



HUB-FS Working Paper Series

FS-2025-E-002

Seasonal variation in the impact of solar power generation on electricity price level and variability

Nobuhiro Fuke

Graduate School of Science, Technology and Innovation,
Kobe University

Kazuhiko Ohashi

Graduate School of Business Administration,
Hitotsubashi University
and
Tokyo Tech Academy of Energy and Informatics,
Tokyo Institute of Technology

This version: August 24, 2025

All the papers in this Discussion Paper Series are presented in the draft form. The papers are not intended to circulate to many and unspecified persons. For that reason any paper can not be reproduced or redistributed without the authors' written consent.

Seasonal variation in the impact of solar power generation on electricity price level and variability

Nobuhiro Fuke^a and Kazuhiko Ohashi^{b,c*}

This version: August 24, 2025

Abstract

This study employs quantile regression to examine the impact of solar photovoltaic (PV) power generation on both the level and variability of wholesale electricity prices. The analysis is based on data from April 2016 to March 2020 for the Kyushu region of Japan, which is particularly suitable for this study given its high solar PV penetration, limited interconnection capacity with other regions, and distinct seasonal variations. Results confirm the merit-order effect and demonstrate a novel finding of seasonal variation in the impact of solar PV power generation on electricity price variability: increased solar PV power generation is associated with reduced price variability in spring and summer, but not in autumn and winter. This seasonal divergence is attributable to changes in the relationship between electricity demand and solar PV output, driven by temperature-dependent demand and positive correlations between temperature, solar radiation, and PV generation. The findings have broader implications for electricity markets with high solar PV penetration and subject to seasonal changes. For policymakers and electricity market participants aiming to mitigate price fluctuations, managing PV-induced variability is more critical during low-temperature (than high-temperature) seasons. Moreover, the valuation of real options for solar PV-based storage facilities may differ between low- and high-temperature periods. A nuanced understanding of seasonal supply–demand dynamics is essential for accurately assessing price risks, evaluating the value of solar PV investments, and formulating effective policies for renewable energy integration.

Keywords: Electricity prices, solar photovoltaic power generation, seasonal variation, price variability, merit-order effect, quantile regression

JEL codes: C21, G19, L94, Q02, Q21, Q41

^aGraduate School of Science, Technology and Innovation, Kobe University, 1-1 Rokkodai-cho, Nada-ku, Kobe, Hyogo 657-8501 Japan, nfuke@port.kobe-u.ac.jp

^bGraduate School of Business Administration, Hitotsubashi University, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8439 Japan, kohashi@hub.hit-u.ac.jp

^cTokyo Tech Academy of Energy and Informatics, Tokyo Institute of Technology, 2-12-1 Ookayama, Meguro-ku, Tokyo 152-8550 Japan

*Corresponding author

Highlights:

- Quantile regression analysis in Kyushu, Japan, shows solar PV impact varies seasonally.
- Solar PV reduces electricity prices across seasons: merit-order effect confirmed.
- Seasonal IQR variation: PV lowers price variability in spring/summer, not autumn/winter.
- Seasonal variation of correlation between PV generation and demand could cause this seasonality.
- Understanding seasonality in the impact of PV on electricity prices is crucial for effective policymaking and risk management.

Acknowledgements:

We thank Hiroshi Ishijima, Shintaro Iwakiri, Kentaro Iwatsubo, Takuji Matsumoto, Soichiro Moridaira, Hiroshi Ohashi, Abhijit Sharma, Yoshiki Shimizu, Yuji Yamada, Yasushi Yoshida, and all participants of the Commodity Finance Study Group of the Japan Association of Real Options and Strategy, the 2021 Spring Meeting of the Japan Economic Association, the 2021 Spring Meeting of Nippon Finance Association, the 2022 Asian Meeting of the Econometric Society in East and Southeast Asia, and the Asian Finance Association Annual Conference 2023 for their helpful comments and discussions. This work was supported by the Grants-in-Aid for Scientific Research of Japan Society for the Promotion of Science; Grant Numbers JP24K04940 (Fuke and Ohashi) and JP24K00270 (Ohashi).

1. Introduction

Over the past few decades, electricity market liberalization has advanced in many countries. Electricity is now traded on power exchanges such as Nord Pool and European Energy Exchange (EEX) in Europe, and the Pennsylvania–New Jersey–Maryland Interconnection (PJM), New York Independent System Operator (NYISO), and Electric Reliability Council of Texas (ERCOT) in the United States. Electricity prices, determined by market-based supply and demand, have changed in response to structural modifications driven by diverse technological innovations. In particular, policy initiatives aimed at mitigating global warming have compelled countries to expand power generation capacity without emitting CO₂. Consequently, the share of electricity generated from renewable energy sources, especially solar photovoltaics (PV) and wind power, has increased substantially, exerting a significant influence on electricity price dynamics.¹

A key advantage of renewable energy sources—in addition to their low CO₂ emissions—is their low marginal cost. Solar PV and wind power, in particular, have near-zero marginal costs. An increase in electricity generation from these sources shifts the supply curve rightward, leading to lower electricity prices. This phenomenon, known as the merit-order effect, is a central topic in the literature analyzing the impact of renewable energy generation on electricity prices.

Regarding recent studies on the merit-order effect, Cludius et al. (2014) analyzed the impacts of solar PV and wind power generation on electricity prices in the German market and showed that they reduced electricity prices. Similar studies were conducted in different countries, such as by Gelabert (2011), focused on the Spanish market; by Ketterer (2014), Paraschiv et al. (2014), Hagfors, Paraschiv, et al. (2016), and Maciejowska (2020), focused on the German market; by Cló et al. (2015), examining the Italian market; by Hagfors, Bunn, et al. (2016), focused on the UK market; by Luňáčková (2017), focused on the Czech market; and by Rintamäki et al. (2017) and Tselika (2022), exploring the Danish and German markets. All the studies confirm that renewable energy generation has a price-reducing effect.

Meanwhile, a major challenge arising from increasing renewable energy penetration is the intermittency of its power generation. Electricity produced by solar PV and wind power, heavily dependent on sunlight and wind conditions, is highly variable and difficult to control. Given their near-zero marginal costs, fluctuations in solar PV and wind power generation shift the entire supply curve, resulting in substantial variability in electricity prices. This challenge is commonly faced by electricity markets with high shares of renewable generation worldwide. Therefore, understanding the impact of renewable energy on electricity price variability constitutes another critical topic in current electricity market research.

¹ For example, in Germany, since the introduction of the feed-in tariff (FIT) law in 2004, the government provided policy support for introducing renewable energy generation, and renewable energy sources accounted for approximately 60% of the total electricity generated (25% wind, 20% solar, and 15% other) by April 2020. In Japan, since the introduction of the FIT system in 2012, the share of electricity from renewable energy sources increased to 19.2%. Owing to Japan's natural environment, the amount of electricity generated by solar PV far exceeds that generated by wind power, and in 2019, the former accounted for 7.5%, whereas the latter accounted for less than 0.8% of total power generation.

Several studies have investigated this issue. For example, Woo et al. (2011) conducted a log-linear regression analysis combined with an ordered-logit model and found that wind power increased electricity price volatility in Texas. Ketterer (2014) used a generalized autoregressive conditional heteroskedasticity (GARCH) model and found a volatility-increasing effect for wind power generation in the German market. Rintamäki et al. (2017) used a seasonally adjusted autoregressive moving average (SARMA) model and found that wind power generation increased electricity price volatility in Germany but decreased it in Denmark; meanwhile, solar PV power generation reduced volatility in Germany. Alternatively, some studies adopted quantile regression approaches. For example, Hagfors, Bunn, et al. (2016) and Hagfors, Paraschiv, et al. (2016) performed quantile regression analysis to examine the impact of renewable energy on electricity prices in the UK and Germany, respectively. Their findings indicated that renewable energy tended to lower electricity prices, with negative price spikes observed particularly during periods of low electricity demand combined with high wind generation. Further, using daily data from the German market, Maciejowska (2020) employed quantile regressions to analyze the impact of wind and solar PV power generation on electricity price variability. The results indicated that wind power and solar PV had different impacts on price variability: wind power increased variability under low demand conditions but decreased variability under high demand, while solar PV reduced variability at intermediate electricity demand levels. Tselika (2022) applied panel quantile regressions using hourly data from Denmark and Germany, and found that wind power generation increased (decreased) price variability for low (high) demand in both countries. Moreover, solar PV power generation was found to reduce electricity price variability strongly under high demand conditions, compared with wind power generation.

In the context of Japanese electricity markets, previous studies have primarily focused on the merit-order effect of renewable energy sources; relatively little attention has been paid to their impact on electricity price variability. For example, Maekawa et al. (2018) conducted panel data analysis and found that renewable power generation reduced electricity prices. Similarly, Yoshihara and Ohashi (2017) performed simulation analysis and showed that an increase in renewable energy generation would lead to lower electricity prices. Sakaguchi and Fujii (2021) applied both ordinary least squares (OLS) and quantile regression methods, revealing that the merit-order effect of wind power (solar PV) increased (decreased) over the 2016–2019 period. Suliman and Farzaneh (2022) conducted panel data analysis of both system-wide and regional electricity prices, and found that increased solar PV and wind power generation, as well as nuclear, hydro, geothermal, and biomass power generation, led to reduced electricity prices.

Against this background, the current study examines the impact of solar PV power generation on both the levels and variability of electricity prices, using data from the Kyushu region of Japan, where solar PV constitutes the dominant renewable energy source. This study makes two key contributions. First, to our knowledge, it is the first to analyze the effect of solar PV power generation on electricity price variability in the context of Japanese electricity markets. Second, it contributes to the global literature by uncovering a novel finding on the seasonal variation in the impact of solar PV power generation on electricity price variability. That is, increased solar PV power generation is associated with reduced price variability in spring

and summer, but not in autumn and winter. As few prior studies have investigated such seasonal effects of renewable generation on price variability, these results extend the existing literature and underscore the importance of accounting for seasonal dynamics when analyzing the influence of renewable energy sources—particularly solar PV—on electricity price variability.

Specifically, following Maciejowska’s (2020) methodology, this study conducts quantile regression analysis using data on electricity prices, electricity demand, solar PV power generation, and other control variables from fiscal years (FYs) 2016 to 2019 (i.e., April 2016 to March 2020) in the Kyushu region of Japan, where Kyushu is one of the four largest islands located in the southwestern part of Japan, whose gross regional product exceeds \$400 billion and is comparable to those of Austria, Norway, and the United Arab Emirates. The Kyushu regional electricity market is particularly well suited for our analysis for the following reasons: it has the highest share of solar PV among Japan’s nine regional electricity markets; it is relatively independent from other regions, connected by a single interconnection line with limited capacity; and the region has four distinct seasons, which significantly influence both electricity demand and solar PV power generation.²

Analysis results confirm the merit-order effect: an increase in solar PV power generation leads to lower electricity prices, whereas an increase in electricity demand results in higher prices. Further, the price-reducing effect of solar PV power generation is more pronounced at higher price quantiles, while the price-increasing effect of electricity demand also intensifies at higher quantiles.

Additionally, similar to Maciejowska (2020), this study measures electricity price variability using the inter-quantile range (*IQR*), and identifies seasonal variation in the impact of electricity demand and solar PV power generation on electricity price variability.³ First, the effect of electricity demand on price variability exhibits modest seasonal differences, with a stronger impact in summer than in other seasons. This outcome is consistent with the upward-sloping nature of the electricity supply curve, combined with higher levels of electricity demand during summer. Second, and more importantly, increased solar PV power generation is associated with reduced electricity price variability in spring and summer, but not in autumn and winter. This variation is attributable to seasonal changes affecting the relationship between electricity demand and solar PV power generation, which are primarily driven by temperature-dependent variation in electricity demand and the generally positive correlations between temperature, amount of sunlight, and solar PV output. For example, on clear days, both solar PV output and temperature increase with sunlight. On the other hand, electricity demand increases with rising temperatures above 18.3°C (65°F), but also increases as

² The nine regional electricity markets in Japan are, from the north-east to the south-west, Hokkaido, Tohoku, Hokuriku, Tokyo, Chubu, Kansai, Chugoku, Shikoku, and Kyushu. The solar power generation to total area demand ratio for each area in 2019 is as follows: 12.4% in Kyushu, 11.7% in Shikoku, 10.1% in Chugoku, 8.5% in Tohoku, 8.4% in Chubu, 6.5% in Hokkaido, 5.9% in Tokyo, 5.4% in Kansai, and 4.0% in Hokuriku.

