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Evaluating the air quality transmission among Southeast Asian cities

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Evaluating the air quality transmission among Southeast Asian cities

ABSTRACT

This study evaluates the air quality transmission among Southeast Asian cities which include Ho Chi Minh City, Hanoi, Bangkok, Singapore, Kuala Lumpur, and Jakarta. We investigate the daily air quality datasets from 28 August 2019 to 04 April 2023 using the multivariate generalized autoregressive conditional heteroskedasticity modeling framework combined with the conditional correlation mechanism. We find significant bilateral interactions between Ho Chi Minh City and Bangkok and between Kuala Lumpur and Singapore. In specific, the air quality in Ho Chi Minh City and Bangkok positively affects to each other. Besides, the air quality in Singapore positively drives the air quality in Kuala Lumpur, but the inverse relation is negative. These findings preliminary suggest bilateral environmental agreements among sub-regions of Southeast Asia. Such treaties are expected to lay the background for future agenda in relation to environmental protection, especially in pursuit of sustainable development.

Key words: Air quality transmission; Environmental agreement; ASEAN.

1. Introduction

Sustainability is the common concern of the occurring era, where economic growth shall come along environmental protection. This objective becomes more necessary for emerging regions such as Southeast Asia, especially in the context of global volatility following the Covid-19 pandemic. There have been several trade agreements in the region issued by the Association of Southeast Asian Nations (ASEAN) which captures the economic aspect of sustainable development goals. Given the regional environment (ASEAN, 2023), Southeast Asian nations have been cooperating in environmental protection (ASEAN, 2017). On the other hand, jointly environmental agreements seem to mismatch the corresponding economic collaboration. Therefore, we design this study to evaluate the environmental interaction among nations of the region, as represented by the air quality transmission between popular cities. Due to geographic characteristics of Southeast Asia, six selected cities include Hanoi (HAN) and Ho Chi Minh City (HCM) of Vietnam, Bangkok (BKK) of Thailand, Singapore City (SIN) of Singapore, Kuala Lumpur (KUL) of Malaysia, and Jakarta (JKT) of Indonesia. Accordingly, findings are expected to suggest whether policymakers of Southeast Asia proceed a jointly environment agreement in future by evaluating the air quality transmission in the region.

In Asia, the ASEAN Agreement on Trans-boundary Haze Pollution exemplifies regional cooperation. Established by ASEAN in 2003, this legally binding treaty aims to combat land

33 and forest fires that cause trans-boundary haze. It emphasizes monitoring, mitigation, response,
34 research, and communication. Recognizing that air pollution knows no borders, ASEAN
35 member states have united to protect their populations and shared environment. The UN
36 ESCAP Regional Action Program on Air Pollution is another important initiative in the fight
37 against transboundary air pollution. Led by the United Nations Economic and Social
38 Commission for Asia and the Pacific (UN ESCAP), this program addresses the Asia-Pacific
39 region, which is facing rapid urbanization and industrial growth. Its goal is to promote
40 cooperation among nations to tackle air pollution and its negative effects collectively. In East
41 Asia, the Acid Deposition Monitoring Network in East Asia (EANET), established in 2001,
42 emerged from intergovernmental collaboration to understand and combat acid deposition. Over
43 the years, EANET has broadened its focus to include various air pollution challenges, resulting
44 in the creation of the EANET Project Fund. Through shared research and knowledge,
45 participating nations work together to enhance decision-making and collaboration in the region.
46 In South Asia, the Malé Declaration on Control and Prevention of Air Pollution and Its Likely
47 Trans-Boundary Effects, adopted in 1998, represents the first regional agreement on pollution
48 in South Asia. This pioneering declaration has inspired collaborative efforts among countries
49 such as India, Pakistan, and Nepal to develop emission inventories, monitor air pollutants, and
50 evaluate their impacts across different sectors. The recent revival of the declaration highlights
51 the region's commitment to addressing air pollution as a shared challenge.

52 In fact, Southeast Asian countries have a sufficient agreement ([ASEAN, 2017](#)) which facilitates
53 each party to cooperate in environmental protection. On the other hand, this background prefers
54 multilateral to bilateral collaboration. This issue is common across international treaties,
55 especially in environment ([Lallas, 2001](#)). Therefore, we design this study to evaluate pairwise
56 correlations of air quality transmission among selected Southeast Asian cities. Indeed, air
57 quality is commonly measured by particulate matter in the atmosphere. Accordingly, air quality
58 of a city is not only affected by its own air quality, but also by neighbors. Therefore, this study
59 focuses on bilateral relationships between air quality of adjacent cities, in terms of geographic
60 distance. This characteristic excludes the Philippines from our investigation due to its specific
61 location. Henceforth, our approach within this study is expected to generate novel findings in
62 relation to regional environmental integration.

63 Following this introduction, [Section 2](#) reviews previous literature, [Section 3](#) proposes methods,
64 [Section 4](#) present findings, and [Section 5](#) concludes.

65 2. Literature review

66 Air quality has a profound effect on environment and public health (Manisalidis, Stavropoulou,
67 Stavropoulos, & Bezirtzoglou, 2020), which contributes to various health issues, including
68 respiratory and cardiovascular diseases, along with mental health disorders such as Seasonal
69 Affective Disorder (SAD) (Rosenthal, et al., 1984). Studies suggest that exposure to air
70 pollution can worsen SAD symptoms, as pollutants may interfere with neurotransmitter activity
71 (Chen, Oliva, & Zhang, 2024), mood regulation (Radua, et al., 2024) and the references therein.
72 For example, fine particulate matter can disrupt circadian rhythms, potentially intensifying
73 mood disorders in seasons with less sunlight. Monitoring and communicating air quality is
74 effectively achieved through the Air Quality Index (AQI). By raising awareness and prompting
75 responses to changes in air quality, the AQI is crucial in managing health risks related to air
76 pollution. Elevated levels of particulate matter (PM_{2.5}) and nitrogen dioxide (NO₂) have been
77 associated with higher rates of asthma, lung cancer, and heart attacks (Cohen, et al., 2017).
78 Research indicates that changes in the AQI can notably affect public health, influencing
79 activities like outdoor exercise, especially during high pollution episodes (McCarron, et al.,
80 2023). In urban centers such as Jakarta, Bangkok, and Hanoi, the AQI provides real-time
81 information on key pollutants like PM_{2.5}, NO₂, and ozone (O₃), helping residents make
82 informed choices about outdoor activities (Rentschler & Leonova, 2022). Trans-boundary
83 pollution from agricultural burning and industrial emissions complicates air quality
84 management, with AQI levels often surpassing safe limits in neighboring countries (Nguyen,
85 et al., 2022). Thus, there is a strong correlation between elevated AQI levels and increased rates
86 of respiratory and cardiovascular diseases, emphasizing the urgent need for effective air quality
87 management.

