São Paulo 2025

IAA AAI SECTIONS

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An Enhanced Risk Management Approach for Life Insurance Companies Using the DCC-GARCH Model：Considering the Volatility Characteristics of Equity Portfolio During the COVID-19

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Outline

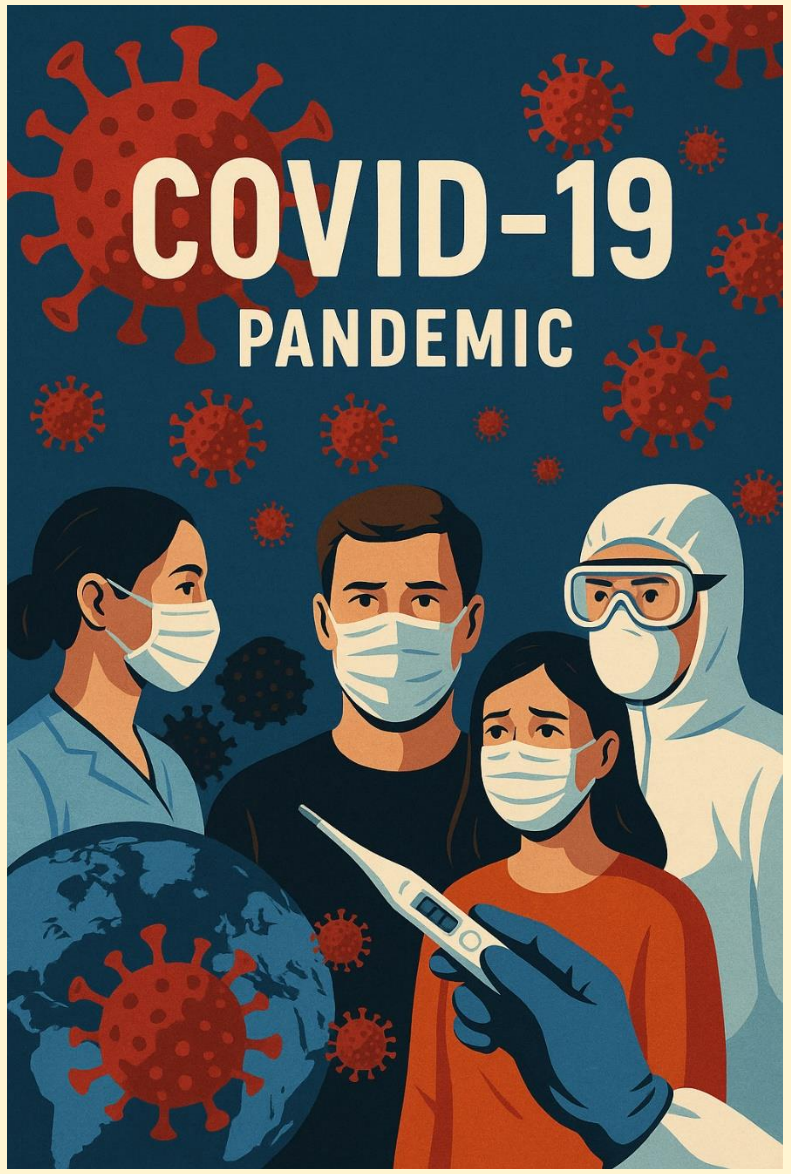
Ⅰ. Impact of the COVID-19 Pandemic on the Global Stock Market

Ⅱ. Risk Management Approaches for Equity Portfolio During the Pandemic

Ⅲ. Numerical Examples

Ⅳ. Verification of GARCH Model's Effectiveness

Ⅴ. Conclusion



An image generated by ChatGPT following the instruction 'Create an image depicting the global spread of the COVID-19 pandemic.'

Ⅰ. Impact of the COVID-19 Pandemic on the Global Stock Market

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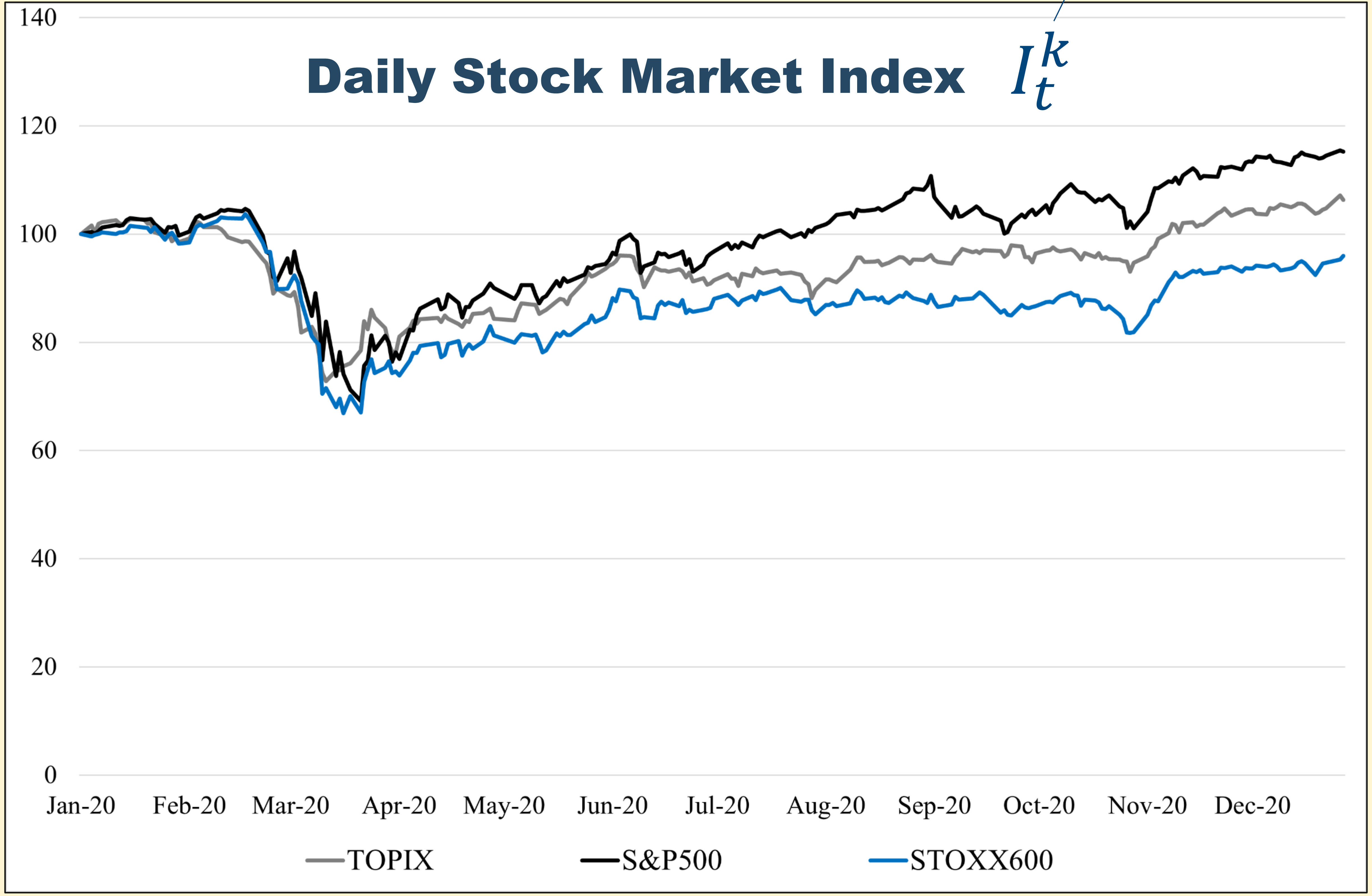
Volatility Indices in Japan, the United States and Europe

Past Events of Volatility Index Surges

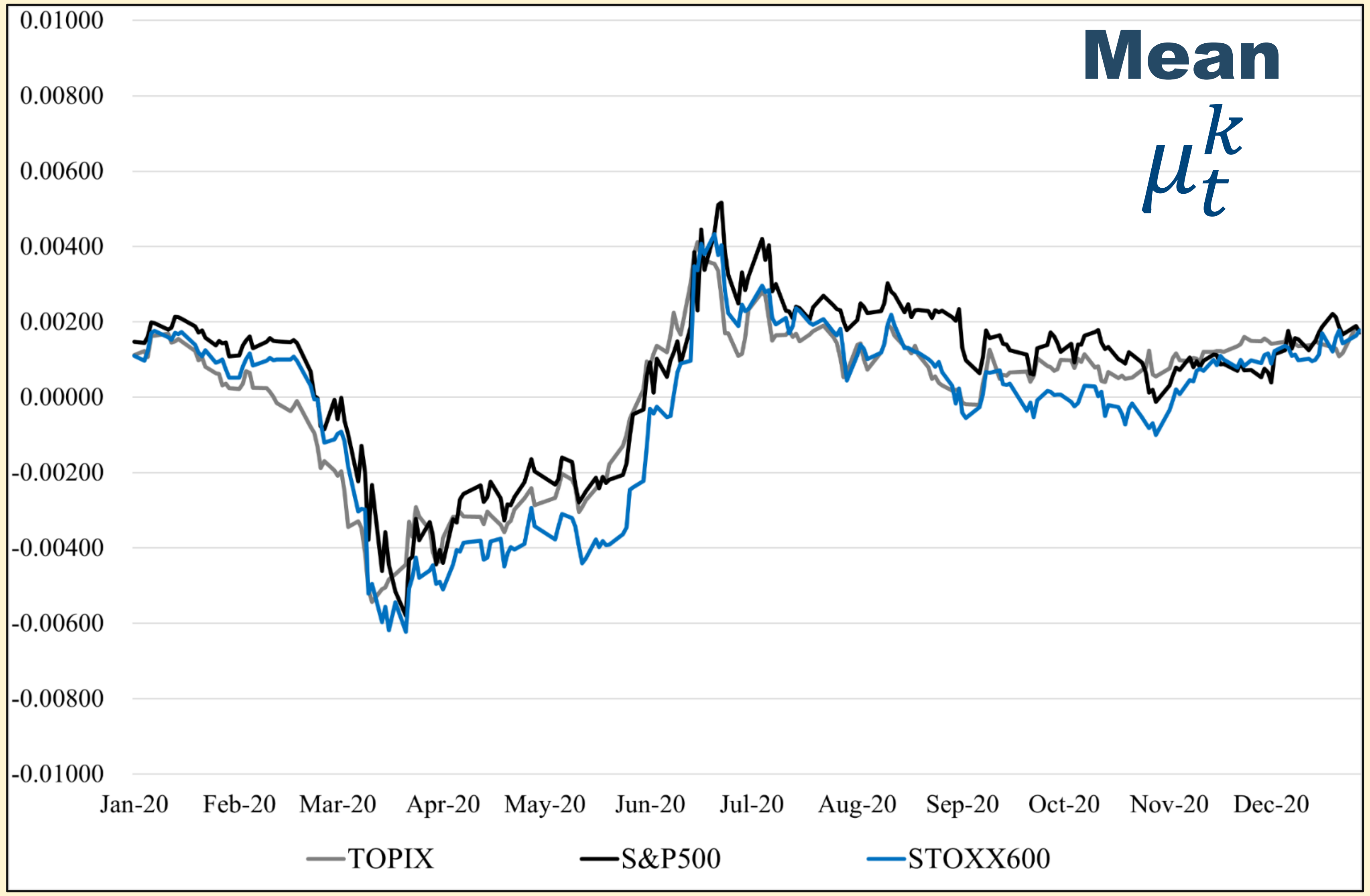
	Date	VIX	Nkvi	VSTOXX
Asian Financial Crisis	October 1997	48.64	N/A	N/A
Russian Financial Crisis	August 1998	49.53	N/A	N/A
9/11 Terrorist Attacks	September 2001	49.53	N/A	N/A
Enron Scandal	January 2002	48.46	N/A	N/A
Global Financial Crisis	October 2008	89.53	N/A	85.44
China Shock	August 2015	53.29	47.01	36.21
COVID-19 Pandemic	March 2020	85.47	58.63	87.48

