional dependence in panels, developed by Pesaran[39]. We also consider the more classical Friedman's[40] and Frees'[41] tests. The test results are presented in the top panel of Table 2. All three tests reject the null hypothesis of cross-section independence with a p-value of 0.00, strongly suggesting the presence of cross-section dependence. This is not a surprising result for financial panels; nor is it a problem since Pakel's method is specifically designed to be robust against cross-section dependence in panels[42]. We also test for non-stationarity using the panel unit root test developed by Pesaran[43]. This test allows for cross-section dependence and so it is suitable for our case. The result of this test is presented in the bottom panel of Table 2. The null hypothesis of this test is the presence of a unit root in all series in the panel, against the alternative that at least one series is stationary. We note that this test has a non-standard distribution; as a result, its critical values, as presented in Pesaran's original paper, are based on simulation results.[44] Unfortunately, critical values for our sample size (T=1783, N=90) are not available. However, a quick glance at Table II(c) in Pesaran's paper[45] reveals that the critical values become stable as T increases. For this reason, we take the critical values for T=200, N=100 as approximate critical values for our case. Clearly, our test statistic of – 6.42 is sufficiently large in absolute value to reject the hypothesis that all series in our panel are non-stationary at 1%, 5% and 10% levels of significance.[46]

We now turn to the main contribution of our paper, which is volatility analysis of BIST 100 constituents. All our results are based on the panel GARCH model in (4) which we estimate using the bias-corrected estimator outlined in equations (6)-(8). As explained in Section 2.2, the integrated

38 Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence, Journal of Applied Econometrics, 22: 279-281.

39 Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels, IZA Discussion Paper Series, No 1240: 1-39.

40 Friedman, M. (1937). The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance, Journal of the American Statistical Association, 32: 675-701.

41 Frees, E. W. (1995). Assessing Cross-Sectional Correlation in Panel Data, Journal of Econometrics, 69: 393-414.

42 Pakel, 2019, 64-80.

43 Pesaran, 2007, 265-312.

44 Pesaran, 2007, 279-281.

45 Pesaran, 2007, 281.

46 We also ran individual augmented Dickey-Fuller tests to check non-stationarity of individual series separately. However, none of the series were found to have a unit root.

likelihood estimator $\hat{\theta}_{IL} = (\hat{\alpha}_{IL}, \hat{\beta}_{IL})$ is obtained for the whole panel of assets, whereas $\tilde{\lambda}_1, \dots, \tilde{\lambda}_N$ are asset specific. For instance, the analysis of BIST 100 constituents obtains $(\hat{\alpha}_{IL}, \hat{\beta}_{IL})$ by constructing the integrated likelihood function in (6) using the panel of all 90 assets under consideration. The analysis for, e.g., financials, on the other hand, obtains $(\hat{\alpha}_{IL}, \hat{\beta}_{IL})$ using the panel of the 30 assets that belong to the sector financials only. Finally, for any given $(\tilde{\lambda}_i, \hat{\alpha}_{IL}, \hat{\beta}_{IL})$, predicted daily volatilities for asset *i* are calculated by replacing $(\lambda_i, \alpha, \beta)$ in equation (4) by $(\tilde{\lambda}_i, \hat{\alpha}_{IL}, \hat{\beta}_{IL})$.

3.1. General Comparison between 2014-2018 and 2018-2020

In this part, we undertake an exploratory analysis and estimate the panel GARCH model of equation (4) for the periods January 2014-April 2018 and May 2018-July 2020.[47] Our aim here is to have a broad comparison of the two periods before delving into the more detailed analysis of Sections 3.2 and 3.3. In particular, as opposed to our analysis in Sections 3.2 and 3.3, in this part we estimate a single set of parameters (α, β) for each period, using the whole panel of observations for that period. We do this both for BIST 100 constituents and the sectors industrials, financials and services.

Table 3. GARCH Parameter Estimates for 2014-2018 and 2018-2020.

