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Advancing financial instruments and market trading framework for local solar power hedging with principal component derivatives☆

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ABSTRACT

In recent years, the integration of renewable energy sources has highlighted the need for effective volume risk hedging at the local level. However, conventional financial instruments, such as Wind Power Futures based on nationwide power output, are insufficient to meet local hedging needs. To address this gap, recent studies have explored efficient hedging methods using Principal Component Analysis (PCA) for diversified local needs, yet challenges persist in pricing and transaction models. In this study, we propose Principal Component (PC) derivatives for the solar power industry to efficiently mitigate cash flow volatility. This entails incorporating our previously developed prediction error derivatives using solar radiation as the underlying asset. Furthermore, we formulate Quanto PC derivatives that combine both solar radiation and price to simultaneously hedge volume and price risks. Empirical analysis shows that our PC derivatives outperform existing wide-area derivatives in terms of hedge effectiveness, requiring only three or four derivatives to achieve comprehensive coverage across different areas. In addition, these derivatives enhance hedge effectiveness by approximately 20 % compared to area-specific derivatives and are expected to improve market liquidity and create an efficient transaction framework. Our work underscores practical benefits and paves the way for further innovations in addressing complex pricing problems as well as in reducing potential transaction costs through countertrading in different areas.

1. Introduction

In recent years, renewable energy sources, including solar power, have been rapidly deployed. According to the International Energy Agency (IEA, 2023), renewable energy will account for 80 % of new power generation capacity by 2030 under current energy policies, with half of this (40 % of the total) coming from the “clear frontrunner” solar power. Against this backdrop, hedging the risks associated with intermittent, weather-dependent renewable energy generation, such as solar power, has become an important issue. However, few financial instruments have been traded to hedge the volumetric risk of renewable energy. One of the few examples is the Wind Power Futures (WPF; see, e.g., Benth and Pircalabu, 2018; Gersema and Wozabal, 2017) listed on the European Energy Exchange (EEX) and Nasdaq. Nevertheless, the effectiveness of WPF for local hedging is constrained by its underlying assets, which are tied to power generation over a broad geographical region. Recognizing this inefficiency, Thomaidis et al. (2023) conducted factor decomposition using principal component analysis (PCA; Wold et al., 1987) on wind power generation in different areas, then proposed a conceptual hedging contract where principal risk components serve as the underlying assets. Indeed, PCA has been employed in spatial data analysis for its effectiveness in dimensionality reduction and elucidating spatial features (Demšar et al., 2013) and has been widely adopted in studies of regionally distributed renewable energy generation.[1] Among these applications, the work by Thomaidis et al. (2023) stands out for its novel application of PCA within a risk management context. However, a realistic hedging scheme and pricing framework for PCA-based derivatives remains an unresolved issue. In other words, while their factor-

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[1] For example, Burke and O'Malley (2011) demonstrated that PCA effectively reduces the number of random variables needed to represent distributed wind power; Fonseca Junior et al. (2014) proposed a highly accurate model using PCA to predict solar power generation at local sites in Japan; and Christodoulou et al. (2024) performed a PCA-based risk analysis of wind power in the context of site selection.

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based approach is conceptually promising, translating it into a workable financial instrument poses a notable challenge.

The objective of this study is to extend the PCA-based wind power generation volume derivative concept proposed by Thomaidis et al. (2023) to the solar photovoltaic (PV) sector and investigate its potential for actual transactions that are both intuitive and easy to trade. To achieve this goal, we introduce PC derivatives by integrating the design principles of weather prediction error derivatives—based on nonparametric trend estimation—presented in our earlier works (Matsumoto and Yamada, 2021; Yamada and Matsumoto, 2021). Specifically, we develop prediction error-based principal component (PC) derivatives on “solar radiation residuals” for multiple areas. These residuals are obtained by first removing annual periodic trends from time-series data of solar radiation in each area, then performing PCA on the bundled residuals (i.e., making the underlying values in each area orthogonal to the time series direction beforehand). This approach enables us to estimate a loading matrix (the transformation matrix to principal component series) that is commonly used throughout the year, resulting in a robust and intuitive hedging scheme. In doing so, our framework bridges the gap between factor-based risk decomposition and a transparent derivative design that market participants can readily adopt.

There are several compelling reasons supporting our proposed derivatives design approach. Firstly, generation data often face issues such as emergency curtailment, which has increased both in the Kyushu region of Japan (Bunodiere and Lee, 2020) and globally (Yasuda et al., 2022) in recent years, as well as changes in installed capacity, delayed information disclosure, and measurement errors. In response, we opt for more uniform and transparent observed weather data, i.e., solar radiation, as the alternative underlying. Secondly, the growing adoption of feed-in premium (FIP) systems in various markets links renewable energy revenues to the market price of electricity. For instance, the shift from the feed-in tariff (FIT) to the FIP system in Japan, beginning in April 2022, exposes producers to risks related to both price and volume. Under a FIT regime, producers receive a fixed price per kWh, which shields them from market fluctuations. In contrast, the FIP mechanism provides a premium on top of the market price, directly exposing generators to spot price volatility. Academic studies such as Meus et al. (2021) have highlighted efficiency of the FIP system, and consequently, the trend toward utilizing market principles to make renewable energy producers bear price risk is expected to proliferate. As a result, hedging the “multiplicative risk” arising from volume and price fluctuations is becoming increasingly important. The concept of hedging the product of price and volume has been explored in several studies (Deng and Oren, 2006), and more recently, “quanto derivatives” have been investigated for efficient risk management (discussed in Section 2). In light of this, we introduce “Quanto PC derivatives” based on the product of residual solar radiation and price, elucidating their effectiveness in mitigating multiplicative risk. Our study thus offers a novel perspective by focusing on readily tradable hedging products, departing from traditional over-the-counter (OTC) transactions.

The empirical analysis conducted in this study indicates that, much like Thomaidis et al. (2023) found, the use of PC derivatives significantly enhances the hedging effectiveness compared to existing wide-area instruments such as WPFs. Moreover, employing multiple PC derivatives delivers an additional improvement of around 20 % in hedging effectiveness relative to using multiple area-specific solar radiation derivatives. In particular, just three or four PC derivatives can effectively cover both volumetric and multiplicative risk across different areas. Furthermore, the loading matrices for these four PC derivatives, expected to be disclosed by product providers (exchanges), also offer an intuitive interpretation. By overlaying the matrices on a heat map, users can visually grasp each instrument's geographic emphasis, fostering greater transparency and confidence among market participants.

