Information Value of Weekly Weather Forecasts: An Empirical Analysis of Electricity Price Forecasting and Forward Arbitrage

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Research Overview

Background and purpose

- Despite the need for **price forecasts** one week ahead, there are few previous studies

We develop:
1. **forecasting methods for the weekly average JEPX spot price**
2. **arbitrage trading strategies in the JEPX forward market**

Research questions

For 1, which modeling approach is more accurate?
- **(i)** For weather value: **measured value** vs. forecasted value
- **(ii)** For price time series: **logarithmic series** vs. original series
- **(iii)** For probability distribution model: **Quantile Regression** vs GARCH

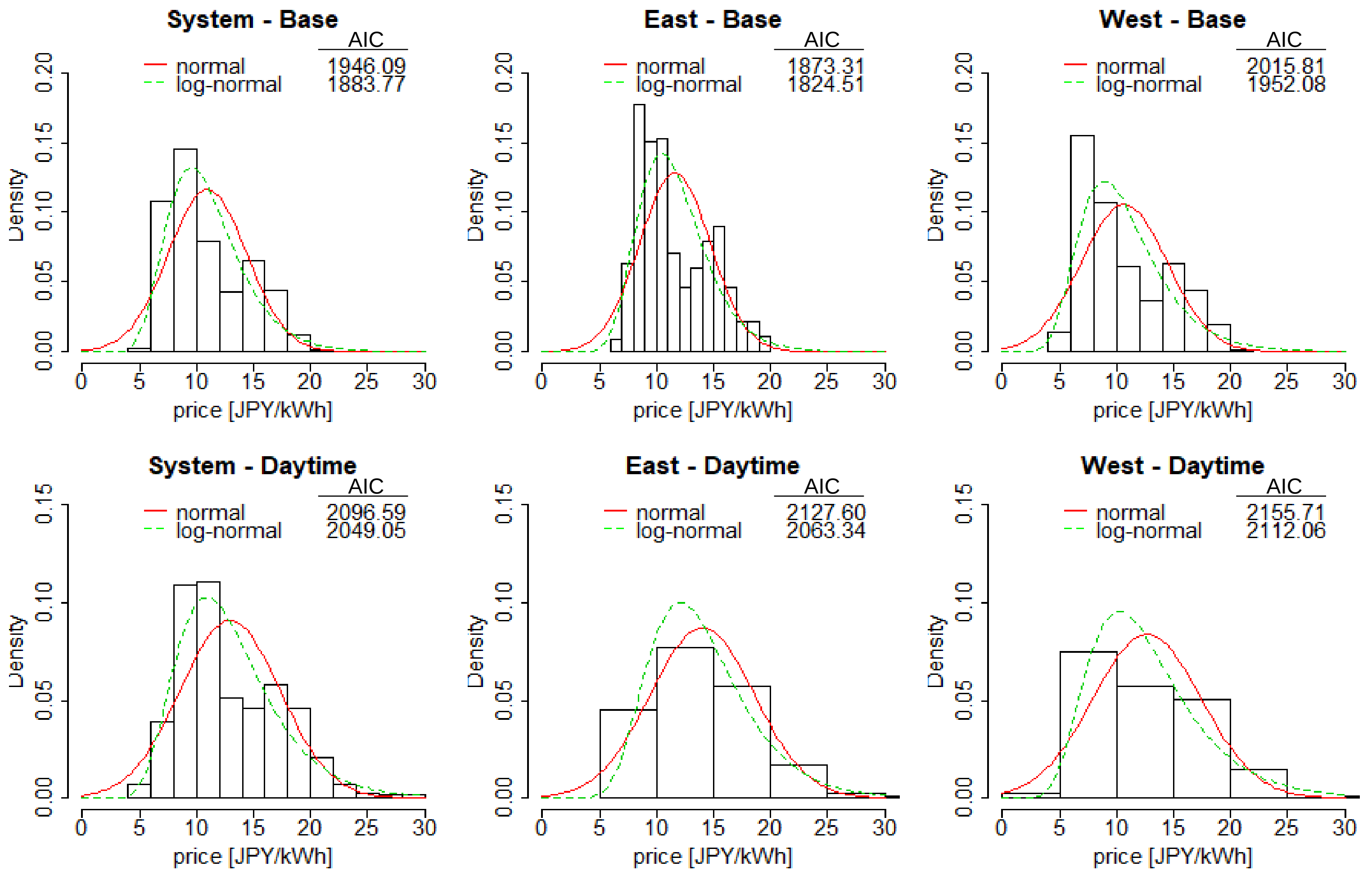
For 1 2, **(iv)** How much is the **information value of the weekly weather forecast**?

In particular...

- Examine **modeling methods to enhance the information value** of weekly weather forecasts
- Identify the **monetary value of weekly weather forecasts in arbitrage trading**