³ *IQR* of price is defined as the difference between the value $P_t(0.9)$ of the 0.9 quantile of prices minus the value $P_t(0.1)$ of the 0.1 quantile, that is, $IQR_t = P_t(0.9) - P_t(0.1)$. A large (small) *IQR* of prices implies corresponding large (small) variability. The *IQR* is a linear transformation of price variance when the distribution of prices is normal or a Student's t-distribution.

temperatures fall below this threshold. Consequently, in warmer seasons, higher solar PV output coincides with higher demand, helping stabilize prices and reduce variability. By contrast, in colder seasons, lower solar PV output coincides with increased demand, contributing to greater price variability.⁴ This changing trend across seasons explains the observed seasonal variation in the impact of solar PV power generation on electricity price variability.

This study focuses on the regional electricity market in Kyushu, Japan; yet, findings regarding seasonal variation in the impact of solar PV power generation on electricity price variability have broader implications for global markets with high solar penetration. From the perspective of price risk management, the results highlight the importance of policies and investment strategies that account for the interaction between weather-dependent supply and electricity demand and its influence on electricity prices.

The remainder of this article is organized as follows. Section 2 presents the data. Section 3 introduces the model used for quantile regression analysis. Section 4 reports the estimation results, effects of electricity demand and solar PV power generation on electricity prices, and related impacts on both the level and variability of electricity prices that vary across seasons. Section 5 examines alternative explanations for seasonal variation and describes the robustness checks performed. Finally, Section 6 concludes the paper.

2. Data

We use electricity supply and demand data, Japan Electric Power eXchange (JEPX) spot market electricity price data, and weather data for the Kyushu Electric Power District. Hourly electricity supply-demand data are obtained from the Kyushu Electric Power Co. website. We define the sum of electricity demand within the Kyushu region and amount of electricity transmitted from the Kyushu region to the Chugoku region via the interconnection line as electricity demand (or load), where during the data period, the average daily electricity demand within the Kyushu region was 10.30 GWh, the average daily electricity transmitted to the Chugoku region via the interconnection line was 1.79 GWh, and the correlation between the two variables was 0.28. JEPX spot market electricity prices are 30-min day-ahead prices because the day-ahead market of the JEPX trades the next day's power supply for 48 products in 30-min increments over 24 h (hereafter, we refer to these as 30-min values.) To match the frequency of the 30-min data with the hourly data, we take the simple average of the odd-numbered and following even-numbered 30-min values of the 48 products and use the 24 averages as hourly prices.⁵ Weather data constitute hourly values based on location. We use the

⁴ During summer, the temperature rises and electricity demand for cooling increases, but the amount of solar PV power generation simultaneously increases. Therefore, as electricity demand increases, supply increases, which suppresses fluctuation in electricity prices. Meanwhile, during autumn, the temperature drops and the demand for electricity for heating increases, but the amount of solar PV power generation decreases. Consequently, electricity supply decreases while demand increases, resulting in more variable electricity prices than in spring and summer.

⁵ JEPX discloses transaction volume data only for the entire system and does not provide region-specific data. Therefore, to create hourly data from 30-min data, it is necessary to either take a simple average or take a weighted average based on the transaction volume for the entire system. In this study, we adopt the simple

weather data for Fukuoka City in Fukuoka Prefecture in Kyushu, where Fukuoka City is the largest city located in the north of Kyushu and is the fifth largest city in Japan. The data period covers four Japanese FYs, from April 1, 2016—when detailed electricity demand and supply data became available—to March 31, 2020. The units are GWh for electricity demand and supply data from each power generation facility, yen/kWh for electricity spot price, and Celsius (°C) for temperature.

Table 1 presents data on annual electricity generation from renewable and nuclear energy sources. Figure 1 presents a graph of solar PV, biomass, and nuclear power generation for the same period.

Table 1 Fiscal Year Trends in Energy Power Generation in the Kyushu Electric Power District

Fiscal year	Power generation (GWh)				
	Solar	Biomass	Wind	Geothermal	Nuclear
2016	7086	185	530	1164	12443
2017	9156	190	537	1122	14334
2018	9897	1405	595	1124	28771
2019	10438	2883	652	1169	28742

During the data period, solar PV power generation ranged from approximately 7,000 to 10,000 GWh, whereas other renewable energy sources ranged from approximately 200 to 3,000 GWh (Table 1). Biomass power generation increased intermittently from 185 GWh in FY2016 to 2883 GWh in FY2019. Geothermal power generation remained stable with no significant change, ranging from 1122 to 1169 GWh. Wind power generation ranged from 530 to 652 GWh, showing a slight annual increase, but remaining low. Solar PV power generation was approximately 15 times higher than wind power in the same year. Nuclear power generation more than doubled from 12443 GWh and 14334 GWh in FY2016 and FY2017, to 28771 GWh and 28742 GWh in FY2018 and FY2019, respectively. The total electricity generation in each fiscal year is 86,916 GWh in FY2016, 87902 GWh in FY2017, 85515 GWh in FY2018, and 84383 GWh in FY2019. Thus, the share of solar PV (nuclear power) generation in each fiscal year is 8.2% (14.3%) in FY2016, 10.4% (16.3%) in FY2017, 11.4% (33.4%) in FY2018, and 12.4% (34.1%) in FY2019.

[Figure 1 around here]

Figure 1 presents the amounts of electricity generated from solar PV, biomass, and nuclear sources over the study period. Solar PV power generation exhibited substantial fluctuations. By contrast, biomass power generation remained relatively stable until it experienced a sharp stepwise increase beginning in October 2018, primarily due to the commissioning of new biomass power plants. Nuclear power generation was more stable than the other sources but showed intermittent changes, with a notable increase observed after mid-

average price. Nevertheless, we confirm that the results remain largely unchanged regardless of which method is used to create hourly data and whether weighted average prices based on hourly electricity demand in the Kyushu region is used.

2018. Based on these trends and considering that generation from other sources such as wind and geothermal power was either minimal or stable, this study focuses on solar PV, biomass, and nuclear power in subsequent analyses.⁶

Although our analysis is based on daily data, careful consideration was given during data preparation. Since solar PV facilities do not generate electricity at night, they have no direct impact on nighttime electricity prices. Consequently, using daily averages computed over a full 24-h period would introduce variation in the measured impact of solar PV power generation due to seasonal fluctuations in daylight hours. Addressing this aspect, the analysis employs daily PV time data—defined as the simple average of hourly solar PV power generation during periods of actual generation i.e., daylight hours. (For example, if solar PV systems generate electricity from 5:00 a.m. to 8:00 p.m. during summer, the PV time data for that day are calculated as the simple average of 15 hourly values recorded between those hours. Similarly, if generation occurs from 7:00 a.m. to 5:00 p.m. in winter, the simple average is computed from 11 hourly values.) Table 2 presents the descriptive statistics for daily PV time data.

Table 2 Descriptive Statistics of PV Time Daily Data for Electricity Price (Price) and Demand (Load) and Solar PV (Solar), Biomass (Biomass), and Nuclear (Nuclear) Power Generation

	Price JPY/kWh	Load GWh	Solar GWh	Nuclear GWh	Biomass GWh
Mean	8.585	12.088	1.930	0.132	2.404
Std.Dev	3.307	1.659	0.889	0.145	1.142
Min	1.568	8.221	0.113	0.010	0.798
Q1	6.482	10.935	1.203	0.020	1.756
Median	7.936	11.881	2.004	0.025	1.796
Q3	9.968	13.238	2.635	0.296	3.224
Max	28.875	16.612	4.063	0.450	4.149
MAD	2.369	1.652	1.032	0.011	1.329
IQR	3.486	2.302	1.432	0.276	1.468
CV	0.385	0.137	0.460	1.100	0.475
Skewness	1.382	0.309	-0.163	0.634	0.366
SE.Skewness	0.064	0.064	0.064	0.064	0.064
Kurtosis	6.333	2.674	2.045	1.573	1.733
Num. obs.	1461	1461	1461	1461	1461

Note. SE. Skewness: Standard error of skewness, Num. obs.: Number of observations

⁶ Similar to previous studies (e.g., Maciejowska (2020); Sakaguchi and Fujii (2021)), this analysis does not include thermal power generation as an explanatory variable since it is used for daily supply adjustment and thus is not exogenous. On the other hand, although it is not a renewable energy source, nuclear power generation is included in the analysis as a control variable because it accounts for a substantial share of total supply and is quasi-exogenous, given that it is not employed for daily supply adjustment owing to its inflexibility.

Descriptive statistics indicate that the mean electricity price is slightly higher than the median, with a third quartile of 9.968 yen/kWh and a maximum of 28.875 yen/kWh. This result suggests a right-skewed distribution with a long tail toward higher values, also supported by the observed positive skewness. The kurtosis of electricity demand is 2.674, indicating thinner tails relative to a normal distribution. The mean of electricity demand is slightly higher than the median, and skewness is 0.309, implying a mild right skew with the peak shifted toward slightly higher demand levels. Regarding solar PV power generation, the mean is slightly smaller than the median, with a skewness of -0.163 and kurtosis of 2.045. These values suggest a left-skewed distribution with thin tails and a concentration of observations at moderately lower generation levels. Nuclear power generation exhibits a mean greater than the median, skewness of 0.634, and kurtosis of 1.573, indicating a positively skewed distribution with thin tails and tendency toward higher generation values. Similarly, biomass power generation shows a mean exceeding the median, skewness of 0.366, and kurtosis of 1.733, suggesting a right-skewed distribution with thin tails and generally higher generation levels.

[Figure 2 around here]

Figure 2 illustrates the relationship between electricity demand (GWh) and wholesale electricity prices (Yen/kWh) across seasons in the Kyushu region; each point represents a daily observation and different symbols denote different seasons. Electricity prices and demand often exhibit a nonlinear relationship—typically visualized in a hockey-stick shape—due to the increasing marginal costs of electricity generation (Barlow, 2002; Kanamura and Ohashi, 2007), where the sensitivity of price to demand becomes more pronounced in high-demand ranges compared with low-demand ranges. These nonlinear patterns have been widely documented in different electricity markets. For example, to capture this nonlinearity, Maciejowska (2020) applied quantile regression and segmented electricity demand into low-, medium-, and high-demand ranges, focusing on the German market. However, these nonlinear relationships are less clear in the Kyushu market. Moreover, Figure 2 shows the seasonality of electricity demand; higher demand levels in summer and winter. Hence, in the Kyushu region, classifying the data by demand levels is closely related to that by seasons. Thus, the current study adopts a seasonal classification scheme and employs quantile regression to investigate the seasonal variation in the relationships between electricity prices, demand, and solar PV power generation.

Temperature is one of the factors that determines the seasonality of electricity demand. The common pattern centered at 65°F (18.3°C), where electricity demand increases whether the temperature rises or falls, is also observed in the Kyushu region. Solar radiation is seasonal and highest in the summer. Thus, to account for the seasonal variation effect, we divide the data into four seasons based on the temperature change trend over time for the period under consideration. Specifically, winter is taken as the period below the mean temperature minus one standard deviation, summer as the period above the mean temperature plus one

standard deviation, and spring as the period between winter and summer and autumn as that between summer and winter within the mean plus or minus one standard deviation of temperature. (The mean temperature is 17.83°C and one standard deviation of temperature is 8.13°C.) Additionally, each period is taken such that the seasons do not overlap or reverse and the four periods are similarly defined for each year. The resulting start and end dates of the four seasons are presented in Table 3. The average temperatures in those seasons are between 8°C and 11°C in winter, between 19°C and 21°C in spring, between 27°C and 29°C in summer, and between 16°C and 18°C in autumn in the data period.

Table 3 Periods of Each Season

	Start	End
Winter	12/16	3/15
Spring	3/16	6/30
Summer	7/1	9/30
Autumn	10/1	12/15

In Japan, the four calendar seasons are typically defined as winter (December to February), spring (March to May), summer (June to August), and autumn (September to November). Thus, this temperature-based seasonal classification is consistent with the general societal perception of seasons in Japan.