PC derivatives also enable liquid and efficient trading by allowing participants in multiple regions to engage simultaneously. Additionally, the underlying concept of prediction error derivatives keeps the expected (or average) payoff near zero throughout the year, eliminating any need for premium at the time of contracting and thus aligning with a risk-neutral pricing framework. Essentially, the effective reduction of cash flow fluctuation risks comes at no additional cost under the risk neutral assumption, presenting a distinct advantage that may further incentivize the widespread adoption of this derivative.[2] We further demonstrate that PC derivatives facilitate efficient countertrading between areas, potentially lowering added transaction costs linked to risk premiums. Altogether, these features suggest that PC derivatives could significantly improve market liquidity while supporting the ongoing expansion of solar power and other renewables.

The following sections are organized as follows. First, in the next section, we conduct a literature review and then present the conceptual problem formulation based on the literature review. In Section 3 we introduce the specific composition method of PC derivatives and then construct the hedging models. Section 4 then presents the results of the empirical analysis of the hedging effect, followed by a discussion of its validity as a hedging instrument, including the results of the PCA, in Section 5. Finally, Section 6 presents our conclusions.

2. Literature review and conceptual framework of PC derivatives

2.1. Literature review

In order to position our PCA-based approach, we first review three categories of derivatives relevant to renewable energy hedging: “weather derivatives,” “quanto derivatives,” and “prediction error derivatives.” Thomaidis et al. (2023) laid the groundwork by applying a PCA-based derivative concept to wind generation risk; here, we further build on and integrate these three strands of research for solar PV.

2.1.1. Weather derivatives

First, as for weather derivatives, they have proven to be invaluable in managing the risks associated with the energy sector (Wieczorek-Kosmala, 2020), with a wide variety of derivatives being traded in several markets in recent years (Roncoroni et al., 2015). For instance, the Chicago Mercantile Exchange (CME), a leading market for weather derivatives has been rapidly increasing trading volumes (CME, 2023). In addition, the methodologies for pricing weather derivatives, along with specific examples of their application, have been described in a number of studies (Alexandridis and Zapranis, 2013). Beyond energy, a variety of weather derivatives can be effectively used to hedge weather risk sectors including agriculture, insurance, tourism, and retail, which is why there is broad research (Brockett et al., 2005). Much of the existing research has focused on weather derivatives with temperature (Berhane et al., 2021; Elias et al., 2014; Groll et al., 2016; Zapranis and Alexandridis, 2008) as the underlying asset, but more recently there has been an increase in research on derivatives based on wind speed (Masala et al., 2022; Rodríguez et al., 2021) and rainfall (Cabrera et al., 2013; Leobacher and Ngare, 2011; Odening et al., 2007; Salgueiro and Tarrazon-Rodon, 2020). Likewise, the growing demand for solar power and carbon neutrality goals has underscored the need for hedging strategies. This, in turn, has led to research focusing on solar radiation derivatives (Alao and Cuffe, 2022; Boyle et al., 2021; Matsumoto and Yamada, 2019; Mosquera-López and Uribe, 2022). As with any of these

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[2] In a strictly risk-neutral framework, once deterministic trends are removed, the expected payoff of these derivatives is close to zero, theoretically eliminating the need for an upfront premium. However, in practical trading, risk-takers (such as insurers or financial intermediaries) are likely to charge some form of premium to compensate for bearing the uncertainty in payoff cash flows. Hence, while our analysis assumes a zero premium for illustrative purposes, real-world pricing may diverge depending on specific market conditions and participants' risk profiles.

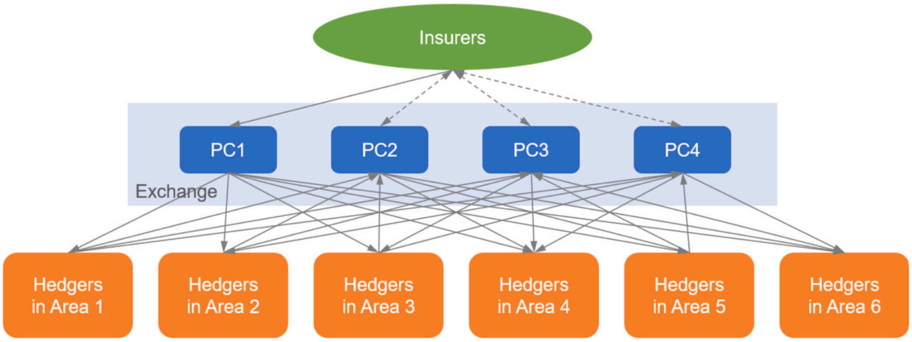

Fig. 1. Conceptual diagram of PC derivatives trading (Note: For arrows connecting to each PC derivative (PC1-PC4), the player located at the end (origin) of the arrow represents the player with the long (short) position for that instrument. Arrows connecting higher-order derivatives (PC2–4) to insurers are shown as dashed lines to indicate that these contracts do not necessarily require dedicated risk-taking counterparties such as insurers).

weather indices, the advantage of weather derivatives is that the underlying climate indices themselves are accurate and reliable (Jewson and Brix, 2005). Furthermore, transparency in derivatives markets is essential from a liquidity perspective (Lannoo and Thomadakis, 2020), so weather indices also have an advantage in this regard, as they are published by a credible public institution and verified by stakeholders from a wide range of sectors.

2.1.2. *Quanto derivatives*

Second, quanto derivatives are financial derivatives related to the product of price and volume, and have long been used in financial markets to hedge the risk of trading a particular asset in different currencies. Among them, “quanto options” (quantity adjusting options), which are related to hedging the risk of fluctuations in the product of exchange rates and stock prices, are widely traded, but their pricing is complex and many researchers have addressed this issue (Battauz et al., 2022; Branger and Muck, 2012; Kim et al., 2015; Marabel-Romo, 2012). In the context of energy markets, derivatives with payoff functions related to the product of energy prices and weather indices have been studied in recent years (Arsat et al., 2023; Benth et al., 2015; Caporin et al., 2012; Thakur et al., 2023). More recently, the need for such hedging approaches has been widely recognized in practice, and some are beginning to be used in the EEX for OTC hedging transactions (Speedwell Climate, 2023). A white paper of Speedwell Climate (2023) discusses in detail the need for hedging strategies using “Renewable Power Quanto Indices” designed for the EEX, linked to the product of price and renewable generation, to hedge risks that cannot be covered by conventional electricity futures or WPFs. In any case, the recent upsurge in research on quanto derivatives in the energy market and the ongoing development of the environment for them in actual exchanges are sufficient motivation for us to expand our research in this direction.