Weekly average price density

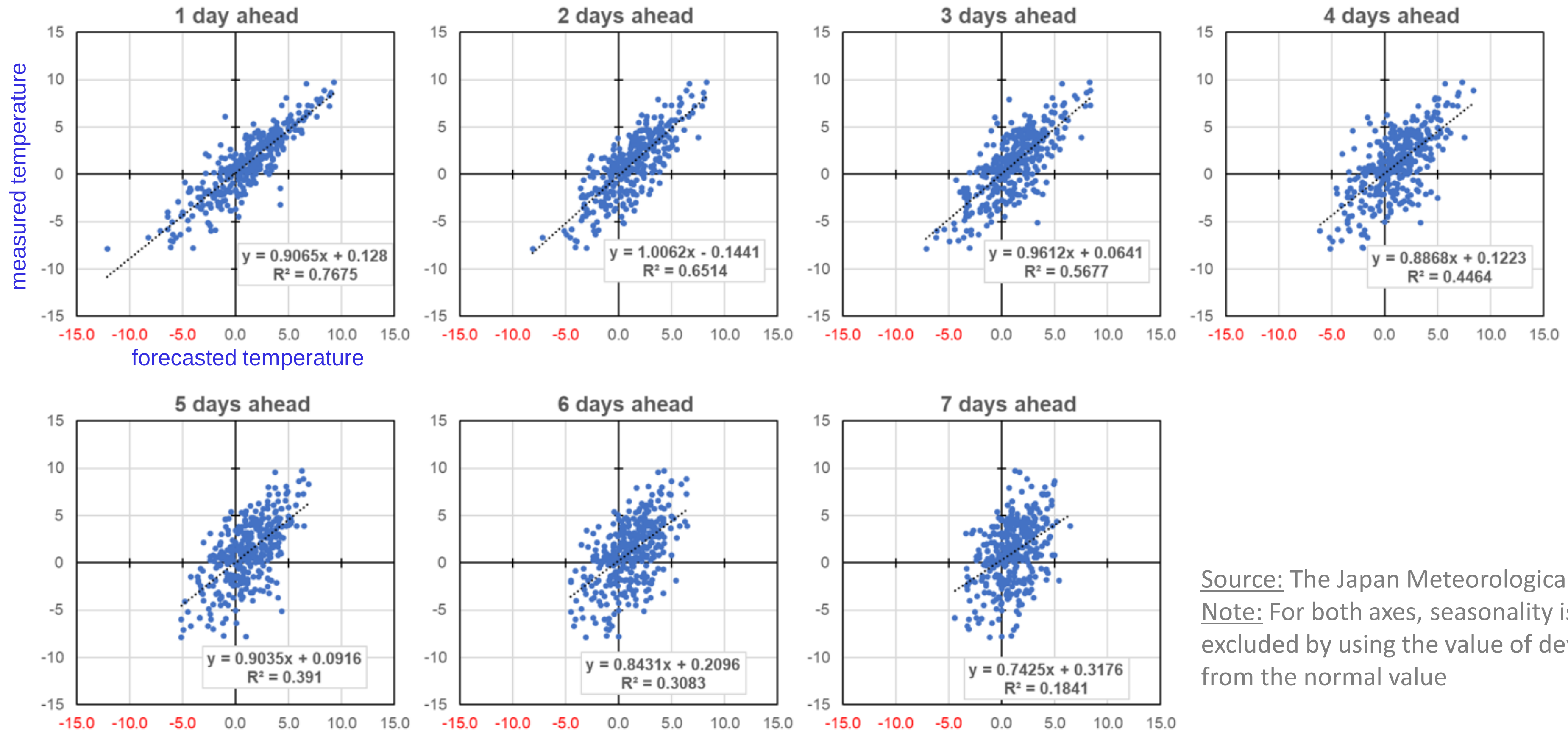
- The weekly average price density (of JEPX) is generally skewed to the right and has a shape closer to the lognormal distribution than the normal distribution



Explanatory power for weekly temperature forecast

◆ The accuracy of the forecasted temperature is about **76% for the day-ahead forecast** but drops to about **18% for the 7-day-ahead forecast**

Explanatory power for weekly temperature forecasts (by forecast horizon; Tokyo, 2019)

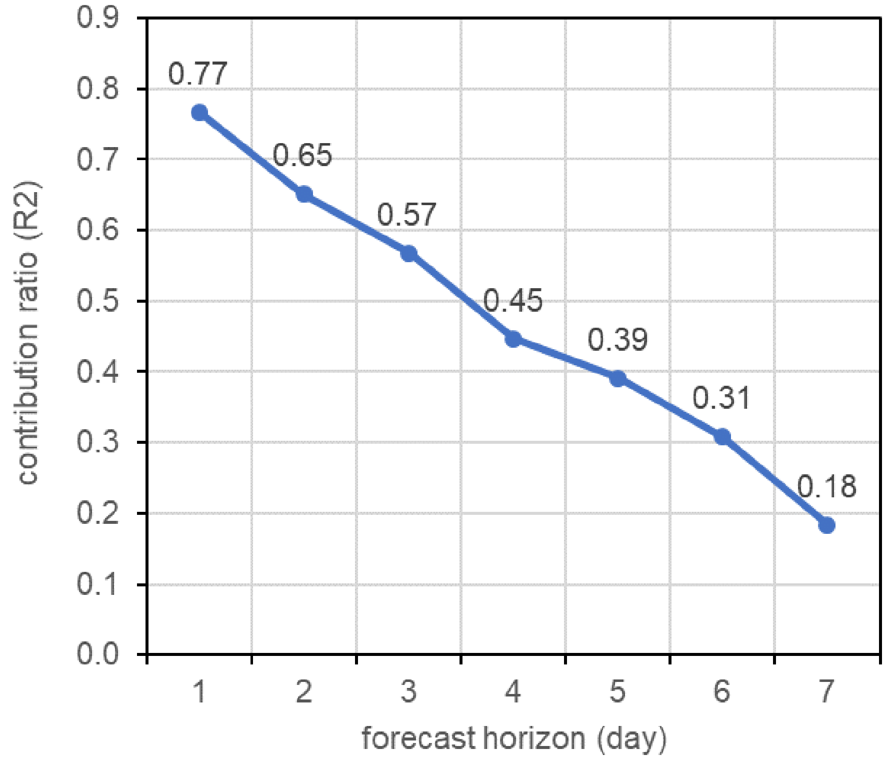


Source: The Japan Meteorological Agency
Note: For both axes, seasonality is excluded by using the value of deviation from the normal value

Explanatory power for weekly temperature forecast

- ◆ Plotted the R2 extracted from the scatter plot on the previous page
- ◆ As the forecast horizon becomes longer, the forecast accuracy decreases linearly
  - ➢ The weather forecast (temperature forecast) that exceeds 7 days hardly hits

