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Research article

The effect of the Covid pandemic on stock market volatility: Separating initial impact from time-to-recovery

Jin Zeng[1], Yijia Zhang[2], Yun Yin[3] and Peter G Moffatt[2,*]

[1] Business school, Guangzhou College of Technology and Business, Guangzhou, China
[2] School of Economics, University of East Anglia, Norwich, UK
[3] Faculty of Business, City University of Macau, Macau

* **Correspondence:** Email: p.moffatt@uea.ac.uk; Tel: +4-416-0359-3477.

Abstract: We develop an extension to the GARCHX model - named GARCHX-NL - that captures a key stylized fact for stock market return data seen during the COVID-19 pandemic: an abrupt jump in volatility at the onset of the crisis, followed by a gradual return to its precrisis level. We apply the GARCHX-NL procedure to daily data on various major stock market indexes. The profile likelihood method is used for estimation. The model decomposes the overall impact of the crisis into two measures: the initial impact, and the "half-life" of the shock. We find a strong negative association between these two measures. Moreover, countries with low initial impact but a long half-life tend to be emerging markets, while those with high initial impact and short half-life tend to be developed economies with well-established stock-markets. We attribute these differences to differences in investors' sensitivity to adverse news, and to differences in the preparedness of stock markets to absorb the effects of crises such as the COVID-19 pandemic.

Keywords: market volatility; COVID-19 pandemic; GARCH; GARCHX; profile likelihood

JEL Codes: C13, C58, G01

1. Introduction

The COVID-19 pandemic has impacted economies in many different ways. One of these is the impact on stock markets. Looking across countries, a common pattern is a sudden increase in stock market volatility at the time when the pandemic took hold, followed by a gradual return to normal levels of volatility. This paper is concerned with identification and measurement of this pattern for a selection of major stock markets.

The pattern differs between different stock markets in important ways. First, the timing of the onset of the crisis appears to differ between stock markets; some experienced the volatility shock later than others. Second, the initial volatility shock and the time taken to return to normal levels also appear to differ between stock markets. This strongly suggests that some sets of investors are more sensitive than others to adverse news, and that some stock markets are better prepared than others to absorb the impact of crises such as the COVID-19 pandemic.

The purpose of this study is first to identify the date at which the pandemic took hold for each of the selected stock markets, and second to estimate the magnitude of the volatility shock, along with the "half-life" of the shock, for each stock market. This enables rankings to be drawn up according to the sensitivity of investors and the preparedness of stock markets for crises. Estimation will be performed using daily data on stock market index returns, in the framework of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (Bollerslev, 1986). We develop a new variant of the GARCH model that separately estimates the magnitude of the initial impact of the crisis and the speed of recovery following the initial impact. We will refer to this variant as the GARCHX-NL model.* The profile likelihood method is used for estimation.

Many studies of the modeling of volatility in financial markets have been conducted in the framework of the GARCH model. An obvious way of allowing for the impact of a crisis such as COVID on the volatility is to include a zero-one dummy variable, covering the period of the crisis, in the conditional volatility equation of the GARCH model. When independent variables are introduced to the conditional volatility equation, the model becomes the GARCHX model. The GARCHX framework has been used in a variety of applications including the impact of market volatility on stock price volatility (Hwang and Satchell, 2005), the impact of day-of-week on electricity-price volatility (Sucarrat et al., 2016), and the impact of macroeconomic factors on food-price volatility (Apergis and Rezitis, 2011).

Studies of the impact of the COVID-19 pandemic on stock markets have been surveyed by Anggraini et al. (2022). Many researchers have already used the GARCHX approach to measure the impact of the pandemic on stock market volatility. These include Onali (2020), Yousef (2020), Kusumahadi and Permana (2021), Bora and Basistha (2021), Duttilo et al. (2021), Golder et al. (2022), Adenomon et al. (2022), Curto and Serrasqueiro (2022), and Apergis and Apergis (2022). As expected, many of these studies find that the COVID-19 pandemic had a positive impact on the volatility of stock prices or stock price indexes. International comparisons of the impact of the COVID-19 pandemic on stock markets have been made by Ledwani et al. (2021).

With the exception of Onali (2020) and Apergis and Apergis (2022), who both use number of COVID cases and number of COVID deaths as explanatory variables in the conditional volatility equation, all of the studies cited in the last paragraph simply use a dummy variable to capture the crisis, and hence they make an implicit assumption that the impact of the crisis is constant over the period of the crisis. The empirical evidence presented in Section 2 below appears to contradict this assumption, and it is for this reason that we develop a model that assumes an initial impact followed by a gradual

*The NL suffix represents the nonlinearity of the volatility equation in the GARCHX model. See Section 2.2.2.

decay. Note that our model nests the dummy variable model, so the importance of our generalization can be easily tested.

A further advantage of the GARCHX-NL model that we propose is that it provides a deterministic prediction of the time path of volatility following a crisis. This is likely to be of practical use to finance professionals since the predicted volatilities may be used as inputs in portfolio management and option pricing (Poon and Granger, 2003).

The paper is organized as follows. Section 2 presents the data used in the analysis, with the objective of conveying the key stylized facts, and then describes the GARCHX-NL model that is used in estimation. Section 3 presents results from estimation of the GARCHX-NL model on the data described in Section 2. Section 4 draws conclusions, in particular by linking the econometric results to theoretical predictions appearing in previous literature.