2.1.3. *Prediction error derivatives*

Third, the concept of prediction error derivatives has wide applicability as a fair design method for derivatives on underlying assets (indices) with deterministic trends. The first approach proposed by Yamada (2008) to hedge the risk of wind generation volume was later applied to hedge the risk of solar generation volume (Matsumoto and Yamada, 2019). Subsequently, strategies to hedge revenue volatility risk in retail electric utilities that also account for price risk (Matsumoto and Yamada, 2021) have brought new perspectives to various energy economics studies. In addition, these prediction error derivative approaches have been applied to the design of derivatives for various types of electric utilities (Yamada and Matsumoto, 2021). As detailed in these studies, prediction error derivatives can effectively eliminate deterministic nonlinear trends using nonparametric regression techniques. Consequently, these derivatives are designed to have an average payoff of zero using a weather index with a prior removed seasonal trend as the underlying (quantitatively verified in Section 5.2), thus requiring no (or minimal) premium payment at the time of contracting, and mitigating pricing challenges. While recent pricing models involve advanced risk-neutral density estimation (Kumar, 2025) or sophisticated parametric modeling with conditional higher moments (Matsumoto et al., 2022), our design avoids these complexities by construction. Moreover, since the payoffs of prediction error derivatives are made orthogonal to the date direction, the hedging model can be constructed in such a way that seasonal dependencies between variables are explicitly decomposed (structured), thereby ensuring relatively high hedging effectiveness against the product of price and volume risk (see, e.g., the empirical results in Matsumoto and Yamada (2021)). Note that even with recent advances in high-performance forecasting, such as hybrid LSTM models that incorporate weather-related features (Kumar et al., 2024), perfect prediction remains unattainable. Ultimately, the irreducible component of forecast error is what must be hedged, and prediction error derivatives are specifically designed to address this residual risk in a transparent and tractable way.

2.2. *Conceptual framework of PC derivatives*

With the above considerations, we now integrate these three derivative concepts—weather derivatives (ensuring transparent and reliable climate-based underlying assets), quanto derivatives (addressing combined price-and-volume risk), and prediction error derivatives (mitigating complex pricing challenges by removing deterministic trends)—under a unified PCA-based methodology to hedge solar PV revenue risk. In essence, our study enhances the existing PCA-based derivative concept by combining the strengths of these methods. More importantly, the primary goal here is to commoditize PC derivatives and establish an efficient, workable trading scheme. In particular, Thomaidis et al. (2023) concluded that their factor contract design was still premature for real-world trading, highlighting the need for a feasible scheme and further empirical research. To address this issue, our framework carefully considers the needs of hedgers—who seek effective risk mitigation with lower transaction costs—and derivatives providers—who aim to design widely applicable products. If a standardized PC derivative can be listed on an exchange (rather than being traded bilaterally), multiple regions can participate, bolstering liquidity and lowering transaction costs. Hedgers will increasingly use such instruments if they exhibit liquidity, given the anticipation of lower transaction costs and higher price reliability. In addition, a flexible trading framework that can address diverse investor risk preferences and liquidity demands is crucial to ensuring that the resulting derivatives align with real-world trading motivations. Against this background, the crucial distinction between our study and that of Thomaidis et al. (2023) is the practical commoditization of PC derivatives integrated into an actual market trading model. In other words, we explicitly define the specific actions of product designers and traders, formulate each step, and then empirically demonstrate the effectiveness of the trading scheme.

Our proposed framework for "PCA-based derivative" proceeds as follows. First, we collect multi-regional weather index (solar radiation) and, if applicable, electricity price data. We then remove the seasonal trend from each area's weather time series to yield prediction-error-type residuals (so that the mean payoff stays close to zero). Next, PCA is applied to these standardized residuals (or their product with prices in the case of quanto derivatives). This decomposition extracts a small number of orthogonal factors (principal components), each representing a distinct pattern of variation across the regions—for example, the first component often captures a "common movement" across all regions, while the second or third may capture more localized or opposing patterns. Finally, we define a derivative payoff on each principal component score. In doing so, we create tradable instruments (PC derivatives) that any market participant across multiple areas can utilize to hedge not just one specific local risk, but also these principal modes of fluctuation as a whole. This combination of weather derivatives, quanto derivatives, and the prediction-error concept, all under the PCA umbrella, is what enables efficient cross-regional hedging while keeping the expected payoff near zero.

A conceptual diagram of the trading of PC derivatives is shown in Fig. 1. In the proposed scheme, an exchange lists PC derivatives (the top four components in this case), which are created based on solar radiation and price data, as standardized products (the commoditization process is detailed in Sections 3.2 to 3.3). The PV generators (hedgers), which are distributed across multiple regions, optimize the trading volume (the amount of short or long positions) of each PC derivative to minimize their individual exposures. The hedger's trading volume optimization is formulated as a problem of minimizing the cash flow variance after hedging (the hedging model is discussed in detail in Section 3.4). A crucial point here is that each PC derivative can be universally traded by all area hedgers. Unlike derivatives using area-specific solar radiation (or area prices) as the underlying, which, in most traditional structures, would only attract traders from the relevant area or adjacent areas, PC derivatives can be traded across regions, potentially attracting a larger and more liquid user base. In terms of counterparties, only the first principal component (PC1)—which represents a common risk direction across all areas—strictly requires a third-party risk taker, such as an insurance company or a financial institution willing to assume net exposure. By contrast, the second and subsequent components (PC2–PC4) often allow hedgers in different areas to naturally offset each other's opposite risk positions. Nevertheless, if net offset is not perfectly matched among hedgers, any residual portion would similarly require the involvement of a risk-taking counterparty. These mechanisms enable efficient cross-regional risk reduction (this will be demonstrated empirically in Section 4.2). It is noteworthy that, although several studies (Matsumoto et al., 2022; Yamada and Matsumoto, 2021) have shown how weather derivatives and electricity derivatives can offset risks between power generators (sellers) and retailers (buyers), no existing work has proposed a derivative that can also offset risks among power generators (sellers) themselves (i.e., those who share the same risk direction), making our proposed PC derivatives the first to demonstrate this capability. In this sense, our empirical insights also distinguish this study from existing proposals.