Explanatory power for weekly temperature forecasts (Tokyo, 2019)

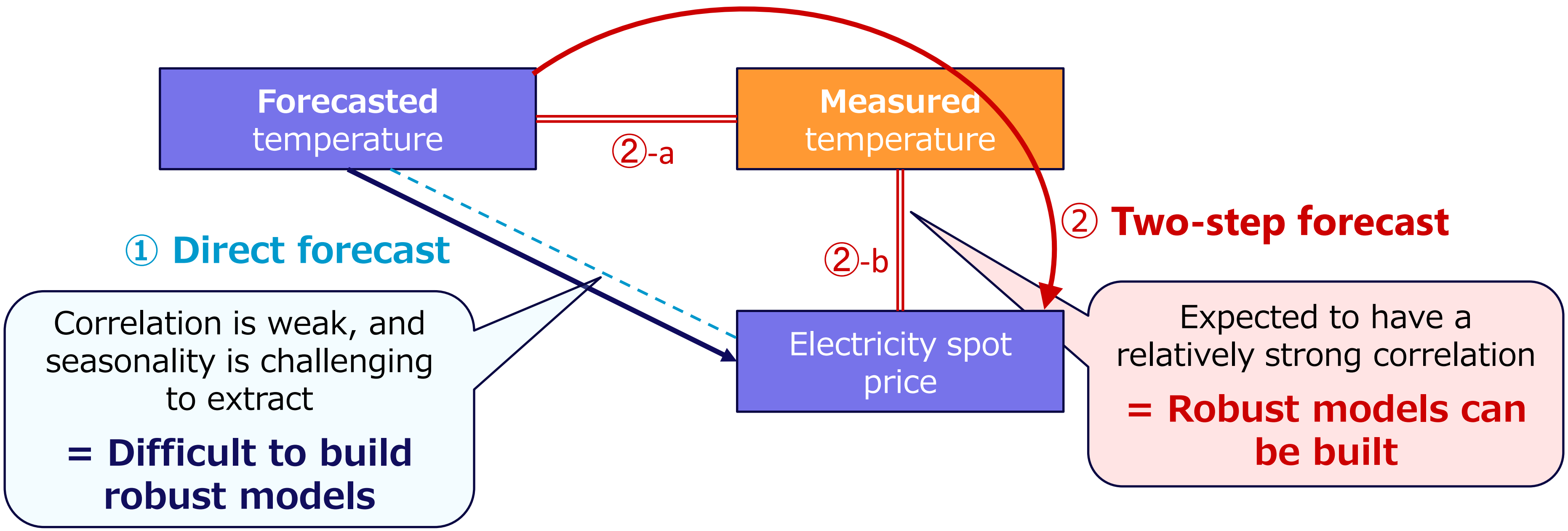


Model comparison (i): Direct forecast vs. two-step forecast

- Weather "forecasts" are often used directly in electricity price forecasting: ① **Direct forecast**
  - However, the correlation between the weather "forecast" and the spot price is small
- Therefore, we combined the following two models:
  - a model that forecasts the temperature density from the forecasted temperature ②-a
  - a model that forecasts the electricity price from the measured temperature ②-b

② **Two-step forecast**

Conceptual diagram of two-step forecast



Model comparison (ii): Original series vs. Logarithmic series

- "Logarithmic series" model is constructed in addition to the "original series" ($\because S_t > 0$)
- For the average spot price S_t of t^{th} week, the following two types of OLS are constructed

Original series model: $S_t = \alpha S_{t-1} + \beta(t) G_t + f(t) + g(t)\epsilon_t + \eta_t$

Logarithmic series model: $\log(S_t) = \alpha \log(S_{t-1}) + \beta(t) \log(G_t) + f(t) + g(t)\epsilon_t + \eta_t$

Outline of symbols in formulas and data to be used

Symbols	Description	Data source
S_t	Electricity spot price	Japan Electric Power Exchange (JEPX)
G_t	LNG spot price	Platts JKM spot price
β, f, g	Seasonal trend (Fourier series expansion) and annual change trend	-
ϵ_t	Temperature deviation from the normal value ($\epsilon_t \coloneqq Temp_t - Temp\_norm_t$)	The Japan Meteorological Agency
η_t	Residual term with average of 0	-

Model comparison (iii): Quantile Regression vs. GARCH

- **For density forecast**, we compare two models, **Quantile Regression (QR) and GARCH**
- We use the **same form of model formulas** as defined on the previous page:

Original series model: $S_t = \alpha S_{t-1} + \beta(t) G_t + f(t) + g(t)\epsilon_t + \eta_t$

Logarithmic series model: $\log(S_t) = \alpha \log(S_{t-1}) + \beta(t)\log(G_t) + f(t) + g(t)\epsilon_t + \eta_t$

- In **Quantile Regression**, the quantile of the price density is calculated directly
  - In this study, 5th percentile interval (the quantiles at {5,10,15,..., 95}) are calculated
- In **GARCH**, volatility (standard deviation) is estimated from past time series data
  - In this study, we obtain the standard deviation of the residuals one period ahead by applying GARCH (1, 1) to the residual term η_t obtained from the OLS