88 In Southeast Asian cities, valuating air quality transmission reveals significant challenges
89 arising from rapid urbanization and industrialization. Research indicates that cities like Jakarta,
90 Bangkok, and Hanoi experience high PM_{2.5} levels due to vehicle emissions, industrial
91 activities, and biomass burning (World Bank and Institute for Health Metrics and Evaluation,
92 2016). Satellite data and ground monitoring studies have shown that air pollution can cross
93 borders, increasing health risks in adjacent areas. Wind patterns and climate conditions in
94 Southeast Asia significantly affect weather and environmental circumstances. The region
95 experiences a tropical climate with distinct wet and dry seasons, largely dictated by monsoonal
96 winds. The southwest monsoon, from May to September, brings heavy rainfall and humidity
97 from the Indian Ocean, while the northeast monsoon, from November to March, leads to cooler,

98 drier weather (World Meteorological Organization, 2022). Studies reveal that winds can carry
99 contaminants across borders, impacting neighboring areas (Cambaliza, Yu, Latif, Lestari, &
100 Wu, 2023). Additionally, local geography and land use interact with wind systems, further
101 influencing micro-climates and agricultural productivity (Cach-Pérez, Villanueva López,
102 Alayón Gamboa, Nahed Toral, & Casanova Lugo, 2022). Understanding these dynamics is
103 essential for effective climate adaptation and environmental management in the region. In
104 response, governments are increasingly implementing stricter environmental regulations
105 (ASEAN, 2017) and fostering regional collaboration to tackle these trans-boundary pollution
106 challenges (ASEAN, 2023). By integrating advanced monitoring technologies and policy
107 strategies, Southeast Asian nations strive for better air quality and improved public health
108 outcomes.

109 Environmental treaties are vital in tackling global environmental issues, fostering international
110 cooperation, and establishing binding commitments among countries. Important agreements
111 like the Paris Agreement aim to mitigate global warming by reducing greenhouse gas
112 emissions, involving nearly 200 countries (UNFCCC, 2015). The Convention on Biological
113 Diversity (CBD) focuses on conserving biodiversity and promoting sustainable resource use,
114 demonstrating a collective commitment to ecosystem preservation (UN & IRB, 1992). The
115 Stockholm Convention on Persistent Organic Pollutants seeks to eliminate harmful chemicals
116 that threaten human health and the environment (Lallas, 2001). Air pollution remains a critical
117 threat to both human health and the environment. As the world faces the urgent challenge of
118 trans-boundary air pollution, these agreements provide a measure of hope. Countries from
119 Southeast Asia to the Arctic are increasingly recognizing the interdependence of our planet and
120 collaborating to ensure cleaner air for future generations. These partnerships reflect a shared
121 responsibility to protect the air we all breathe, transcending borders for a healthier future—
122 together as #TogetherForCleanAir. The Climate and Clean Air Coalition (CCAC), convened
123 by the United Nations Environment Program, is the sole international initiative focused on
124 reducing potent but short-lived climate pollutants that contribute to climate change and air
125 pollution. This coalition includes 80 countries and over 80 non-state organizations.

126 Based on this theoretical framework, we expect to determine the literature gap on evaluating
127 the air quality transmission. Accordingly, we design this study to capture the issue among
128 selected Southeast Asian cities. Since air quality datasets are constructed daily, we employ the
129 multivariate stochastic modeling, which is commonly used on financial economics, to
130 investigate the air quality transmission among selected cities. Accordingly, expected results

131 include daily interactions and volatility spillovers between pairwise correlations. As a result,
132 both rights and obligations of each city are quantitatively examined with statistical significance.
133 This methodological framework reflects multidisciplinary and interdisciplinary aspects in the
134 digital era.

135 **3. Materials and methods**

136 **3.1. Data and preliminary analysis**

137 We use the daily datasets of air quality in six southeast Asian cities¹, which include Hanoi
138 (HAN), Bangkok (BKK), Ho Chi Minh City (HCM), Singapore (SIN), Kuala Lumpur (KUL),
139 and Jakarta (JKT). In which, the regional environment is represented by the particulate matter
140 (PM_{2.5}) index, except Kuala Lumpur whose proxy is the Air Quality Index (AQI)². We merge
141 the sub-dataset of each city to obtain an integrated dataset from 28 August 2019 to 04 April
142 2023. This period captures the Covid-19 outbreak and international conflicts in recent years.
143 [Figure 1](#) visualizes our used data with 1,000 observations. Based on geographic locations and
144 the visual air quality of cities, we further consider two sub-samples. In which, the northwestern
145 sub-sample include Hanoi, Bangkok, and Ho Chi Minh City; and the southeastern sub-sample
146 include Singapore, Kuala Lumpur, and Jakarta.

147 [Table 1](#) presents summary statistics of the dataset. The air quality in each city is preliminarily
148 described with mean, standard deviation, skewness, and kurtosis. In addition, we consider the
149 stochasticity which include normality, autocorrelation, heteroskedasticity, and stationarity. In
150 accordance, we find statistically significant evidence of these characteristics. In summary, we
151 reach initial bases which facilitate to proceed the modeling strategy. Descriptive statistics allow
152 to construct the air quality network across selected southeast Asian cities. At the same time,
153 reliable stochastic properties support our usage of the multivariate generalized autoregressive
154 conditional heteroskedasticity to investigate the air quality transmission. This confirmation is
155 tremendous for our further modeling strategy.