In summary, our goal is to design PC derivatives as standardized hedging instruments suitable for multi-regional adoption and establish a market trading scheme. This approach aims to empirically demonstrate the utility of such derivatives and the potential benefits of its commoditization.

Finally, it should also be noted that, to the best of our knowledge, there are no studies proposing any PCA-based derivatives in the context of the electricity market, nor in traditional financial markets. This remains true aside from our study and its foundation, Thomaidis et al. (2023). While PCA-based analysis methods find widespread use in financial market applications, encompassing forecasting (Ghorbani and Chong, 2020; Wang and Wang, 2015; Waqar et al., 2017), arbitrage (Avellaneda and Lee, 2010), trading strategies (Zhong and Enke, 2017), indexing (Feeney and Hester, 1964), portfolio selection (Basilio et al., 2018; Fulga et al., 2009; Jothimani et al., 2017; Yu et al., 2014), and risk premia analysis of foreign currency futures (Barkoulas and Baum, 1996), limited research has delved into the realm of risk hedging and associated derivative design. This scarcity may be attributed to potential practical challenges, particularly in ensuring the transparency and interpretability essential for derivative contracts within financial markets. Nevertheless, our study is anticipated to offer valuable insights for the development of derivatives in more general financial markets.

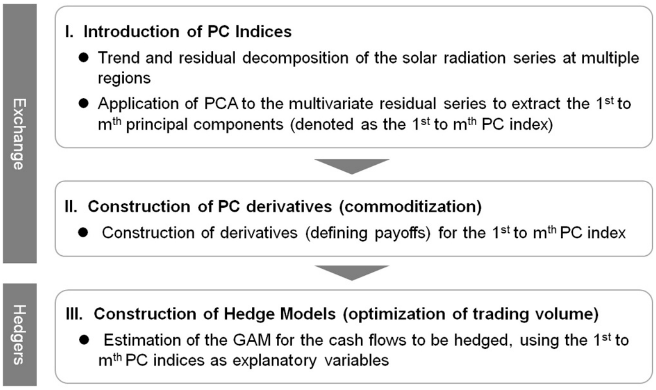

Fig. 2. Flow chart of PC derivatives transactions.

3. PC derivatives and hedging models

As mentioned earlier, conventional hedging problems using traditional derivatives usually entail applying the observed underlying indices as they are. However, in our proposed PC weather derivatives, where we envision the design of highly liquid instruments by exchanges, the crucial aspect lies in the process of designing effective underlying indices. With this objective, this section first outlines the overall flow of the PC derivative transactions. It then formulates a specific hedging model and establishes the metric for assessing hedging effectiveness.

3.1. Transaction flow of PC derivatives

The transaction flow of PC derivatives is shown in Fig. 2. First, an exchange introduces the PC indices (I in Fig. 2). To do this, the exchange decomposes the observed solar radiation series into annual periodic trends and residuals, and extracts the indices of the 1st to m^{th} principal components by applying PCA to the multivariate series of the residuals. It then introduces derivatives whose payoffs are the indices of the 1^{st} to m^{th} principal components thus defined (II in Fig. 2). Hedgers, on the other hand, use the generalized additive model (GAM; Hastie and Tibshirani (1990)) to estimate the trading volume of the PC derivatives so that their own cash flow variance is minimized (III in Fig. 2). Hedgers find the optimal trading volume that varies with the seasons by estimating the coefficient of variation as an annual periodic spline function, using the PC indices of the 1^{st} to m^{th} principal components as explanatory variables. To illustrate the above procedure more clearly, the following Sections 3.2 to 3.4 present the formulation of the calculation of PC indices and the introduction of PC derivatives performed by the exchanges and the hedging models constructed by the hedgers, respectively.

3.2. Introduction to PC indices

First, we demonstrate the step-by-step process of constructing underlying indices of solar radiation PC derivatives ("Rad PC indices") for in-sample and out-of-sample periods using historical time series data of solar radiation only.

3.2.1. Rad PC indices

1. *Trend and residual decomposition*: An exchange first estimates the following GAM for the daily integrated solar radiation observed in each area $i \in \{1, \ldots, A\}$[3]:

$$ObsRad_{i,t} = \gamma_i(Seasonal_t) + \varepsilon_{i,t}. \tag{1}$$

where $ObsRad_{i,t}$ denotes the observed daily integrated solar radiation for area i at day t, γ_i denotes the periodic spline function, $Seasonal_t$ $(= 1, \ldots, 365(366))$ denotes annual periodic dummy variables, $\varepsilon_{i,t}$ is the residual of the mean 0. This residual corresponds to the "Rad area indices" and is denoted as $Rad_{i,t} := \varepsilon_{i,t}$ for clarity in the following. Then, the daily integrated solar radiation $Rad_{i,t}$ (N samples) observed in each area $i \in \{1, \ldots, A\}$ is bundled to create the solar radiation residual matrix $R^{(in)}_{[N\times A]}$.

2. *Computing loading matrix with PCA:* Each element of the area-specific solar radiation residual matrix $R^{(in)}_{[N\times A]}$ is standardized (z-score normalization) to obtain the standardized matrix $\overline{R}^{(in)}_{[N\times A]}$ [4]. By performing PCA on $\overline{R}^{(in)}_{[N\times A]}$, a loading matrix $V_{R[A\times A]}$ and a principal component score $T_{R^{(in)}_{[N\times A]}}$ (corresponding to the in-sample "Rad PC indices") are obtained as follows[5]:

$$T_{R^{(in)}_{[N\times A]}} = \overline{R}^{(in)}_{[N\times A]} V_{R[A\times A]}. \tag{2}$$

here, the exchange should disclose the 1 $^{\text{st}}$ to m $^{\text{th}}$ components of the loading matrix $V_{R:,(1:m)}$ so that the out-of-sample Rad PC indices can be explicitly calculated.