Bias correction in forecasts using logarithmic series

- In log-price OLSs, it is not appropriate to use the predictor parts of the model by just converting them to the original price ($e^{\gamma(t)+g(t)\widehat{\epsilon_t}}$), as the desired forecast values
- Such forecast method includes a **downward bias** due to not considering the variances of the random variables; therefore, we consider **"bias correction"** as follows:

$$log(S_t) = \gamma(t) + g(t)\epsilon_t + \eta_t$$

$$\gamma(t) \coloneqq \alpha log(S_{t-1}) + \beta(t) log(G_t) + f(t)$$

$$\hat{S}_{t|t-1} \neq e^{\gamma(t)+g(t)\widehat{\epsilon_t}}$$

$$\begin{aligned}\hat{S}_{t|t-1} &= \mathrm{E}\left[S_t \middle| \mathcal{F}_{t-1}\right] \\ &= \mathrm{E}\left[e^{\gamma(t)+g(t)\epsilon_t+\eta_t} \middle| \mathcal{F}_{t-1}\right] \\ &= e^{\gamma(t)}\mathrm{E}\left[e^{g(t)\epsilon_t} \middle| \mathcal{F}_{t-1}\right]\mathrm{E}\left[e^{\eta_t} \middle| \mathcal{F}_{t-1}\right] \\ &= e^{\gamma(t)+g(t)\widehat{\epsilon_t}+\left\{\left(g(t)\sigma_{\epsilon,t}\right)^2+\left(\sigma_{\eta,t}\right)^2\right\}/2}\end{aligned}$$

assuming that the random variables ϵ_t and η_t follow normal distributions independent of each other

- **The appropriate forecast price is $e^{\left\{\left(g(t)\sigma_{\epsilon,t}\right)^2+\left(\sigma_{\eta,t}\right)^2\right\}/2}$ times larger** than the forecast without bias correction
- The forecasted values of $\sigma_{\epsilon,t}$ and $\sigma_{\eta,t}$ are obtained by applying the GARCH (1,1) model

Empirical analysis – Used data

Used data and sources

- Spot price $\boldsymbol{S_t}$ and forward price $\boldsymbol{F_t}$ [JPY/kWh]: JEPX system, Tokyo/Kansai area price
- LNG spot price $\boldsymbol{G_t}$ [JPY/MMBtu]: Platts JKM spot price
- Measured temperature $\boldsymbol{Temp_t}$ [℃]: Maximum temperature measured by the JMA*
- Forecasted temperature $\boldsymbol{\widehat{Temp}_t}$ [℃]: Maximum temperature forecasted by the JMA*

*the Japan Meteorological Agency

In sample period

- the past three years in a "weekly rolling" manner

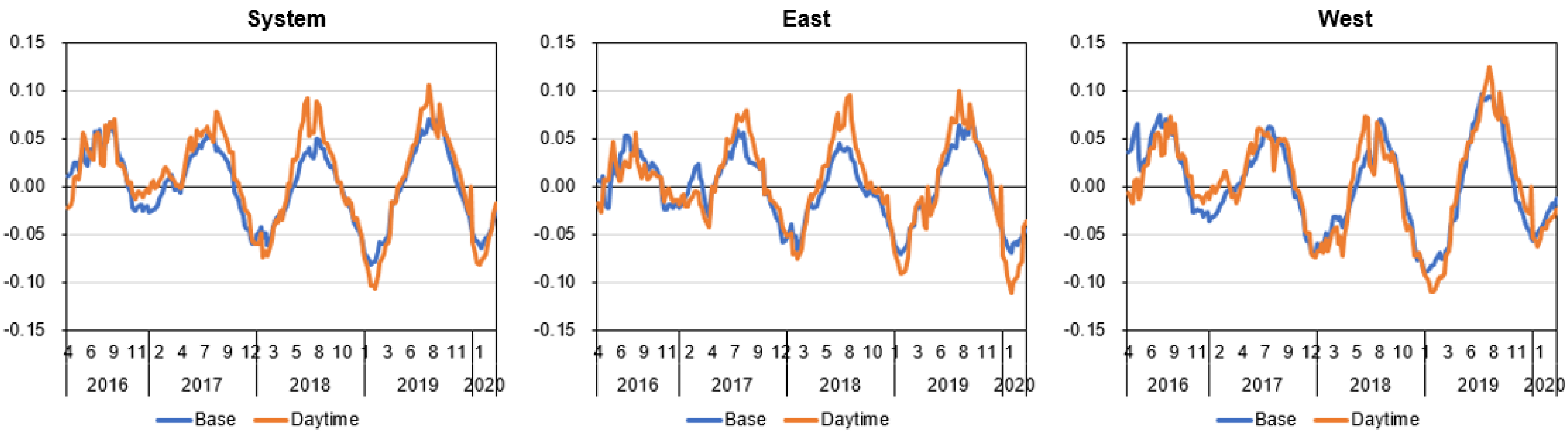
Out-of-sample period

- **April 1st, 2016 - March 31st, 2020** (4 years)