2. Materials and method

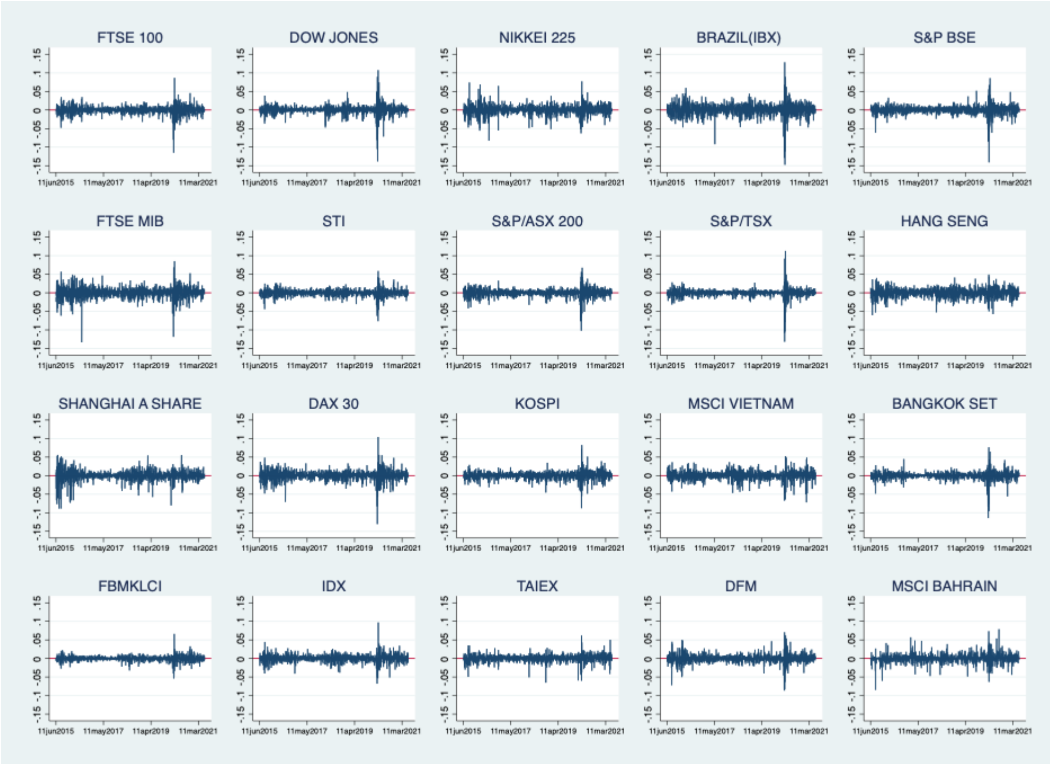
2.1. Data

We consider stock market indexes for 20 major economies (see Table 1 below). We have taken care to include emerging as well as developing economies. In Figure 1a, we present time series plots of the daily returns for each of the stock market indexes, from 11 June 2015 to 10 June 2021.[†] The reason for choosing the start date in 2015 is to ensure that the data set contains a reasonably long stretch of pre-pandemic data, which is useful for identifying the "baseline" volatility process.

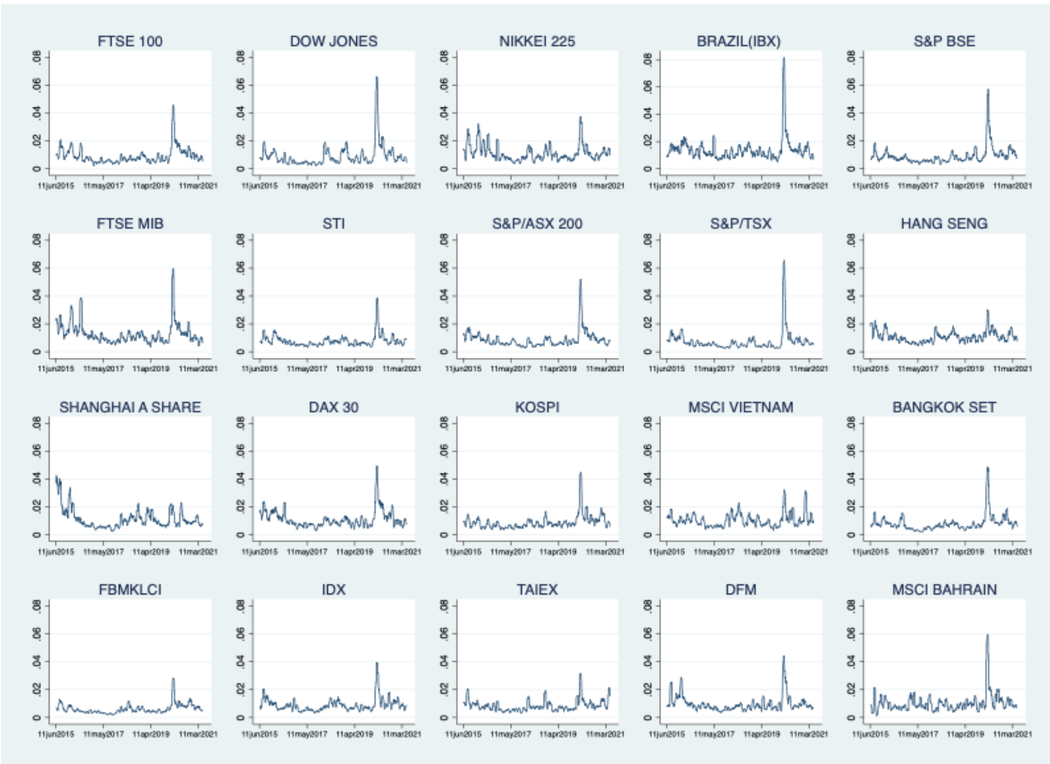
The key stylized fact in which we are most interested is the sudden boost in volatility seen for the majority of the indexes in early 2020. Importantly, this sudden boost appears to occur on different dates for different indexes, and the first part of the econometric exercise will be to identify the most likely date for each index. We are interpreting this date as the time at which the COVID-19 pandemic started to have an impact on the financial market of the economy in question. Another important feature of most of the plots is that following the sudden boost, the volatility remains higher than it was before the pandemic, but appears to fall steadily toward the pre-pandemic volatility level. This feature is made even clearer in Figure 1b, in which we plot volatility over time, with volatility measured as a 20-day rolling standard deviation of returns. Our econometric model will also incorporate this feature.

Another feature of Figure 1 that informs the econometric modeling is that some of the graphs do not appear to exhibit an episode of higher volatility in 2020. One notable example is the Shanghai (A) Index, as already noted by Ledwani et al. (2021). This is interesting because it suggests that the impact of the pandemic on these financial markets was negligible.

[†]Time series plots of the indexes themselves are presented in Figure A1 of the Appendix.



(a) Daily returns of 20 different stock market indexes; 11 June 2015 to 10 June 2021.



(b) Volatility over time of the 20 stock market indexes shown in in (a), measured as 20-day rolling standard deviation of return.

Figure 1

2.2. *Econometric methodology*

2.2.1. Sup-Wald test for identifying onset of COVID period

The first task is to establish the date at which the COVID-19 pandemic started to have an impact on each stock market. For this purpose we apply a structural break test to the following version of the ARCH(1) model:

$$r_t^2 = \gamma_0 + \gamma_1 r_{t-1}^2 + \epsilon_t \tag{1}$$

where r_t is the daily return on a stock market index, defined as $r_t = ln(P_t) - ln(P_{t-1})$, with P_t being the stock market index on day t. Equation (1) is estimated by OLS, and this is a very basic method of estimating the ARCH(1) model (see Gujarati and Porter (2009)).

The objective here is simply to identify the most likely break-point in the ARCH(1) process. Since the ARCH equation (1) has been estimated by OLS, we may follow Bai (1994) by applying a standard structural break test at every possible break-point, and then choosing the break-point giving the most significant test result. Since we use a Wald-test for structural stability testing, we refer to this procedure as the Sup-Wald test.