Sectors	01/2014-04/2018 (period-1)		05/2018-07/2020 (period-2)		
	α	β	α	β	Number of Equities
BIST 100	0.10	0.90	0.11	0.80	90
Industrials	0.17	0.82	0.13	0.85	43
Financials	0.12	0.88	0.19	0.79	30
Services	0.08	0.92	0.18	0.80	13

Our results, presented in Table 3, suggest a general shift in the parameters (α, β) — or, equivalently, in volatility dynamics — between the two periods. For BIST 100 constituents as a whole, although the shift in α is minimal, there is a sizeable change in β from 0.9 to 0.8. Results for sector-specific parameters reveal substantial changes in both parameters between the two periods. For financials and services, we observe an increase in α, paired with a decrease in β. For industrials, we observe the opposite. A further observation is that there is considerable heterogeneity across sectors in terms of their volatility parameters. This is especially evident in the first period. Interestingly, in the second period the estimated parameters for financials and services are almost identical. From a technical point, an increase in α means that the effect of the lagged shock process (ε_{it-1}^2) on current volatility is greater, which usually leads to a noisier volatility process. An increase in β, on

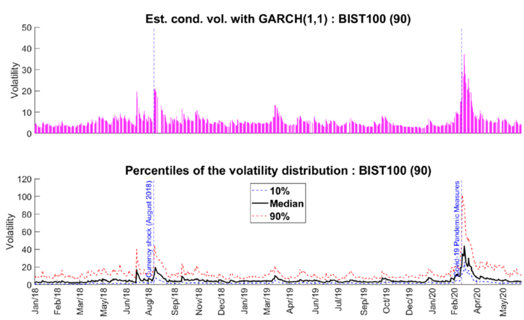
47 We start the first period in January 2014 mainly to have a long enough period of comparison, and not because the period between January 2014 and April 2018 is thought to be a homogenous period for the stock market. As for starting the second period in May 2018, we note that although the currency shock occurs in August 2018, the TL/USD exchange rate begins to exhibit fluctuations around May 2018 (see Figure 1). Therefore, we choose to start the second period in May 2018.

the other hand, implies that the effect of lagged volatility on current volatility is higher, resulting in a smoother volatility behaviour. However, we again note that the results of this part provide a very broad overview, and therefore we refrain from reaching an overall conclusion. The analysis presented in the following parts will provide a much clearer picture of the behaviour of volatility.

3.2. Analysis of Daily Volatilities Between 2018-2020

In this part, we study the daily volatility process throughout the period from January 2018 to July 2020. Calculation of the daily volatility for a particular equity i requires the parameter estimates $(\tilde{\lambda}_i, \hat{\alpha}, \hat{\beta})$. To ensure that our results are as robust as possible to potential changes in the parameters $(\lambda_i, \alpha, \beta)$, we obtain a new set of estimates $(\tilde{\lambda}_i, \hat{\alpha}, \hat{\beta})$ for every date in our sample (using an estimation window of the 150 most recent data points). This approach, made possible by the bias-corrected panel GARCH method of Section 2.2, ensures that our results reflect only the most recent history at any given point in time (as opposed to using information from several years of data, as would be the case with standard GARCH estimation methods). The estimates $(\tilde{\lambda}_i, \hat{\alpha}, \hat{\beta})$ obtained for date t are used to construct $\hat{\sigma}_{it}^2$, the estimated volatility for equity i at that date. The (weighted) average volatility for BIST 100 at date t is then given by $\sum_{i=1}^{90} w_i\, \hat{\sigma}_{it}^2$, where w_i is the weight of equity i in the BIST 100 index (since we consider 90 out of the 100 BIST 100 constituents, the weights are normalised so that $\sum_{i=1}^{90} w_i = 1$)). In calculating the average volatilities for sectors, we use the weights for the corresponding sector index, which we also normalise to add up to one.[48]

Figure 2. Behaviour of Daily Volatility for BIST 100 Constituent Equities between 2 January 2018 and 2 July 2020.