156 [\[Figure 1 and Table 1 around here\]](#)

157 We expect to visualize the connections between air quality six Southeast Asian cities using
158 dendrogram and graph theory. In specific, the air quality distance d_{ij} between cities i and j are
159 calculated as follow:

¹ Source: Air quality historical data platform, retrieved from <https://aqicn.org/data-platform/register/>.

² AQI is retrieved from the weight average of PM_{2.5}, PM₁₀, O₃, NO₂, SO₂, and CO.

$$d_{ij} = \sqrt{2(1 - \rho_{ij})} \quad (1)$$

160 In (1), ρ_{ij} is the correlation between air quality of cities i and j during the studied period. The
 161 distance is accordingly standardized to lie between 0 and 2.

162 Based on the air quality distance matrix as retrieved from (1), we expect to construct the visual
 163 dendrogram and graph. We may compare this visualization to geographical distances between
 164 selected cities to initially affirm the air quality transmission effect.

165 [Table 2 around here]

166 3.2. Modeling strategy

167 Thanks to the timeseries characteristic of the air quality datasets, we employ the multivariate
 168 generalized autoregressive conditional heteroskedasticity (GARCH) model along the dynamic
 169 conditional correlation (DCC) process to investigate the air quality transmission between cities
 170 from Southeast Asia. In specific, we use the DCC-GARCH model (Engle, 2002) to estimate
 171 the air quality transmission as follow:

$$\left\{ \begin{array}{l} y_t = \mu + \sum_{l=1}^s \Phi_{t-l} y_{t-l} + u_t \\ u_t = H_t^{1/2} \eta_t \\ \text{diag}(H_t) \begin{pmatrix} 1 \\ 1 \end{pmatrix} = C + \sum_{k=1}^q A_{t-k} u_{t-k}^2 + \sum_{m=1}^p B_{t-m} \text{diag}(H_{t-m}) \begin{pmatrix} 1 \\ 1 \end{pmatrix} \\ h_t^{ij} = \rho_t \sqrt{h_t^i h_t^j} \end{array} \right. \quad (2)$$

172 In (2), $y_t = (y_t^i \ y_t^j)'$ is the vector representing air quality of cities i and j on day t . $\mu =$
 173 $(\mu^i \ \mu^j)'$ is a vector of intercepts. Φ is a fully sized matrix of coefficients reflecting the vector
 174 autoregressive (VAR) process. $u_t = (u_t^i \ u_t^j)'$ is the vector of error terms. $\eta_t = (\eta_t^i \ \eta_t^j)'$ is
 175 the vector of standardized errors, assumed to be independently and identically distributed.
 176 Given the datasets, we are supposed to select the number of lags (s) thanks to Akaike (AIC),
 177 Schwarz Bayesian (SBC), and Hannan-Quinn (HQ) information criteria for the VAR
 178 estimation. H_t is the time-varying conditional covariance matrix between air quality of cities i
 179 and j . $C = (c^i \ c^j)'$ is a vector of intercepts in the GARCH process. $A = \text{diag}\{a^i, a^j\}$ is a
 180 diagonal matrix which covers short-term volatility. $B = \text{diag}\{b^i, b^j\}$ is a diagonal matrix
 181 which covers long-term volatility. In fact, we shall determine the optimal lag of both short-

182 term (q) and long-term (p) volatilities to construct the GARCH(p, q) estimation. h_t^{ij} is the
 183 conditional covariance between air quality of cities i and j . ρ_t is the conditional correlation
 184 term between air quality of cities i and j . h_t^i and h_t^j are conditional variances of air quality in
 185 cities i and j , respectively. Under the DCC-GARCH model, ρ_t in (2) is further decomposed as
 186 follow:

$$\begin{cases} H_t = D_t P_t D_t = \begin{pmatrix} \sqrt{h_t^i} & 0 \\ 0 & \sqrt{h_t^j} \end{pmatrix} \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix} \begin{pmatrix} \sqrt{h_t^i} & 0 \\ 0 & \sqrt{h_t^j} \end{pmatrix} \\ P_t = (Q_t^*)^{-1/2} Q_t (Q_t^*)^{-1/2} \\ Q_t = \begin{pmatrix} q_t^i & q_t^{ij} \\ q_t^{ij} & q_t^j \end{pmatrix} = (1 - \alpha - \beta) \bar{Q} + \alpha \eta_{t-1} \eta'_{t-1} + \beta Q_{t-1} \end{cases} \quad (3)$$

187 In (3), $Q_t > 0$ is a symmetric positive definite matrix, $(Q_t^*)^{-1/2} = \text{diag}(Q_t)$, $\bar{Q} = E(\eta_t \eta'_t)$ is
 188 the matrix of unconditional correlations between standardized errors η_t , and α and β are non-
 189 negative scalars such that $\alpha + \beta < 1$. The superiority of this modeling framework is its
 190 capability of capturing the return and volatility transmission, which is previously applied in
 191 evaluating the relation between stock market and air quality (Nguyễn & Lê, 2023).

192 In terms of robustness check, we evaluate the air quality transmission between most adjacent
 193 cities using the constant conditional correlation GARCH modeling. From Table 2, those pairs
 194 are Singapore – Kuala Lumpur and Ho Chi Minh City – Bangkok. Under this estimation, ρ_t in
 195 (2) becomes ρ which is constant during the examined timeframe. Specific players include
 196 CCC-GARCH (Bollerslev, 1990) and VARMA-GARCH (Ling & McAleer, 2003) models. In
 197 which, the CCC-GARCH model chooses diagonal matrices A and B in (2) while the VARMA-
 198 GARCH model employs full matrices A and B . The generalization in the VARMA-GARCH
 199 model captures short- and long-term volatility transmissions between examined variables. To
 200 ensure stationarity, both CCC- and VARMA-GARCH models require that eigenvalue(s) of
 201 matrices A and B should be inside the unit circle.