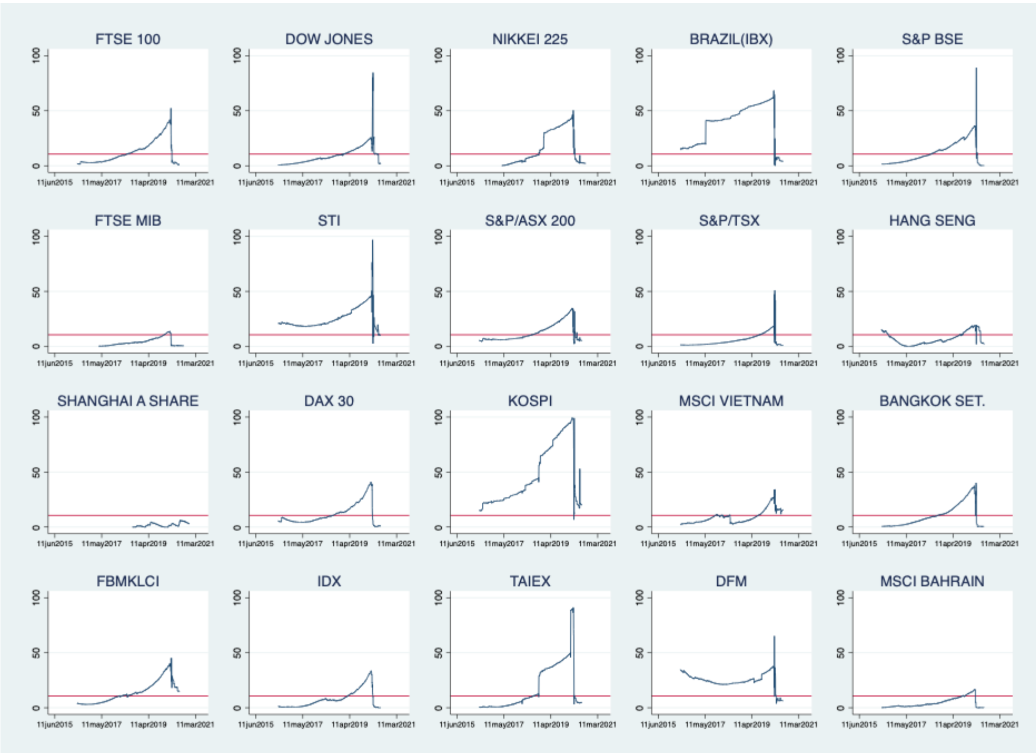


Figure 2. The Sup-Wald test. Structural break test statistic measured on vertical axis. Horizontal line drawn at (size-adjusted) 5% critical value. Break-point identified by highest point (above size-adjusted critical value) attained by test statistic.

Figure 2 shows the Sup-Wald test applied to each return series. We see that, for nearly all of the indexes, a single break-point is clearly identified in early 2020. We will refer to this point as t_{COVID}, since this point will be taken to represent the time of onset of the crisis. For one index, Shanghai (A), the test statistic is never above the (size-adjusted) critical value, indicating that there is no evidence that the crisis had any impact on volatility in this stock market.

2.2.2. GARCHX-NL model

A popular way of measuring the impact of independent variables on volatility is to estimate the GARCH(1,1) model (Bollerslev, 1986) with multiplicative heteroscedasticity.‡ Such a model is referred to as the GARCHX model. A feature of this model is that the determinants of volatility enter the model linearly. Most of the studies cited in the fifth paragraph of Section 1 use this approach, with the independent variable in the conditional volatility equation simply being a dummy variable indicating the period of the COVID crisis.

A complication faced here is that the specification required in the conditional volatility equation is nonlinear, and hence the model will be referred to as the GARCHX-NL model. The GARCHX-NL model is defined as follows:

$$\begin{aligned} r_t &= \gamma_0 + \gamma_1 r_{t-1} + \epsilon_t \\ h_t &\equiv V(\epsilon_t|\epsilon_{t-1}) = \exp\left[\theta_0 + \theta_1 \exp(-\theta_2 \tau_t)\mathbb{I}(\tau_t \geq 0)\right] + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} \end{aligned} \tag{2}$$

where $\tau_t \equiv (t - t_{COVID})/260$ is the lapse of time, measured in years, since the structural break (t_{COVID}) identified using the procedure outlined in Section 2.2.1, and $\mathbb{I}(.)$ is the indicator function.

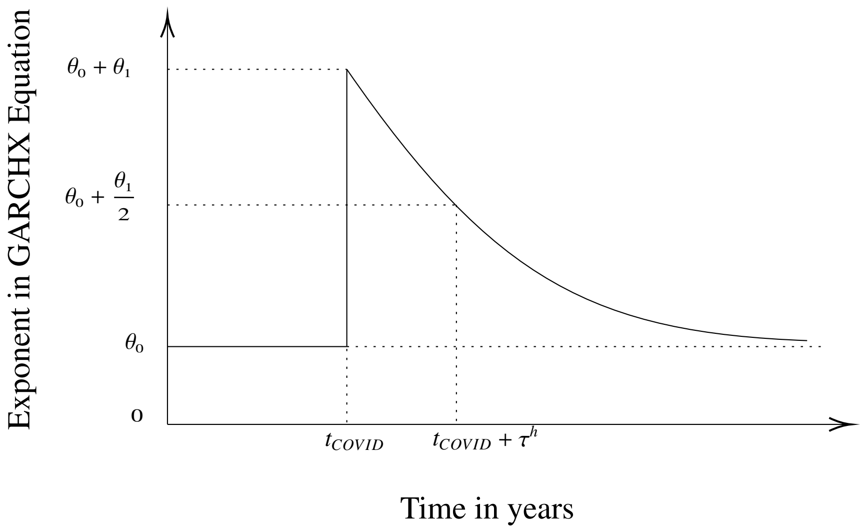


Figure 3. The impact of the COVID crisis on the time-path of stock market volatility, according to the GARCHX-NL model defined in (2). θ_0 represents the baseline (pre-COVID) volatility; θ_1 represents the initial impact of the crisis on volatility; τ^h is the "half-life" of the shock, defined in (6) below.

‡See Judge (1985) for a full explanation of multiplicative heteroscedasticity.

The parameters α and β in model (2) are respectively the ARCH and GARCH parameters, representing the volatility structure prevailing at normal times. The parameters of central interest are θ_1 and θ_2: θ_1 represents the initial impact of the crisis on volatility; θ_2 represents the speed at which the market returns to pre-pandemic levels of volatility.