Note: The upper panel presents the daily (weighted) average volatility across the 90 BIST 100 constituent equities included in the analysis. The lower panel shows the 10th, 50th (median), and 90th percentiles of daily volatility across the same equities at each point in time. Daily volatility is modelled using the panel GARCH model of equation (4). The in-sample size for each date is equal to 150. For more details, see Section 3.2.

48 This normalisation is necessary since our sector analysis is also restricted to firms that are among BIST 100 constituents. For example, the sector industrials contains 163 firms. However, only 43 of these are among BIST 100 constituents. Hence, their sector index weights do not add up to one without normalisation.

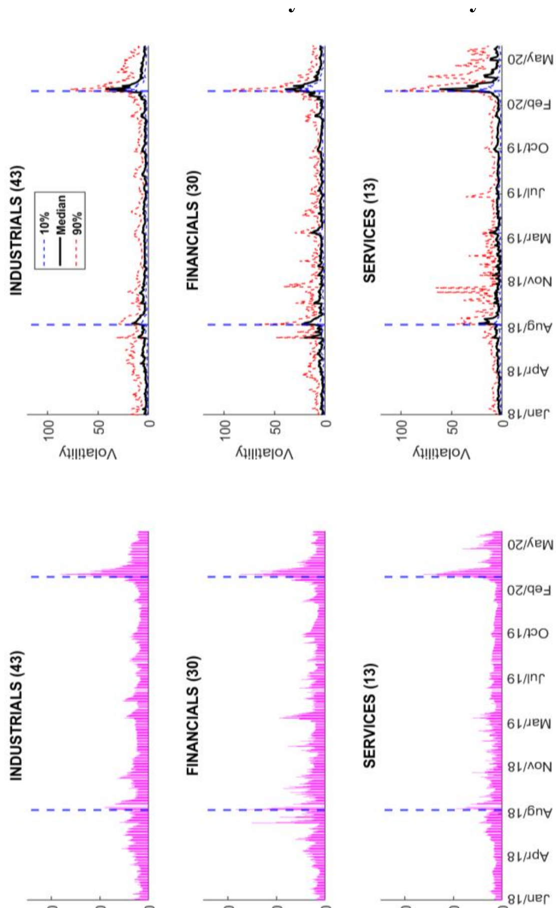
The upper panel of Figure 2 provides the daily average predicted volatility over all the index constituents considered in our analysis. The lower panel of this figure, on the other hand, presents the 10th, 50th (median) and 90th percentiles of daily volatility across all assets. This provides a general snapshot of the sample distribution of volatility across assets on a daily basis.

The upper panel of Figure 2 reveals that the average volatility of BIST 100 has increased by a substantial amount during both shock periods. However, it is striking that the volatility increase during the COVID shock period is far greater and a lot less transitory: the jump in volatility in August 2018 is high, but it quickly returns to pre-shock levels; the jump following COVID in March 2020, on the other hand, takes longer to subside. Given that the COVID pandemic is widely considered to be far from over, it is possible that similar significant volatility movements will be observed in the future as the pandemic runs its course. On the other hand, it is also possible that due to the experience gained in the fight against the pandemic (especially in healthcare) since March 2020, future COVID waves will not be accompanied by significant volatility movements.

Turning to the sample distribution of volatility, presented in the lower panel, a much stronger shift in the volatility distribution following the COVID shock is apparent. Not surprisingly, the 10th percentile and median are quite close, while the 90th percentile is farther away from the median. This asymmetric distribution of volatility is quite standard. The variation in the size of the right tail is still important, as an increase in the skewness of the distribution is a sign of higher tail risk. We see that the distribution becomes more skewed during both the currency and COVID shocks. However, it is revealing that the jump in the size of the right tail during the COVID pandemic is of a much greater magnitude compared to the currency shock period. In other words, the pandemic period has witnessed a higher amount of tail risk in the stock market.