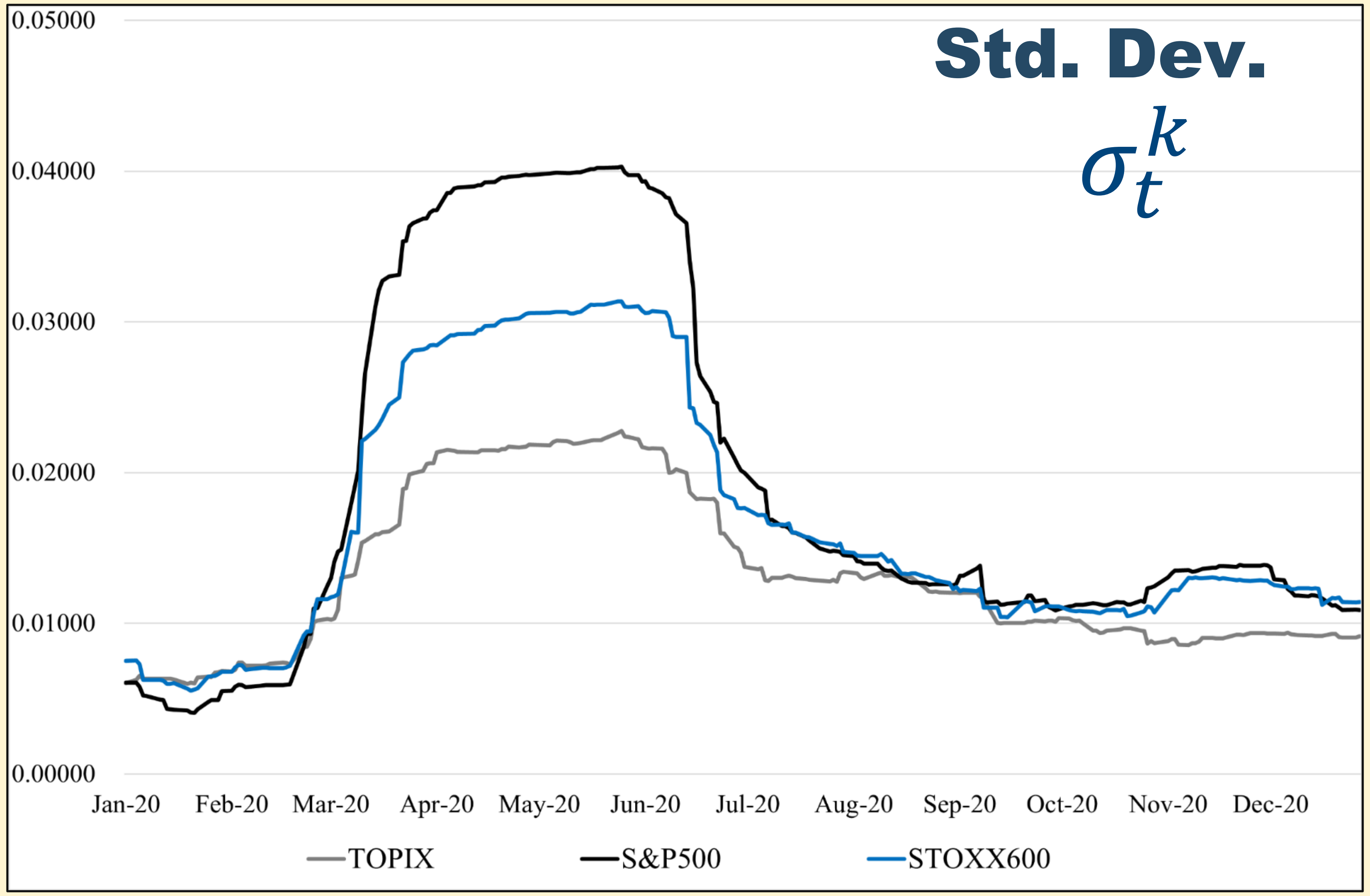
Stock Market Indices in Japan, the United States and Europe

k = TOPIX, S&P00 and STOXX600



Trends in Daily Return Mean and Standard Deviation





Daily Return Rate

k = TOPIX, S&P00 and STOXX600

$$X_t^k = \ln\left(I_t^k\right) - \ln\left(I_{t-1}^k\right), \quad I_t^k = e^{X_t^k} I_{t-1}^k ,$$