The time-path of the exponent of leading term of the conditional volatility equation (2) is illustrated in Figure 3. This graph makes it clear that (conditional on the prevailing GARCH process) the parameter θ_0 represents "baseline" (i.e. pre-COVID) volatility, and that at time t_{COVID}, volatility jumps suddenly by an amount represented by θ_1. Thereafter, volatility returns gradually toward the baseline level represented by θ_0.

Certain special cases are of interest. First, if $\theta_1 > 0$ and $\theta_2 = 0$ in (2), this implies that the impact of the pandemic is permanent and constant, and the model is equivalent to one that simply includes, in the conditional volatility equation, a "COVID dummy" $\mathbb{I}(\tau_t > 0)$, taking the value 1 after the onset of the crisis and never reverting to 0. Second, if $\theta_1 > 0$ and $\theta_2 = \infty$ in (2), this implies that the impact of COVID is only felt on day t_{COVID} and has no effect thereafter. This model is similar to an "event study" model in which the impact of COVID on volatility is captured by the presence of a dummy variable taking the value 1 on day t_{COVID} only. Third, if $\theta_1 = 0$ in (2), this implies that the pandemic has no effect whatsoever on volatility. Note that in this case, the parameter θ_2 is not identified and is therefore not estimated.

2.2.3. Estimation of the GARCHX-NL model using the profile likelihood method

Estimation of the GARCHX-NL model specified in (2) is not completely straightforward. This is because, while GARCH estimation routines in some econometric software packages do include features that allow the volatility to depend on independent variables, the equation in which these variables are introduced is assumed to be linear in parameters.[§] The exponent of the leading term in the conditional volatility equation in (2) is clearly nonlinear, and hence (2) cannot be estimated directly using these routines.

We address this problem using the profile likelihood method. This method consists of a grid search on the parameter θ_2. A grid of values of θ_2 is chosen including $\theta_2 = 0$. For each value of θ_2 in the grid, the variable $\exp(-\theta_2\tau_t)\mathbb{I}(\tau_t \geq 0)$ is generated, and enters the conditional volatility equation of the GARCHX model. The MLE of θ_2 is the value in the grid at which the maximized log-likelihood, from estimation of the GARCHX model, is highest. Let us denote the MLE as $\hat{\theta}_2$.

Of course, we would also like to make inferences about the parameter θ_2. Let the maximized log-likelihood obtained assuming a given value of θ_2 be $l(\theta_2)$. Consider the likelihood ratio (LR) test for testing the null hypothesis $\theta_2 = 0$. This test statistic is given by:

$$LR = 2\left[l(\hat{\theta}_2) - l(0)\right] \tag{3}$$

The LR test statistic (3) has a $\chi^2(1)$ distribution (asymptotically) under the null hypothesis $\theta_2 = 0$. Acceptance of this null implies that the impact of the pandemic is constant and persists indefinitely,

[§]For example, the arch command in STATA has a het(.) option, in which one or more independent variables may be introduced.

while rejection implies that the impact of the pandemic decays over time.

An alternative test of the null hypothesis $\theta_2 = 0$ is the Wald test, carried out using the statistic:

$$W = \left[\frac{\hat{\theta}_2}{ase(\hat{\theta}_2)}\right]^2 \tag{4}$$

It is well-known that the two test statistics (3) and (4) are asymptotically equivalent (Buse, 1982). This asymptotic equivalence may be exploited in order to obtain an expression for the asymptotic standard error of the MLE of θ_2 in terms of the LR test statistic given in (3):

$$ase(\hat{\theta}_2) = \frac{\hat{\theta}_2}{\sqrt{LR}} \tag{5}$$

Another quantity that may be deduced from the model estimates is the "half-life" of the shock, τ^h. By this, we mean the time taken (in years) for the initial shock to halve in magnitude, as illustrated in Figure 3 above. This quantity is obtained using:

$$\exp(-\hat{\theta}_2\tau^h) = 0.5 \implies \tau^h = \frac{\ln(2)}{\hat{\theta}_2}. \tag{6}$$

2.3. *Illustration of estimation of GARCHX-NL model*

Here, we illustrate the estimation procedure described in Section 2.2.3 using data on the returns of a selection of the indexes presented in Figure 1a above.

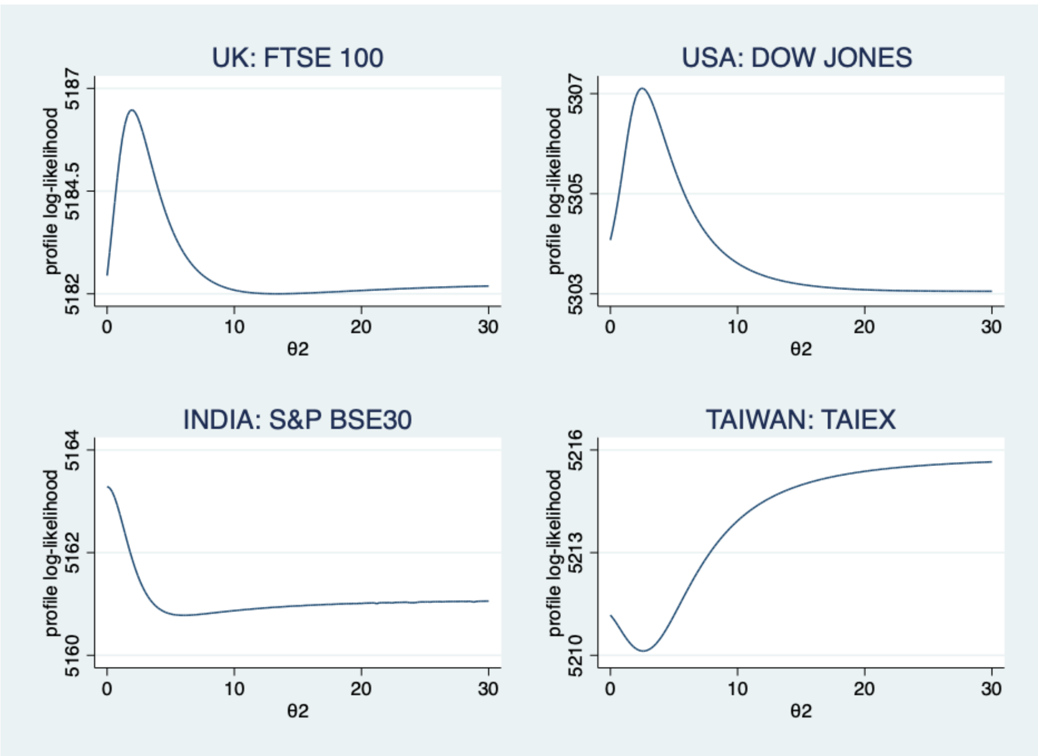


Figure 4. Profile log-likelihood against θ_2 for selected Indexes

Figure 4 shows the profile likelihood, obtained using the procedure outlined in Section 2.2.3, for four of the indexes. For both the FTSE100 and the Dow-Jones, we see that the profile likelihood has an interior maximum, giving estimates of θ_2 of 2.00 and 2.40 respectively. For India's BSE30 index, we see that the profile log-likelihood has a maximum at zero, meaning that the estimate of θ_2 is zero, implying that volatility does not recover at all after the initial onset. For Taiwan's TAIEX index, we see that the profile log-likelihood has a maximum at a large value (possibly ∞), meaning that the estimate of θ_2 is ∞, implying that volatility returns to normal levels immediately after the onset of the crisis.