Estimated temperature sensitivity

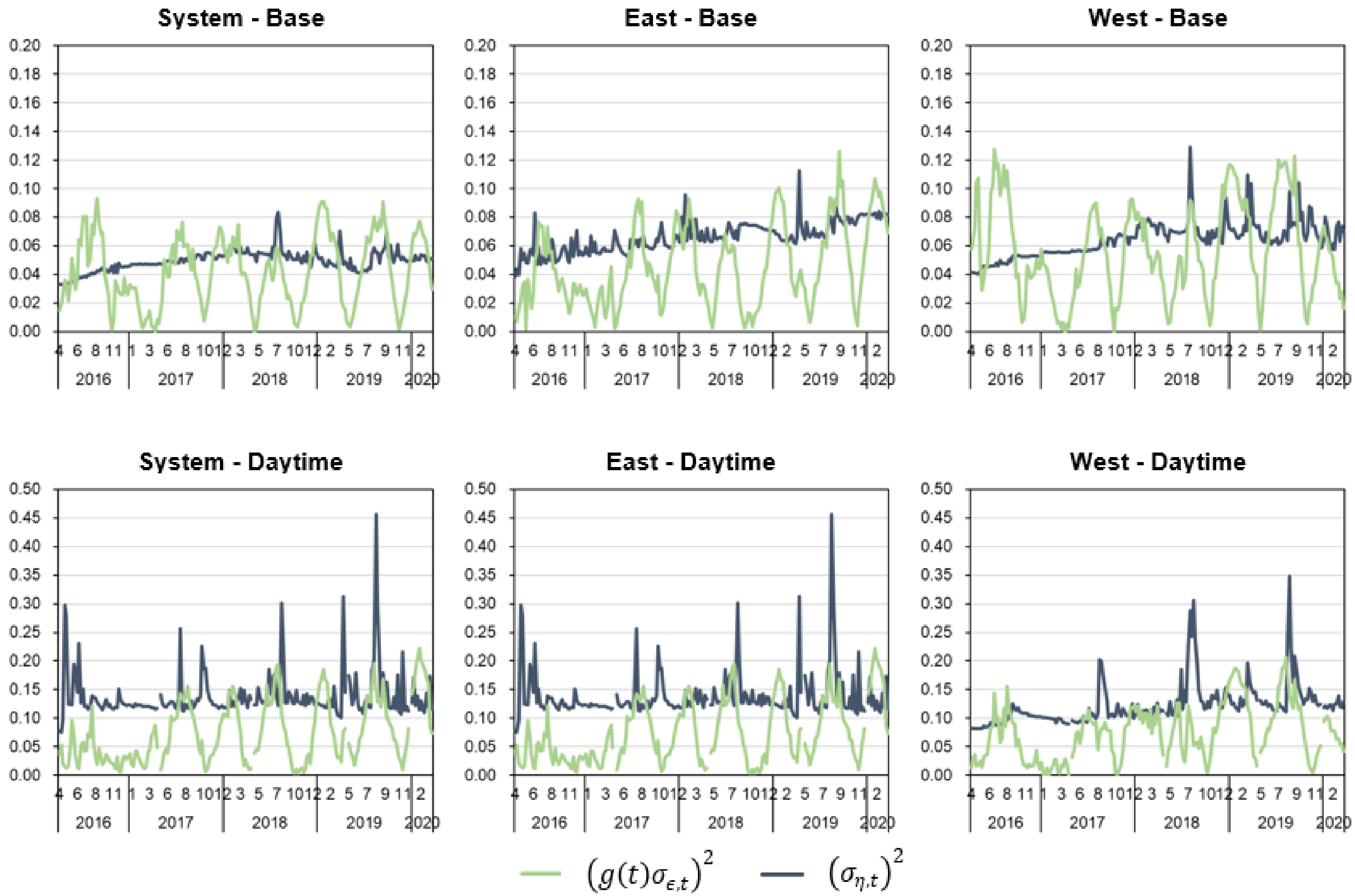
- Temperature sensitivity of the spot price is **negative in winter and positive in summer**
- The absolute value of sensitivity is larger on the daytime load than on the base load
- The sensitivities' **amplitudes have increased significantly year by year**
  - Probably due to the recent expansion of renewable energies (especially PV in Japan)

Time-series transition of estimated temperature sensitivity



Estimated $\left(g(t)\sigma_{\epsilon,t}\right)^2$ and $\left(\sigma_{\eta,t}\right)^2$ for bias correction

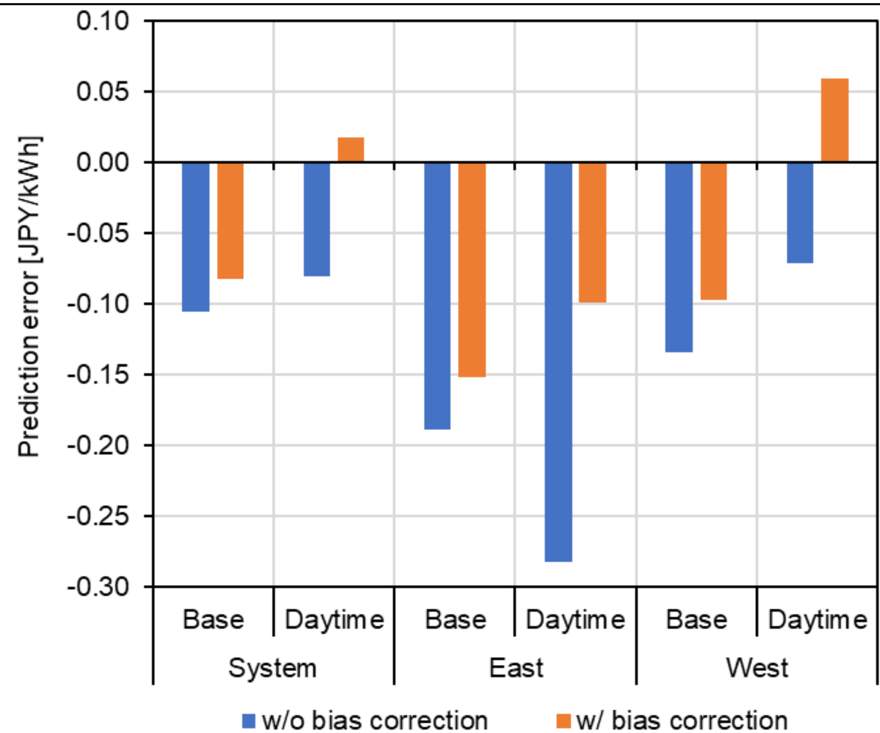
◆ Both variances have expanded over time due to the increasing competitiveness since the full liberalization of the market in 2016, in addition to the expansion of renewable energies



Verification of bias correction effect

- In the **"forecast w/o bias correction,"** when the predictor of the logarithmic series OLS was used as it was, the forecast errors were negative in all six cases (**downward biases**)
- In the **"forecast w/ bias correction,"** the forecast values were revised upward, and the forecast errors **approached 0 as a whole**