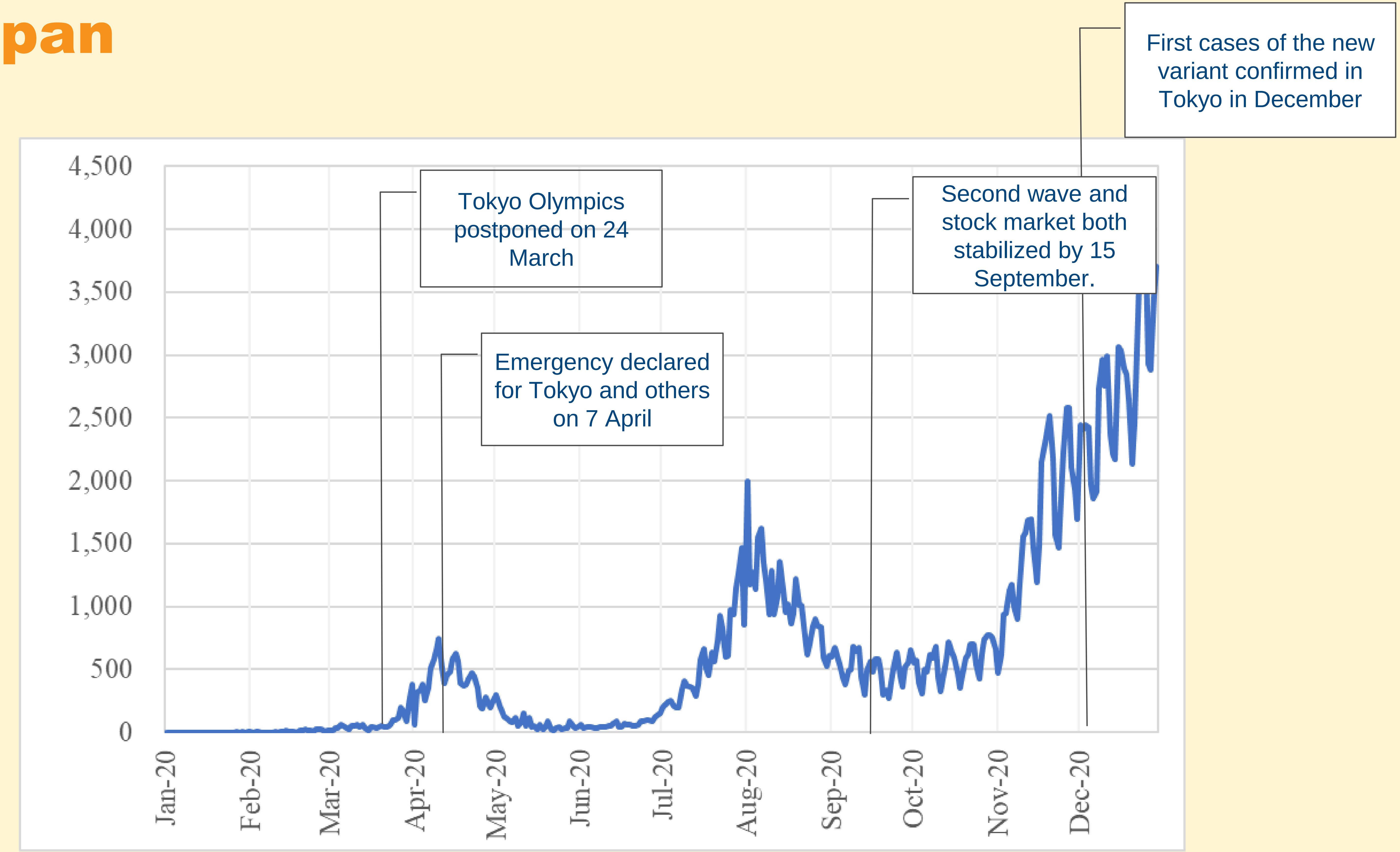
Mean

$$\mu_t^k = \frac{1}{n}\sum_{j=0}^{n-1} X_{t-j}^k$$

Standard Deviation

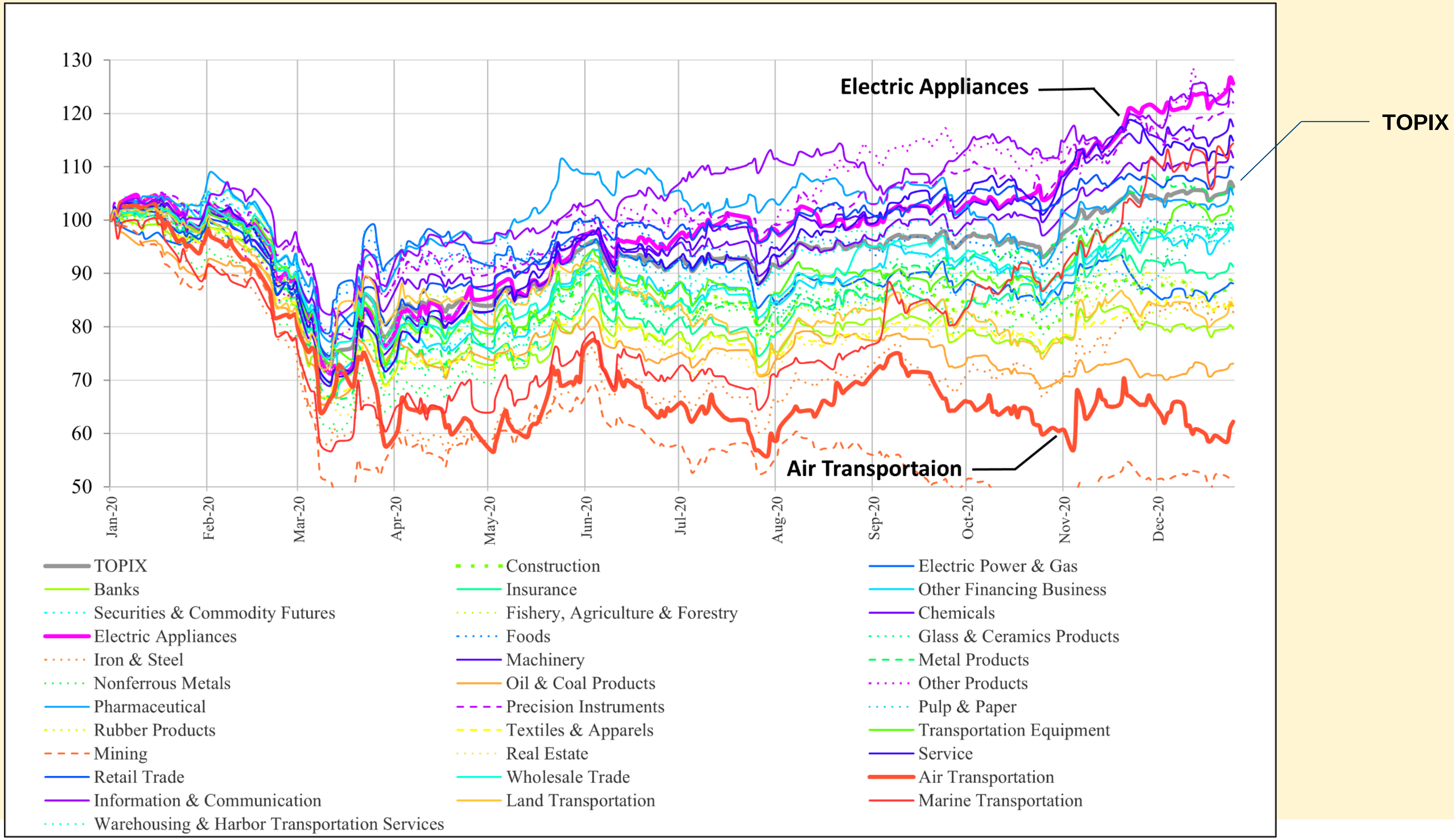
$$\sigma_t^k = \sqrt{\frac{1}{n-1}\sum_{j=0}^{n-1}\left(X_{t-j}^k - \mu_t^k\right)^2} \qquad n = 30$$

Trends in the number of new COVID-19 infections in Japan



The Japanese Stock Market by 33 Sectors

The TOPIX is a market-cap-weighted index of these sectors. To facilitate comparison, each sector ’s index is normalised to 100 as of 6 January 2020.



Ⅱ. Risk Management Approaches for Equity Portfolio During the Pandemic

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Asset balance before and after portfolio rebalancing

	Pre-Reconst. Market Value	Post-Reconst. Market Value
Air Transportation	I_A	I_A
Electric Appliances	0	$k\ I_E$
Total	I_A	$I_A + \ k\ I_E$

Portfolio Reconstruction Strategy

- **Initial Scenario**
  - Insurer held only equities in the Air Transportation sector.
- **Date of Evaluation**
  - As of 15 September 2020, after the second wave of COVID-19 infections had subsided.
- **Portfolio Adjustment**
  - Decision to add the Electric Appl. sector, which showed significant recovery.
- **Goals**
  - Maximize market value of the portfolio by the fiscal year-end on 30 December 2020.
- **Risk Management**
  - Overall portfolio risk is capped at twice the risk level of the Air Transp. sector, in accordance with internal risk management policies, for example.

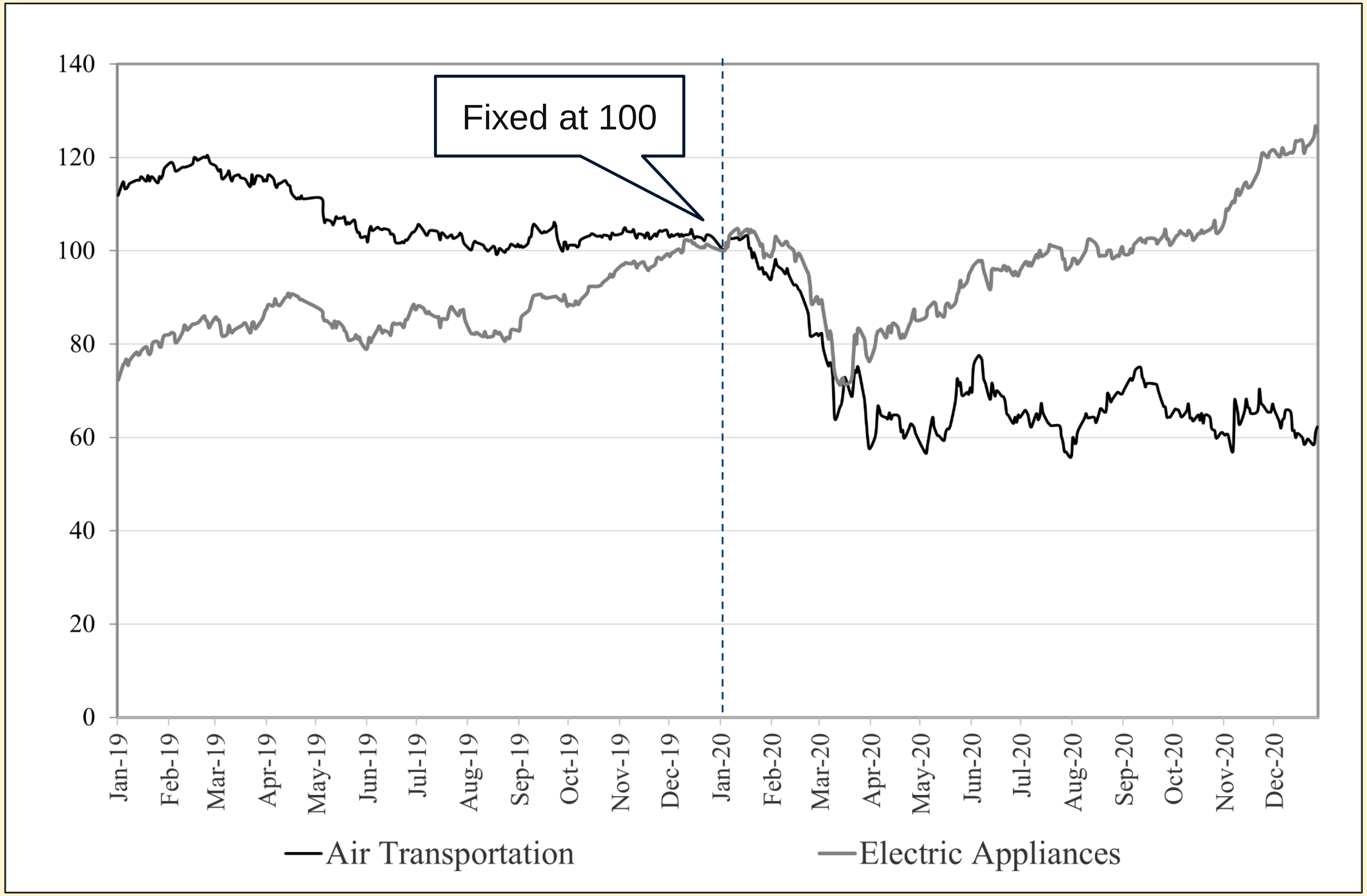
Risk-return efficiency of the asset portfolio

<table>
<tr><th colspan="3">Post-Reconstructed Asset Balance</th></tr>
<tr><td rowspan="3">Air Transp.</td><td>(i) Projected Return</td><td>r_A</td></tr>
<tr><td>(ii) Projected Risk</td><td>R_A</td></tr>
<tr><td>(iii) Sharp Ratio</td><td>r_A/R_A</td></tr>
<tr><td rowspan="3">Elec. Appl.</td><td>(i) Projected Return</td><td>$k\ r_E$</td></tr>
<tr><td>(ii) Projected Risk</td><td>$k\ R_E$</td></tr>
<tr><td>(iii) Sharp Ratio</td><td>r_E/R_E</td></tr>
<tr><td colspan="2">Correlation Effect</td><td>C</td></tr>
<tr><td rowspan="3">Total</td><td>(i) Projected Return</td><td>$r_A\ + k\ r_E$</td></tr>
<tr><td>(ii) Projected Risk</td><td>$R_A +\ k\ R_E - C$</td></tr>
<tr><td>(iii) Sharp Ratio</td><td>$(r_A\ + k\ r_E)/(R_A +\ k\ R_E - C)$</td></tr>
</table>

- The purchase ratio *k* of the Electric Appliances relative to the Air Transportation is determined such that