202 Regarding multivariate assessments, we expand (2) into tri-variate and hexa-variate DCC-
 203 GARCH models to further assess the air quality transmission in Southeast Asia. The trilateral
 204 assessments include two sub-samples of this study, those are (i) Hanoi-Bangkok-Ho Chi Minh
 205 City; and (ii) Singapore-Kuala Lumpur-Jakarta. We expect to consider Gaussian, Student's t
 206 (which requires to find ν , the degree of freedom of errors), and skew- t density (Bauwens &
 207 Laurent, 2005) to evaluate tail behaviors relating to the tri-variate GARCH process. We further

208 assess a multilateral assessment which includes all six cities in an estimation. Since CCC- and
209 VARMA-GARCH models are characterized by constant conditional correlations, this class
210 shall not be applied for multivariate examinations unless otherwise reasonable.

211 **4. Findings**

212 This section presents air quality interactions based on bivariate GARCH models along the
213 dynamic conditional correlation mechanism. Potential results indicate how air quality of a city
214 interacts to air quality of another city. We expect to summarize interactions between 15 pairs
215 combined from six cities. During each estimation, we shall select the best-suited model thanks
216 to selection criteria and diagnostic tests for stochasticity (autocorrelation and heteroskedasticity
217 effects) of residuals. We expect that bilateral interactions within each sub-sample, those are,
218 (i) HCM-BKK-HAN; and (ii) JKT-KUL-SIN are more reliable and specific in terms of
219 statistical significance and geographic distances, as demonstrated in [Table 2](#). Accordingly, we
220 construct the time-varying conditional correlation plots between six pairs, those are, (a) HCM-
221 BKK; (b) HAN-BKK; (c) HCM-HAN; (d) KUL-SIN; (e) JKT-KUL; and (f) JKT-SIN.

222 [Table 3](#) reports the bilateral air quality transmission among selected Southeast Asian cities
223 based on the DCC-GARCH model. The statistical significance of each estimation is determined
224 thanks to (i) lags in the VAR equation (s); (ii) lags in the GARCH process (p and q); (iii) signs
225 of characterized coefficients (α , β , and $\alpha + \beta$) and; (iv) disappearances of stochasticity in final
226 residuals, those are, the autocorrelation effect under Ljung-Box and McLeod-Li tests and
227 heteroskedasticity under the ARCH test. Thus, estimations from [Table 3](#) exclude HCM-HAN,
228 JKT-KUL, and JKT-SIN transmissions due to negative α . The KUL-SIN interaction is slightly
229 unpersuasive as α and β are statistically insignificant. Respective disqualified criteria are
230 bolded and highlighted in [Table 3](#). Following these model selection procedures, we find reliable
231 air quality transmissions among HCM-BKK and HAN-BKK correlations. In specific, the air
232 quality transmissions among these pairs are mutually positive. Results are more obvious while
233 $s = p = q = 1$ and all coefficients in VAR mean equations are statistically significant, as key
234 results are bolded and highlighted. Henceforth, we find mutually positive linkage in quality
235 between Ho Chi Minh City and Bangkok as well as between Hanoi and Bangkok. This finding
236 confirms the necessity of a bilateral environmental agreement between Vietnam and Thailand,
237 which is expected to boost the air quality among popular cities of both countries.

238 [\[Table 3, Table 4, and Table 5 around here\]](#)

239 Given geographic distances between Southeast Asian cities (in [Table 2](#)) and DCC-GARCH
240 estimations (in [Table 3](#)), we further analyze the air quality transmission between Ho Chi Minh
241 City and Bangkok as well as between Kuala Lumpur and Singapore using competing bivariate
242 GARCH models. [Table 4](#) reports the HCM-BKK and KUL-SIN air quality transmissions under
243 VARMA-, CCC-, and DCC-GARCH models. The model selection procedure shall include (i)
244 maximum log likelihood or minimum information criteria; (ii) disappearances of stochasticity;
245 (iii) significance of characterized coefficients (constant or dynamic conditional correlation);
246 and (iv) number of lags during the VAR mean equation and the GARCH process.

247 Model selection criteria reveal the advantage of constant conditional correlation models in
248 explaining the air quality transmission between Ho Chi Minh City and Bangkok. In which, log
249 likelihood and Akaike information criterion favor the VARMA-GARCH model while Schwarz
250 Bayesian and Hannan-Quinn information criteria favor the CCC-GARCH model. Under this
251 circumstance, the VARMA-GARCH model gains advantage thanks to its more complicated
252 time-varying covariance matrix. Key numbers are highlighted in [Table 4](#). Nevertheless,
253 estimated results are consistent with the output from the DCC-GARCH model that air quality
254 in Ho Chi Minh City and Bangkok positively affect to each other. At the same time, the DCC-
255 GARCH model turns superior in explaining the air quality transmission between Kuala Lumpur
256 and Singapore, despite its insignificant coefficients of the dynamic conditional correlation. In
257 general, empirical results under all three models indicate a trade-off between air quality of
258 Kuala Lumpur and Singapore. It is noticeable that the past air quality of Singapore positively
259 influences the air quality of Kuala Lumpur, but the past air quality of Kuala Lumpur negatively
260 drives the air quality of Singapore. Considering the geographic distance between two cities, a
261 bilateral environmental agreement is therefore in need for this situation. The case between
262 Singapore and Malaysia is even more necessary than the case between Vietnam and Thailand.

263 These findings are reasonably robust compared to trilateral and multilateral evaluations as
264 reported in [Table 5](#). Our bilateral findings are consistent with HCM-BKK-HAN, JKT-KUL-
265 SIN, and all-city estimations. In which, noticeable results are the mutually positive linkage
266 between Ho Chi Minh City and Bangkok and the negative co-movement between Kuala
267 Lumpur and Singapore. Key numbers in [Table 5](#) are bolded and highlighted to emphasize the
268 robustness among our findings. [Figure 2](#) illustrates the time-varying dynamic conditional
269 correlation of air quality among Southeast Asian cities. In general, those correlations are
270 positive. This pattern lays the background for future environmental agreement across sub-
271 regions of Southeast Asia.