Estimates of the parameters of central interest are presented, for all indexes, in the next section.

3. Results

Complete sets of results from all GARCHX-NL estimations are presented in Tables A1 and A2 in the Supplementary section. Only the key results for each index are presented here in Table 1. The indexes are ordered by the date of onset, which is estimated separately for each index using the method outlined in Section 2.2.1. It is notable that these dates are spread over the period of exactly one month, from 24 February 2020 to 24 March 2020. Also shown in Table 1 are estimates of the key parameters θ_1 and θ_2, along with asymptotic standard errors. The asymptotic standard error for θ_2 has been obtained using (5).

The next column of Table 1 contains the LR test statistic, obtained using (3), for testing $H_0 : \theta_2 = 0$ against $H_1 : \theta_2 > 0$ for each index. An accompanying p-value is also shown. Note that a rejection of H_0 by this LR test amounts to evidence that the GARCHX-NL model (2) is statistically superior to a GARCHX model containing only a COVID dummy. This is the case for 12 of the 19 indexes. In nearly all of these 12 cases, the evidence is strong.

The final column of Table 1 contains the estimate of the half-life of the shock for each index, obtained using (6). Markets for which θ_2 is estimated to be zero are (arbitrarily) assigned a half-life of one year.

We may now consider differences in impacts between stock markets. Figure 5 shows a scatterplot of initial impact (θ_1) against date of onset (t_{COVID}). It appears that later dates of onset are associated with smaller initial impacts. Figure 6 shows a scatterplot of half-life against initial impact (θ_1). Here we see a very clear negative relationship: markets with higher initial impacts tend to have shorter half-lives.

It is natural to ask which types of market appear in different regions of these plots. In Figure 6 we see that markets with low initial impact and long half-life tend to be emerging markets such as Vietnam, India, and Thailand. In contrast, markets with high initial impact and short half-life tend to be well-established stock markets in developed countries, such as Germany, Singapore, and Japan.

Table 1. Key results from estimation of GARCHX-NL model (2), using profile likelihood method, applied to all indexes. Indexes ordered by date of onset. Date of onset estimated using procedure outlined in Section 2.2.1. Estimates of θ_1 and θ_2 shown with asymptotic standard errors (a.s.e.). a.s.e for θ_2 obtained using (5). LR test stat (with p-value) shown for testing $H_0 : \theta_2 = 0$ against $H_1 : \theta_2 > 0$. LR test stat computed using (3). Final column contains estimate of half-life, obtained using (6). Maximum half-life set (arbitrarily) to 1 year.

REGION	INDEX	onset date	θ_1 (a.s.e.)	θ_2 (a.s.e.)	LR (p-value)	half-life
Australia	SP/ASX	24-Feb-20	4.77	4.60	36.59	0.15
			(0.485)	(0.76)	(0.00)	
Germany	DAX 30	24-Feb-20	5.75	14.80	38.02	0.05
			(0.376)	(2.40)	(0.00)	
Italy	FTSE MIB	24-Feb-20	4.88	8.00	38.78	0.09
			(0.366)	(1.28)	(0.00)	
Brazil	BRAZIL(IBX)	26-Feb-20	5.01	12.00	58.40	0.06
			(0.479)	(1.57)	(0.00)	
Indonesia	IDX	26-Feb-20	3.63	4.00	15.64	0.17
			(0.383)	(1.01)	(0.00)	
Bahrain	MSCI BAHRAIN	2-Mar-20	3.74	4.40	148.69	0.16
			(0.152)	(0.36)	(0.00)	
Hong Kong	HANG SENG	9-Mar-20	5.04	30.00	14.42	0.02
			(0.514)	(7.90)	(0.00)	
UK	FTSE100	10-Mar-20	2.80	2.00	8.07	0.35
			(0.377)	(0.7)	(0.00)	
Japan	NIKKEI 225	11-Mar-20	4.53	28.00	5.86	0.02
			(0.956)	(11.57)	(0.02)	
Korea	KOSPI	11-Mar-20	1.88	1.80	5.50	0.39
			(0.336)	(0.77)	(0.02)	
Taiwan	TAIEX	11-Mar-20	4.52	30.00	8.95	0.02
			(0.976)	(10.03)	(0.00)	
UAE	DFM	11-Mar-20	0.44	0.80	0.26	0.87
			(0.220)	(1.56)	(0.61)	
Canada	SP/TSX	17-Mar-20	1.93	1.40	1.91	0.50
			(0.464)	(1.01)	(0.17)	
Malaysia	FBMKLCI	17-Mar-20	1.23	0.80	0.23	0.87
			(0.835)	(1.66)	(0.63)	
USA	DOW JONES	17-Mar-20	2.79	2.40	6.06	0.29
			(0.507)	(0.98)	(0.01)	
Singapore	STI	19-Mar-20	5.21	29.80	3.29	0.02
			(1.427)	(16.43)	(0.07)	
Vietnam	MSCI VIETNAM	19-Mar-20	0.49	0.00	0.00	1.00
			(0.157)	-	(1.00)	
Thailand	BANGKOK S.E.T	20-Mar-20	1.22	0.00	0.00	1.00
			(0.286)	-	(1.00)	
India	SP BSE	24-Mar-20	0.75	0.00	0.00	1.00
			(0.196)	-	(1.00)	
China	SHANGHAI (A)			No evidence of structural break		