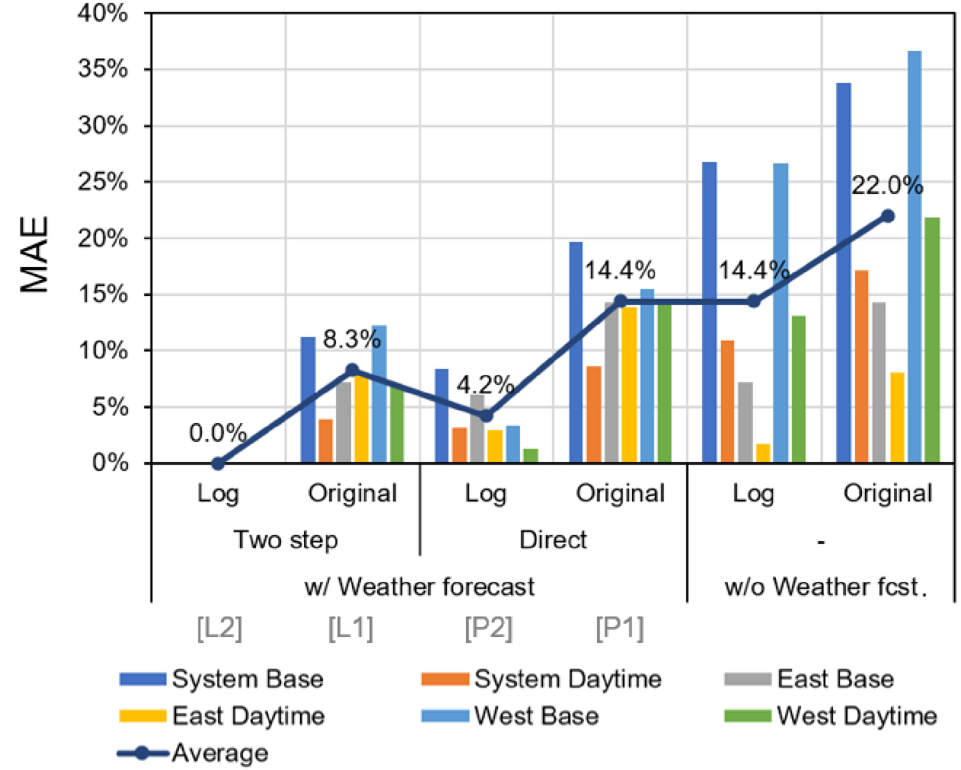
Average forecast error with and without bias correction



Forecast error verification: mean value forecast

- For verifying the forecast error of the mean value forecast, (i) direct forecast vs. two-step forecast and (ii) logarithmic series vs. original series are compared
- As a result, **the two-step forecast is generally more accurate** than the direct forecast, and the **logarithmic series model is more accurate** than the original series model

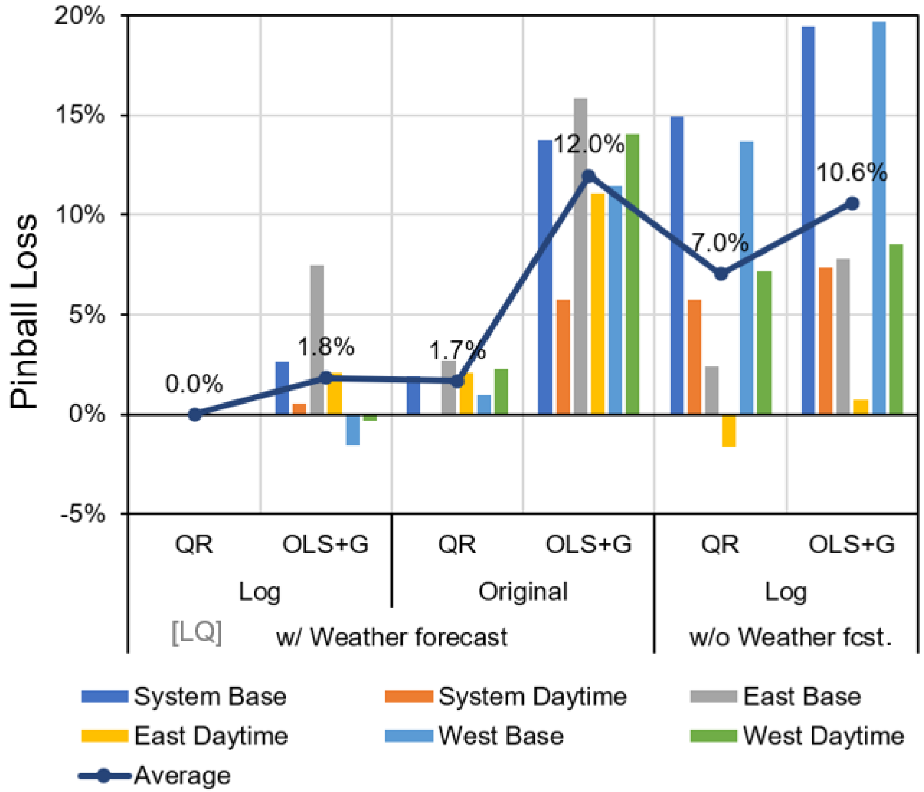
Comparison of prediction error (mean absolute value error: MAE)



Forecast error verification: density forecast

- For density forecast, (ii) log series vs. original series and (iii) QR vs. GARCH are compared
- As a result, in general, the **log series model is more accurate** than the original series model, and the **QR is more accurate** than the GARCH

Comparison of density forecast accuracy (Pinball Loss: PL)