272

[Figure 2 around here]

273 **5. Conclusion**

274 This study evaluates the air quality transmission among six selected cities in Southeast Asia,
275 which includes Ho Chi Minh City, Hanoi, Bangkok, Singapore, Kuala Lumpur, and Jakarta.
276 We find reliable evidence on the mutually positive interaction between Ho Chi Minh City and
277 Bangkok and the negative relationship between Kuala Lumpur and Singapore. While the air
278 quality of neighbors is considered one of externalities, our results internalize such impacts to
279 seek regional or sub-regional environmental agreements. In terms of theory, we employ the
280 multivariate GARCH framework to investigate bilateral and multilateral particulate matter
281 transmissions in Southeast Asia. This interdisciplinary approach is expected to generate good
282 precedents for future studies which examine environmental and social relations using financial
283 economics modeling. In terms of practice, our findings affirm the necessity for sub-regional
284 environmental agreements among Southeast Asia countries based on empirical findings, those
285 are, the interchangeable benefit of Vietnam and Thailand and the inverse connection between
286 Singapore and Malaysia. Those bilateral memoranda lay the background for comprehensive
287 environmental agreements all over the globe in future, especially in pursuit of sustainable
288 development goals.

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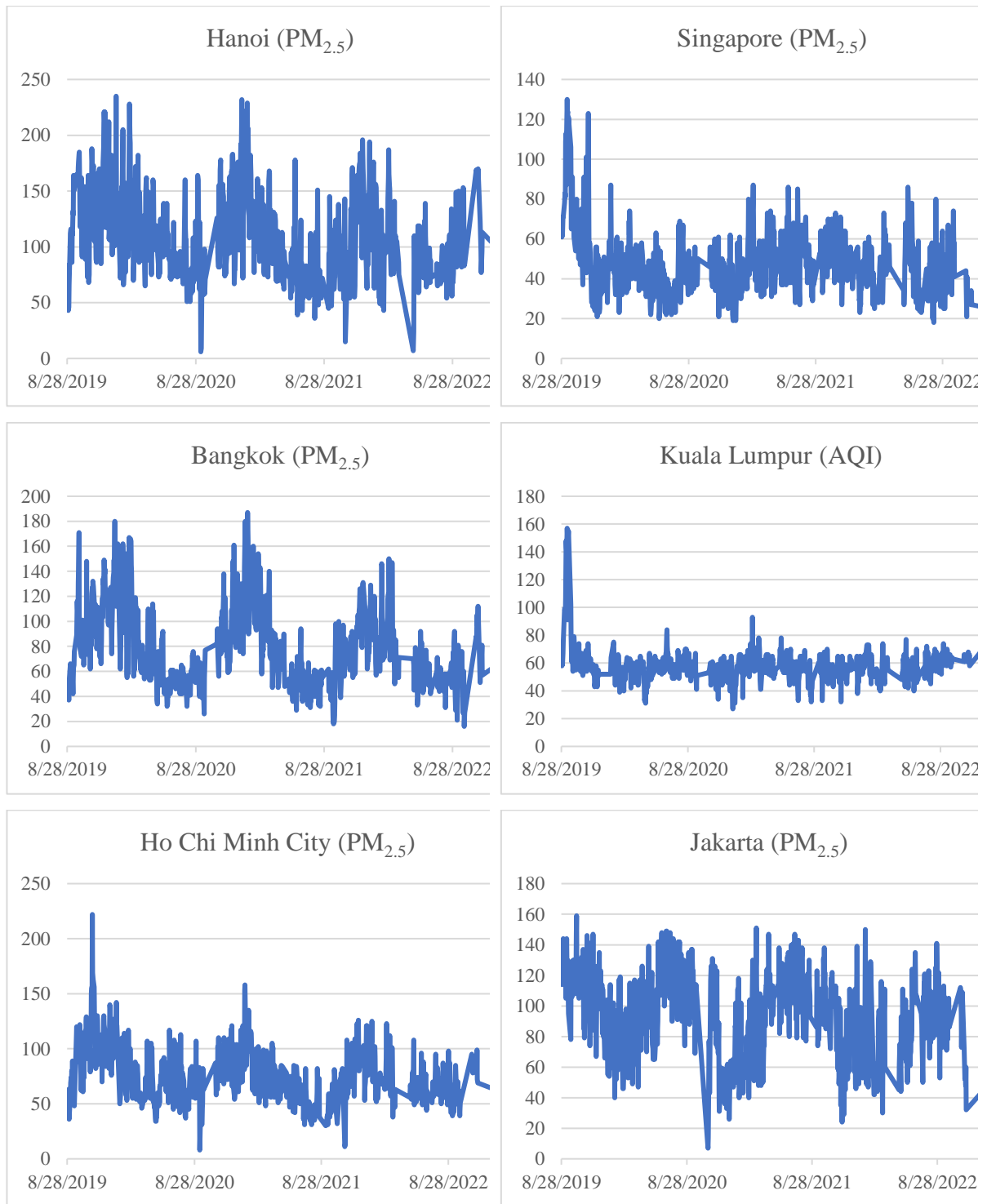
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FIGURES

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Figure 1. Data illustration from 28 August 2019 to 04 April 2023



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Source: Air quality historical data platform, retrieved from <https://aqicn.org/data-platform/register/>.