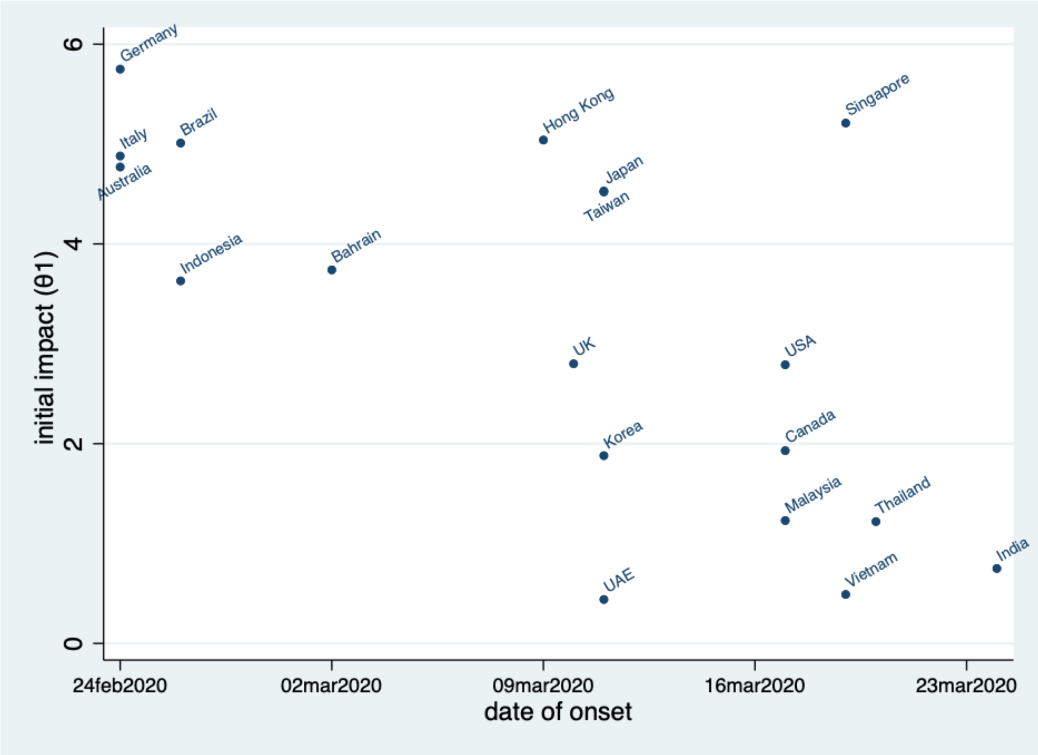


Figure 5. Initial impact (θ_1) against date of onset. Regression R^2 = 0.47.

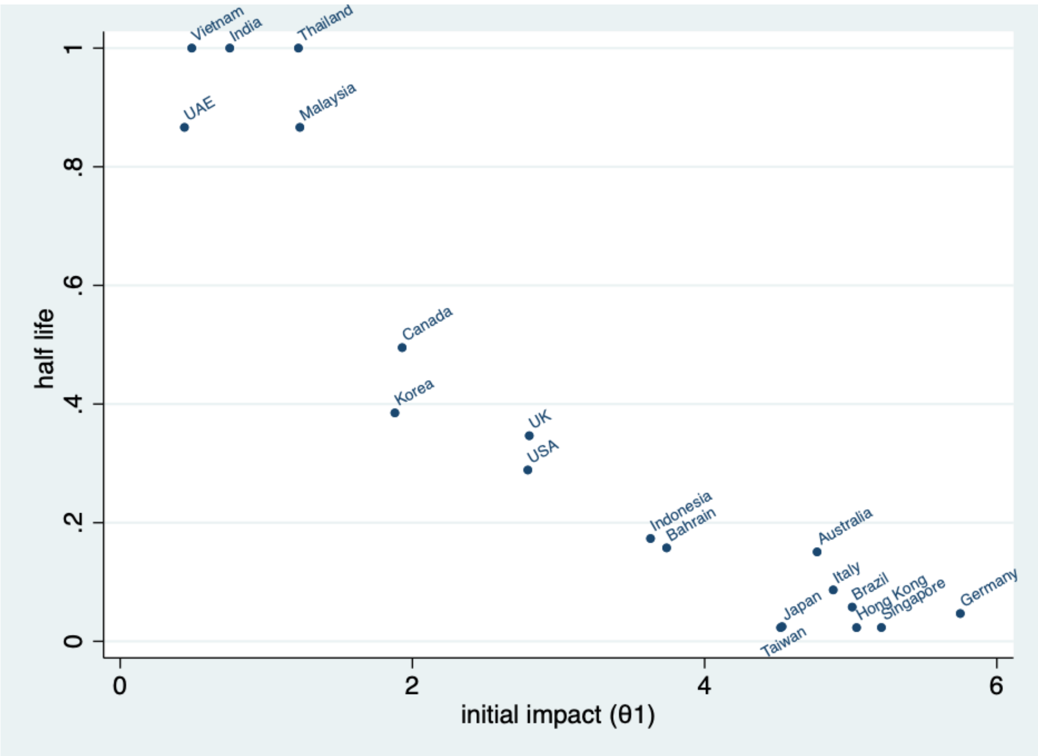


Figure 6. Half-life (years) against initial impact (θ_1). Half-life set (arbitrarily) to 1 year for indexes for which θ_2 is estimated to be zero. Regression R^2 = 0.88.

4. Discussion

This study builds on the recent literature that tests the impact of the COVID-19 pandemic on financial market volatility. Most of the previous literature uses a dummy variable to capture the COVID period, in the context of the GARCHX model. Our model (GARCHX-NL) adds a layer to the GARCHX model, whereby the conditional volatility is assumed to jump suddenly at the onset of the crisis, and then to decay gradually toward its previous levels. To the best of our knowledge, this is the first study that decomposes the impact into two separate measures in this way. The specification of the model requires the use of the method of profile likelihood for estimation.

The first step in the estimation procedure has been to identify the date of onset of the crisis, and this was done using a structural stability testing procedure. Note that if the crisis is modeled using a single 0/1 dummy variable, an end-date for the crisis must also be assumed, but the end-date is much less clearly identifiable than the date of onset. A clear advantage of the modeling approach adopted in this paper is that there is no need to identify an end-date, since it is instead assumed that the impact of the crisis diminishes exponentially toward zero.

Another advantage of the approach adopted in this study is that the GARCHX-NL model (2) nests the more conventional GARCHX model in which the crisis is represented by a 0/1 dummy variable. A straightforward LR test has been used to test the statistical superiority of GARCHX-NL over GARCHX, and this superiority has been established for the majority of the indexes considered.

As mentioned at the outset, a yet further advantage of the proposed approach is that it leads to a deterministic prediction of the time path of volatility in the period following a crisis. This is made clear by Figure 3 above, which illustrates a typical deterministic time path of volatility. The problem of predicting volatility into the future is central to areas of finance such as portfolio management and option pricing (Poon and Granger, 2003). Having a deterministic prediction of the future path of volatility is likely to be highly useful in such applications.