Table 4 Correlations for Electricity Price (*Price*) and Demand (*Load*) and Solar PV (*Solar*), Nuclear (*Nuclear*), and Biomass (*Biomass*) Power Generation

	<i>Price</i>	<i>Load</i>	<i>Solar</i>	<i>Nuclear</i>	<i>Biomass</i>
<i>Price</i>	1				
<i>Load</i>	0.648	1			
<i>Solar</i>	-0.203	0.034	1		
<i>Nuclear</i>	-0.347	0.069	0.161	1	
<i>Biomass</i>	-0.436	-0.050	0.159	0.770	1

Table 4 presents the correlations among the variables. Electricity demand (supply) is positively (negatively) correlated with electricity prices, indicating that higher demand (supply) is associated with higher (lower) prices. The correlation between nuclear power generation and biomass power generation is notably high at 0.77, attributable to the fact that both variables exhibit similar step-function-like movements in the same direction (Figure 1). Further, both variables exhibit similarly low correlations with solar PV power generation, at approximately 0.16. The correlation between load and solar PV power generation is small but positive at 0.034, suggesting that, on average, higher electricity demand is associated with slightly higher levels of solar PV power generation. However, this relationship varies seasonally: the correlations are -0.057 in winter, -0.050 in spring, 0.477 in summer, and -0.171 in autumn. Thus, a strong positive correlation emerges between load and solar PV power generation during the summer season.

Finally, normality and unit root tests are performed to examine the distribution and stationarity of the main variables. Results of the Jarque–Bera (J–B) test for normality are summarized in Table 5; the null hypothesis

is rejected at a significance level of 1%, and no variables follow a normal distribution. This outcome is expected from their skewness and kurtosis values; in particular, electricity price is positively skewed and has a fat tail.

Table 5 Goodness-of-Fit Test for Normal Distribution (J–B Test)

J–B test					
	Price	Load	Solar	Nuclear	Biomass
Test	1146.00	29.68	61.69	129.90	221.60
P-value	<0.001	<0.001	<0.001	<0.001	<0.001

Note. Price: electricity price, Load: electricity demand, Solar: solar PV power generation, Nuclear: nuclear power generation, Biomass: biomass power generation

Results of the augmented Dickey–Fuller (ADF) test (with drift) for unit root are summarized in Table 6; the lag for the test was set at 7 because of the one-week periodicity in the data due to the day-of-the-week effect. In the quantile regressions, we do not use the variables themselves but use their cross terms with the indicators of four seasons; accordingly, in Table 6, the results for the cross terms are also presented for the four seasons.

Table 6 Unit Root Test (ADF Test with Drift)

ADF test (with drift)						
		Price	Load	Solar	Nuclear	Biomass
All seasons	Test	-4.700	-5.164	-9.059	-1.471	-0.498
	P-value	<0.01	<0.01	<0.01	<0.10	>0.10
Winter	Test	-5.002	-21.332	-7.501	-3.004	-1.418
	P-value	<0.01	<0.01	<0.01	<0.01	<0.10
Spring	Test	-8.000	-23.822	-7.471	-4.372	-1.265
	P-value	<0.001	<0.01	<0.01	<0.01	>0.10
Summer	Test	-8.008	-17.609	-6.963	-5.649	-0.919
	P-value	<0.01	<0.01	<0.01	<0.01	>0.10
Autumn	Test	-6.469	-23.062	-7.009	-3.545	-1.583
	P-value	<0.01	<0.01	<0.01	<0.01	<0.10

Note. Price: electricity price, Load: electricity demand, Solar: solar PV power generation, Nuclear: nuclear power generation, Biomass: biomass power generation

The null hypothesis of the existence of a unit root is rejected at the 1% significance level for electricity prices, demand, and solar PV power generation across all seasons and for each season (Table 6). For nuclear power generation, the null hypothesis is rejected at the 10% significance level across all seasons and at the

1% level for each season. However, the null hypothesis is not rejected for biomass power generation across all seasons or for spring and summer, suggesting the existence of a unit root. This result is expected considering the graph of biomass power generation in Figure 1, where it suddenly soared upward in October 2018 and was nearly constant before and after that point of rise, suggesting the non-stationarity of biomass power generation.⁷ Based on these results, we exclude biomass power generation from the explanatory variables in the quantile regressions and instead include a dummy variable that captures the rise in biomass power generation in October, 2018.

3. Quantile regression model

Following Maciejowska (2020), we conduct quantile regression analysis of electricity prices and variability in the Kyushu region of Japan. The explained variable is the electricity price of the Kyushu region in JEPX, where $P(\tau)$ denotes the τ -th quantile of electricity price. The main explanatory variables are electricity demand (or load), denoted by L , and the amount of solar power generation, denoted by S . As a control variable, the amount of nuclear power generation, denoted by A , is added. To incorporate the day-of-the-week effect of electricity price, we include the i -day lag value of the price denoted by P_{t-i} and set the lag number to 7. Moreover, to incorporate weekend and holiday effects, a dummy variable that takes the value of 1 on Saturdays, Sundays, and public holidays is added, denoted by D_{hday} . Furthermore, we introduce the dummy variable D_{bio} , which takes the value of 1 after October 1, 2018 to incorporate the large and abrupt increase in biomass power generation after this point caused by the introduction of new biomass power plants.

The choice of explanatory variables in this study follows a similar approach to that of Maciejowska (2020). The underlying rationale is that the aggregate electricity supply curve comprises three main components: a relatively stable upward-sloping segment associated with thermal power generation, which is flexible and used for supply adjustment; a relatively fixed segment corresponding to nuclear power generation, which is inflexible and not subject to short-term adjustment; and a flat but volatile segment driven by solar PV power generation. Thus, fluctuations in solar PV output shift the overall supply curve horizontally—leftward with reduced generation and rightward with increased generation—thereby inducing variability in electricity prices. Furthermore, electricity demand and solar PV power generation are strongly influenced by temperature and solar radiation, both of which are exogenously determined, respectively.

To analyze the impact of the season on the relationship between electricity prices, electricity demand, and solar PV power generation, we conduct a quantile regression with cross terms between dummy variables indicating the seasons and explanatory variables (electricity demand, solar PV power generation, and nuclear power generation). To determine the season, instead of dividing a year into four equal parts, we divide it such that the temperatures do not differ significantly within the same season, and set each season as shown

⁷ The Phillips–Perron (PP) test yields results similar to those of the ADF test, except that the null hypothesis is not rejected for nuclear and biomass power generation across all seasons.

in Table 3. Each season is represented by an indicator function whose value is 1 for that period: $I_{1,t} = 1_{12/16 \leq t \leq 3/15}$ (winter, taking 1 from December 16 to March 15), $I_{2,t} = 1_{3/16 \leq t \leq 6/30}$ (spring, taking 1 from March 16 to June 30), $I_{3,t} = 1_{7/1 \leq t \leq 9/30}$ (summer, taking 1 from July 1 to September 30), and $I_{4,t} = 1_{10/1 \leq t \leq 12/15}$ (autumn, taking 1 from October 1 to December 15). We then define the intersection terms $L_{k,t} = I_{k,t} \times L_t$ with electricity demand, $S_{k,t} = I_{k,t} \times S_t$ with solar PV power generation, and $A_{k,t} = I_{k,t} \times A_t$ with nuclear power generation ($k = 1, 2, 3, 4$, where 1 means winter, 2 means spring, 3 means summer, and 4 means autumn).

Using the above setup, we perform the following quantile regression with seasonality:

$$P_t(\tau) = \alpha_{0,\tau} + \alpha_{1,\tau} D_{\text{holiday},t} + \alpha_{2,\tau} D_{\text{bio},t} + \sum_{k=1}^4 \beta_{k,\tau}^L L_{k,t} + \sum_{k=1}^4 \beta_{k,\tau}^S S_{k,t} + \sum_{k=1}^4 \beta_{k,\tau}^A A_{k,t} + \sum_{i=1}^7 \theta_{i,\tau} P_{t-i} \quad (1)$$

where $\alpha_{0,\tau}, \alpha_{1,\tau}, \alpha_{2,\tau}$ are the constant term, coefficient of the holiday dummy variable, and coefficient of the dummy variable representing the rise in biomass power generation, respectively. $\beta_{k,\tau}^L, \beta_{k,\tau}^S$, and $\beta_{k,\tau}^A$ are the coefficients of demand, solar PV power generation, and nuclear power generation when the season is k ($k = 1, 2, 3, 4$ where 1 means winter, 2 means spring, 3 means summer, and 4 means autumn). $\theta_{i,\tau}$ ($i = 1, \dots, 7$) is the coefficient of i -day lagged value of electricity price.

In a quantile regression, coefficients represent the marginal effects of explanatory variables on specified conditional quantiles of the dependent variable, hence capturing the heterogeneous effects of explanatory variables across the distribution. This contrasts with OLS, which estimates the average effect on the conditional mean. For example, when analyzing the impact of solar PV power generation on electricity prices, a negative coefficient at the 0.9 quantile of price indicates that a one-unit increase in solar PV power generation is associated with a reduction in the 0.9 quantile of electricity prices, which suggests that solar PV power generation has a moderating effect on the upper tail of electricity prices.

We measure the variability of electricity prices by *IQR*—defined as the difference between the value of the 0.9 quantile of the price minus the value of the 0.1 quantile; that is, $IQR_t = P_t(0.9) - P_t(0.1)$.⁸ A large (small) *IQR* of electricity prices implies corresponding large (small) variability. When the *IQR* is expressed as the difference between quantiles obtained by quantile regression, coefficients of the explanatory variables are interpreted as indicating the degree of their impact on the variability of electricity prices. Therefore, we use the *IQR* to analyze the impact of the explanatory variables on the variability of electricity prices.

The *IQR* obtained from quantile regression analysis of the seasonality effect is shown in Equation (2).

⁸ The wide 0.9–0.1 quantile range is used to capture the overall dispersion of the distribution. In the context of electricity prices, this wider *IQR* provides a more representative and robust summary of dispersion than narrower ranges (e.g., 0.7–0.3), which may underestimate variability under skewed or heavy-tailed distributions.

$$IQR_t = \alpha_0 + \alpha_1 D_{hday,t} + \alpha_2 D_{bio,t} + \sum_{k=1}^4 \beta_k^L L_{k,t} + \sum_{k=1}^4 \beta_k^S S_{k,t} + \sum_{k=1}^4 \beta_k^A A_{k,t} + \sum_{i=1}^7 \theta_i P_{t-i} \quad (2)$$

where the respective coefficients are $\alpha_h = \alpha_{h,0.9} - \alpha_{h,0.1}$ ($h = 0, 1, 2$)、 $\beta_k^* = \beta_{k,0.9}^* - \beta_{k,0.1}^*$ ($* = L, S, A$ and $k = 1, 2, 3, 4$)、and $\theta_i = \theta_{i,0.9} - \theta_{i,0.1}$ ($i = 1, \dots, 7$).

From Equation (2), we derive the electricity demand and solar PV power generation coefficients for each season. If the coefficient β_k^* is positive (i.e., $\beta_{k,0.9}^* > \beta_{k,0.1}^*$), then an increase in this variable has the effect of increasing price variability in season k . Conversely, if the coefficient β_k^* is negative (i.e., $\beta_{k,0.9}^* < \beta_{k,0.1}^*$), then an increase in this variable reduces price variability in season k . Thus, for example, if the coefficient β_k^L of electricity demand $L_{k,t}$ in Equation (2) is positive, an increase in electricity demand is associated with greater electricity price variability in season k . Similarly, if the coefficient β_k^S of the amount of solar PV power generation $S_{k,t}$ is negative, then an increase in the amount of solar PV power generation is associated with reduced electricity price variability in season k .

Using Equation (2), we determine the seasonal impact of changes in electricity demand and solar PV power generation on electricity price variability: the coefficients of the IQR equation are tested for significance through a bootstrap method with 1,000 replications under the null hypothesis—that is, the estimated values of the coefficients of the 0.9 and 0.1 quantiles of the quantile regression used to calculate them are equal.

4. Results

4.1 Impacts of demand and solar PV power generation on electricity price level

To examine seasonal changes in the effects of electricity demand and solar PV power generation on electricity price levels, we estimate the quantile regression model specified in Equation (1). The estimation is conducted using the bootstrap method with 1,000 replications. Results for the full sample period from FY2016 to FY2019 are presented below.