3. *Determination of out-of-sample indices:* On each observation day (payment day), the annual periodic trend is subtracted from the observed solar radiation for each area to produce a vector $R^{(out)}_{[1\times A]} \left(= R^{(out)}_{t,:} \right)$ (corresponding to out-of-sample "Rad area indices"); a scale transformation is performed on it to obtain the standardized series $\overline{R}^{(out)}_{[1\times A]} \left(= \overline{R}^{(out)}_{t,:} \right)$; then the out-of-sample "Rad PC indices" $T_{R^{(out)}_{t,(1:m)}}$ are calculated by using the pre-calculated (pre-disclosed) loading matrix $V_{R:,(1:m)}$ as

$$T_{R^{(out)}_{t,(1:m)}} = \overline{R}^{(out)}_{t,:} V_{R:,(1:m)}. \tag{3}$$

Note that each component series of T_R is represented by a linear sum of residual series with a mean value of 0, and therefore also exhibits a mean value of 0 (i.e., $mean\left[T_{R^{(out)}_{t,k}}\right] = mean\left[\overline{R}^{(out)}_{t,:}\right] V_{R:,k} = 0$ for any $k \in \{1, \ldots, m\}$). This implies that the payoffs of the PC derivatives are designed to have a mean value of 0, as will be empirically verified in Section 5.2.

3.2.2. Quanto PC indices

Next, we introduce the Quanto PC indices using a similar procedure to that of the Rad PC indices.

1. *Definition of area-specific quanto series:* Calculate the Hadamard product (element-by-element product of matrices) of the solar radiation residual matrix and the spot price matrix for the same area using the following formula: $Q^{(in)}_{[N\times A]} := R^{(in)}_{[N\times A]} \circ S^{(in)}_{[N\times A]}$. This corresponds to the in-sample "Quanto area indices" by area[6].

2. *Computing loading matrix with PCA:* Similar to the case of Rad PC indices case, quanto series matrix $Q^{(in)}_{[N\times A]}$ is also standardized to obtain the standardized matrix $\overline{Q}^{(in)}_{[N\times A]}$. Then, perform PCA on $\overline{Q}^{(in)}_{[N\times A]}$ to obtain the loading matrix $V_{Q[A\times A]}$ and the principal component score $T_{Q^{(in)}_{[N\times A]}}$ (corresponding to the in-sample "Quanto PC indices").

$$T_{Q^{(in)}_{[N\times A]}} = \overline{Q}^{(in)}_{[N\times A]} V_{Q[A\times A]}. \tag{4}$$

here, the exchange should disclose the 1 $^{\text{st}}$ to m $^{\text{th}}$ components of the loading matrix $V_{Q:,(1:m)}$ so that the out-of-sample Quanto PC indices can be explicitly calculated.

3. *Determination of out-of-sample indices:* Obtain the Hadamard product series from the out-of-sample solar radiation residual and the spot price: $Q^{(out)}_{t,:} := R^{(out)}_{t,:} S^{(out)}_{t,:}$ (corresponding to the out-of-sample "Quanto area indices"); a scale transformation is performed on it to obtain the standardized series $\overline{Q}^{(out)}_{t,:}$; then the out-of-sample "Quanto PC indices" $T_{Q^{(out)}_{t,(1:m)}}$ is calculated by using the pre-calculated (pre-disclosed) loading matrix $V_{Q:,(1:m)}$ as

$$T_{Q^{(out)}_{t,(1:m)}} = \overline{Q}^{(out)}_{t,:} V_{Q:,(1:m)}. \tag{5}$$

3.3. Construction of PC derivatives

For the PC indices introduced in the previous subsection, the exchange introduces PC derivatives as hedging instruments. Specifically, derivatives with payoffs in the 1 $^{\text{st}}$ to m $^{\text{th}}$ components of the Rad PC indices and Quanto PC indices defined in the previous subsection ($T_{Rt,(1:m)}$ or $T_{Qt,(1:m)}$) are referred to as "Rad PC derivatives" and "Quanto PC derivatives," respectively. In this study, as benchmarks for evaluating the performance of these PC derivatives, derivatives with payoffs in the area indices (Rad area indices and Quanto area indices) defined in the previous section are also introduced as "Rad area derivatives" and "Quanto area derivatives". The key point here is that these (area and PC) derivatives are designed to have an expected (or average) payoff of zero because the original underlying indices are residual series with the trend removed, thus requiring no premium payment at the time of contracting. This can be interpreted as follows; when the exchange commoditizes the derivatives, they simultaneously provide a fair price of zero for each derivative to engage in market making. Such an advance procedure may be quite similar to subtracting the futures price (predicted value) from the spot price (realized value) in the futures market, marking the future price to the market in advance by the exchange.

It should be noted that when exchanges commoditize derivatives, they must also publish the information necessary to calculate payoffs so that traders can verify the accuracy of the payoffs. For area derivatives, it would be sufficient for exchanges to publish their estimated annual periodic trends of solar radiation (or the meteorological normal values published by a weather information provider, if used), while for PC derivatives it would be necessary to publish the loading matrix as well. This is discussed in more detail in Section 5.

Additionally, although incorporating PCA may seem to increase modeling complexity compared to simpler region-specific indices, the payoff structure of both Rad and Quanto PC derivatives remains linear. As a result, the computational cost for pricing and settlement is relatively low, especially when contrasted with many option-based hedging instruments featuring nonlinear payoffs. In those approaches, more

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[3] In this study the seasonality is removed by estimating the annual periodic trends with GAM, but the same can be done using published meteorological normal values.

[4] Although standardization is used in this study for ease of interpretation of the empirical analysis, the hedging effects shown in Section 4.1 would hardly change even without standardization.

[5] In this study, PCA is performed using the function prcomp() of the R package "stats".

[6] In this study, the daily average price from 9:00 to 16:00 is used for spot price S.

elaborate pricing models and parameter estimates are often required, whereas our method focuses on linear payoffs derived from residual series—thus mitigating computational overhead. Moreover, PCA leverages spatial correlations across multiple areas, enabling higher hedging effectiveness with relatively few instruments—making the additional preprocessing step worthwhile.