$$R_A + kR_E - \mathrm{C} = 2R_A$$

Trends in Sector Indices during 2019 and 2020

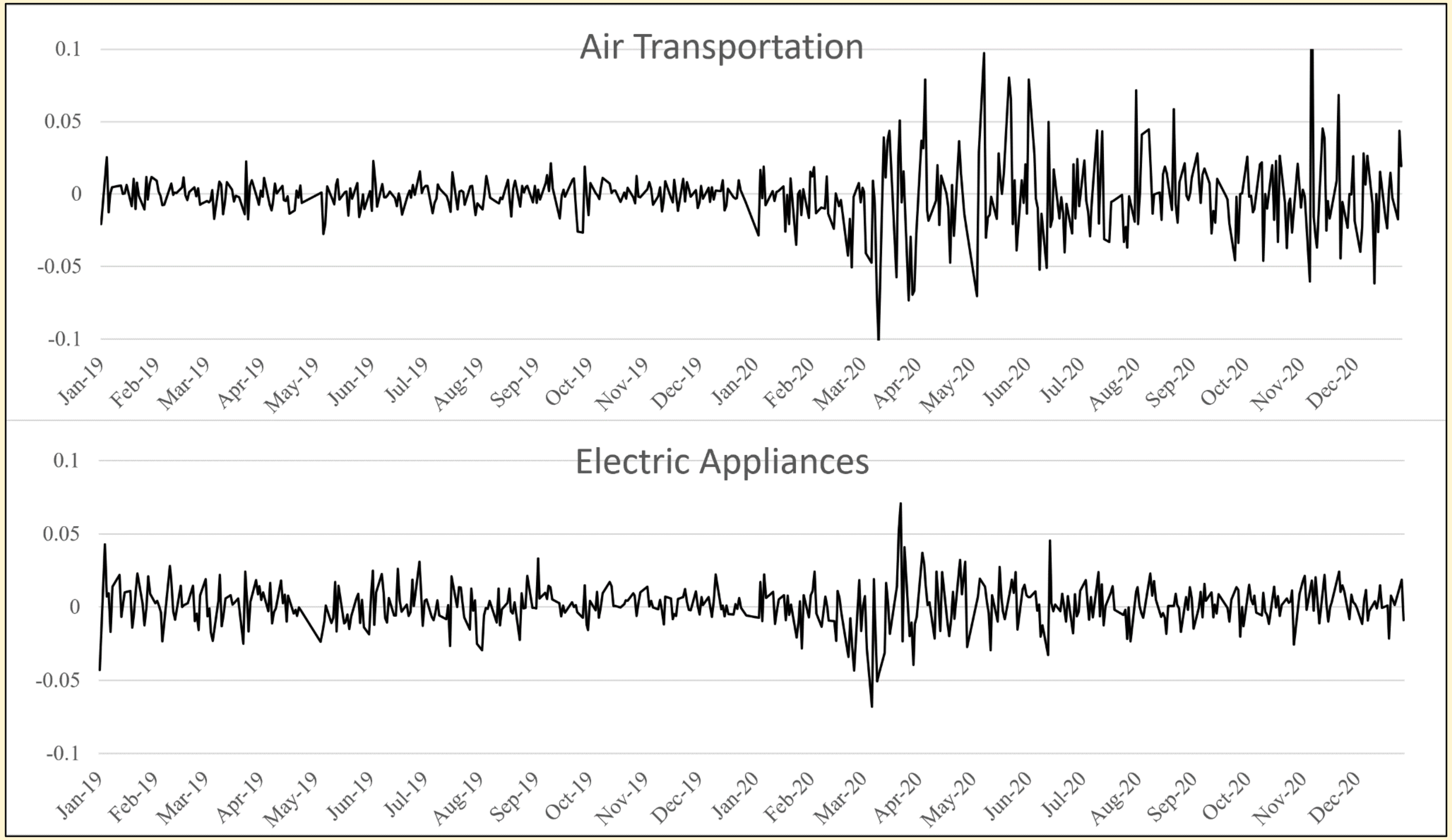


Electric Appliances

Air Transportation

Trends in Daily Return Rates during 2019 and 2020

The volatility in 2020 is significantly higher than that in 2019, and it persists over an extended period, a phenomenon observed across all 33 TOPIX sectors. This indicates the necessity of employing an appropriate risk measurement model during a pandemic.



Advances in ARCH-Type Models for Economic Time Series Analysis

- **ARCH Model (Autoregressive Conditional Heteroskedasticity Model)（1982）**

  Engle's ARCH model is the original volatility model designed to capture the phenomenon of volatility clustering.

- **GARCH Model (Generalized ARCH Model)(1986)**

  The ARCH model was generalised by Engle’s disciple, Bollerslev. GARCH(1,1) corresponds to an ARCH model of infinite order.

- **EGARCH Model (Exponential GARCH Model)(1991), GJR Model（1993）**

  These are models that account for the asymmetry of volatility fluctuations. EGARCH was developed by Nelson, while GJR was devised by Glosten, Jagannathan, and Runkle.

- **Multivariate GARCH Model（VEC、BEKK 、CCC、DCC）**

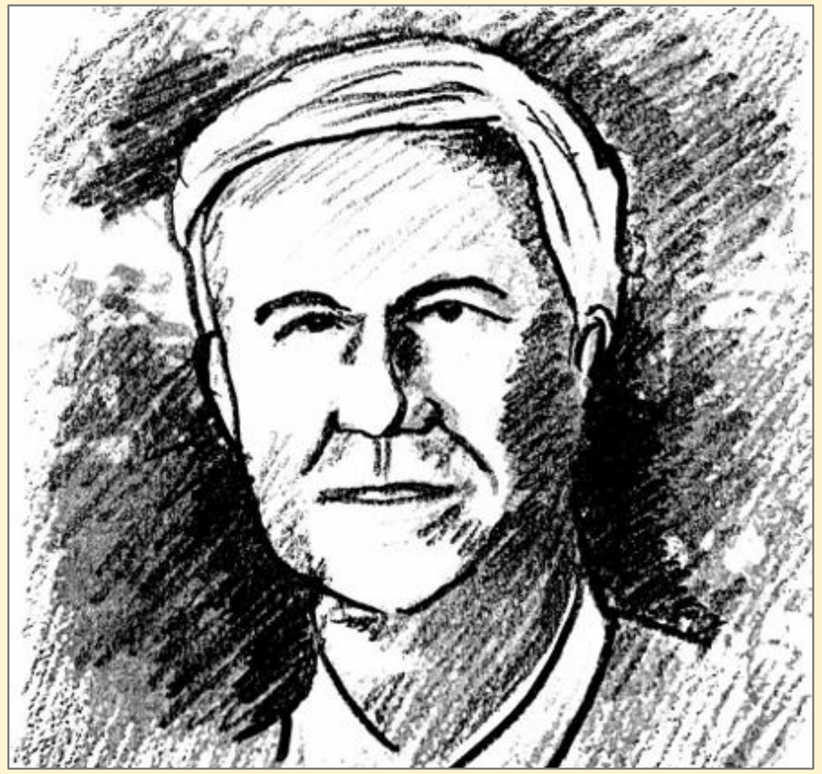
  The multivariate GARCH model is one that models multiple time series data while incorporating the correlation structure.

Bonus Slide
Awarding of the 2003 Nobel Prize in Economic Sciences

Contributions of the 2003 Nobel Laureates in Economic Sciences

In 2003, Robert Engle and Clive Granger were awarded the Nobel Prize in Economic Sciences for their groundbreaking work on the statistical analysis of economic time series. Engle developed the ARCH model to capture time-varying volatility, a key feature of financial data, enabling better risk assessment in markets. Granger introduced the concept of cointegration, showing how combinations of non-stationary time series can yield meaningful and reliable results.

Robert F. Engle,
New York University, USA
“for methods of analyzing economic time series with time-varying volatility (ARCH)”



Clive W. J. Granger,
University of California at San Diego, USA
“for methods of analyzing economic time series with common trends (cointegration)”.

DCC-GARCH(1,1) Model

Column vector of bivariate daily return rate

- $$\boldsymbol{x}_t = \underbrace{\boldsymbol{\mu}_t}_{\text{Expected value of } \boldsymbol{x}_t} + \underbrace{\boldsymbol{u}_t}_{\text{Disturbance term}} = \boldsymbol{\mu}_t + \boldsymbol{D}_t\,\boldsymbol{\epsilon}_t \qquad \begin{pmatrix} x_{1,t} \\ x_{2,t} \end{pmatrix} = \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} = \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix} + \begin{pmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{pmatrix} \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix}$$

Conditional correlation matrix

- $$E[\,\boldsymbol{\epsilon}_t\,\boldsymbol{\epsilon}_t^T \mid \Omega_{t-1}\,] = \begin{pmatrix} 1 & \rho_{12,t} \\ \rho_{21,t} & 1 \end{pmatrix} =: R_t$$

Conditional covariance matrix

- $$E[\,\boldsymbol{u}_t\,\boldsymbol{u}_t^T \mid \Omega_{t-1}\,] = \boldsymbol{D}_t\,E[\,\boldsymbol{\varepsilon}_t\,\boldsymbol{\varepsilon}_t^T \mid \Omega_{t-1}\,]\boldsymbol{D}_t = \boldsymbol{D}_t\,\boldsymbol{R}_t\,\boldsymbol{D}_t = \begin{pmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{pmatrix} \begin{pmatrix} 1 & \rho_{12,t} \\ \rho_{21,t} & 1 \end{pmatrix} \begin{pmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{pmatrix}$$
$$= \begin{pmatrix} h_{11,t} & \rho_{12,t}\sqrt{h_{11,t}h_{22,t}} \\ \rho_{12,t}\sqrt{h_{11,t}h_{22,t}} & h_{22,t} \end{pmatrix}$$

Equations in the GARCH(1,1) Model for the conditional variance

- $$h_{11,t} = \omega_1 + \alpha_1\epsilon_{1,t-1}^2 + \beta_1\,h_{11,t-1}$$
- $$h_{22,t} = \omega_2 + \alpha_2\epsilon_{2,t-1}^2 + \beta_2\,h_{22,t-1}$$

DCC-GARCH(1,1) Model

Column vector of bivariate daily return rate

- $\boldsymbol{x}_t = \boldsymbol{\mu}_t + \boldsymbol{u}_t = \boldsymbol{\mu}_t + \mathbf{H}_t^{1/2}\boldsymbol{v}_t$, $\mathbf{H}_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix}$, $\begin{pmatrix} x_{1,t} \\ x_{2,t} \end{pmatrix} = \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix} + \mathbf{H}_t^{1/2} \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix}$

Conditional covariance matrix

- $E[\, \boldsymbol{u}_t \boldsymbol{u}_t^T \mid \Omega_{t-1} \,] = \mathbf{H}_t^{1/2} E\,[\, \boldsymbol{v}_t \boldsymbol{v}_t^T \mid \Omega_{t-1} \,]\, \mathbf{H}_t^{1/2} = \mathbf{H}_t^{1/2}\, \mathbf{I} \;\; \mathbf{H}_t^{1/2} = \mathbf{H}_t$

$$\mathbf{H}_t = \boldsymbol{D}_t\, \boldsymbol{R}_t\, \boldsymbol{D}_t, \quad h_{12,t} := \rho_{12,t}\sqrt{h_{11,t}h_{22,t}}$$

Conditional correlation matrix

- $\boldsymbol{R}_t = diag(\boldsymbol{Q}_t)^{-1/2}\boldsymbol{Q}_t\ diag(\boldsymbol{Q}_t)^{-1/2} = \begin{pmatrix} 1/\sqrt{q_{11,t}} & 0 \\ 0 & 1/\sqrt{q_{22,t}} \end{pmatrix} \begin{pmatrix} q_{11,t} & q_{12,t} \\ q_{21,t} & q_{22,t} \end{pmatrix} \begin{pmatrix} 1/\sqrt{q_{11,t}} & 0 \\ 0 & 1/\sqrt{q_{22,t}} \end{pmatrix}$

$$= \begin{pmatrix} 1 & q_{12,t}/\sqrt{q_{11,t}q_{22,t}} \\ q_{21,t}/\sqrt{q_{11,t}q_{22,t}} & 1 \end{pmatrix} \Rightarrow \rho_{12,t} := \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}$$

DCC-GARCH(1,1) Model

Variance-covariance matrix

- $$\mathbf{Q}_t = \begin{pmatrix} q_{11,t} & q_{12,t} \\ q_{21,t} & q_{22,t} \end{pmatrix}, \quad q_{21,t} = q_{12,t}$$

$$= (1-a-b)\bar{\mathbf{Q}}_t + a\,\boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}_{t-1}^T + b\,\mathbf{Q}_{t-1}$$

$$= \begin{pmatrix} (1-a-b)\bar{q}_{11} + a\epsilon_{1,t-1}\epsilon_{1,t-1} + bq_{11,t-1} & (1-a-b)\bar{q}_{12} + a\epsilon_{1,t-1}\epsilon_{2,t-1} + bq_{12,t-1} \\ (1-a-b)\bar{q}_{21} + a\epsilon_{2,t-1}\epsilon_{1,t-1} + bq_{21,t-1} & (1-a-b)\bar{q}_{22} + a\epsilon_{2,t-1}\epsilon_{2,t-1} + bq_{22,t-1} \end{pmatrix}$$