Table 7 Seasonal Changes in Estimated Coefficients of Electricity Demand (Load) and Solar PV (Solar) and Nuclear (Nuclear) Power Generation on Electricity Prices

Quantile	0.100	0.200	0.300	0.400	0.500	0.600	0.700	0.800	0.900
Load: Winter	0.623*** (0.049)	0.625*** (0.057)	0.608*** (0.051)	0.603*** (0.053)	0.653*** (0.058)	0.628*** (0.062)	0.643*** (0.069)	0.670*** (0.076)	0.811*** (0.125)
Load: Spring	0.553*** (0.062)	0.524*** (0.063)	0.501*** (0.054)	0.475*** (0.056)	0.564*** (0.068)	0.561*** (0.071)	0.587*** (0.078)	0.617*** (0.090)	0.748*** (0.129)
Load: Summer	0.428*** (0.051)	0.428*** (0.059)	0.434*** (0.057)	0.454*** (0.056)	0.501*** (0.060)	0.498*** (0.062)	0.525*** (0.071)	0.590*** (0.083)	0.753*** (0.128)

Load: Autumn	0.534*** (0.057)	0.521*** (0.063)	0.497*** (0.054)	0.458*** (0.053)	0.536*** (0.063)	0.524*** (0.065)	0.561*** (0.068)	0.605*** (0.083)	0.746*** (0.124)
Solar: Winter	-0.782*** (0.120)	-0.920*** (0.145)	-0.876*** (0.113)	-0.912*** (0.098)	-0.879*** (0.101)	-0.869*** (0.093)	-0.849*** (0.117)	-0.973*** (0.167)	-1.063*** (0.263)
Solar: Spring	-0.454*** (0.091)	-0.454*** (0.064)	-0.451*** (0.064)	-0.444*** (0.071)	-0.504*** (0.077)	-0.590*** (0.092)	-0.603*** (0.090)	-0.729*** (0.086)	-0.681*** (0.094)
Solar: Summer	-0.163 (0.101)	-0.301*** (0.111)	-0.344** (0.136)	-0.449*** (0.105)	-0.423*** (0.111)	-0.468*** (0.108)	-0.506*** (0.156)	-0.496*** (0.168)	-0.518* (0.294)
Solar: Autumn	-0.607*** (0.126)	-0.572*** (0.101)	-0.517*** (0.087)	-0.463*** (0.086)	-0.507*** (0.089)	-0.545*** (0.102)	-0.643*** (0.108)	-0.720*** (0.141)	-0.803*** (0.273)
Nuclear: Winter	-0.551*** (0.087)	-0.482*** (0.088)	-0.453*** (0.082)	-0.431*** (0.078)	-0.427*** (0.080)	-0.353*** (0.087)	-0.368*** (0.119)	-0.250* (0.132)	-0.165 (0.192)
Nuclear: Spring	-0.277* (0.151)	-0.110 (0.094)	-0.038 (0.089)	-0.001 (0.095)	-0.022 (0.100)	0.018 (0.090)	-0.012 (0.102)	0.187* (0.105)	0.268* (0.144)
Nuclear: Summer	-0.088 (0.084)	-0.056 (0.108)	-0.073 (0.126)	-0.130 (0.108)	-0.075 (0.103)	-0.107 (0.106)	-0.158 (0.163)	-0.279* (0.162)	-0.292 (0.239)
Nuclear: Autumn	-0.078 (0.119)	-0.022 (0.087)	0.021 (0.075)	0.054 (0.076)	0.013 (0.087)	0.048 (0.083)	0.031 (0.097)	0.111 (0.112)	0.232 (0.165)
Dummy: holiday	-1.227*** (0.156)	-1.289*** (0.158)	-1.389*** (0.136)	-1.400*** (0.130)	-1.293*** (0.137)	-1.208*** (0.148)	-1.138*** (0.155)	-1.213*** (0.186)	-1.099*** (0.280)
Dummy: biomass	-0.477*** (0.184)	-0.297* (0.158)	-0.327* (0.171)	-0.353** (0.170)	-0.289* (0.165)	-0.350** (0.146)	-0.387** (0.175)	-0.610*** (0.206)	-0.837*** (0.290)
Num. obs.	1454	1454	1454	1454	1454	1454	1454	1454	1454

Note. *** p<0.01, ** p<0.05, * p<0.1; standard errors in parentheses; *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

In Table 7, all estimated coefficients for electricity demand are significantly positive at the 1% significance level, reflecting the price-increasing effect of higher electricity demand. By contrast, the estimated coefficients for solar PV power generation are significantly negative at the 1% significance level across all quantiles in winter, spring, and autumn. In summer, the coefficients are also significant at the 1% level for most quantiles, except for the 0.1 quantile (not significant) and the 0.3 and 0.9 quantiles, which are significant at the 5% level. These results indicate that increased solar PV power generation lowers electricity prices, consistent with the merit-order effect.

Regarding the control variables, all holiday dummy coefficients are significantly negative at the 1% significance level, reflecting reduced electricity demand on holidays. The estimated coefficients for the biomass power generation dummy are also significantly negative at the 1% level for the 0.1, 0.8, and 0.9

quantiles. By contrast, the effects of nuclear power generation are mixed. In winter, the coefficients are significantly negative for all quantiles except the 0.9 quantile, with significance at the 1% level from the 0.1 to 0.7 quantiles and at the 5% level for the 0.8 quantile. In spring and summer, only the coefficients for the 0.1 quantile (spring) and 0.8 quantile (summer) are significantly negative at the 10% level. Additionally, the coefficients for the 0.8 and 0.9 quantiles in spring are significantly positive at the 10% level. All other coefficients are statistically insignificant. These mixed results are likely due to the lack of flexibility in nuclear power generation operations. Nuclear power plants cannot be easily adjusted and operate at a constant output over a certain period of time. Thus, they have a less clear impact on daily electricity prices than demand and solar PV power generation, which fluctuate daily.

The estimated coefficients for the main explanatory variables exhibit consistent signs across all seasons: positive for electricity demand and negative for solar PV power generation, indicating that the qualitative effects of electricity demand and solar PV power generation on electricity prices do not vary seasonally. However, the magnitudes of the estimated coefficients differ slightly by season, particularly for solar PV power generation, suggesting mild seasonality in its quantitative impact. Figure 3 presents the seasonal variation in the estimated coefficients for electricity demand and solar PV power generation across quantiles. Confidence intervals are computed using the bootstrap method with 1,000 replications.

[Figure 3 around here]

The upper panels of Figure 3 show that the estimated coefficients for electricity demand (Load) are positive and generally increase, or exhibit a mild U-shaped pattern, as the quantile level of electricity prices rises. The coefficients in summer are slightly lower than those in other seasons. Specifically, the estimated coefficients at the 0.1, 0.5, and 0.9 quantiles are 0.623, 0.653, and 0.811 in winter; 0.553, 0.564, and 0.748 in spring; 0.428, 0.501, and 0.753 in summer; and 0.534, 0.536, and 0.746 in autumn. These results indicate that the impact of electricity demand on electricity prices shows little seasonal variation, except for a slightly weaker effect in summer.

Meanwhile, the lower panels of Figure 3 show that the estimated coefficients for solar PV power generation (Solar) are negative and generally decrease, or exhibit a slight inverse U-shaped pattern, as the quantile level of electricity prices increases. This outcome indicates that the extent to which an increase in solar PV power generation lowers electricity prices becomes larger at higher price quantiles. Mild seasonality in the impact of solar PV power generation on electricity price levels is also noted: the coefficients are most negative in winter, least negative in summer, and fall in between in spring and autumn. Specifically, the estimated coefficients at the 0.1, 0.5, and 0.9 quantiles are -0.782, -0.869, and -1.063 in winter; -0.454, -0.504, and -0.681 in spring; -0.163, -0.423, and -0.518 in summer; and -0.607, -0.507, and -0.803 in autumn.

[Figure 4 around here]

The results discussed above are based on the full period data from FY2016 to FY2019. Notably, solar PV power generation in Kyushu increased substantially over this period. Figure 4 illustrates the relationship between electricity prices and solar PV power generation, revealing a consistent annual increase in solar PV power generation and very low electricity prices beginning in FY2018. This trend suggests that the relationship between electricity prices and solar PV power generation may have changed over time. To investigate this possibility, we divide the sample period into two subperiods—the first half-period (FY2016–FY2017) and the second half-period (FY2018–FY2019)—and compare the results for each. The estimated coefficients for both periods are reported in Table 8. (Note that the biomass power generation dummy is omitted in the first half-period because by construction, it takes only the value of 0 throughout that period.)

Table 8 Estimated Coefficients of Electricity Demand (Load) and Solar PV Power Generation (Solar) on Electricity Prices

First half-period (FY2016–FY2017)									
Quantile	0.100	0.200	0.300	0.400	0.500	0.600	0.700	0.800	0.900
Load: Winter	0.908*** (0.136)	0.901*** (0.116)	0.826*** (0.122)	0.747*** (0.120)	0.738*** (0.112)	0.709*** (0.109)	0.721*** (0.116)	0.636*** (0.157)	0.962*** (0.264)
Load: Spring	0.731*** (0.139)	0.654*** (0.123)	0.553*** (0.123)	0.435*** (0.118)	0.498*** (0.125)	0.438*** (0.152)	0.420** (0.177)	0.568*** (0.189)	0.945*** (0.290)
Load: Summer	0.484*** (0.139)	0.518*** (0.103)	0.560*** (0.111)	0.629*** (0.086)	0.632*** (0.078)	0.667*** (0.091)	0.636*** (0.125)	0.755*** (0.158)	1.010*** (0.221)
Load: Autumn	0.809*** (0.156)	0.851*** (0.131)	0.702*** (0.130)	0.629*** (0.119)	0.633*** (0.119)	0.584*** (0.131)	0.561*** (0.146)	0.541*** (0.171)	0.900*** (0.275)
Solar: Winter	- 0.796*** (0.187)	- 0.598*** (0.191)	- 0.769*** (0.197)	- 0.746*** (0.187)	- 0.956*** (0.202)	- 0.943*** (0.218)	- 1.065*** (0.235)	- 1.071*** (0.270)	-1.322*** (0.354)
Solar: Spring	- 0.487*** (0.137)	- 0.495*** (0.107)	- 0.610*** (0.106)	- 0.528*** (0.110)	- 0.568*** (0.125)	- 0.459*** (0.135)	- 0.571*** (0.181)	-0.374* (0.198)	-0.378* (0.213)
Solar: Summer	-0.026 (0.249)	-0.157 (0.201)	-0.352* (0.202)	- 0.550*** (0.158)	- 0.595*** (0.124)	- 0.527*** (0.129)	-0.431** (0.183)	-0.499* (0.266)	-1.006** (0.418)
Solar: Autumn	- 0.702*** (0.156)	- 0.522*** (0.127)	- 0.563*** (0.138)	- 0.663*** (0.171)	- 0.710*** (0.209)	- 0.865*** (0.211)	- 0.793*** (0.226)	- 1.023*** (0.262)	-1.203*** (0.283)
Nuclear: Winter	-0.360 (0.732)	-0.023 (0.445)	-0.200 (0.375)	0.038 (0.398)	0.392 (0.384)	0.234 (0.411)	0.177 (0.543)	1.045 (0.803)	0.946 (1.017)
Nuclear: Spring	0.556 (1.042)	1.418 (0.894)	1.313* (0.760)	1.579** (0.760)	1.137 (0.794)	1.248 (0.856)	1.617* (0.923)	0.549 (0.990)	0.083 (0.881)

Nuclear: Summer	1.452 (1.107)	1.616 (0.989)	0.706 (0.893)	0.025 (0.780)	-0.053 (0.784)	-0.655 (0.836)	-0.509 (1.070)	-1.354 (1.171)	-0.876 (1.509)
Nuclear: Autumn	0.528* (0.275)	0.416 (0.260)	0.547** (0.246)	0.742*** (0.270)	0.707** (0.333)	1.048*** (0.340)	1.215*** (0.374)	1.640*** (0.429)	1.176*** (0.449)
Dummy: holiday	- 1.349*** (0.261)	- 1.523*** (0.220)	- 1.799*** (0.246)	- 1.924*** (0.220)	- 1.945*** (0.204)	- 2.071*** (0.217)	- 2.273*** (0.253)	- 2.392*** (0.293)	-1.826*** (0.526)
Num. obs.	723	723	723	723	723	723	723	723	723