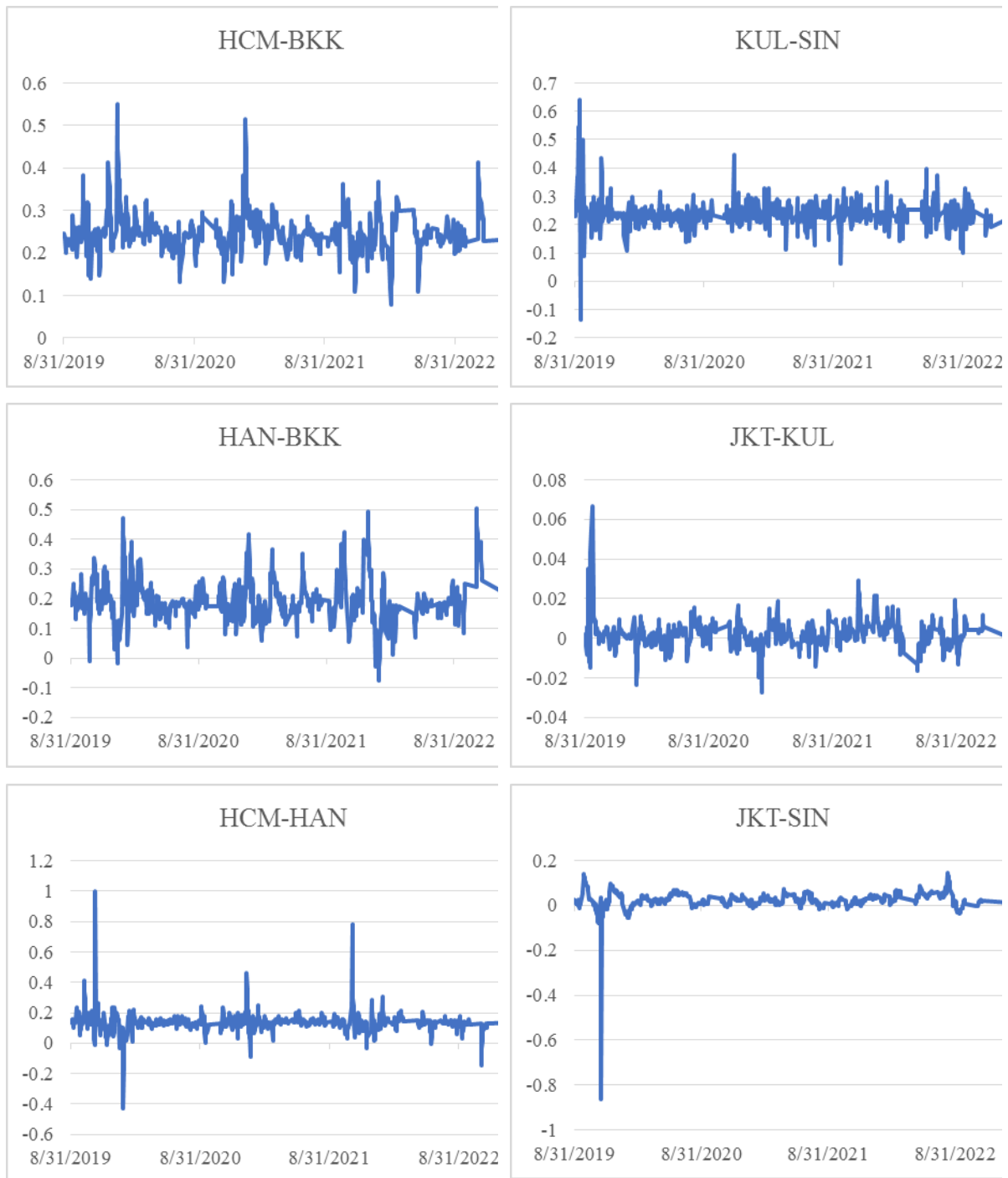
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Figure 2. Bilateral air quality transmission in terms of time-varying dynamic conditional

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correlation



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Source: Authors' calculations.

TABLES

Table 1. Descriptive statistics and stochastic properties

	HAN	BKK	HCM	SIN	KUL	JKT
Observations	1000	1000	1000	1000	1000	1000
Mean	108.82	79.19	75.05	46.76	57.62	91.53
Std dev	37.41	32.22	23.86	15.16	11.51	28.10
Skewness	0.5656	0.8634	0.8159	1.3374	3.8124	-0.1451
Kurtosis	-0.0292	0.1723	1.6203	4.1381	28.47	-0.7636
Jarque-Bera	53.36***	125.49***	220.35***	1012***	36188***	27.81***
Ljung-Box	2613***	5656***	3676***	2791***	2344***	3925***
McLeod-Li	2369***	4674***	3265***	2989***	2581***	3772***
ARCH	580***	745***	582***	513***	527***	552***
ADF	-12.04***	-7.96***	-11.56***	-12.99***	-10.78***	-12.30***
PP	-11.61***	-7.50***	-10.92***	-12.53***	-10.42***	-11.54***

Descriptive statistics include observations, mean, standard deviation (std dev), skewness, and kurtosis. Stochastic properties include normality with the Jarque-Bera test, autocorrelation effect with 15-lagged Ljung-Box and McLeod-Li tests, heteroskedasticity effect with the 15-lagged ARCH test, and stationarity with the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) and unit root tests. *, **, and *** represent statistical significance of 90%, 95%, and 99%, respectively.

Table 2. Bilateral AQI and geographic distances (from min to max)

Pair	AQI Distance	Pair	Distance (km)
BKK-HCM	0.872347	SIN-KUL	315.07
BKK-HAN	0.907469	BKK-HCM	750.42
HCM-HAN	1.016609	SIN-JKT	893.36
SIN-KUL	1.029175	BKK-HAN	988.01
SIN-JKT	1.284425	KUL-HCM	1010.30
KUL-JKT	1.308775	SIN-HCM	1100.91
SIN-HCM	1.402543	HCM-HAN	1143.52
SIN-HAN	1.413401	KUL-JKT	1182.49
KUL-HAN	1.423730	KUL-BKK	1186.12
SIN-BKK	1.449364	SIN-BKK	1434.09
KUL-HCM	1.449577	JKT-HCM	1884.95
KUL-BKK	1.485206	KUL-HAN	2037.33
JKT-HCM	1.536472	SIN-HAN	2205.60
JKT-HAN	1.601476	JKT-BKK	2323.35
JKT-BKK	1.665171	JKT-HAN	3026.71

AQI distances by Authors' calculations. Geographic distances are retrieved from <https://www.distancecalculator.net/>.