Figure 3 provides the corresponding pictures for the sectors industrials, financials and services. The average daily volatilities and the sample distributions of volatility are calculated in the same way as before, except that model parameters are estimated by using the assets that belong to a given sector only. The general observation from the left panel of this figure is that the average volatility across all sectors increased significantly during both the currency and COVID shock periods. However, we see some heterogeneity across sectors. For example, similar to BIST 100, the sectors industrials and services exhibit a lot more sensitivity during the COVID pandemic. On the other hand, the increase in volatility for financials during the currency and COVID shocks are of similar magnitudes. A further pattern observed for financials is the presence of intermittent volatility spikes following the currency shock. This sector also exhibits volatility jumps in the period leading to the currency shock. What is common to all sectors is something we have also observed for BIST 100: the volatility increase during the currency shock is more of a transitory nature, whereas the volatility jump during the COVID pandemic appears to take some time to go back to pre-COVID levels. Distribution of daily volatility within different sectors, presented on the right panel of Figure 3 provides a better understanding of the behaviour of volatility across sectors. As before, the skewness of the right tail varies across time, and all sectors exhibit a widening of the right tail around shock periods. However, there is some variation in individual behaviour. For example, the size of the right tail decreases for financials following the initial COVID shock. For industrials this is not the case and, in general, the tail size remains relatively large in the following period. For services the 90^{th} percentile actually shows wide fluctuations. Services does stand out in terms of its behaviour following the currency shock, as well: in the months after the currency shock we observe several wide swings of the right tail, suggesting that the tail risk of this sector remains significant.

Figure 3. Behaviour of Daily Volatility for the Sectors Industrials, Financials and Services between 2 January 2018 and 2 July 2020.



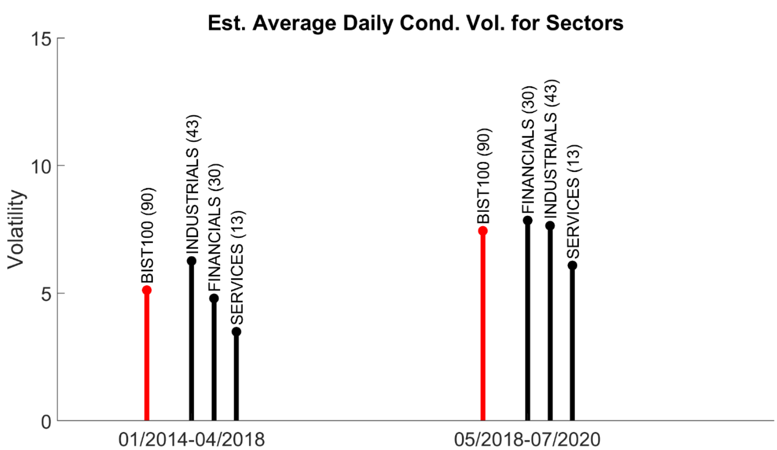
Note: The number of equities in each sector is given in parentheses. The left panel presents the daily (weighted) average volatility across equities belonging to each sector. The right panel shows the 10th, 50th (median), and 90th percentiles of daily volatility for the corresponding sector. For more details, see the caption to Figure 2.

3.3. Volatility Ranking of Sectors

In this last part, we look at the average volatilities of BIST 100 constituents and the three sectors under consideration across different sub-periods. Given the risk interpretation of volatility, the main motivation of this part is to analyse the general risk ranking of sectors. In particular, we are interested in looking at whether the general level of riskiness changes between periods, whether all sectors uniformly become riskier during a certain period, and whether the risk ranking between sectors changes across different periods. We use average volatility to measure the level of risk within a given time period. This is calculated as follows: let $\bar{T}$ be the number of trading days in the chosen period. Let w_i and $\hat{\sigma}_{it}^2$ be as defined in Section 3.2. For illustration, suppose that w_i is the weight of equity i in the BIST 100 index. Then, the average volatility of BIST 100 constituents in this period is given by $\bar{T}^{-1}\sum_{t=1}^{\bar{T}}\sum_{i=1}^{90} w_i\,\hat{\sigma}_{it}^2$. The same quantity for a particular sector is obtained by using the equity weights for that sector's index.