Conditional sample covariance matrix

- $$\bar{\mathbf{Q}} = \frac{1}{n}\sum_{t}^{n} \epsilon_t\,\epsilon_t^T := \begin{pmatrix} \bar{q}_{11} & \bar{q}_{12} \\ \bar{q}_{21} & \bar{q}_{22} \end{pmatrix}$$

Correlation efficient

- $$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} = \frac{(1-a-b)\bar{q}_{12} + a\epsilon_{1,t-1}\epsilon_{2,t-1} + bq_{12,t-1}}{\sqrt{\left((1-a-b)q_{11} + a\epsilon_{1,t-1}^2 + bq_{11,t-1}\right) \times \left((1-a-b)\bar{q}_{22} + a\epsilon_{2,t-1}^2 + bq_{22,t-1}\right)}}$$

Summary of key points

$$\begin{pmatrix} x_{1,t} \\ x_{2,t} \end{pmatrix} = \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix} + \mathbf{H}_t^{1/2} \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix} \qquad \mathbf{H}_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix}$$

$$h_{11,t} = \omega_1 + \alpha_1 \epsilon_{1,t-1}^2 + \beta_1\, h_{11,t-1} \qquad h_{22,t} = \omega_2 + \alpha_2 \epsilon_{2,t-1}^2 + \beta_2\, h_{22,t-1}$$

$$h_{12,t} = \rho_{12,t} \sqrt{h_{11,t} h_{22,t}}$$

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} = \frac{(1-a-b)\bar{q}_{12} + a\epsilon_{1,t-1}\epsilon_{2,t-1} + b q_{12,t-1}}{\sqrt{\left((1-a-b)q_{11} + a\epsilon_{1,t-1}^2 + b q_{11,t-1}\right) \times \left((1-a-b)\bar{q}_{22} + a\epsilon_{2,t-1}^2 + b q_{22,t-1}\right)}}$$

By determining these 10 parameters using observational data, it becomes possible to make future projections.

$\mu_{1,t}$ $\mu_{2,t}$ ω_1 ω_2 α_1 α_2 β_1 β_2 a b

Mathematical Definitions of Return and Risk

The index 72 days ahead is given as a probability distribution, as it represents a future projection. By performing N = 10, 000 simulations using the DCCGARCH model, it becomes possible to estimate the projected returns and risks of the index 72 days ahead

Air Transportation

Projected Return

$$r_A = \left(\frac{1}{N} \sum_{i=1}^{N} I_A^{(i)} \right) - I_{A,0}$$

Projected Risk

$$R_A = \left| VaR_A(99.5\%) - I_{A,0} \right|$$

$$VaR_A(99.5\%) \coloneqq F_A^{-1}(0.005)$$

Electric Appliances

Projected Return

$$r_E = \left(\frac{1}{N} \sum_{i=1}^{N} I_E^{(i)} \right) - I_{E,0}$$

Projected Risk

$$R_E = \left| VaR_E(99.5\%) - I_{E,0} \right|$$

$$VaR_E(99.5\%) \coloneqq F_E^{-1}(0.005)$$

Post-Reconstructed Asset Balance		
Total	(i) Projected Return	$r_A + k\, r_E$
	(ii) Projected Risk	$R_A + k\, R_E - C$
	(iii) Sharp Ratio	$(r_A + k\, r_E)/(R_A + k\, R_E - C)$

The purchase ratio *k* of the Electric Appliances is determined such that

$$R_A + kR_E - C = 2R_A$$

Ⅲ. Numerical Examples

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Basic Statistics of Daily Return Rates

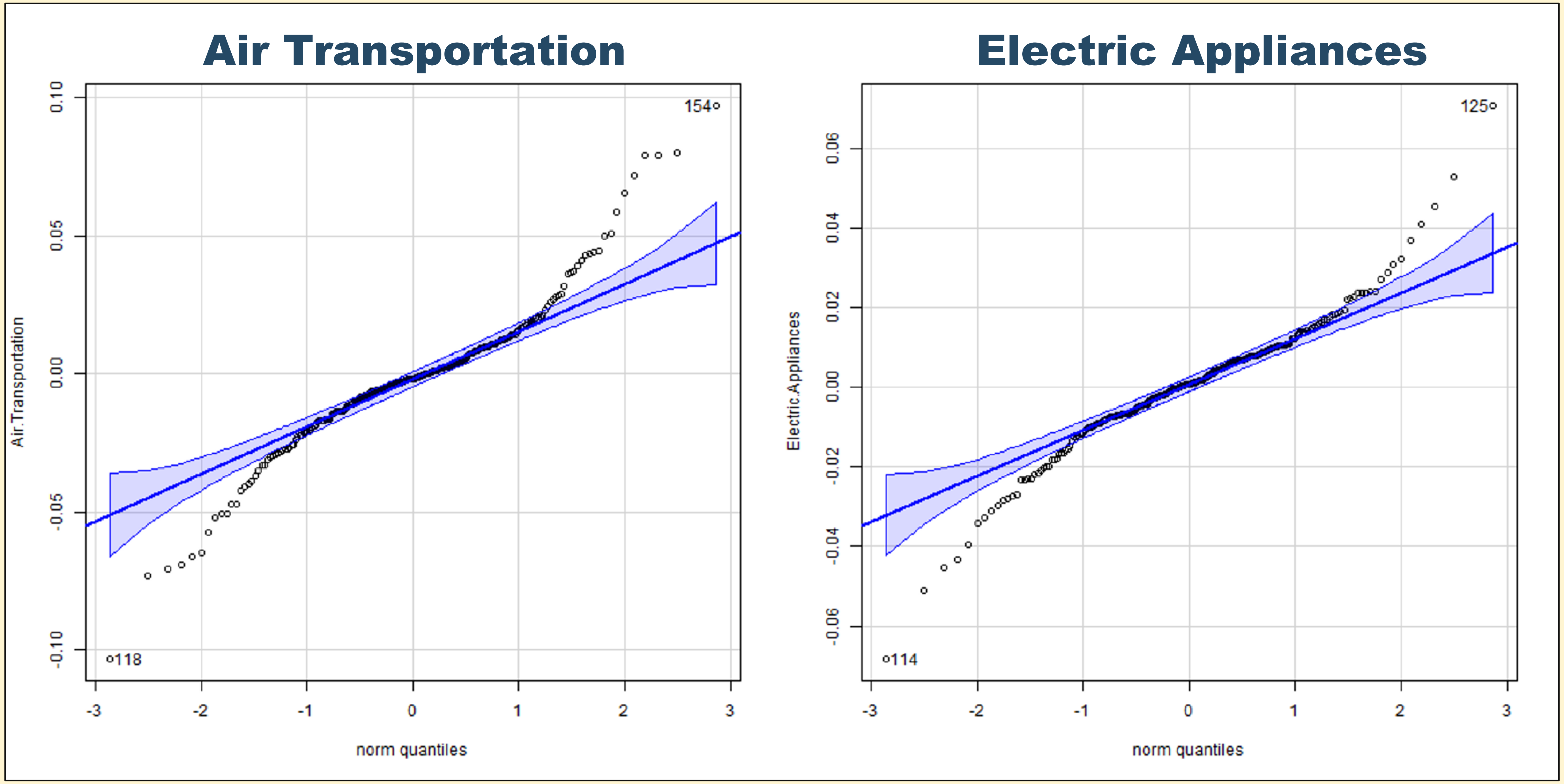
The skewness is 0 for a normal distribution.

Air Transportation (Sample size:242)						
Basic Statistics	Mean	Std.Dev.	Max	Min	Skew	Kurt
Observed Value	-0.00152	0.02567	0.0972	-0.1031	0.1818	2.9264
Std.Error	0.00165	-	-	-	0.1574	0.3419
Electric Appliances (Sample size:242)						
Basic Statistics	Mean	Std.Dev.	Max	Min	Skew	Kurt
Observed Value	0.00049	0.01591	0.0709	-0.0681	-0.1159	3.4469
Std. Error	0.00102	-	-	-	0.1574	0.3419

Regarding the mean and skewness, both sectors show standard errors of similar magnitude, indicating that the estimates are not particularly reliable. In contrast, the kurtosis for both sectors significantly exceeds the standard error of 0.3419. Therefore, the distributions for both sectors are leptokurtic, with longer tails, deviating from the normal distribution.

Normal Q-Q Plot of Daily Return Rates

The graph is shaded in light blue, and if the data lies within this range, it can be judged to follow a normal distribution.



Normality Test

- The Shapiro-Wilk test is known to have good power to reject normality, especially for small sample sizes (below 50), with a maximum sample size of around 5000.
- The Anderson-Darling test is particularly sensitive to deviations in the tails of the distribution.
- The Kolmogorov-Smirnov test, although not as powerful, can be applied to any distribution.