Table 3. Bilateral AQI transmission in Southeast Asia under the DCC-GARCH estimation

	HCM-BKK		HAN-BKK		HCM-HAN		KUL-SIN		JKT-KUL		JKT-SIN	
	$i = HCM$	$j = BKK$	$i = HAN$	$j = BKK$	$i = HCM$	$j = HAN$	$i = KUL$	$j = SIN$	$i = JKT$	$j = KUL$	$i = JKT$	$j = SIN$
	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j
μ	13.9599***	1.7076*	18.5396***	3.1048**	9.1051***	13.7257***	17.6733***	15.2135***	10.5098***	17.3438***	19.8326***	12.2352***
y_{t-1}^i	0.6750***	0.1423***	0.6683***	0.0889***	0.6488***	0.2007***	0.6766***	-0.1082**	0.5988***	0.0202***	0.7496***	0.0196***
y_{t-1}^j	0.1143***	0.8277***	0.2093***	0.8235***	0.0321***	0.7711***	0.0672***	0.5910***	-0.0840***	0.7064***	0.0703	0.6871***
y_{t-2}^i					0.0422***	-0.0394***	-0.0288	0.0427	0.0886***	0.0068**		
y_{t-2}^j					-0.0050***	-0.1854***	-0.0177	0.1503***	0.1178***	-0.0593**		
y_{t-3}^i					0.0625***	-0.0005			0.1539***	-0.0182**		
y_{t-3}^j					0.0530***	0.1659***			0.0432***	0.0332**		
C	9.5053*	6.3651**	7.5185	5.4795*	107.29***	265.36***	4.7045	22.3720**	269.4607***	6.7690**	46.0930**	15.1751***
A_{t-1}	0.0512***	0.0931***	0.0481***	0.1022***	0.0606*	0.1186***	0.2266***	0.1302***	0.1134***	0.2355***	0.0440*	0.1577***
A_{t-2}					0.0839***	0.0660***	-0.1181	0.1324**	0.1255***	-0.0231		
A_{t-3}					0.0673***	0.0619***			0.0946***	-0.0307		
B_{t-1}	0.9093***	0.8832***	0.9417***	0.8775***	0.0862***	0.0822***	0.7661	0.1220	-0.3234***	0.3896***	0.8280***	0.7014***
B_{t-2}					0.0792***	0.0884***	-0.0011	0.4289***	-0.3763***	0.3119***		
B_{t-3}					0.1349***	0.1451***			0.6625***	-0.0601		
α	0.0269		0.0406		-0.0291***		0.0424		-0.0042**		-0.0097***	
β	0.7597***		0.7618***		0.6712***		0.0970		0.7919***		0.9423***	
ν	6.1787***		7.9353***		8.4241***		8.9796***		10.4092***		26.8381***	
JB	221.67***	85.9450***	79.8640***	95.4400***	130.43***	26.3389**	160.37***	7.1080**	0.7250	151.38***	27.0590***	10.5280**
LB	34.0915***	18.1478	42.1671***	19.6517	28.8270***	13.2039	39.5060***	35.4544***	49.2598***	28.2965**	83.4011***	64.2257***
ML	13.4092	13.9785	15.3177	11.9858	23.0461**	15.5127	10.0992	13.3362	13.8879	7.5952	6.2012	13.8395
ARCH	12.7820	14.4720	15.6310	12.2390	21.9540	15.6920	7.3950	15.1020	14.2390	7.3110	6.0790	16.8150
$\alpha + \beta$	0.7866		0.8024		0.6420		0.1395		0.7877		0.9326	

*, **, and *** represent statistical significance of 10%, 5%, and 1%, respectively. Diagnostic tests for stochastic properties of residuals include normality with the Jarque-Bera (JB) test; autocorrelation with 15-lagged Ljung-Box (LB) and McLeod-Li (ML) tests; and heteroscedasticity with the 15-lagged ARCH test. Estimation with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

Table 4. Bilateral AQI transmission within adjacent cities under competing GARCH models