Second half-period (FY2018–FY2019)									
Quantile	0.100	0.200	0.300	0.400	0.500	0.600	0.700	0.800	0.900
Load: Winter	0.622*** (0.087)	0.599*** (0.085)	0.546*** (0.088)	0.524*** (0.098)	0.550*** (0.097)	0.546*** (0.106)	0.390*** (0.116)	0.391*** (0.118)	0.340*** (0.153)
Load: Spring	0.564*** (0.098)	0.531*** (0.088)	0.480*** (0.089)	0.443*** (0.095)	0.535*** (0.094)	0.567*** (0.101)	0.487*** (0.108)	0.504*** (0.133)	0.542*** (0.164)
Load: Summer	0.352*** (0.090)	0.347*** (0.093)	0.414*** (0.094)	0.424*** (0.091)	0.479*** (0.088)	0.561*** (0.098)	0.635*** (0.105)	0.702*** (0.133)	0.939*** (0.198)
Load: Autumn	0.464*** (0.108)	0.388*** (0.097)	0.401*** (0.090)	0.391*** (0.083)	0.435*** (0.080)	0.435*** (0.085)	0.407*** (0.096)	0.459*** (0.117)	0.594*** (0.141)
Solar: Winter	- 0.989*** (0.168)	- 0.992*** (0.143)	- 0.904*** (0.133)	- 0.839*** (0.127)	- 0.832*** (0.119)	- 0.726*** (0.114)	- 0.756*** (0.124)	- 0.828*** (0.125)	-0.916*** (0.167)
Solar: Spring	- 0.477*** (0.112)	- 0.571*** (0.103)	- 0.522*** (0.093)	- 0.588*** (0.100)	- 0.564*** (0.105)	- 0.654*** (0.093)	- 0.709*** (0.097)	- 0.794*** (0.109)	-0.807*** (0.110)
Solar: Summer	-0.136 (0.168)	-0.335** (0.132)	-0.360** (0.140)	- 0.350*** (0.119)	-0.326** (0.132)	- 0.454*** (0.151)	- 0.496*** (0.168)	-0.558** (0.242)	-0.659 (0.451)
Solar: Autumn	- 0.778*** (0.169)	- 0.785*** (0.175)	- 0.707*** (0.152)	- 0.710*** (0.119)	- 0.551*** (0.107)	- 0.539*** (0.114)	- 0.613*** (0.137)	- 0.581*** (0.161)	-0.530*** (0.190)
Nuclear: Winter	-0.683** (0.272)	- 0.628*** (0.235)	-0.523** (0.217)	-0.505* (0.261)	-0.292 (0.273)	-0.234 (0.305)	0.179 (0.334)	0.328 (0.306)	0.709* (0.386)
Nuclear: Spring	- 0.582*** (0.155)	- 0.364*** (0.099)	-0.285** (0.124)	-0.118 (0.130)	-0.093 (0.123)	-0.021 (0.118)	0.123 (0.124)	0.248* (0.149)	0.407* (0.240)
Nuclear: Summer	-0.083 (0.218)	-0.038 (0.186)	-0.325* (0.193)	- 0.446*** (0.166)	-0.327** (0.166)	-0.458* (0.235)	- 0.873*** (0.307)	- 0.981*** (0.357)	-1.551*** (0.461)
Nuclear: Autumn	-0.000 (0.322)	0.207 (0.273)	0.114 (0.235)	0.116 (0.209)	0.170 (0.187)	0.254 (0.175)	0.257 (0.177)	0.220 (0.181)	-0.034 (0.207)
Dummy: holiday	- 0.899***	- 0.846***	- 1.006***	- 0.901***	- 0.830***	- 0.812***	- 0.997***	- 1.009***	-0.871***

	(0.209)	(0.172)	(0.189)	(0.196)	(0.176)	(0.175)	(0.188)	(0.250)	(0.285)
Dummy: biomass	-0.290	-0.213	-0.531**	-0.629**	-0.523**	-	-	-	-1.581***
	(0.298)	(0.250)	(0.260)	(0.260)	(0.255)	0.719***	1.075***	1.408***	(0.523)
Num. obs.	731	731	731	731	731	731	731	731	731

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses; *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 8 presents the results for the first and second half-periods in the upper and lower panels, respectively. For all seasons, the estimated coefficients of electricity demand are significantly positive at the 1% significance level in both sub-periods, indicating a consistent price-increasing effect. In the case of solar PV power generation, almost all coefficients are significantly negative at the 1% significance level for winter, spring, and autumn in both the first and second half-periods, except for the 0.8 and 0.9 quantiles in spring during the first half-period, which are significant at the 10% significance level. For summer, the estimated coefficients for solar PV power generation at the 0.4, 0.5, and 0.6 quantiles are significantly negative at the 1% significance level and those at 0.7 and 0.9 (0.3 and 0.8) are significantly negative at the 5% (10%) level in the first half-period, while those at the 0.4, 0.6, and 0.7 (0.2, 0.3, 0.5, and 0.8) quantiles are significantly negative at the 1% (10%) level in the second half-period. Overall, the results for electricity demand and solar PV power generation are qualitatively similar to those for the full period reported in Table 7.

For the control variables, all coefficients for the holiday dummy are significantly negative at the 1% level in both sub-periods, reflecting consistently lower electricity prices on holidays. In the second half-period, the coefficients for the biomass power generation dummy are significantly negative at the 1% level for the 0.6–0.9 quantiles, at the 5% level for the 0.3–0.5 quantiles, and are not statistically significant for the 0.1 and 0.2 quantiles. However, the results for nuclear power generation are mixed and differ from those for the full period reported in Table 7. In the first half-period, the coefficients are generally insignificant in winter, spring, and summer, except in spring where they are significantly positive at the 5% level for the 0.4 quantile and at the 10% level for the 0.3 and 0.7 quantiles. In autumn, most coefficients are significantly positive, with significance at the 1% significance level for the 0.4 and 0.6–0.9 quantiles, at the 5% level for the 0.3 and 0.5 quantiles, and at the 10% level for the 0.1 quantile; only the 0.2 quantile is not significant. In the second half-period, the coefficients are significantly negative in winter (0.1–0.4 quantiles) and spring (0.1–0.3 quantiles), with positive effects at the 10% level for the 0.9 quantile in winter and the 0.8 and 0.9 quantiles in spring. In summer, significantly negative coefficients are found at the 1% level (0.4 and 0.7–0.9 quantiles), 5% level (0.5 quantile), and 10% level (0.3 and 0.6 quantiles). In autumn, no coefficients are statistically significant.

[Figure 5 around here]

Figure 5 illustrates the relationship between the estimated coefficients and the quantile points of electricity prices; the upper and lower panels present the coefficients for electricity demand (Load) and solar PV power generation (Solar) in the first and second half-periods, respectively, across the electricity price quantiles. The patterns for electricity demand are consistent across both periods: the coefficients are positive and increase with higher quantiles in summer, while exhibiting a mild U-shaped pattern in other seasons. However, compared with Figure 3, the upward trend in coefficients with increasing quantiles is slightly less pronounced in seasons other than summer.

Meanwhile, the estimated coefficients for solar PV power generation are negative and generally decline with increasing quantiles, with this trend being most pronounced in summer. This pattern is observed across all seasons except for winter and autumn in the second half-period, where the coefficients exhibit a mild inverse U-shape pattern or increase. Similar to Figure 3, mild seasonality in the impact of solar PV power generation on electricity price levels is observed: the coefficients tend to be most negative in winter, least negative in summer, and fall in between in spring and autumn. Specifically, the estimated coefficients at the 0.1, 0.5, and 0.9 quantiles are -0.796, -0.956, and -1.322 in winter; -0.487, -0.568, and -0.378 in spring; -0.026, -0.595, and -1.006 in summer; and -0.702, -0.710, and -1.203 in autumn in the first half-period, while they are -0.989, -0.832, and -0.916 in winter; -0.477, -0.564, and -0.807 in spring; -0.136, -0.326, and -0.659 in summer; and -0.778, -0.551, and -0.530 in autumn in the second half-period.

4.2 Impact of solar PV power generation on electricity price variability

Using *IQR* as a measure of variability, we investigate the impact of solar PV power generation on the variability of electricity prices. Following Maciejowska (2020), the *IQR* is defined as the difference between the electricity prices at the 0.9 and 0.1 quantiles. The corresponding effect of solar PV power generation is estimated as the difference between the regression coefficients at these two quantiles. The statistical significance of this difference is assessed using a bootstrap method. The estimated coefficients of the *IQR* on the impact of seasonality using Equation (2) are listed in Table 9.

Table 9 Seasonal Estimates of the Coefficients of Electricity Demand (Load) and Solar PV Power Generation (Solar) on the *IQR* of Electricity Price

	<i>Load</i>				<i>Solar</i>			
	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn
FY2016–19	0.189 (0.131)	0.195 (0.134)	0.325** (0.139)	0.212 (0.132)	-0.280 (0.288)	-0.228* (0.125)	-0.356 (0.312)	-0.197 (0.292)
FY2016–17	0.054 (0.292)	0.214 (0.314)	0.526** (0.244)	0.091 (0.310)	-0.526 (0.403)	0.108 (0.250)	-0.980** (0.468)	-0.501 (0.314)
FY2018–19	-0.282	-0.213	0.587***	0.131	0.073	-0.330**	-0.523	0.249

(0.173) (0.188) (0.200) (0.180) (0.217) (0.148) (0.461) (0.245)

Note. Including nuclear power generation and excluding outliers; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; FY2016–19 (entire period), FY2016–17 (first half-period), and FY2018–19 (second half-period); standard errors in parentheses; *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

As shown in Table 9, the estimated *IQR* coefficients for electricity demand (*Load*) are significantly positive at the 5% level in summer for the full sample period. When the sample is divided into two sub-periods, the coefficients remain significantly positive in summer at the 5% (1%) level in the first (second) half-period, indicating that increased electricity demand during summer is associated with greater variability in electricity prices. For the other seasons, the *IQR* coefficients are generally insignificant. By contrast, the estimated *IQR* coefficients for solar PV power generation (*Solar*) are significantly negative for spring (at the 10% level) and summer (at the 1% level) during the full period. However, when examining the sub-periods, these negative effects remain statistically significant in summer at the 5% level during the first half-period and in spring at the 5% level during the second half-period. The coefficient for summer remains negative but not significant in the second half-period. For winter and autumn, the coefficients are generally insignificant.

These results show that the impact of electricity demand and solar PV power generation on electricity price variability exhibits seasonal variation. The finding that electricity demand in summer has a greater effect on price variability than in other seasons is consistent with the characteristics of the electricity supply curve, namely, its upward-sloping nature with increasing marginal costs as well as with higher levels of electricity demand observed during summer. Notably, the analysis reveals a novel and important finding: higher solar PV power generation contributes to a reduction in electricity price variability in spring and summer, but not in autumn or winter.

This seasonal variation can be attributed to differences in the correlation between electricity demand and solar PV power generation across spring/summer and autumn/winter, which are driven by seasonal changes in the relationship between temperature, solar PV power generation, and electricity demand. On clear days, generally, a positive relationship exists between the amount of sunlight and both temperature and solar PV power generation across all seasons. However, the relationship between temperature and electricity demand is known to change with temperature levels: when the temperature exceeds approximately 18.3°C (65°F), an increase in temperature raises electricity demand. Conversely, when the temperature is below 18.3°C, a decrease in temperature raises electricity demand. Consequently, in high-temperature seasons such as summer and late spring, increased solar PV power generation (i.e., supply) tends to coincide with higher temperatures and increased electricity demand. This positive correlation between supply and demand contributes to reduced variability in electricity prices; thus, solar PV power generation is associated with lower variability in electricity prices. By contrast, in low-temperature seasons such as autumn and winter, decreased solar PV power generation (i.e., supply) is accompanied with lower temperatures and increased electricity demand, amplifying electricity price variability; hence, solar PV power generation is associated

with higher price variability.⁹ These changing trends explain the seasonal variation between solar PV power generation and electricity price variability observed in the quantile regression.