3.4. Hedging models with PC derivatives

We now examine the decision making on the hedger's side, i.e., the problem of optimizing the trading volume for the commoditized derivatives described above. We consider the hedging of the daily fluctuation risk and construct two types of models, for volumetric risk and multiplicative risk, respectively[7]. In this context, the volumetric risk is defined as the daily total electricity generation from the solar PV unit $V_{i,t,h}$ at time h on day t in area i: $V_{i,t} := \sum_{h=1}^{24} V_{i,t,h}$. For the multiplicative risk, we use the indicator of daily integrated electricity sales $M_{i,t} := \sum_{h=1}^{24} V_{i,t,h}S_{i,t,h}$. For hedging model, we employ two strategies based on "area derivatives" and "PC derivatives". This indicates that a total 4 hedging models ("VA", "VP", "MA", or "MP") = 2 (volume or multiplicative) x 2 (area or PC) are constructed. Assuming that $m \in \{1, \dots, A\}$ types of derivatives are tradable, the GAM-estimated volumetric risk hedging models are constructed as follows (for the logical background that estimating these GAM-based hedging models corresponds to calculating the volume of derivative transactions that minimize the variance of the hedger's cash flows, see, e.g., the detailed explanation in Yamada and Matsumoto (2023)):

$$\text{Model} - \text{VA}: V_{i,t} = Trend_{i,t} + \sum_{j=1}^{m} f_{i,R,a(j)}(Seasonal_t)Rad_{a(j),t} + \eta_{i,t}. \tag{6}$$

$$\text{Model} - \text{VP}: V_{i,t} = Trend_{i,t} + \sum_{k=1}^{m} f_{i,PR,k}(Seasonal_t)PCrad_{k,t} + \eta_{i,t}. \tag{7}$$

where $Trend_{i,t} := \beta_i Period_t + f_i(Seasonal_t)$, $Period_t$ denotes number of elapsed days. In other words, $Trend_{i,t}$ corresponds a discount bond payoff that depends only on deterministic date information. $Rad_{a(j),t}$ denotes the payoff of the Rad area derivative in area $a(j)$ (corresponding to the element $\overline{R}_{t,a(j)}$ in the matrix introduced in Section 3.2). We assume that the Rad area derivatives are commoditized in the order of the areas with the highest installed PV capacity, and $a(j)$ denotes the area number with the j th highest PV capacity. Also, $PCrad_{k,t}$ denotes the payoff of the Rad PC derivative in the k th component (corresponding to the principal component score $T_{Rt,k}$). The $f_{i,R,a(j)}$ or $f_{i,PR,k}$, estimated as a smooth annual periodic trend, represents the contract volume of these derivatives, and $\eta_{i,t}$ denotes the residual with mean 0 and provides hedging errors. Here, regardless of whether Rad or PC derivatives are used, if m different instruments are listed in the market, we assume that all instruments are used to hedge in order to maximize the hedging effect. In estimating all functions f, we use cyclic cubic splines (see, Wood, 2017) and include a constraint that the starting and ending points are connected to ensure the robustness of the hedging model[8].

The model for hedging multiplicative risk is constructed in the same way. Since electricity futures are available for hedging price risk, we introduce quanto derivatives and construct the following hedging model against the multiplicative risk:

$$\begin{aligned} \text{Model} - \text{MA}: M_{i,t} = {} & Trend_{i,t} + f_{i,S}(Seasonal_t)S_{i,t} \\ & + \sum_{j=1}^{m} f_{i,Q,a(j)}(Seasonal_t)Quanto_{a(j),t} + \eta_{i,t}. \end{aligned} \tag{8}$$

$$\begin{aligned} \text{Model} - \text{MP}: M_{i,t} = {} & Trend_{i,t} + f_{i,S}(Seasonal_t)S_{i,t} \\ & + \sum_{k=1}^{m} f_{i,PQ,k}(Seasonal_t)PCquanto_{k,t} + \eta_{i,t}. \end{aligned} \tag{9}$$

where $S_{i,t}$ denotes the daily spot electricity price in area i (the terminal payoff of the electricity futures), $Quanto_{a(j),t}$ denotes the payoff of the Quanto area derivatives, which is equivalent to $\overline{Q}_{t,a(j)}$, and $PCquanto_{k,t}$ denotes the payoff of the Quanto PC derivative and corresponds to the principal component score $T_{Qt,k}$. The estimated spline functions $f_{i,S}$, $f_{i,Q,a(j)}, f_{i,PQ,k}$ are the contract volumes of each derivative.

3.5. Measurement of the hedge effects

Finally, to examine the hedging effect, we use the variance reduction ratio (VRR), which has been used in previous studies (e.g. Matsumoto and Yamada (2021)); VRR is defined as follows for each of the volumetric and multiplicative risk hedging models, and we refer to 1 − VRR as hedge effect.

$$\text{Model} - \text{VA or VP}: VRR_i := \text{Var}\left[\eta_{i,t}\right] / \text{Var}\left[V_{i,t} - Trend_{i,t}\right]. \tag{10}$$

$$\begin{aligned} \text{Model} - \text{MA or MP}: VRR_i : \\ = \text{Var}\left[\eta_{i,t}\right] \Big/ \text{Var}\Big[M_{i,t} - Trend_{i,t} - f_{i,S}(Seasonal_t)S_{i,t}\Big]. \end{aligned} \tag{11}$$

Note that when calculating VRRs for the out-of-sample data, they are obtained by substituting the out-of-sample exogenous variables into the hedging models (6)–(9) using the in-sample estimated β and f (the hedging error $\eta_{i,t}$ is obtained in the same way). In this way, we can precisely calculate the variance reduction effect (or contribution ratio) of the introduced derivatives. In other words, our metric quantifies the additional contribution of the introduced solar radiation (quanto) derivatives to variance reduction, by assuming that the hedger has prehedged the volatility of the deterministic seasonal fluctuations and the price risk by discount bond $Trend_{i,t}$ and electricity futures $S_{i,t}$. Specifically, as a baseline in our "multiplicative model", we assume that price risk is initially hedged with standard electricity futures, followed by the use of Quanto PC derivatives to address the remaining multiplicative exposure. One may wonder whether simply using Quanto derivatives without electricity futures (i.e., "Quanto-only") could provide a sufficient hedge. We tested this scenario separately and found that the out-of-sample hedge effect was negligible or even negative, reaffirming the necessity of pairing standard futures (for linear price risk) with our proposed Quanto derivatives (for second-order, volume–price risk). For details, see Appendix A.