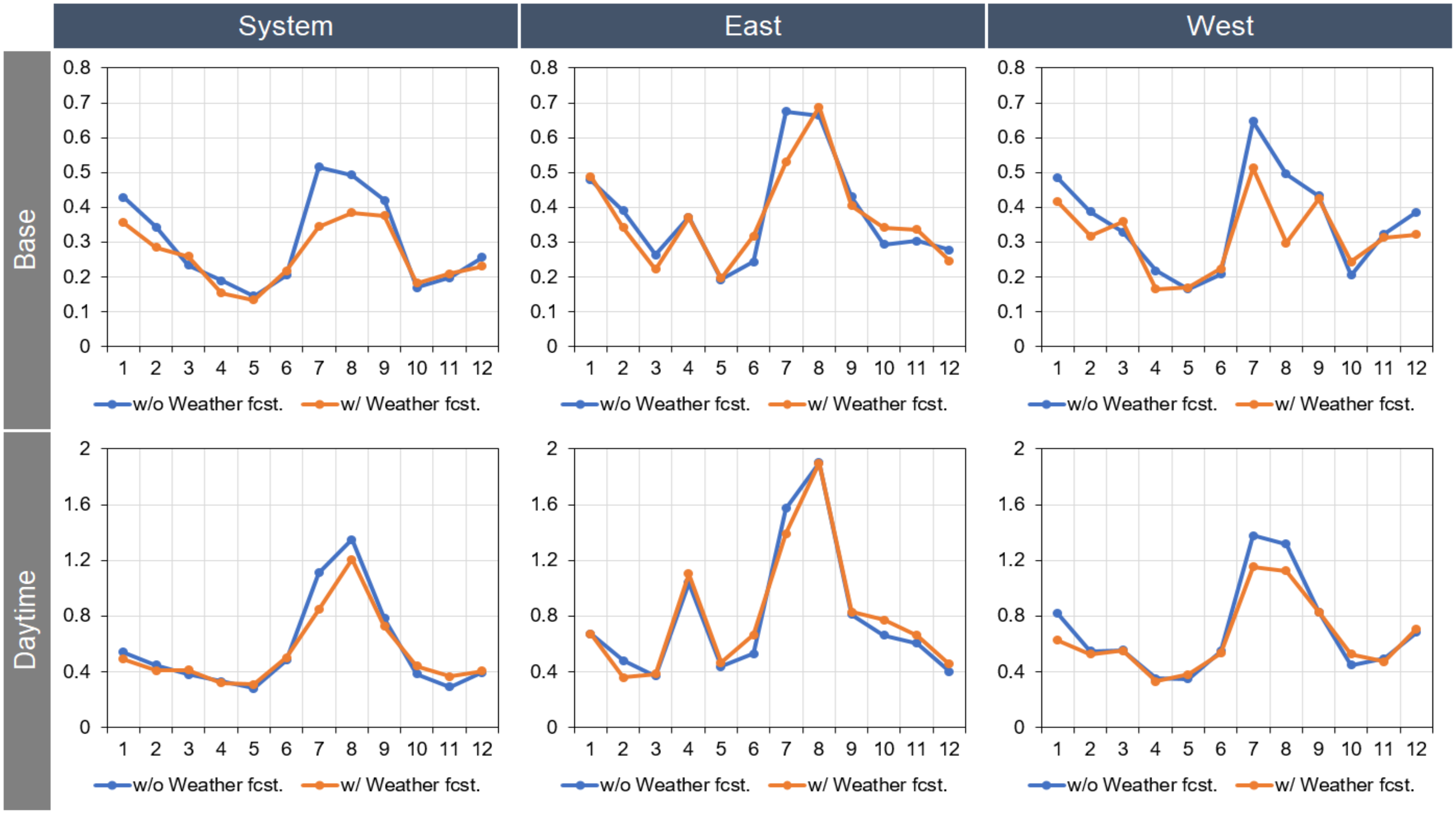


* "OLS + G" means OLS and GARCH. The price density is forecasted by combining these models.

Effect of improving forecast accuracy by weather forecast

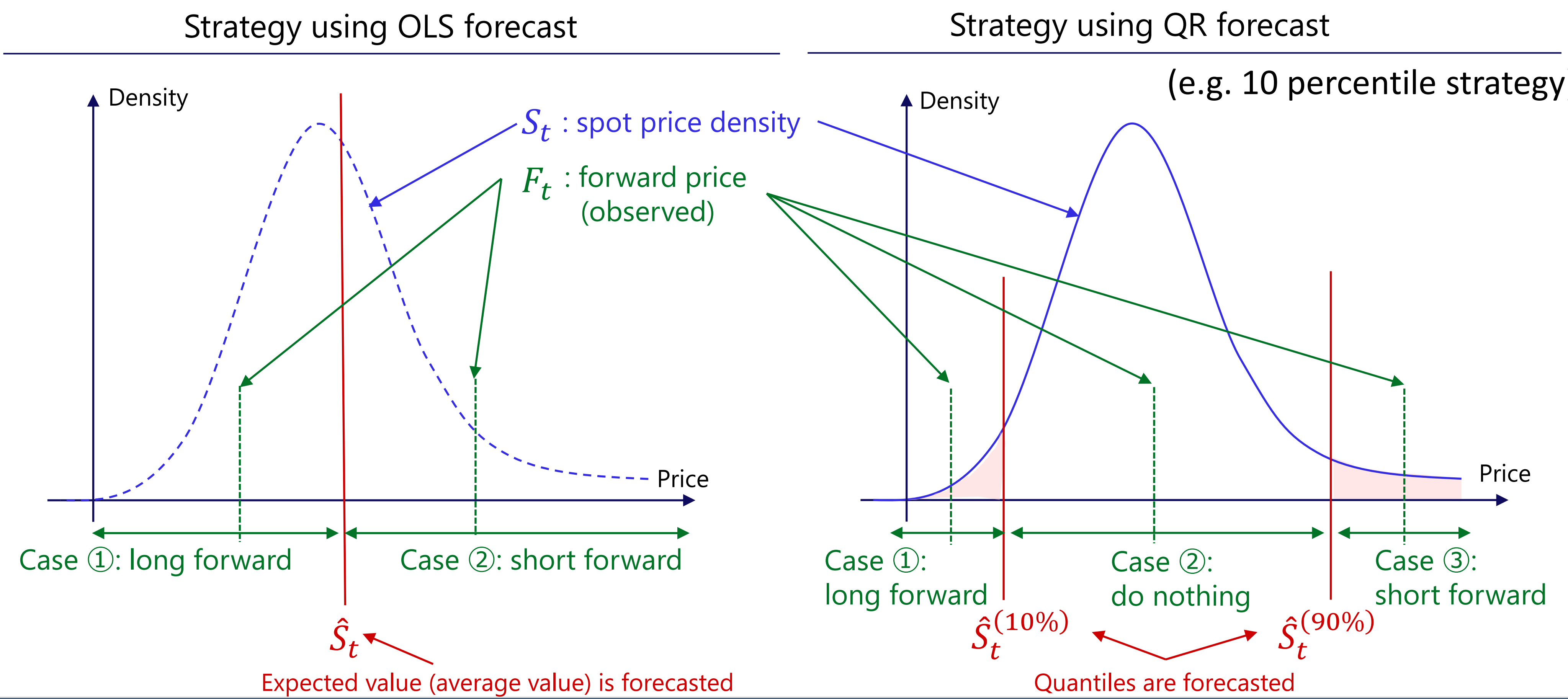
◆ When the weather forecast is incorporated, the **prediction error is reduced mainly in the summer** compared to when the weather forecast is not incorporated