Our analysis considers the following four sub-periods: (i) the period before the two shocks (2 January 2014 – 30 April 2018), (ii) the period of the two shocks (2 May 2018 – 2 July 2020), (iii) the period around the currency shock (2 May 2018 – 30 December 2018), and (iv) the period around the COVID shock (30 January 2020 – 2 July 2020).[49]

Figure 4. Average Volatility of BIST 100 Constituents and Individual Sectors for 2014-2018 and 2018-2020.

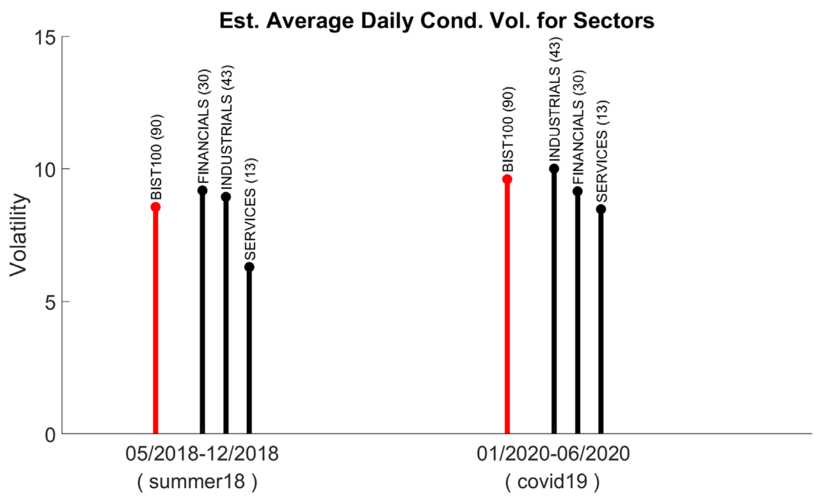


Note: See Section 3.3 for details of calculation of average volatilities. The number of equities contained in each sector is given in parentheses.

49 We choose 30 January 2020 as the starting date of the COVID shock, which is when the World Health Organization declared the outbreak a Public Health Emergency of International Concern.

Our first set of results, provided in Figure 4, compares average volatilities across sectors for the periods January 2014-April 2018 and May 2018-July 2020, and reveals a striking result: the lowest average volatility for May 2018-July 2020 (services) is only marginally below the highest average volatility for January 2014-April 2018 (industrials). More importantly, the risk level across sectors has increased uniformly in the second period. For services, this increase is enormous in relative terms, as the average volatility almost doubles. Financials also exhibits a significant jump, so much that it actually overtakes industrials and becomes the sector with highest average volatility. The results for BIST 100 yield a similar picture; in particular, the average volatility increases by around 50%. Clearly, and not surprisingly, the general level of riskiness (as measured by average volatility) has increased in the second period.

Figure 5. Average Volatility of BIST 100 Constituents and Individual Sectors for the Currency Shock Period (summer18) and the COVID Pandemic Period (covid19).



Note: See Section 3.3 for details of calculation of average volatilities. The number of equities contained in each sector is given in parentheses.

While it is evident that the period of the two shocks between May 2018-July 2020 has witnessed substantial movements in the stock market volatility, it is also clear that the two shocks are not of the same nature: in particular, the COVID pandemic is a global shock of an unprecedented magnitude that emerged outside the global economic and financial systems. For this reason, we next look at the two shock periods separately. The results of this analysis are presented in Figure 5. We note that the average volatility of all assets in BIST 100 during the COVID period is higher compared to the currency shock period. This is also reflected in the behaviour of individual sectors, although the difference between the two periods is not huge. Services is an exception whose average volatility jumps up in the COVID period. We also observe a mild increase for industrials. Financials, on the other hand, declines marginally. One final observation is that the dispersion of average volatility across sectors is almost negligible during the COVID period, compared to the same during May 2018-December 2018. In other words, all sectors are equally volatile during the COVID period. In comparison, average volatilities during the currency shock period seem to be somewhat more heterogeneous; in particular, services is much less risky compared to other sectors.