We have found striking differences between the responses to the crisis in different stock markets. First, we have found that stock markets which responded to the crisis earliest, tended to have higher initial impacts. Second, we have found that markets whose initial impacts were higher tended to recover more quickly, and therefore displayed shorter "half-lives". Furthermore, stock markets with low initial impacts and long half-lives tend to be emerging markets, while those with high initial impacts and short half-lives tend to be developed economies with well-established stock-markets. These findings may be seen as building on the extant literature which explains cross-country differences in stock market volatility using variables such as the education level of investors (Xing, 2004).

Our new findings can also be linked to theories of investment. The early days of the COVID-19 pandemic was undoubtedly a period of abnomally high uncertainty. According to the theoretical model of Veronesi (1999), investors become more sensitive to news during such periods, hence increasing financial market volatility. This theory suggests that the reason why well-developed stock-markets exhibited higher initial impacts is because investors in these markets are more sensitive to news. The strong relationship between news stories relating to COVID and stock-market volatility in the USA has been quantified using text-based methods by Baker et al. (2020). However, the reason why the well-developed stock markets also appeared to recover faster is likely to be because these markets are better able to absorb the longer-term effects of a crisis. This is confirmed by the recent empirical evidence of Uddin et al. (2021), who found key country-level mitigation factors to be capitalism score, governance score, productivity score, quality of health system, and development of financial institutions index.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this article.

References

Adenomon MO, Maijamaa B, John DO (2022) The Effects of COVID-19 outbreak on the Nigerian Stock Exchange performance: Evidence from GARCH Models. *J Stat Model Anal* 4: 25–38. https://doi.org/10.22452/josma.vol4no1.3

Anggraini PG, Utami ER, Wulandari E (2022) What happens to the stock market during the COVID-19 pandemic? A systematic literature review. *Pac Account Rev* 34: 406–425. https://doi.org/10.1108/PAR-11-2021-0184

Apergis N, Apergis E (2022) The role of Covid-19 for Chinese stock returns: Evidence from a GARCHX model. *Asia-Pac J Account Econ* 29: 1175–1183. https://doi.org/10.1080/16081625.2020.1816185

Apergis N, Rezitis A (2011) Food Price Volatility and Macroeconomic Factors: Evidence from GARCH and GARCH-X Estimates. *J Agric Apppl Econ* 43: 95–110. https://doi.org/10.1017/S1074070800004077

Bai J (1994) Least Squares Estimation of a Shift in Linear Processes. *J Time Ser Anal* 15: 453–472. https://doi.org/10.1111/j.1467-9892.1994.tb00204.x

Baker SR, Bloom N, Davis SJ, et al. (2020) The Unprecedented Stock Market Reaction to COVID-19. *Rev Asset Pricing Stud* 10: 742–758. https://doi.org/10.1093/rapstu/raaa008

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. *J Econometrics* 31: 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bora D, Basistha D (2021) The outbreak of COVID-19 pandemic and its impact on stock market volatility: Evidence from a worst-affected economy. *J Public Aff* 21: e2623. https://doi.org/10.1002/pa.2623

Buse A (1982) The likelihood ratio, wald, and lagrange multiplier tests: An expository note. *Am Stat* 36: 153–157. https://doi.org/10.2307/2683166

Curto JD, Serrasqueiro P (2022) The impact of COVID-19 on S&P500 sector indices and FATANG stocks volatility: An expanded APARCH model. *Financ Res Lett* 46: 102247. https://doi.org/10.1016/j.frl.2021.102247

Duttilo P, Gattone SA, Di Battista T (2021) Volatility Modeling: An Overview of Equity Markets in the Euro Area during COVID-19 Pandemic. *Mathematics* 9: 1212. https://doi.org/10.3390/math9111212

Golder U, Rimaly N, Shahriar A, et al. (2022). The Impact of COVID-19 on the Volatility of Bangladeshi Stock Market: Evidence from GJR-GARCH Model. *J Asian Financ Econ* 9: 29–38. https://doi.org/10.13106/JAFEB.2022.VOL9.NO4.0029

Gujarati DN, Porter D (2009) *Basic Econometrics*, Mc Graw-Hill International Edition.

Hwang S, Satchell SE (2005) GARCH model with cross-sectional volatility: GARCHX models. *Appl Financ Econ* 15: 203–216. https://doi.org/10.1080/0960310042000314214

Judge GG (Ed.) (1985) *The Theory and Practice of Econometrics* (2. ed., 7. [print.] ed.). Wiley Series in Probability and Mathematical Statistics. New York: Wiley.

Kusumahadi TA, Permana FC (2021) Impact of COVID-19 on Global Stock Market Volatility. *J Econ Integr* 36: 20–45. https://doi.org/10.11130/jei.2021.36.1.20

Ledwani S, Chakraborty S, Shenoy SS (2021) Spatial tale of G-7 and BRICS stock markets during COVID-19: An event study. *Invest Manag Financ Innov* 18: 20–36. https://doi.org/10.21511/imfi.18(2).2021.03

Onali E (2020) COVID-19 and Stock Market Volatility. *SSRN Electronic J*. https://doi.org/10.2139/ssrn.3571453

Poon SH, Granger CWJ (2003) Forecasting volatility in financial markets: A review. *J Econ Lit* 41: 478–539. https://doi.org/10.1257/002205103765762743

Sucarrat G, Grønneberg S, Escribano A (2016) Estimation and inference in univariate and multivariate log-GARCH-X models when the conditional density is unknown. *Comput Stat Data Anal* 100: 582–594. https://doi.org/10.1016/j.csda.2015.12.005

Uddin M, Chowdhury A, Anderson K, et al. (2021) The effect of COVID – 19 pandemic on global stock market volatility: Can economic strength help to manage the uncertainty? *J Bus Res* 128: 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061

Veronesi P (1999) Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model. *Rev Financ Stud* 12: 975–1007. https://doi.org/10.1093/rfs/12.5.975

Xing X (2004) Why does stock market volatility differ across countries? Evidence from thirty-seven international markets. *Int J Bus* 9: 2004.

Yousef I (2020) Spillover of COVID-19: Impact on Stock Market Volatility. *Int J Psychosoc Rehabil* 24: 18069–18081.