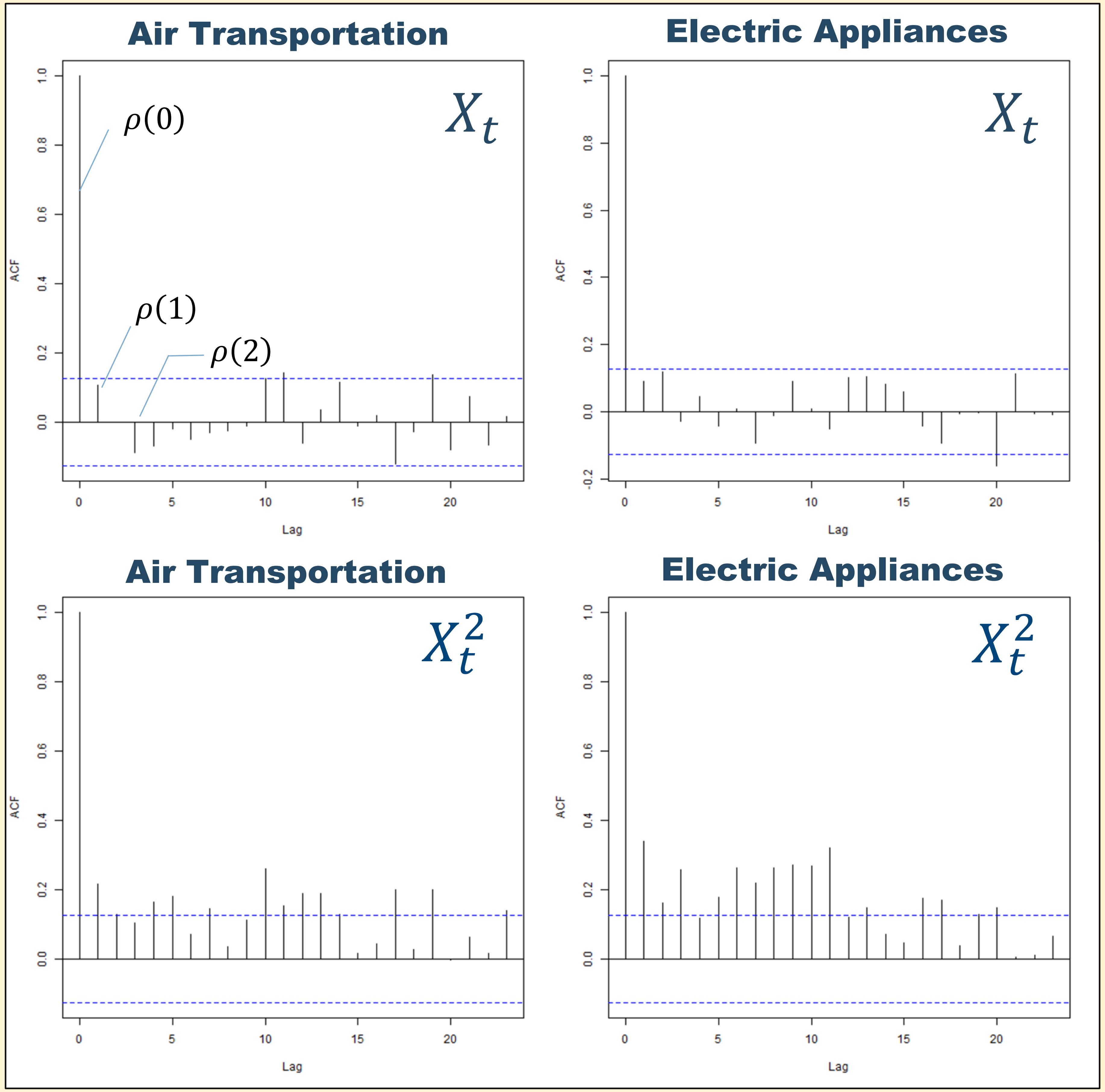
	Air Transportation		Electric Appliances	
	Test statistics	P-Value	Test statistics	P-Value
Shapiro-Wilk Test	0.9388	0.000000	0.9508	0.000000
Anderson-Darling Tes	4.9245	0.000000	2.9569	0.000000
Kolmogorov-Smirnov Test	0.1029	0.000001	0.0886	0.000089

The results of these tests led to **the rejection of the null hypothesis** that ”the population distribution is normal.”

Autocorrelation correlograms

$$\rho(k) = \frac{\mathrm{Cov}[X_t, X_{t-k}]}{\sqrt{\mathrm{V}[X_t]}\sqrt{\mathrm{V}[X_{t-k}]}}$$

- In the case of the autocorrelation correlogram of X_t, the values are below 0.1 for all lags, indicating that there is no correlation.
- On the other hand, for X_t^2, the levels of the autocorrelation coefficients are higher, showing that there is persistence in the variance.
- These results suggest that while predicting X_t itself is difficult, there is predictability in the square of X_t^2 .



Ljung-Box Test

Autocorrelation correlograms of the daily return rate						
Lag	Air Transportation			Electric Appliances		
	Corr.Coef.	Test Stat.Q	P-Value	Corr.Coef.	Test Stat. Q	P-Value
1	0.1080	2.1214	0.1453	0.0921	1.5426	0.2142
2	0.0032	2.1233	0.3459	0.1198	4.1699	0.1243
3	-0.0840	3.4213	0.3311	-0.0283	4.3173	0.2292
4	-0.0644	4.1886	0.3811	0.0455	4.7001	0.3195
5	-0.0166	4.2399	0.5154	-0.0401	4.9995	0.4159
10	0.1275	8.0519	0.6238	0.0106	8.2847	0.6010
15	-0.0091	15.6692	0.4044	0.0594	15.1046	0.4439
20	-0.0741	23.7010	0.2557	-0.1588	22.3177	0.3235

Autocorrelation correlograms of the ***squared*** daily return rate						
Lag	Air Transportation			Electric Appliances		
	Corr.Coef.	Test Stat.Q	P-Value	Corr.Coef.	Test Stat. Q	P-Value
1	0.3520	22.5463	0.0000	0.4449	36.0293	0.0000
2	0.2796	36.8525	0.0000	0.2935	51.7942	0.0000
3	0.2592	49.2241	0.0000	0.3767	77.9133	0.0000
4	0.3090	66.8993	0.0000	0.2573	90.1667	0.0000
5	0.3228	86.3035	0.0000	0.3098	108.0425	0.0000
10	0.3901	163.1742	0.0000	0.3869	243.0457	0.0000
15	0.1912	246.6030	0.0000	0.2008	325.2658	0.0000
20	0.1732	315.8221	0.0000	0.2870	402.3522	0.0000

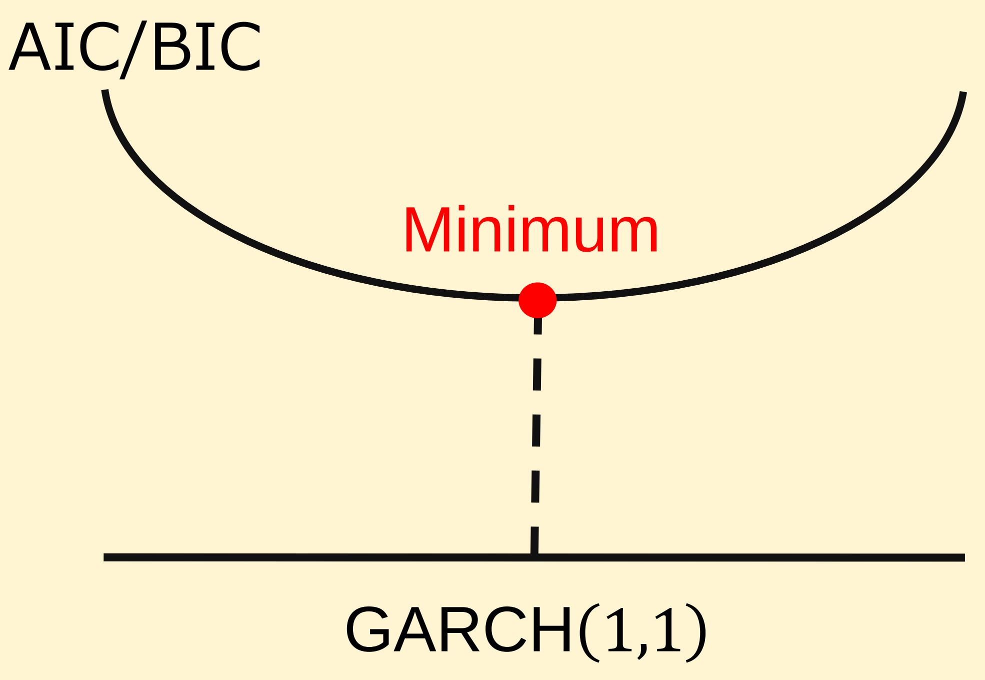
The null hypothesis :
“ there is no autodorrelation (i.e. the time series is white noise).”

Test statistics :
$$Q = n(n+1)\sum_{k=1} \rho(k)^2/n-k$$

Model evaluation using AIC and BIC

- Before estimating the parameters, we first evaluate whether the GARCH(1,1) model used is appropriate by performing model selection.
- We apply various GARCH-type models to the daily returns data for the Air Transp. and Elec. Appl., using the sample period from 16 September 2019 to 15 September 2020.

	Air Transportation		Electric Appliances	
	AIC	BIC	AIC	BIC
GARCH(0,1)	-4.4851	-4.4418	-5.4286	-5.3854
GARCH(1,0)	-0.3854	-0.3421	-5.6319	-5.5887
GARCH(1,1)	-4.9128	-4.8551	-5.7762	-5.7185
ARMA(1,0)+GARCH(1,1)	-4.9048	-4.8327	-5.7686	-5.6965
ARMA(1,1)+GARCH(1,1)	-4.8965	-4.8100	-5.7606	-5.6743



These information criteria assess the balance between model fit and the complexity of the parameters, and both criteria indicate that the pure GARCH(1,1) model results in the minimum values, confirming that it is an appropriate model.

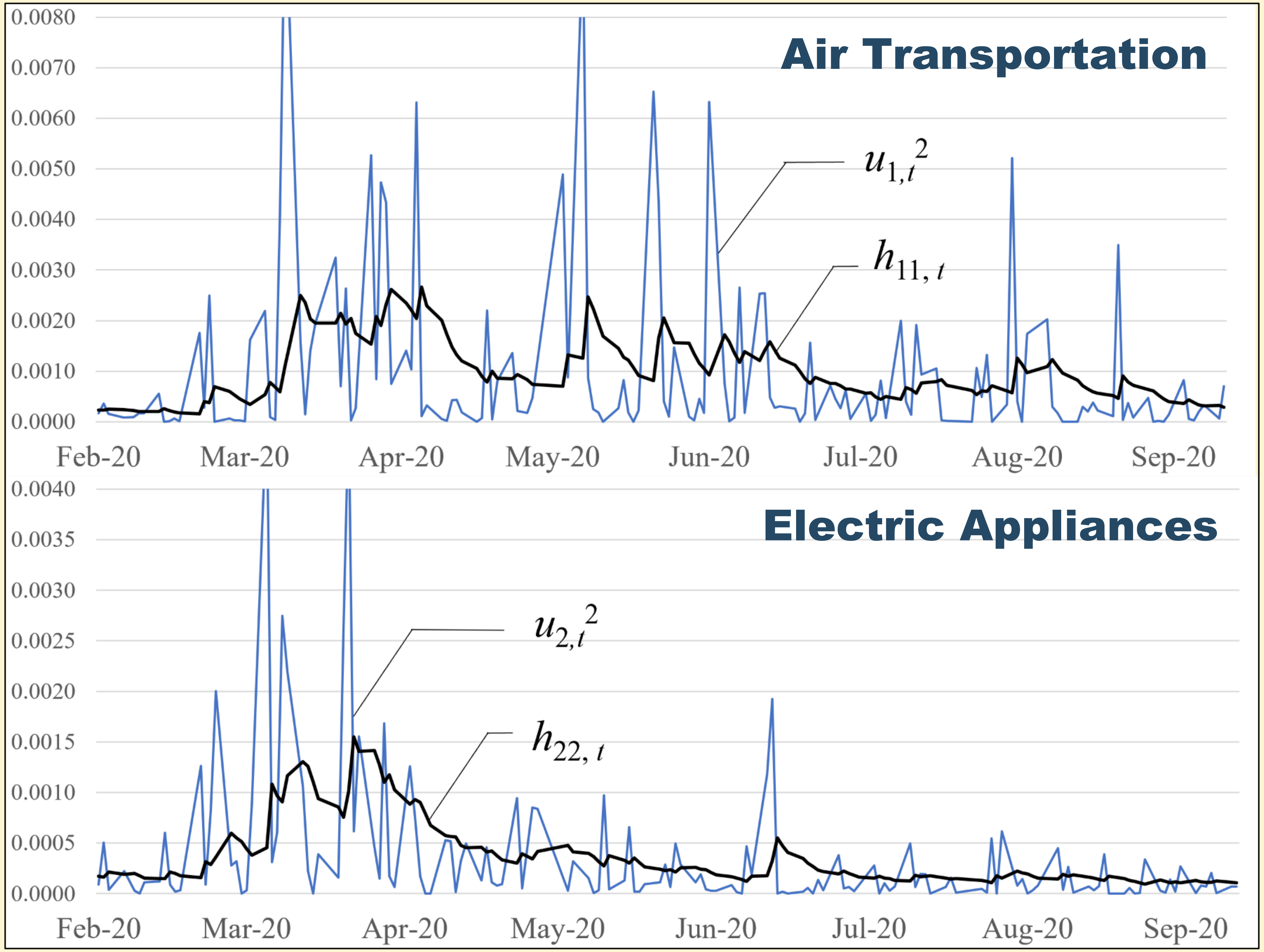
Parameter estimation using DCC-GARCH model

The null hypothesis states that each parameter is equal to zero. If the P-Value is small (typically below 5%), the parameter is considered statistically significant and thus regarded as an essential component of the model.