4. Conclusion

This paper has undertaken the volatility analysis of BIST 100 index constituents between May 2018-July 2020. Our results reveal increased stock market volatility during this period, both across individual equities, as well as sectors. In particular, we observe that the general level of risk (as measured by average volatility) across sectors has increased substantially in the period May 2018-July 2020.

More importantly, it appears that the volatility increase during the COVID pandemic has been more substantial and less transitory, pervading all sectors equally. It is possible to interpret this observation in different ways. One interpretation is that further possible waves of COVID will be accompanied by the same type of reaction in the stock markets. Currently, the general view is that the pandemic has still not run its course; consequently, the possibility of further waves is not ruled out. This puts things into a rather grim perspective. However, it is possible that this interpretation is an overly pessimistic one. One can also argue that the first wave of COVID was so sudden and unexpected that it caught governments around the world entirely off guard. Although it is clear that it will take some time for the world to develop effective final measures against COVID, it is also evident that much has been learned and much experience has been gained in the fight against COVID. Consequently, it is possible that further waves will witness less seismic movements in the stock markets. As things stand, one thing is certain: it is difficult to make an accurate prediction of the future effects of the COVID pandemic before we observe the development of the disease. We therefore consider it an important future project to update our results as the disease runs its course and more results become available.

As explained earlier, we underline that our analysis was not causal. In particular, we refrain from making any claims as to whether there exists a direct causal link between individual shocks and volatility. Undertaking a causal analysis of the underlying transition mechanisms between the volatility movements and shock processes remains a challenging but interesting future task.

Another interesting extension of our analysis would be to consider other examples of the GARCH family, such as the EGARCH or GJR-GARCH models. We refrained from doing so as bias-corrected estimation methods for these models is not yet available. It is likely that the integrated likelihood method can directly be applied to any GARCH-type model by using the appropriate likelihood function in calculating the integrated likelihood in equation (6). However, given that the integrated likelihood estimator is obtained via numerical methods, it is not immediately obvious whether application of this method to more complicated models such as EGARCH would be numerically straightforward. Given that GARCH is the least complicated member of this family, we expect difficulties to arise with other models. For instance, a possible consequence would be the need for larger datasets (compared to what we considered here). We leave the investigation of this interesting problem to future work.

References

ALPER, C. E., Fendoglu, S., Saltoglu, B. (2012). MIDAS Volatility Forecast Performance under Market Stress: Evidence from Emerging Stock Markets, Economics Letters, 117: 528-532.

ARELLANO, M., Bonhomme, S. (2009). Robust Priors in Nonlinear Panel Data Models, Econometrica, 77: 489-536.

BATCHELOR, R., Orakcioglu, I. (2003). Event-related GARCH: The Impact of Stock Dividends in Turkey, Applied Financial Economics, 13: 295-307.

BİLDİK, R., Elekdag, S. (2004). Effects of Price Limits on Volatility: Evidence from the Istanbul Stock Exchange, Emerging Markets Finance and Trade, 40: 5-34.

BOLLERSLEV, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, Journal of Econometrics, 51: 307-327.

BOLLERSLEV, T. (2010). Glossary to ARCH (GARCH*). T. Bollerslev, J. Russell, and M. Watson (Eds.), Volatility and Time Series Econometrics: Essays in Honor of Robert Engle, Oxford University Press, 137-163.

BOLLERSLEV, T., Wooldridge, J. M. (1992). Quasi-maximum Likelihood Estimation and Inference in Dynamic Models with Time-varying Covariances, Econometric Reviews, 11: 143-172.

BROWNLEES, C. T. (2019). Hierarchical GARCH, Journal of Empirical Finance, 51: 17-27.

CAKAN, E., Doytch, N., Upadhyaya, K. P. (2015). Does U.S. Macroeconomic News Make Emerging Financial Markets Riskier? Borsa Istanbul Review, 15: 37-43.