5. Discussion and robustness analysis

5.1 Relationship between price levels and variability

We argue that the observed seasonal variation in the impact of solar PV power generation on electricity price variability is likely attributable to seasonal changes in the correlation between solar PV power generation and electricity demand. However, when the electricity supply curve exhibits an increasing slope, the impact of solar PV power generation on price volatility may be amplified during periods of high electricity prices. Therefore, if electricity prices tend to be higher in autumn and winter than in spring and summer, the positive contribution of solar PV power generation to price variability could become more pronounced in those seasons. This perspective offers a plausible alternative explanation for the absence of a significant negative effect of solar PV power generation on price variability in autumn and winter, in contrast to the significant negative impact observed in spring and summer

[Figure 6 around here]

To investigate this possibility concerning the relationship between electricity price levels and their variability, in Figure 6, we plot the 0.9 quantile of electricity prices against the estimated *IQR* of solar PV power generation for each season. The 0.9 quantile reflects high-end electricity prices, while the *IQR* represents the estimated impact of solar PV power generation on price variability.

In the left panel (FY2016–FY2017), the 0.9 quantile price in autumn (12.417 Yen/kWh) is slightly lower than that in summer (13.700 Yen/kWh), but the *IQR* in autumn (-0.501) is smaller in magnitude (i.e., less negative) than that in summer (-0.98). Meanwhile, in the right panel (FY2018–FY2019), the 0.9 quantile price in winter (8.859 Yen/kWh) is the lowest among all seasons, but the corresponding *IQR* (0.073) is notably higher than those in summer (-0.523) and spring (-0.33). Moreover, the 0.9 percentile price in autumn (9.399 Yen/kWh) is significantly lower than that in summer (14.895 Yen/kWh), but its *IQR* (0.249) is much larger than that in summer (-0.523).

These findings suggest that higher electricity price levels do not necessarily correspond to larger impacts of solar PV power generation on price variability, implying that other seasonal factors, such as the seasonal

⁹ The correlations between electricity demand and solar PV power generation from FY2016 to FY2019 were positive only in summer (-0.151 in winter, -0.144 in spring, 0.451 in summer, and -0.413 in autumn). Further, the correlations between temperature and solar PV power generation (electricity demand) from FY2016 to FY2019 were -0.015 (-0.492) in winter, 0.007 (0.131) in spring, 0.552 (0.751) in summer, and 0.191 (-0.389).

changes in the correlation between solar PV and electricity demand discussed above, play a more prominent role.

5.2 Effect of tariff system penalizing high loads

With increased integration of variable renewable energy sources (e.g., solar and wind power) and wider deployment of smart electricity meters, several countries have adopted time-of-use (TOU) or real time pricing schemes. These pricing mechanisms penalize electricity consumption during peak periods and may reduce price variability at higher quantiles. Consequently, in regions where summers are substantially hotter than winters, TOU pricing can lead to reduced use of air conditioning in summer relative to heating in winter, potentially leading to asymmetric electricity demand in summer and winter. This effect could influence the result of solar PV power generation on electricity price variability between the two seasons.

However, this potential explanation based on tariff structures is not likely applicable to this study. During the observation period, electricity tariffs for residential consumers in Japan remained largely unchanged, with limited implementation of TOU or real-time pricing schemes. As such, it is unlikely that asymmetric consumer demand responses to TOU pricing, such as those documented by Andruszkiewicz et al. (2019, 2021), have been a significant factor in this setting.

Nonetheless, in more recent years, some electricity retailers in Japan have begun introducing more flexible TOU tariffs, facilitated by the broader adoption of smart meters. These developments reflect ongoing liberalization of Japan's electricity market and related policy shifts, as discussed by Goto and Sueyoshi (2016). While the current study period is characterized by limited tariff-induced demand responses, future research should account for these evolving dynamics, particularly when examining more recent data periods that feature changing pricing structures and renewable energy incentives (e.g., Rudolph and Damien, 2023).

5.3 Robustness analysis with temperature indicators: heating and cooling degree days

Since electricity demand is strongly influenced by temperature, which in turn affects solar power generation, we divided the seasons based on temperature and conducted quantile regressions for each season. However, the analysis may not have fully captured the impact of temperature on electricity prices. Therefore, for robustness testing, we perform a quantile regression that includes temperature indicators—specifically, heating degree day (HDD) and cooling degree day (CDD)—as follows:¹⁰

¹⁰ Let $AveTemp_t$ be the average temperature (°C) of date t . Take 18.3°C ($= 65^\circ\text{F}$). HDD on date t is defined as $HDD_t = \text{Max}[18.3 - AveTemp_t, 0]$, while CDD on date t is defined as $CDD_t = \text{Max}[AveTemp_t - 18.3, 0]$. If the temperature is above (below) 18.3°C , a rise (drop) in temperature increases electricity demand. Thus, HDD and CDD more accurately represent the impact of temperature on electricity demand than temperature itself.

$$P_t(\tau) = \alpha_{0,\tau} + \alpha_{1,\tau}D_{hday,t} + \alpha_{2,\tau}D_{bio,t} + \alpha_{3,\tau}HDD_t + \alpha_{4,\tau}CDD_t + \sum_{k=1}^4 \beta_{k,\tau}^L L_{k,t} + \sum_{k=1}^4 \beta_{k,\tau}^S S_{k,t} + \sum_{k=1}^4 \beta_{k,\tau}^A A_{k,t} + \sum_{k=1}^7 \theta_{i,\tau} P_{t-i} \quad (3)$$

$$IQR_t = \alpha_0 + \alpha_1 D_{hday,t} + \alpha_2 D_{bio,t} + \alpha_{3,\tau} HDD_t + \alpha_{4,\tau} CDD_t + \sum_{k=1}^4 \beta_k^L L_{k,t} + \sum_{k=1}^4 \beta_k^S S_{k,t} + \sum_{k=1}^4 \beta_k^A A_{k,t} + \sum_{i=1}^7 \theta_i P_{t-i} \quad (4)$$

where HDD_t (CDD_t) is the HDD (CDD) at date t , and the other variables are as defined above.¹¹

We focus on the impact of solar PV power generation on electricity price variability and report only the results of regression (4) for the *IQR*. Table 10 presents results of the effect of solar PV power generation on electricity price variability. Compared with Table 9 (reporting results of tests excluding HDD and CDD), results after controlling for HDD and CDD remain qualitatively similar: the coefficients of *Load* are significantly positive in summer for all full, first half-, and second half-periods, while the coefficients of *Solar* are significantly negative in summer for the first half-period (FY2016–17), and in spring for the second half-period (FY2018–19). The key difference is that, once HDD and CDD are included, the coefficients on *Solar* are no longer statistically significant in any season for the full period (FY2016–19). Quantitatively, the values of coefficients in Table 11, when they are significant, are similar to those in Table 9 without HDD and CDD (e.g., the coefficient of *Solar* in summer (spring) for the first (second) half-period is -0.916 (-0.335) with HDD and CDD, but -0.980 (-0.330) without HDD and CDD). These results confirm the robustness of the observed seasonal variation in the effect of solar PV power generation on electricity price variability.

Table 11 Seasonal Estimates of the Coefficients of Solar PV Power Generation (*Solar*) on the *IQR* of Electricity Prices with HDD and CDD

	<i>Load</i>				<i>Solar</i>			
	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn
FY2016-19	0.0472 (0.135)	0.067 (0.148)	0.314** (0.149)	0.063 (0.141)	-0.345 (0.255)	-0.181 (0.129)	-0.287 (0.327)	-0.097 (0.267)
FY2016-17	-0.258 (0.270)	-0.161 (0.273)	0.590** (0.261)	-0.174 (0.279)	-0.562 (0.350)	-0.163 (0.238)	-0.916** (0.402)	-0.469 (0.284)
FY2018-19	-0.156 (0.186)	0.204 (0.208)	0.776*** (0.217)	0.210 (0.186)	0.066 (0.227)	-0.335** (0.158)	-0.426 (0.457)	0.273 (0.268)

Note. Including nuclear power generation and the outliers; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses; *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

¹¹ Since multicollinearity occurs in analyses using cross terms with HDD/CDD and dummy variables representing seasons, we conduct the analysis using HDD and CDD.

5.4 Robustness analysis with liquefied natural gas prices

Fuel prices can affect both the level and variability of electricity prices by shaping the electricity supply curve, particularly through their influence on marginal costs. In Japan, liquefied natural gas (LNG) prices have become a central determinant of electricity price formation. Following the Fukushima nuclear accident and subsequent shutdown of nuclear power plants, the share of LNG-fired power generation increased substantially, establishing LNG as a key energy source. To investigate the impact of LNG prices on electricity prices, Suliman and Farzaneh (2022) conducted panel analysis during 2016–2020, employing the same LNG variable used in this study as an explanatory variable. Rassi and Kanamura (2023) demonstrated that LNG spot prices began to exert an immediate influence on electricity spot prices in Japan during FY2020–21. Moreover, in November 2021, stakeholders from JERA and Tohoku Electric Power—two of the main power generation companies in Japan—announced that they would more strongly reflect LNG spot prices in electricity spot auction prices. Given these developments, we consider it relevant to examine whether LNG prices alter the estimated effects of solar PV power generation on electricity prices. For robustness analysis, we incorporate LNG prices as an additional explanatory variable into regressions (1) and (2), and assess whether their inclusion affects the main results. The following regression analysis was conducted:

$$P_t(\tau) = \alpha_{0,\tau} + \alpha_{1,\tau}D_{hday,t} + \alpha_{2,\tau}D_{bio,t} + \alpha_{3,\tau}G_{t-1} + \sum_{k=1}^4 \beta_{k,\tau}^L L_{k,t} + \sum_{k=1}^4 \beta_{k,\tau}^S S_{k,t} + \sum_{k=1}^4 \beta_{k,\tau}^A A_{k,t} + \sum_{i=1}^7 \theta_{i,\tau} P_{t-i} \quad (5)$$

$$IQR_t = \alpha_0 + \alpha_1 D_{hday,t} + \alpha_2 D_{bio,t} + \alpha_3 G_{t-1} + \sum_{k=1}^4 \beta_k^L L_{k,t} + \sum_{k=1}^4 \beta_k^S S_{k,t} + \sum_{k=1}^4 \beta_k^A A_{k,t} + \sum_{i=1}^7 \theta_i P_{t-i} \quad (6)$$

where G_t is the LNG price at date t , and the other variables are as defined above. As LNG price, we use the CIF (Cost, Insurance and Freight) price of LNG from the trade statistics of Japan. The monthly data are provided by the Ministry of Finance, Japan.

We focus on the impact of solar PV power generation on electricity price variability and report only the results of regression (6) for the IQR . Table 12 presents the results of seasonal analysis of the effect of solar PV power generation on electricity price variability. Compared with Table 9 (reporting results of tests excluding LNG prices), the results remain qualitatively similar: the coefficients on *Load* are significantly positive in summer across the full period (FY2016–19) as well as the two sub-periods (FY2016–17 and FY2018–19). The coefficients on *Solar* remain significantly negative in spring for the full period, in summer for the first half-period, and in spring for the second half-period. A notable difference is that when LNG prices are included, the coefficient on *Solar* is also significantly negative in winter during the first half-period (FY2016–17). Quantitatively, the absolute values of the significant coefficients tend to be slightly smaller when LNG prices are included. For example, the coefficient on *Solar* in summer (spring) for the first

(second) half-period is -0.933 (-0.271) with LNG prices, compared with -0.980 (-0.330) without LNG prices. Overall, these results reinforce the robustness of the observed seasonal variation in the effect of solar PV power generation on electricity price variability.

Table 12 Seasonal Estimates of the Coefficients of Solar PV Power Generation (Solar) on the *IQR* of Electricity Price with Liquefied Natural Gas Prices

	<i>Load</i>				<i>Solar</i>			
	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn
FY2016–19	0.1187 (0.119)	0.0757 (0.120)	0.259** (0.126)	0.166 (0.120)	-0.125 (0.253)	-0.236* (0.128)	-0.385 (0.255)	-0.281 (0.296)
FY2016–17	-0.035 (0.281)	0.186 (0.299)	0.421** (0.249)	-0.034 (0.294)	-0.748** (0.407)	0.090 (0.314)	-0.933** (0.454)	-0.485 (0.295)
FY2018–19	-0.218 (0.191)	0.067 (0.182)	0.715*** (0.221)	0.121 (0.185)	-0.168 (0.260)	-0.271* (0.140)	-0.496 (0.476)	0.051 (0.252)

Note. Including nuclear power generation and excluding outliers; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses; *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

6. Conclusion

In this study, we employed quantile regression to examine the impact of solar PV power generation on electricity prices, using data on electricity demand, solar PV power generation, nuclear power generation, and wholesale electricity prices for the Kyushu region from the period FY2016–2019.