Air Transportation			Electric Appliances			Bivariate Correlation		
Param.	Estim.	P-Value	Param.	Estim.	P-Value	Param.	Estim.	P-Value
μ_1	-0.0005	0.5385	μ_1	0.0015	0.0232	a	0.0255	0.1983
ω_1	0.0000	0.5370	ω_1	0.0000	0.4736	b	0.9058	0.0000
α_1	0.1461	0.0000	α_1	0.1424	0.0039	-	-	-
β_1	0.8528	0.0000	β_1	0.8473	0.0000	-	-	-

$$\alpha_1 + \beta_1 \sim \ 0.998, \ \ \alpha_2 + \beta_2 \sim \ 0.989, \ \ \ a \ + \ b \ \sim \ 0.931$$

Trend of the conditional variances

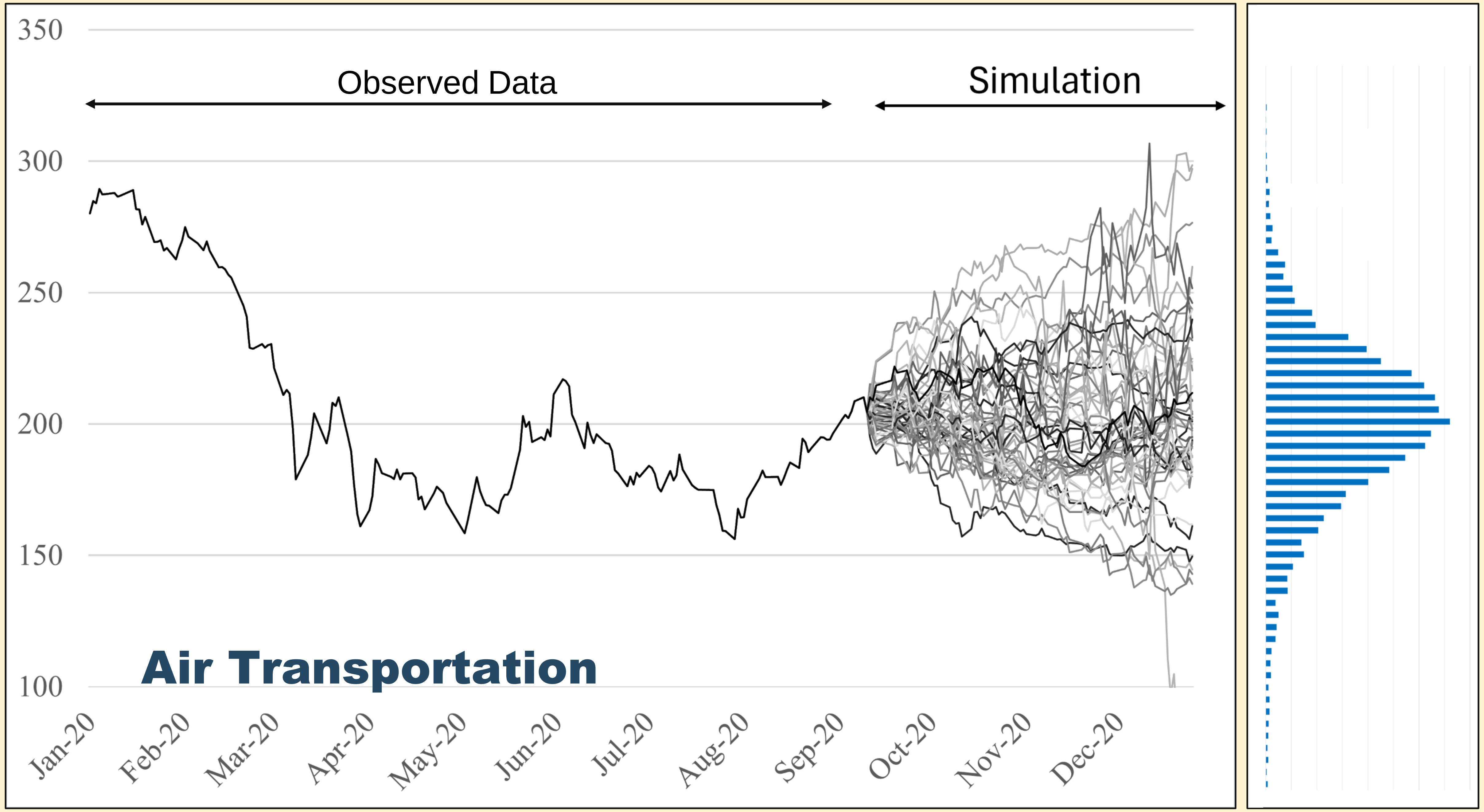


Projection of the Sector Index 72 days ahead

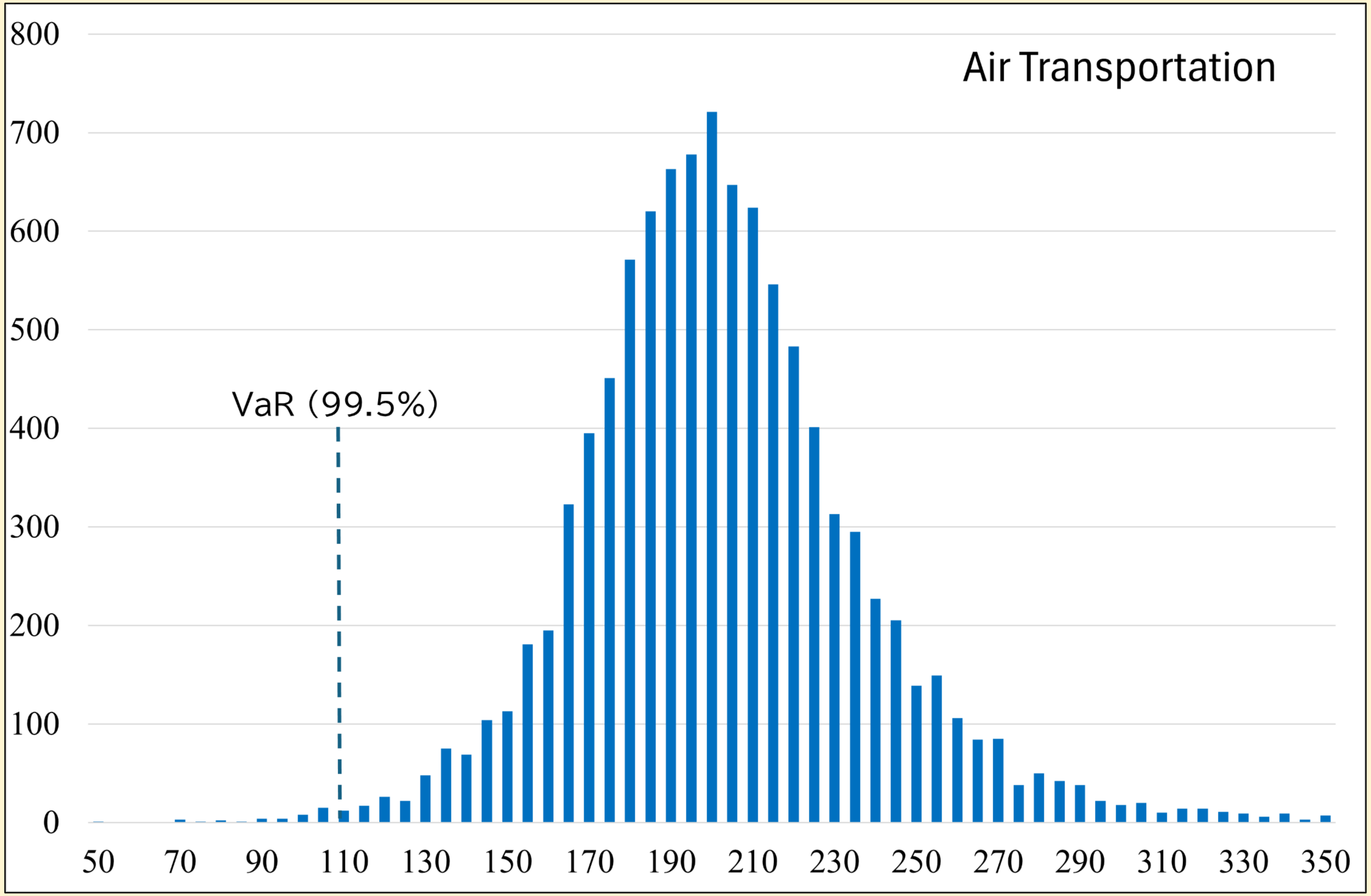
- We estimate the index values for the Air Transp. and Elec. Appl. 72 days after the evaluation date of 15 September 2020. Using the parameter estimates, we sequentially calculate the conditional variances and covariances for the 72-day period, then project the daily returns for the 72 days.

- Furthermore, using the projected daily returns, we convert them to index values.

- By performing N =10,000 simulations, we obtain 10,000 different projected index values for 72 days ahead.