	VARMA-GARCH		CCC-GARCH		DCC-GARCH		VARMA-GARCH		CCC-GARCH		DCC-GARCH	
	$i = HCM$	$j = BKK$	$i = HCM$	$j = BKK$	$i = HCM$	$j = BKK$	$i = KUL$	$j = SIN$	$i = KUL$	$j = SIN$	$i = KUL$	$j = SIN$
	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j	y_t^i	y_t^j
μ	16.3662***	4.1604***	16.2404***	3.8419***	13.9599***	1.7076*	17.3763***	14.4372***	16.9888***	14.5794***	17.6733***	15.2135***
y_{t-1}^i	0.6533***	0.1128***	0.6508***	0.1251***	0.6750***	0.1423***	0.6792***	-0.0877***	0.6877***	-0.0859**	0.6766***	-0.1082**
y_{t-1}^j	0.1115***	0.8197***	0.1119***	0.8105***	0.1143***	0.8277***	0.0591***	0.5918***	0.0577***	0.5857***	0.0672***	0.5910***
y_{t-2}^i							-0.0267***	0.0355	-0.0232	0.0334	-0.0288	0.0427
y_{t-2}^j							-0.0115	0.1504***	-0.0149	0.1538***	-0.0177	0.1503***
C	87.4391***	43.3668***	10.6774	4.3843**	9.5053*	6.3651**	10.2882***	55.1501***	15.5872**	29.9170	4.7045	22.3720**
A_{t-1}	0.1726***	-0.0172	0.0454**		0.0512***		0.2242***	-0.0020***	0.2510***		0.2266***	
	0.0880***	0.0816***		0.0907**		0.0931***	0.0184***	0.1584***		0.1568**		0.1302***
A_{t-2}							-0.0916***	0.0358***	0.0657		-0.1181	
							0.5831***	0.0876**		0.1401*		0.1324**
B_{t-1}	0.3706**	0.1010*	0.9080***		0.9093***		0.8992***	-0.1959***	-0.0008		0.7661	
	-0.2920**	0.9428***		0.8941***		0.8832***	-2.5474***	0.0416***		0.0597		0.1220
B_{t-2}							-0.1848***	0.1226***	0.3051*		-0.0011	
							1.2371***	0.4593***		0.3606		0.4289***
ρ	0.2371***		0.2344***				0.2196***		0.2165***			
α					0.0269						0.0424	
β					0.7597***						0.0970	
ν					6.1787***						8.9796***	
LL	-8136.61		-8143.34		-8582.30		-6883.40		-6893.75		-6865.37	
AIC	16.3240		16.3290		17.2120		13.8520		13.8570		13.8040	
SBC	16.4070		16.3930		17.2850		13.9950		13.9600		13.9170	
HQ	16.3550		16.3530		17.2120		13.9070		13.8960		13.8470	
JB	189.47***	42.7310***	210.05***	67.0830***	221.67***	85.9450***	133.00***	4.9800*	138.84***	7.7620**	160.37***	7.1080**
LB	41.7949***	20.2234	39.6835***	19.2315	34.0915***	18.1478	38.3928***	35.3577***	34.2500***	36.3444***	39.5060***	35.4544***
ML	19.6561	15.1097	14.3138	14.2976	13.4092	13.9785	10.9784	15.5621	11.1151	13.2356	10.0992	13.3362
ARCH	19.4320	15.2460	13.7570	15.0330	12.7820	14.4720	8.5610	17.0700	7.9300	15.4890	7.3950	15.1020
λ_{t-1}	-0.5818	-0.9859	-0.9533	-0.9848			0.1831	-1.5065	-0.2165	-0.2502		
λ_{t-2}							0.5413	-0.8118	-0.3708	-0.5007		
$\alpha + \beta$					0.7866						0.1395	

*, **, and *** represent statistical significance of 10%, 5%, and 1%, respectively. Model selection is referred to log likelihood (LL), Akaike (AIC), Schwarz Bayesian (SBC), and Hannan-Quinn (HQ) information criteria. Diagnostic tests for stochastic properties of residuals include normality with the Jarque-Bera (JB) test; autocorrelation with 15-lagged Ljung-Box (LB) and McLeod-Li (ML) tests; and heteroscedasticity with the 15-lagged ARCH test. Estimation with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

Table 5. Multilateral AQI transmission in Southeast Asia under the DCC-GARCH estimation

	Trilateral HCM-BKK-HAN			Trilateral JKT-KUL-SIN			Multilateral interactions					
	$i = HCM$	$j = BKK$	$k = HAN$	$i = JKT$	$j = KUL$	$k = SIN$	$i = HCM$	$j = BKK$	$k = HAN$	$l = JKT$	$m = KUL$	$n = SIN$
	y_t^i	y_t^j	y_t^k	y_t^i	y_t^j	y_t^k	y_t^i	y_t^j	y_t^k	y_t^l	y_t^m	y_t^n
μ	13.2211***	-0.5655	13.1222***	18.5430***	15.7288***	14.6292***	16.7589***	9.0425***	13.4444***	28.2201***	16.0255***	15.4285***
y_{t-1}^i	0.6652***	0.1214***	0.1354***	0.7561***	0.0130***	0.0199**	0.6595***	0.1178***	0.1448***	0.0792***	-0.0052	-0.0078
y_{t-1}^j	0.0979***	0.7724***	0.1458***	0.0086	0.6577***	-0.0455***	0.0882***	0.7494***	0.1213***	-0.1115***	0.0027	0.0107*
y_{t-1}^k	0.0266**	0.0748***	0.6710***	0.0770***	0.0542***	0.6901***	0.0341***	0.0744***	0.6541***	-0.0227**	0.0002	-0.0046
y_{t-1}^l							-0.0121	-0.0525***	-0.0717***	0.7041***	0.0148***	0.0222***
y_{t-1}^m							0.0015	-0.0483**	0.1849***	0.0235	0.6492***	-0.0629**
y_{t-1}^n							-0.0433**	0.0050	-0.0263	0.0719***	0.0581***	0.6951***
C	13.4276	5.8469**	170.25*	29.8084	9.7109***	16.2293**	12.5401*	4.6620**	154.00***	39.6641	8.4600**	15.4594**
A	0.0524**	0.0880***	0.1589***	0.0340	0.1902***	0.1679***	0.0486**	0.0876***	0.1647***	0.0454	0.1810***	0.1622***
B	0.8879***	0.8867***	0.5712***	0.8870**	0.5501***	0.6917***	0.8938***	0.8923***	0.5799***	0.8482***	0.6017***	0.7044***
α	0.0193			-0.0049***			0.0139					
β	0.7259***			0.8955***			0.0408					
ν	8.1557***			12.8969***			13.6556***					
JB	186.02***	76.1140***	35.0020***	30.5030***	149.52***	7.9230**	192.71***	62.5210***	35.4440***	17.3950***	158.49***	7.8080**
LB	34.6794***	16.5881	38.2664***	80.3393***	32.6534***	66.3146***	36.3277***	17.5765	36.7684***	56.3070***	35.9734***	64.4665***
ML	14.3456	14.7609	13.8783	6.7874	12.4148	13.7185	13.7024	13.6797	12.6818	9.1751	11.4733	13.5606
ARCH	13.7370	15.4550	12.8700	6.5370	9.7130	16.9090	13.1190	14.3920	11.2680	8.8300	9.3540	16.6360
$\alpha + \beta$	0.7452			0.8906			0.0548					

*, **, and *** represent statistical significance of 10%, 5%, and 1%, respectively. Diagnostic tests for stochastic properties of residuals include normality with the Jarque-Bera (JB) test; autocorrelation with 15-lagged Ljung-Box (LB) and McLeod-Li (ML) tests; and heteroscedasticity with the 15-lagged ARCH test. Estimation with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.