The main findings are as follows. First, consistent with several previous studies, the merit order effect was identified: increased solar PV power generation exerts a negative effect on electricity prices, and the magnitude of this effect generally increases (or follows a slight inverse U-shaped pattern) at higher quantiles. This result indicates that the extent to which solar PV power generation reduces electricity prices intensifies toward the upper end of the price distribution.

Second, the effect of increased electricity demand on prices is positive and increases (or exhibits a mild U-shaped pattern) as price quantiles rise, suggesting that the upward pressure of demand on electricity prices is more pronounced at higher price levels. Moreover, the impact of demand on price variability exhibits modest seasonal differences, with a notably stronger effect in summer than in other seasons.

Third, and importantly, the analysis revealed a clear seasonal variation in the effect of solar PV power generation on electricity price variability: increased solar PV power generation is associated with reduced price variability in spring and summer, but not in autumn and winter. This result can be attributed to seasonal

variation in the relationship between electricity demand and solar PV power generation, primarily driven by temperature-dependent changes in electricity demand, and the generally positive correlation between temperature, amount of sunlight, and solar PV output.

Finally, robustness of the findings was confirmed through additional regressions that included HDD/CDD or LNG prices as explanatory variables. The main results remained qualitatively similar.

These results—particularly the observed seasonal variation in the impact of solar PV power generation on electricity price variability—have broader relevance and implications, especially for electricity markets with high solar PV penetration, even though the analysis focuses on the regional market in Kyushu, Japan. The findings suggest that for policymakers and market participants seeking to mitigate price variability, efforts to manage price fluctuations caused by solar PV power generation are more critical during low-temperature (than high-temperature) seasons. For energy storage businesses, the results imply that the valuation of real options for solar PV-based storage facilities may differ between low- and high-temperature seasons. These insights underscore the importance of carefully examining supply–demand dynamics, particularly the correlation between weather-dependent solar PV power generation and electricity demand, when assessing the effects of renewable energy on electricity prices.

Finally, a key direction for future research relates to the use of hourly data. While this study relies on aggregated daily PV time data, electricity markets operate on an hourly (or even half-hourly, as in the case of JEPX) basis and exhibit substantial intra-day price variation. Utilizing hourly data would enable a more detailed analysis of the impact of solar PV power generation on electricity prices and their variability. Several previous studies, including those by Sakaguchi and Fujii (2021) and Suliman and Farzaneh (2022) on the Japanese electricity markets, have involved analyses using hourly data; however, a particularly promising approach is the panel quantile regression framework proposed by Tselika (2022), which incorporates hour-specific characteristics and can reveal latent intra-day market dynamics. By leveraging this temporal granularity, the approach facilitates a more nuanced understanding of price relationships across time intervals and improves hourly price forecast accuracy. Such insights are particularly valuable for assessing the impact of supply-side changes (e.g., expansion of storage batteries and pumped-storage facilities capable of shifting the timing of electricity supply) on price variability, contributing to more accurate valuations of these assets and better-informed investment decisions. Further refinement of the model remains an important task for its practical application.

References

- Andruszkiewicz, J., Lorenc, J., Weychan, A., 2019. Demand price elasticity of residential electricity consumers with zonal tariff settlement based on their load profiles. *Energies*. 12(22), 4317. <https://doi.org/10.3390/en12224317>
- Andruszkiewicz, J., Lorenc, J., Weychan, A., 2021. Price-based demand side response programs and their effectiveness on the example of tou electricity tariff for residential consumers. *Energies*. 14(2), 287. <https://doi.org/10.3390/en14020287>
- Barlow, M.T., 2002. A diffusion model for electricity prices. *Math. Finance*. 12, 287–298. <https://doi.org/10.1111/j.1467-9965.2002.tb00125.x>.
- Cabinet Office of Japan, n.d. Date data for holidays. <https://www8.cao.go.jp/chosei/shukujitsu/syukujitsu.csv> (accessed 17 August 2025).
- Cló, S., Cataldi, A., Zopoli, P., 2015. The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices. *Energy Policy*. 77, 79–88. <https://doi.org/10.1016/j.enpol.2014.11.038>.
- Cludius, J., Hermann, H., Matthes, F., Graichen, V., 2014. The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: Estimation and distributional implications. *Energy Econ*. 44, 302–313. <https://doi.org/10.1016/j.eneco.2014.04.020>.
- Gelabert, L., Labandeira, X., Linares, P., 2011. An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices. *Energy Econ*. 33, 59–65. <https://doi.org/10.1016/j.eneco.2011.07.027>.
- Goto, M., Sueyoshi, T., 2016. Electricity market reform in Japan after Fukushima. *Econ. Energy Environ. Policy*. 5(1). <https://doi.org/10.5547/2160-5890.5.1.mgot>
- Hagfors, L.I., Bunn, D., Kristoffersen, E., Staver, T.T., Westgaard, S., 2016. Modeling the UK electricity price distributions using quantile regression. *Energy*. 102, 231–243. <https://doi.org/10.1016/j.energy.2016.02.025>.
- Hagfors, L.I., Paraschiv, F., Molnar, P., Westgaard, S., 2016. Using quantile regression to analyze the effect of renewables on EEX price formation. *Renew. Energy Environ. Sustain*. 1, 32. <https://doi.org/10.1051/rees/2016036>.
- Japan Electric Power eXchange (JEPX), n.d. Trading Information. <https://www.jepx.jp/en/electricpower/market-data/spot/> (accessed 17 August 2025).
- Japan Meteorological Agency, n.d. Data and Materials. <https://www.jma.go.jp/jma/indexe.html> (accessed 17 August 2025).
- JERA Co., Inc, 2021, Measures to Address the Heavy-Load Winter Season for FY2021 (Nov. 24, 2021) https://www.jera.co.jp/en/news/information/20211124_792 (accessed 17 August 2025).
- Kanamura, T., Ohashi, K., 2007. A structural model for electricity prices with spikes: Measurement of spike risk and optimal policies for hydropower plant operation. *Energy Econ*. 29, 1010–1032. <https://doi.org/10.1016/j.eneco.2006.05.012>.
- Ketterer, J., 2014. The impact of wind power generation on the electricity price in Germany. *Energy Econ*. 44, 270–280. <https://doi.org/10.1016/j.eneco.2014.04.003>.
- Kyushu Electric Power Transmission and Distribution Co., Inc., n.d. Regional Demand and Supply Data (in Japanese): https://www.kyuden.co.jp/td_area_jukyu/jukyu.html (accessed 17 August 2025).

- Luňáčková, P., Průšaa, J., Jandaa, K., 2017. The merit order effect of Czech photovoltaic plants. *Energy Policy*. 106, 138–147. <https://doi.org/10.1016/j.enpol.2017.02.053>.
- Maciejowska, K., 2020. Assessing the impact of renewable energy sources on the electricity price level and variability – A quantile regression approach. *Energy Econ.* 85, 104532. <https://doi.org/10.1016/j.eneco.2019.104532>.
- Maekawa, J., Hai, B.H., Shinkuma S., Shimada, K., 2018. The Effect of Renewable Energy Generation on the Electric power Spot Price of the Japan Electric Power Exchange. *Energies*. 11, 2215. <https://doi.org/10.3390/en11092215>.
- Ministry of Finance, Japan, n. d. The trade statistics of Japan https://www.customs.go.jp/toukei/info/index_e.htm (accessed 17 August 2025).
- Paraschiv, F., Erni, D., Pietsch R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. *Energy Policy*. 73, 196–210.
- Rassi, S., Kanamura, T., 2023. Electricity price spike formation and LNG prices effect under gross bidding scheme in JEPX. *Energy Policy* 177, 113552. <https://doi.org/10.116/j.enpol.2023.113552>
- Rintamäki, T., Siddiqui, A.S., Salo, A., 2017. Does renewable energy generation decrease the volatility of electricity prices? An analysis of Denmark and Germany. *Energy Econ.* 62, 270–282. <https://doi.org/10.1016/j.eneco.2016.12.019>.
- Rudolph, M., Damien, P., 2023. The impact of renewable energy tax incentives on electricity pricing in Texas. *Appl. Sci.* 13(14), 8532. <https://doi.org/10.3390/app13148532>
- Sakaguchi, M., Fujii, H., 2021. The Impact of Variable Renewable Energy Penetration on Wholesale Electricity Prices in Japan Between FY 2016 and 2019. *Front. Sustain.* 2, 770045. <https://doi.org/10.3389/frsus.2021.770045>.
- Suliman, M.S., Farzaneh, H., 2022. Econometric analysis of pricing and energy policy regulations in Japan electric power exchange spot market. *Clean. Eng. Technol.* 9, 100523. <https://doi.org/10.1016/J.CLET.2022.100523>.
- Tselika K., 2022. The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach. *Energy Econ.* 113, 106194 <https://doi.org/10.1016/j.eneco.2022.106194>
- Tohoku Electric Power, 2021, Considerations Regarding Marginal Costs in Bidding on the Japan Electric Power Exchange (JEPX) Spot Market (Updated Nov. 22, 2021, in Japanese) https://www.tohoku-epco.co.jp/information/1222535_2521.html?BZB_TOKEN=d9dda47870e17b047d66e8b6c08ed9fd (accessed 17 August 2025).
- Woo, C.K., Horowitz, I., Moore, J., Pacheco, A., 2011. The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy*. 39, 3939–3944. <https://doi.org/10.1016/j.enpol.2011.03.084>.
- Yoshihara, K., Ohashi, H., 2017. Assessing the Impact of Renewable Energy Sources: Simulation analysis of the Japanese electricity market. Research Institute of Economy, Trade and Industry (RIETI) Discussion Paper Series 17-E-063.

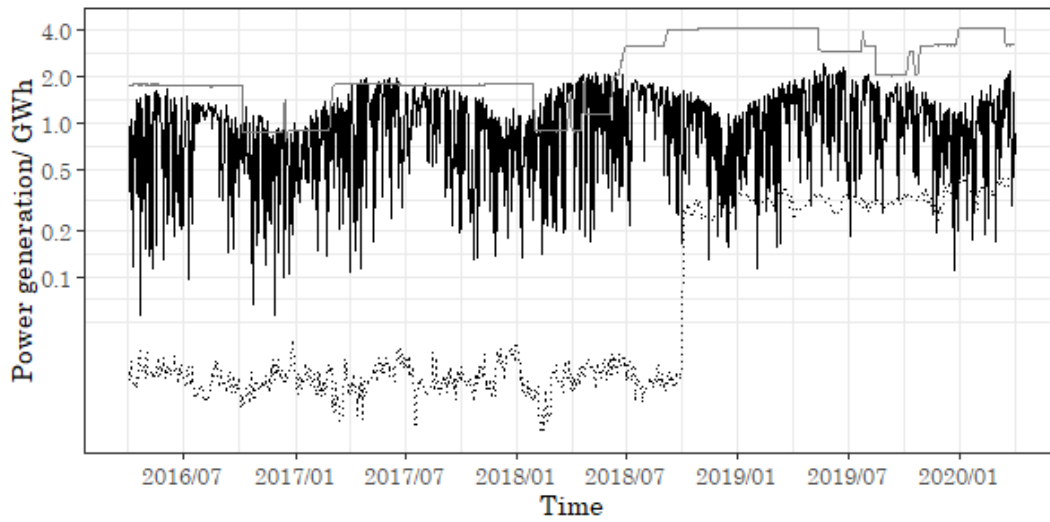


Figure 1 Time series data of daily average power generation in the Kyushu Electric Power District (black solid line: solar PV power generation, black dotted line: biomass power generation, solid grey line: nuclear power generation, data period: 4/1/2016–3/31/2020, vertical axis in natural logarithm)