Monthly density forecast error (PL) comparison



Application to arbitrage strategy in the forward market

- Compare two arbitrage strategies: trading based on OLS forecasts and QR forecasts
- The QR forecasting strategy incorporates **quantile forecasts** into trading decisions, allowing traders to **trade according to their risk tolerance**



Profit and loss risk brought about by arbitrage

- **Risk of loss**: lower with quantile prediction (QR) strategy than with OLS
- **Profit**: Higher with OLS ➔ **Trade-off between risk reduction and return capture**
- In the JEPX forward market, there is an **arbitrage opportunity of about 10% of the price**

Profit and loss risk brought about by arbitrage (by bidding strategy / 3 areas / 2 loads)

Load	Area	N	Model	Percentile	N_{arb}	N_{loss}	Loss	VaR 95%	CVaR 95%	Mean profit		p-value	
Base	System	35	QR	5%	19	2	6%	-0.18	-0.28	0.59	(6.6%)	0.0013	**
				10%	23	2	6%	-0.18	-0.28	0.82	(9.1%)	0.0002	**
				25%	28	2	6%	-0.18	-0.28	0.96	(10.7%)	0.0000	**
			OLS	-	35	6	17%	-2.35	-2.45	0.81	(9.0%)	0.0012	**
	East	17	QR	5%	3	0	0%	0.00	0.00	0.23	(2.3%)	0.1227	
				10%	4	0	0%	0.00	0.00	0.24	(2.4%)	0.1005	
				25%	10	2	12%	-1.70	-1.70	0.73	(7.4%)	0.0525	*
			OLS	-	17	5	29%	-1.70	-1.70	1.04	(10.6%)	0.0437	**
	West	7	QR	5%	2	0	0%	N/A	N/A	0.32	(3.7%)	0.2949	
				10%	3	0	0%	N/A	N/A	0.57	(6.7%)	0.1418	
				25%	6	0	0%	N/A	N/A	0.89	(10.4%)	0.0192	**
			OLS	-	7	0	0%	N/A	N/A	1.07	(12.5%)	0.0043	**
Daytime	System	78	QR	5%	19	2	3%	0.00	-0.84	0.68	(6.4%)	0.0022	**
				10%	25	5	6%	-0.42	-1.42	0.73	(6.9%)	0.0020	**
				25%	42	13	17%	-1.89	-2.18	0.84	(7.9%)	0.0021	**
			OLS	-	78	25	32%	-1.75	-2.09	1.34	(12.6%)	0.0000	**
	East	19	QR	5%	2	0	0%	0.00	0.00	0.04	(0.3%)	0.1901	
				10%	3	0	0%	0.00	0.00	0.08	(0.7%)	0.1261	
				25%	10	2	11%	-0.88	-0.88	1.05	(8.8%)	0.0776	*
			OLS	-	19	6	32%	-12.81	-12.81	0.9	(7.6%)	0.3926	
	West	22	QR	5%	6	0	0%	0.00	0.00	0.82	(7.9%)	0.0215	**
				10%	6	0	0%	0.00	0.00	0.82	(7.9%)	0.0215	**
				25%	13	3	14%	-1.42	-1.42	1	(9.6%)	0.0125	**
			OLS	-	22	7	32%	-6.43	-6.43	0.67	(6.5%)	0.2238	

Arbitrage profit with and without weather forecast

- Compared arbitrage profits by QR/OLS strategy with and without weather forecasting
- Arbitrage profit increased by **1.5 to 3.3 times** with the use of weekly weather forecasts

Arbitrage profit with and without weather forecast (by bidding strategy / 3 areas / 2 loads)

Summary

- This study proposed "**forecasting methods** for the weekly average JEPX spot price" and "**arbitrage trading strategies** in the JEPX forward market"
- We **constructed several models** and verified the forecast accuracy of the weekly average spot price and found the following results:
  - **Two-step models** using actual temperatures as a mediator have higher forecast accuracy than models that use forecasted temperatures directly
  - **Log-series models** have higher forecast accuracy than price-series models
  - **QR**, which can model any distribution shape, has higher forecast accuracy than GARCH, which assumes a normal distribution
- The use of **weekly weather forecasts** contributes significantly to **both "improving forecast accuracy" and "earning profits from forward contracts."**
- The value of weather information can be increased through modeling ingenuity, **yielding gains of 1.5 to 3.3 times** in the case of JEPX forward arbitrage