Supplementary

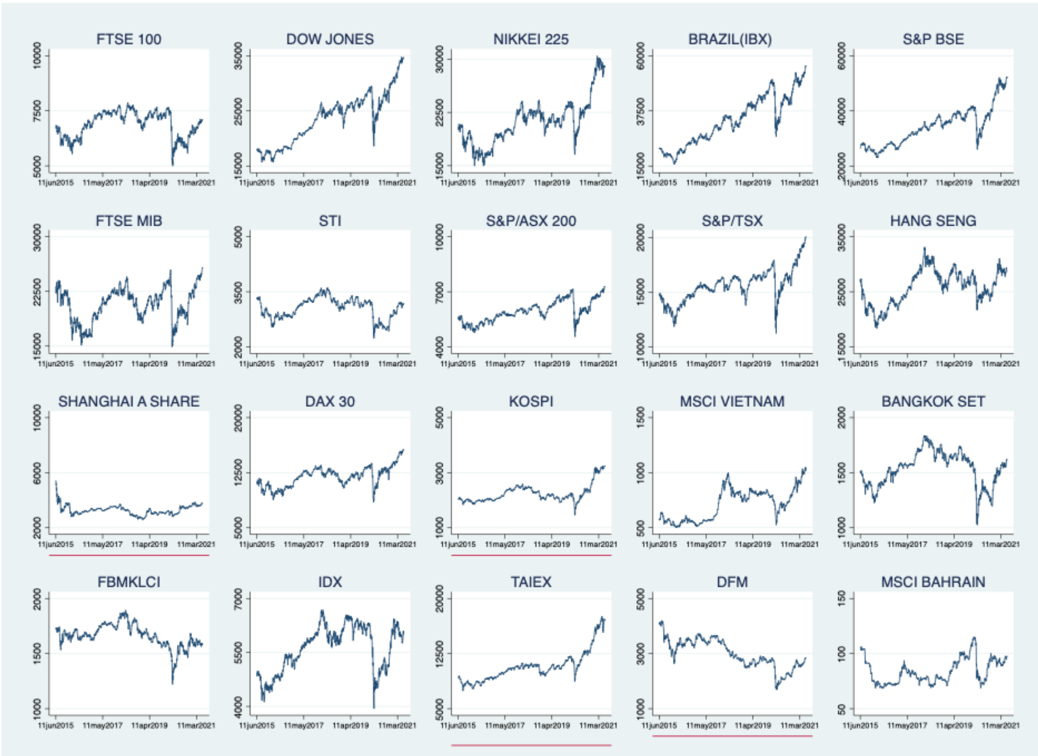

Figure A1. The stock market indexes over time. Daily data; 11 June 2015 to 10 June 2021.

Table A1. GARCHX-NL.

	UK FTSE100	USA DowJones	Japan NIKKEI225	Brazil BRAZIL(IBX)	India SP BSE	Italy FTSE MIB	Singapore STI	Australia SP/ASX	Canada SP/TSX	Hong Kong HangSeng
main										
γ_1	0.0168	-0.0286	-0.0484	-0.0532	0.0339	-0.0780**	0.0554	-0.0197	0.0485	-0.00217
	(0.0293)	(0.0298)	(0.0283)	(0.0294)	(0.0301)	(0.0274)	(0.0297)	(0.0262)	(0.0305)	(0.0269)
γ_0	0.000256	0.000904***	0.000640*	0.000971**	0.000769***	0.000541*	0.000181	0.000396*	0.000482***	0.000316
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0003)
HET										
θ_1	2.803***	2.791***	4.529***	5.008***	0.751***	4.879***	5.206***	4.767***	1.930***	5.041***
	(0.3771)	(0.5073)	(0.9561)	(0.4790)	(0.1958)	(0.3661)	(1.4269)	(0.4854)	(0.4637)	(0.5143)
θ_2	2.00***	2.40**	28.00*	12.00***	0.00	8.00***	29.80	4.60***	1.40	30.00***
	(0.7039)	(0.9751)	(11.5687)	(1.5703)	-	(1.2846)	(16.4343)	(0.7605)	(1.0130)	(7.9008)
θ_0	-12.00***	-12.35***	-11.72***	-11.24***	-12.92***	-11.88***	-12.42***	-13.12***	-13.12***	-13.29***
	(0.1708)	(0.1259)	(0.1483)	(0.1989)	(0.2440)	(0.1816)	(0.1920)	(0.2281)	(0.2091)	(0.2474)
ARCH										
α	0.158***	0.228***	0.127***	0.0606***	0.100***	0.116***	0.124***	0.0966***	0.213***	0.0372***
	(0.0173)	(0.0209)	(0.0124)	(0.0121)	(0.0103)	(0.0114)	(0.0147)	(0.0108)	(0.0198)	(0.0056)
β	0.760***	0.727***	0.819***	0.862***	0.873***	0.841***	0.817***	0.871***	0.758***	0.948***
	(0.0271)	(0.0227)	(0.0171)	(0.0226)	(0.0153)	(0.0162)	(0.0225)	(0.0137)	(0.0242)	(0.0068)
N	1564	1564	1564	1564	1564	1564	1564	1564	1564	1564

Table A2. GARCHX-NL.

	Germany DAX30	Korea KOSPI	Vietnam MSCI VIETNAM	Thailand BANGKOK SET	Malaysia FBMKLCI	Indonesia IDX	Taiwan TAIEX	UAE DFM	Bahrain MSCI BAHRAIN
main									
γ_1	-0.0187	-0.0000595	0.0526	0.0463	0.0301	0.0183	0.0189	0.114***	0.0143
	(0.0257)	(0.0305)	(0.0282)	(0.0281)	(0.0262)	(0.0273)	(0.0269)	(0.0291)	(0.0328)
γ_0	0.000530*	0.000375	0.000404	0.000197	-0.0000516	0.000321	0.000653**	-0.00000906	0.000168
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
HET									
θ_1	5.748***	1.878***	0.486**	1.216***	1.227	3.633***	4.518***	0.445*	3.740***
	(0.3757)	(0.3360)	(0.1568)	(0.2857)	(0.8352)	(0.3832)	(0.9760)	(0.2203)	(0.1518)
θ_2	14.80***	1.80*	0.00	0.00	0.80	4.00***	30.00***	0.80	4.40***
	(2.4002)	(0.7675)	-	-	(1.6609)	(1.0114)	(10.0268)	(1.5629)	(0.3608)
θ_0	-13.07***	-12.15***	-12.21***	-14.30***	-14.77***	-12.35***	-11.95***	-11.94***	-10.53***
	(0.1898)	(0.1967)	(0.1462)	(0.2176)	(0.3523)	(0.1885)	(0.1439)	(0.1540)	(0.2311)
ARCH									
α	0.0561***	0.106***	0.110***	0.0969***	0.0758***	0.0973***	0.0810***	0.135***	0.0614***
	(0.0072)	(0.0142)	(0.0130)	(0.0083)	(0.0076)	(0.0128)	(0.0076)	(0.0120)	(0.0094)
β	0.923***	0.821***	0.850***	0.900***	0.917***	0.843***	0.835***	0.799***	0.669***
	(0.0091)	(0.0230)	(0.0141)	(0.0078)	(0.0089)	(0.0195)	(0.0184)	(0.0188)	(0.0701)
N	1564	1564	1564	1564	1564	1564	1564	1564	1564