Projection of the Sector Index 72 days ahead



Basic statistics, VaR, Projected Return and Risk

Air Transportation (Sample size:10,000)							
Mean	Q1st	Q3rd	VaR(99.5%)	VaR(95%)	r_A	R_A(99.5%)	R_A(95%)
201.5	178.8	218.9	108.3	149.0	-3.1	96.2	55.5
Electric Appliances (Sample size:10,000)							
Mean	Q1st	Q3rd	VaR(99.5%)	VaR(95%)	r_E	R_E(99.5%)	R_E(95%)
3009.2	2789.3	3200.4	2097.1	2482.5	342.6	569.5	184.1

Actual Index Values as of the evaluation date, 15 September 2020
- Air Transp. Sector : 204.5
- Electric Appl. Sector : 2666.6

Calculation of Projected Returns and Risks
Example: Air Transp. Sector

Projected Return r_A = 201.5 - 204.5 = -3.1

Projected Risk R_A(99.5%) = 204.5 - VaR(99.5%) = 204.5 – 108.3 =96.2

Risk-Return Efficiency of the Asset Portfolio

Post-Reconstructed Asset Balance			
Air Transp.	(i) Market Value at Val. Date	$I_{A,0}$	204.5
	(ii) Market Value in 72 Days	I_A	201.5
	(iii) Projected Return	r_A	−3.1
	(iv) Projected Risk	R_A	96.2
	(v) Sharp Ratio	r_A/R_A	−0.032
Elec. Appl.	(i) Market Value at Val. Date	$k\ I_{E,0}$	657.6
	(ii) Market Value in 72 Days	$k\ I_E$	742.1
	(iii) Projected Return	$k\ r_E$	84.5
	(iv) Projected Risk	$k\ R_E$	140.5
	(v) Sharp Ratio	r_E/R_E	0.601
Correlation Effect		C	44.3
Total	(i) Market Value at Val. Date	$I_{A,0} + k\ I_{E,0}$	862.2
	(ii) Market Value in 72 Days	$I_A + k\ I_E$	943.6
	(iii) Projected Return	$r_A + k\ r_E$	81.4
	(iv) Projected Risk	$R_A + k\ R_E - C$	192.4
	(v) Sharp Ratio	$(r_A + k\ r_E)/(R_A + k\ R_E - C)$	0.423

Ⅳ. Verification of GARCH Model’s Effectiveness

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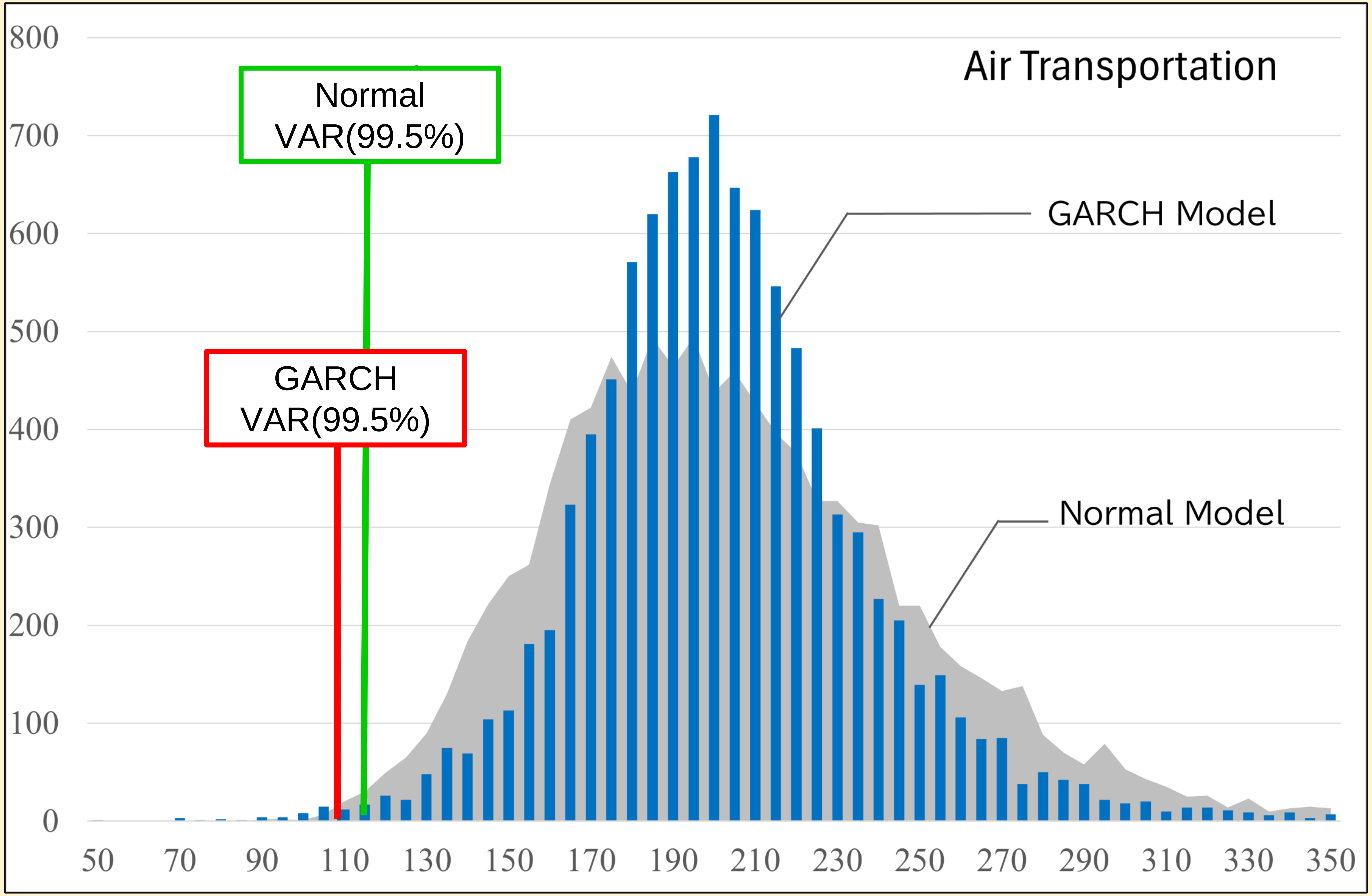
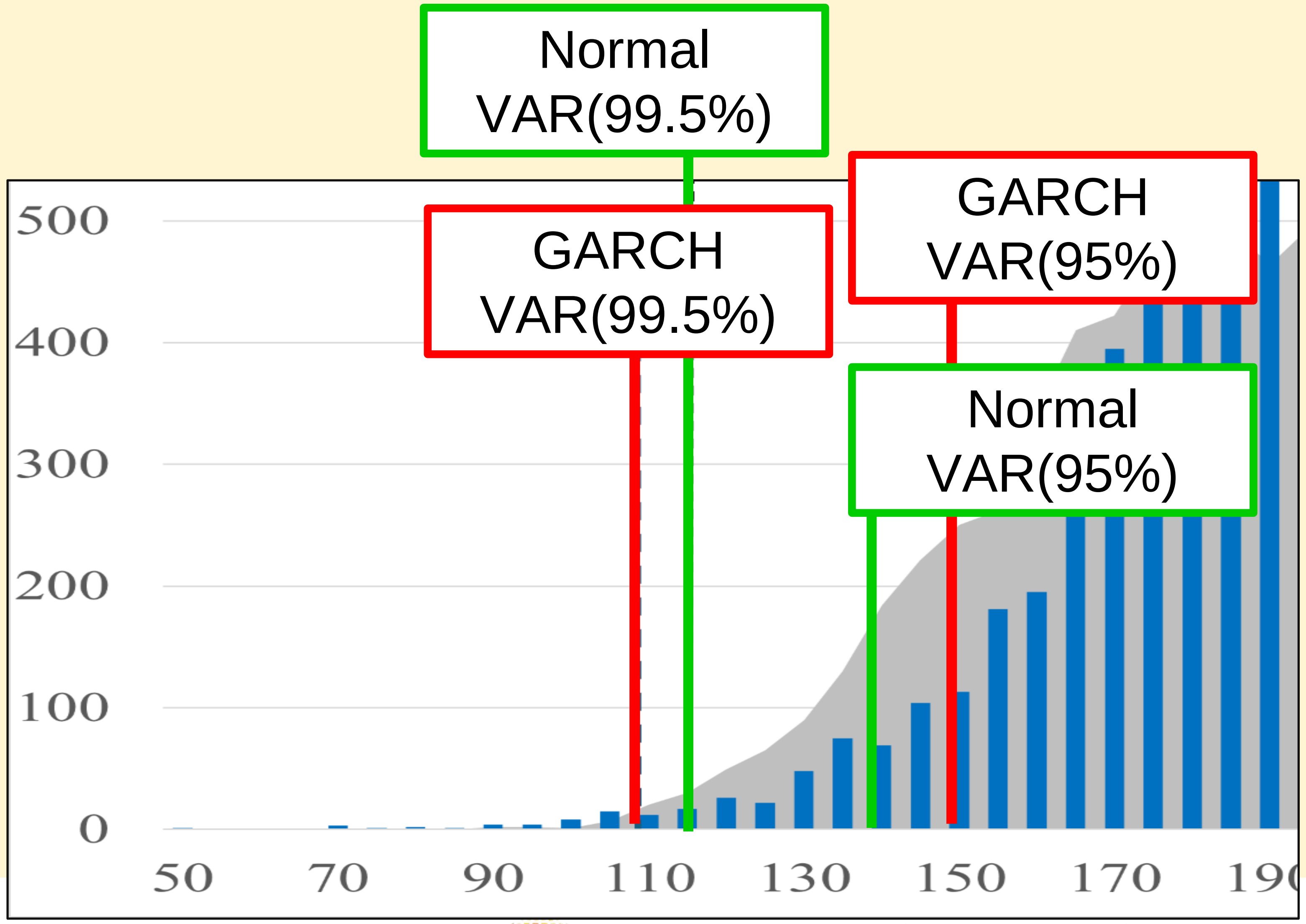
São Paulo 2025

Histogram of Projected the Sector Index 72 days ahead



Basic statistics, VaR, Projected Return and Risk

GARCH Model (Sample size:10,000)							
Mean	Q1st	Q3rd	VaR(99.5%)	VaR(95%)	r_A	R_A(99.5%)	R_A(95%)
201.5	178.8	218.9	108.3	149.0	-3.1	96.2	55.5
Normal Model (Sample size:10,000)							
Mean	Q1st	Q3rd	VaR(99.5%)	VaR(95%)	r_E	R_E(99.5%)	R_E(95%)
201.5	170.1	228.3	113.1	137.8	-3.1	91.4	66.7



Ⅴ. Conclusion

- This study proposed a risk management approach for equity assets held by life insurance companies during a pandemic.
- For life insurers, accurate measurement of risk levels, as well as the assessment of returns and capital, is vital for internal management.
- During the pandemic, volatility in daily equity returns increased sharply and remained elevated.
- The study used the TOPIX index and the DCC-GARCH model to reconstruct an optimal portfolio.
- The impact of the proposed techniques on equity portfolios was quantitatively analysed from a risk assessment perspective.

Lessons from Past Crises: A Call to Actuaries

“The only thing that was useful was what we had prepared for. Simply being prepared was not enough.”

— Crisis management manual, MLIT Japan, reflecting on the 2011 Great East Japan

- ➢ The COVID-19 pandemic in 2020 reaffirmed this truth
- ➢ Crises are unpredictable and often beyond our assumptions
- ➢ As actuaries, we must:
  - ✓ Learn from past global and local crises
  - ✓ Share insights across borders
  - ✓ Lead preparation for the next unforeseen event

Thank you! Obrigado!

Any Questions?

Contact Us
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