4. Empirical performance of the PC derivatives

In this section, we will verify the hedging effectiveness of the PC derivatives modeled above and assess the validity of the trading scheme based on actual data. Such verification is crucial to demonstrate the practicality of PC derivative and elucidate the entire implementation process in practice. To this end, we undertake a comprehensive empirical analysis using data from the Japanese market, which has witnessed rapid adoption of PV technologies in recent years.

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[7] While this paper focuses on daily granularity, the future deployment of fully digital or blockchain-based trading platforms could further reduce transaction costs and support similarly fine-grained PC derivatives. Agarwal et al. (2024) outline a technical framework for implementing derivatives via smart contracts, while Alao and Cuffe (2022) propose blockchain-based solutions for daily weather-risk hedging. Such platforms would likely appeal to smaller participants seeking to regularly stabilize their digital positions and benefit from more granular risk management. As power systems continue to diversify and decentralize, demand for such flexible instruments is expected to grow.

[8] In this study, we use gam() in the R package "mgcv" (Wood, 2023) for estimation, with "cc" (cyclic cubic spline) as the basis function.

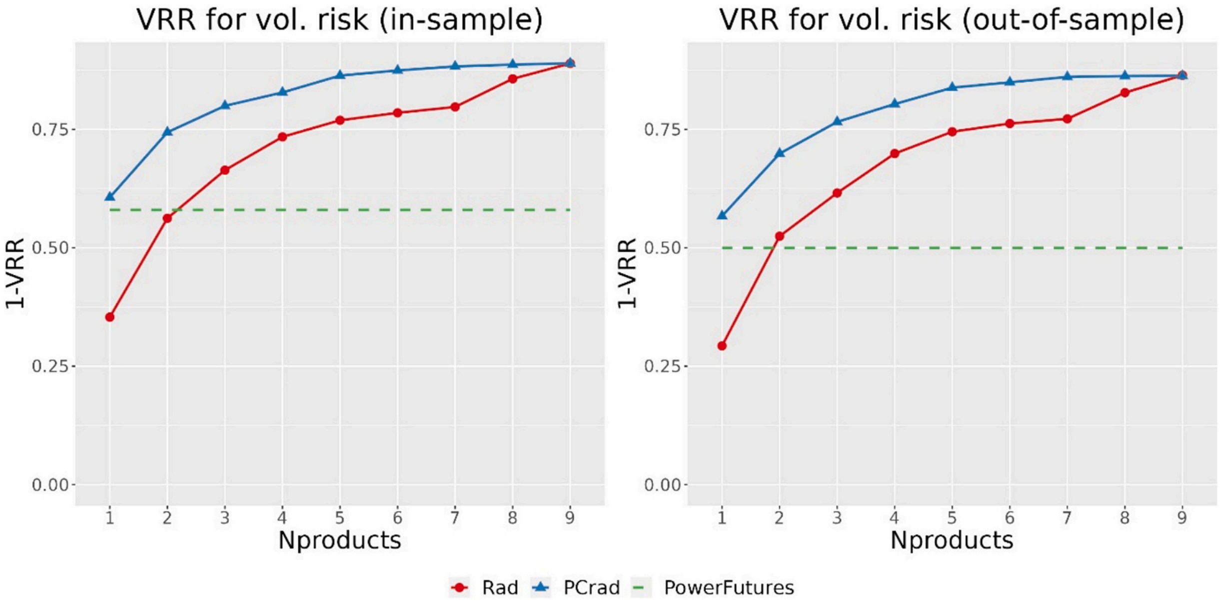

Fig. 3. Cumulative hedge effects for volumetric risk.

The data and sources of information used in this study are outlined below (See also Appendix B for a more detailed description of the data for the nine different areas used):

- Electricity spot price S [JPY/kWh]: Japan Electric Power Exchange (JEPX)[9],
- Daily integrated solar radiation $ObsRad$ [MJ/m^2]: Japan Meteorological Agency[10],
- Solar power generation V: each regional electricity utility[11]. Note that the amount of electricity generated for the entire area is divided back by the generation capacity data within the area (the amount of installed capacity data at the end of each year[12] is converted to daily granularity using GAM) to calculate the amount of electricity generated by a 1 MW PV system, which is used as V.

In the following subsections, we will elucidate the results of the empirical analysis from the hedger's perspective. During this analysis, the PCA loading matrices and hedging models are estimated using the three-year in-sample period of 2019–2021, while the hedging effects are assessed for the one-year out-of-sample period of 2022 (Note that our out-of-sample period, the year 2022, coincided with relatively high price volatility in the Japanese electricity market, thereby serving as a practical stress test for evaluating hedging performance under more turbulent market conditions[13]). Subsequently, the trend analysis of the hedger's optimal trading volume will be presented in Section 4.2.

4.1. Evaluations of hedge effects

In terms of the hedging effect, Figs. 3 and 4 illustrate the nine-area average (i.e. $1-(1/9)\sum_{i=1}^{9} VRR_i$) for the volumetric and multiplicative risks, respectively. Additionally, the area-specific hedge effects $1 - VRR_i$ for both risks without averaging are shown in Figs. 5 and 6, respectively.

It is worth noting a couple of remarks. First, our PC derivatives are generally more effective as hedges than conventional “power futures” that use total power generation as the underlying asset (constructed similarly to existing WPF), as can be seen by the higher curve of hedge effectiveness (1–VRR) in each figure. This advantage arises because wide-area instruments do not capture the region-specific risks. By contrast, the proposed PC approach extracts regional factors that facilitate optimal hedge trades across areas more flexibly.

Second, when compared to simpler area-specific derivatives, PC derivatives using the first four components show, on average, about 20 % higher effectiveness. This difference stems from the fact that area-based instruments are assumed to be introduced in a “practical” order of regions (based on installed capacity), while the PC derivatives reflect the largest orthogonal risk components in descending order of importance (PC1, PC2, etc.)[14]. By systematically covering the most impactful risk factors first, the PCA-based design aligns more closely with actual risk exposure across areas, ultimately delivering higher overall hedge

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[9] Downloaded from https://www.jepx.jp/ (accessed on December 22, 2023).