ENGLE, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, Econometrica, 50: 987-1008.

ERDEM, C., Arslan, C. K., Erdem, M. S. (2005). Effects of Macroeconomic Variables on Istanbul Stock Exchange Indexes, Applied Financial Economics, 15: 987-994.

FERNÁNDEZ-VAL, I., Weidner, M. (2018). Fixed Effects Estimation of Large-T Panel Data Models, Annual Review of Economics, 10: 109-138.

FRANCQ, C., Horváth, L., Zakoïan, J. M. (2011). Merits and Drawbacks of Variance Targeting in GARCH Models, Journal of Financial Econometrics, 9: 619-656.

FRANCQ, C., Zakoïan, J. M. (2010). GARCH Models: Structure, Statistical Inference and Financial Applications, Wiley.

FREES, E. W. (1995). Assessing Cross-Sectional Correlation in Panel Data, Journal of Econometrics, 69: 393-414.

FRIEDMAN, M. (1937). The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance, Journal of the American Statistical Association, 32: 675-701.

GULAY, E., Emec, H. (2018). Comparison of Forecasting Performances: Does Normalization and Variance Stabilization Method Beat GARCH(1,1)-type Models? Empirical Evidence from the Stock Markets, Journal of Forecasting, 37: 133-150.

KAYRAL, İ. E., Tandoğan, N. Ş. (2020). BİST100, Döviz Kurları ve Altının Getiri ve Volatilitesinde COVID-19 Etkisi, Gaziantep University Journal of Social Sciences, 19: 687-701.

KELEŞ, E. (2020). COVID-19 ve BİST-30 Endeksi Üzerine Kısa Dönemli Etkileri, Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi, 42: 91-105.

KILIÇ, R. (2004). On the long Memory Properties of Emerging Capital Markets: Evidence from Istanbul Stock Exchange, Applied Financial Economics, 14: 915-922.

KILIÇ, Y. (2020). Borsa İstanbul'da COVID-19 (Koronavirüs) Etkisi, Journal of Emerging Economies and Policy, 5: 66-77.

KÖKSAL, B. (2009). A Comparison of Conditional Volatility Estimators for the ISE National 100 Index Returns, Journal of Economic and Social Research, 11: 1-29.

ÖZDEMİR, L. (2020). COVID-19 Pandemisinin BIST Sektör Endeksleri Üzerine Asimetrik Etkisi, Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 5: 546-556.

ÖZKAN, O. (2020). Volatility Jump: The Effect of COVID-19 on Turkey Stock Market, Gaziantep University Journal of Social Sciences, 19: 386-397.

ÖZTÜRK, Ö., Şişman, M. Y., Uslu, H., Çıtak, F. (2020). Effects of COVID-19 Outbreak on Turkish Stock Market: A Sectoral-Level Analysis, Hitit University Journal of Social Sciences Institute, 13: 56-68.

PAKEL, C. (2019). Supplementary Appendix for Bias Reduction in Nonlinear and Dynamic Panels in the Presence of Cross-section Dependence, unpublished manuscript, 1-80.

PAKEL, C., Shephard, N., Sheppard, K. (2011). Nuisance Parameters, Composite Likelihoods and a Panel of GARCH Models, Statistica Sinica, 21: 307-329.

PESARAN, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels, IZA Discussion Paper Series, No 1240: 1-39.

PESARAN, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence, Journal of Applied Econometrics, 22: 265-312.

SEVÜTEKİN, M., Nargeleçekenler, M. (2004). İstanbul Menkul Kıymetler Borsasında Getiri Volatilitesinin Modellenmesi ve Önraporlanması, Ankara Üniversitesi SBF Dergisi, 61: 243-265.

SHEPPARD, K. (2020). Financial Econometrics Notes, https://www.kevinsheppard.com/files/teaching/mfe/notes/financial-econometrics-2020-2021.pdf, (Last accessed: 16.11.2020).