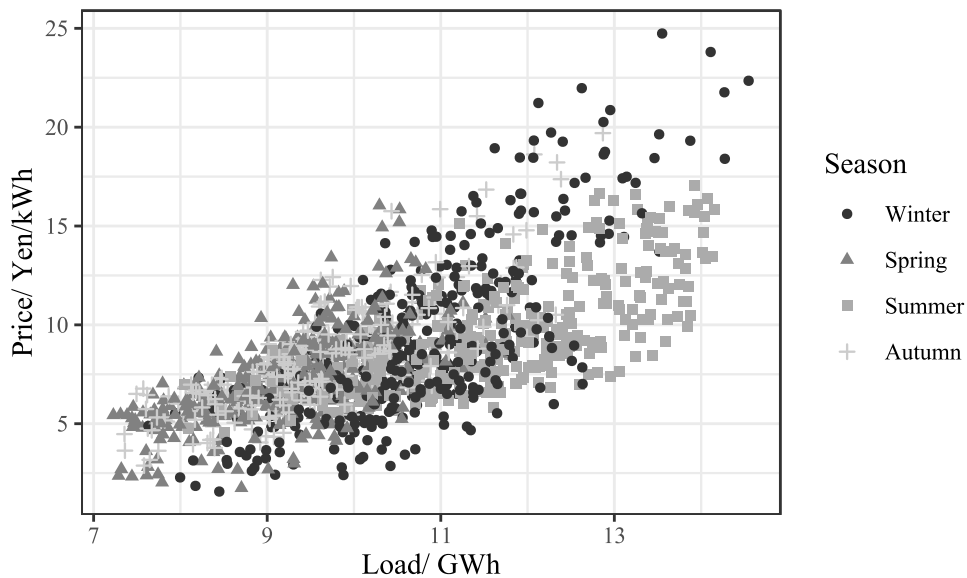


Figure 2 Relationship between electricity demand and price

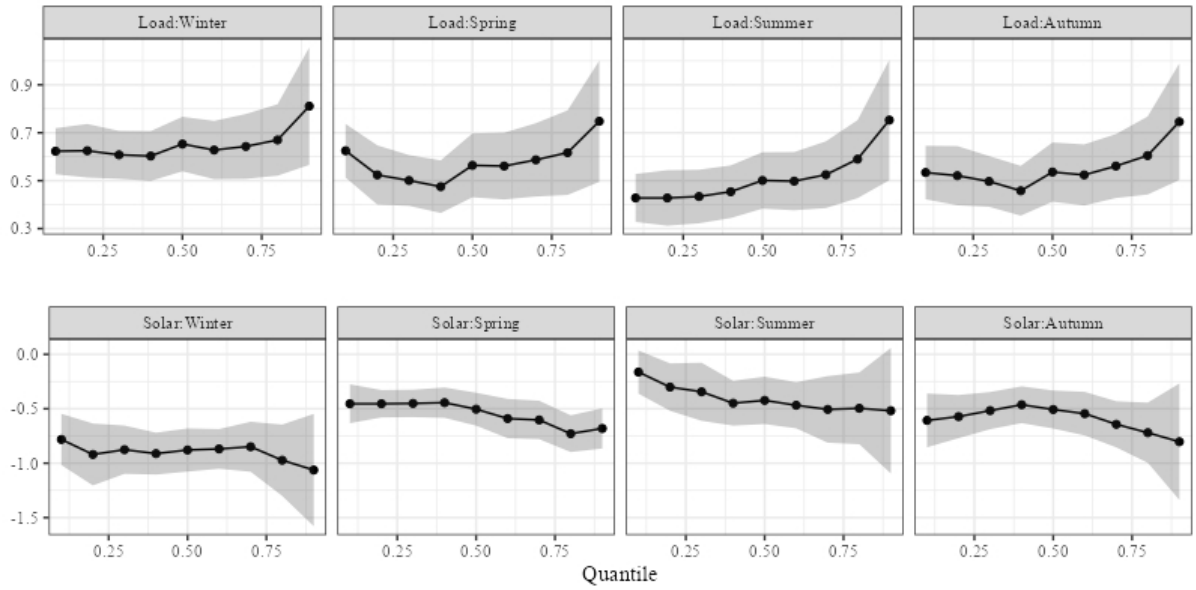


Figure 3 Estimated coefficients of electricity demand (Load) and solar PV power generation (Solar) with 95% confidence intervals (shadow) for the quantile of electricity price in each season

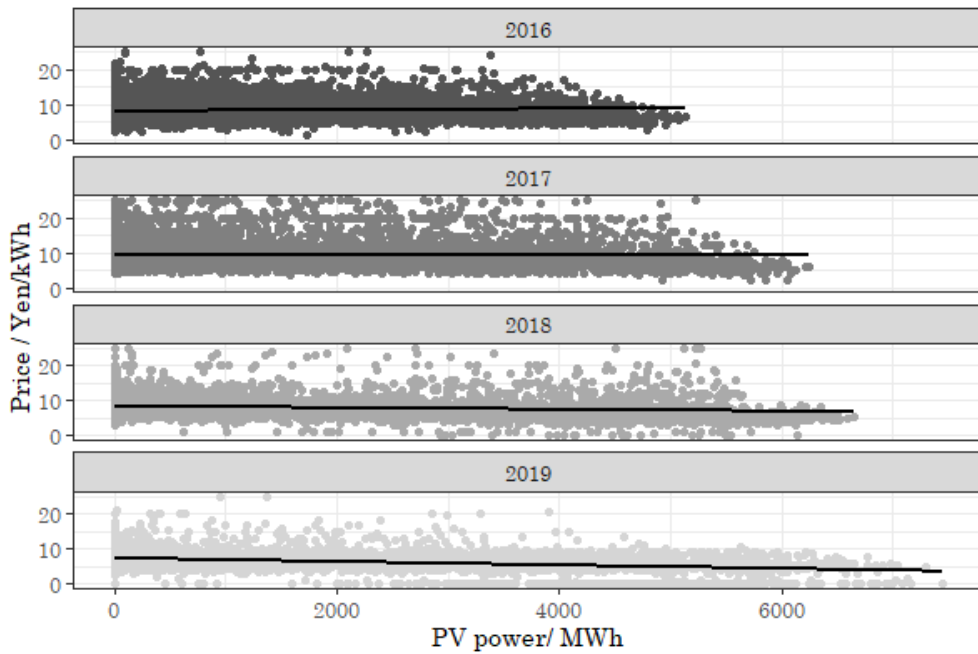


Figure 4 Annual changes in electricity prices and solar PV power generation in the Kyushu region

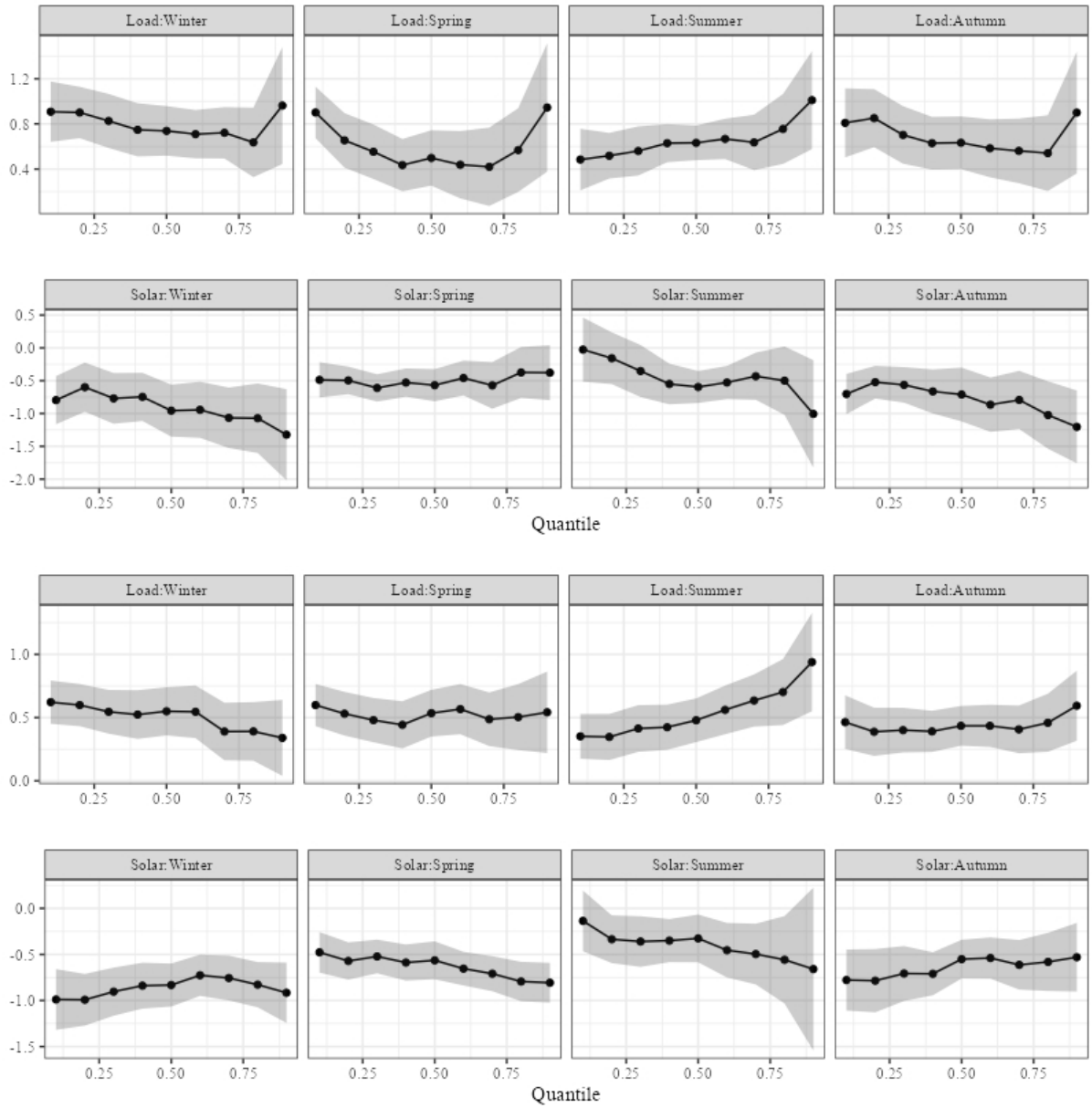


Figure 5 Seasonal effects on changes in estimated coefficients of electricity demand (Load) and solar power (Solar) on electricity prices by quantile with 95% confidence intervals (shadow) (upper two rows: FY2016–2017 (first half); lower two rows: FY2018–FY2019 (second half))

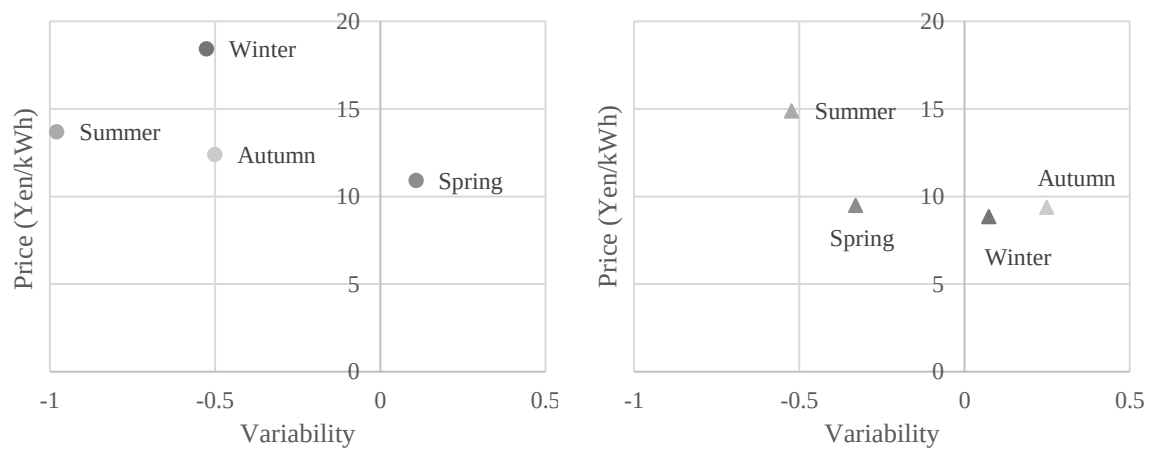


Figure 6 Relationship between the 0.9 quantile of electricity prices and IQR for PV by season. Left graph: FY2016–FY2017; right graph: FY2018–FY2019