[10] Downloaded from https://www.data.jma.go.jp/gmd/risk/obsdl/ (accessed on December 22, 2023).

[11] Downloaded from: (Hokkaido) https://www.hepco.co.jp/network/renewable_energy/fixedprice_purchase/supply_demand_results.html; (Tohoku) https://setsuden.nw.tohoku-epco.co.jp/download.html; (Tokyo) https://www.tepco.co.jp/forecast/html/area_data-j.html; (Chubu) https://powergrid.chuden.co.jp/denkiyoho/; (Hokuriku) https://www.rikuden.co.jp/nw_jyukyudata/area_jisseki.html; (Kansai) https://www.kansai-td.co.jp/denkiyoho/; (Chugoku) https://www.energia.co.jp/nw/service/retailer/data/area/Index.html; (Shikoku) https://www.yonden.co.jp/nw/renewable_energy/data/supply_demand.html; (Kyushu) https://www.kyuden.co.jp/td_service_wheeling_rule-document_disclosure.html (accessed on December 22, 2023).

[12] Downloaded from https://www.fit-portal.go.jp/PublicInfoSummary (accessed on December 22, 2023).

[13] While the year 2022 provided a useful stress test for price volatility, the volumetric risk of solar power has physical bounds (e.g., maximum possible daily radiation), making extreme output fluctuations inherently less dramatic than they might be for wind or other resources. Exploring PC derivatives under even higher volatility scenarios—such as wind power in regions prone to severe weather—remains an important avenue for future work.

[14] Considering the practical incentives of exchanges to commoditize area-based derivatives, we assume that instruments are listed in the order of areas with the largest amount of electricity generation (installed capacity). The order of instruments in hedging models (6) and (8) is $a = [3, 9, 4, 2, 6, 7, 8, 1, 5]$ (i.e., Tokyo, Kyushu, …, Hokuriku; see Fig. B1 in Appendix B).

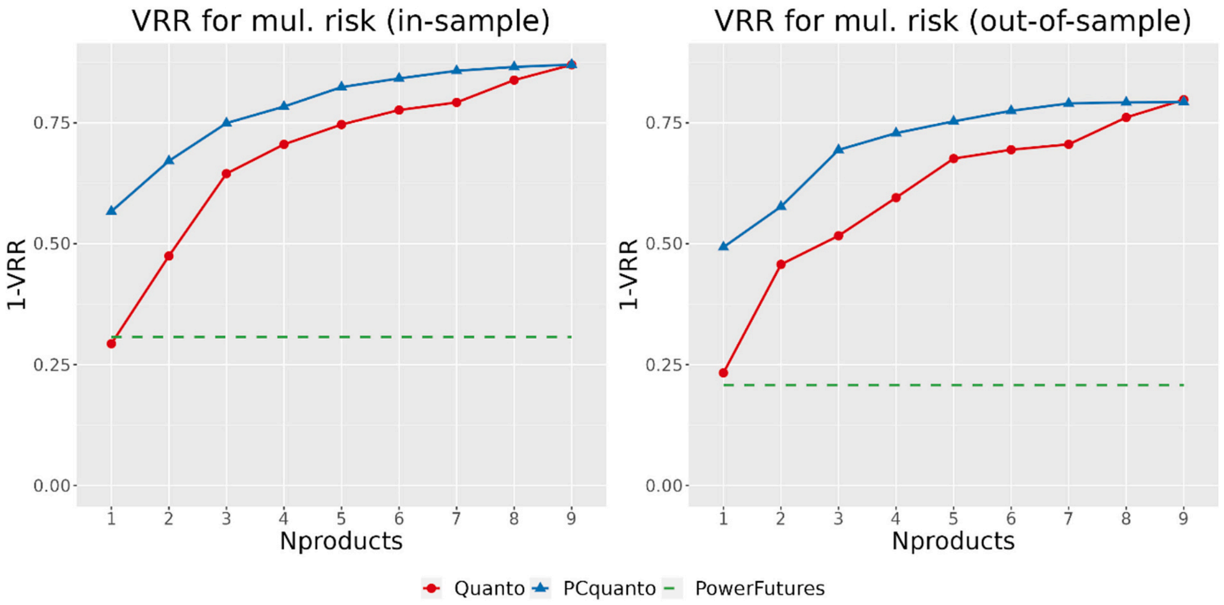

Fig. 4. Cumulative hedge effects for multiplicative risk.

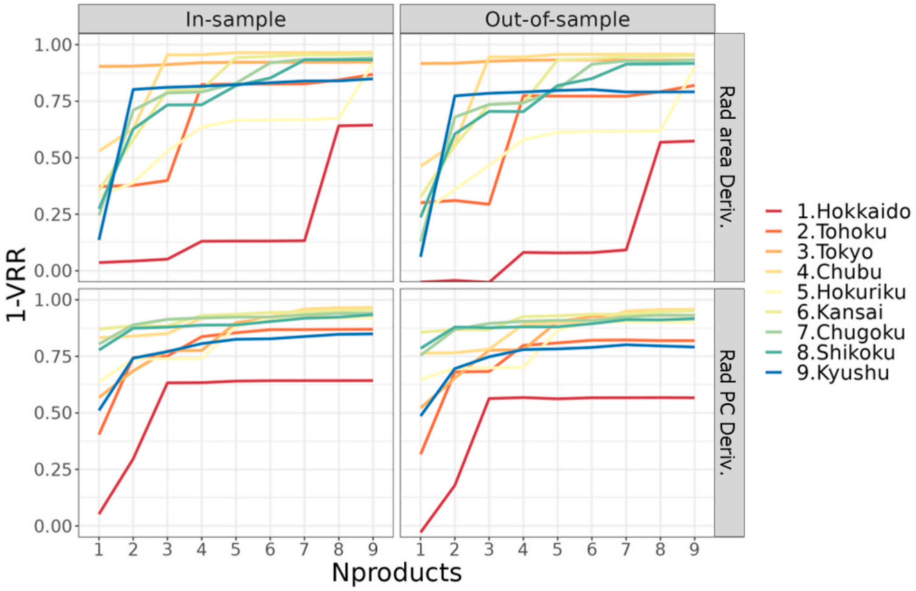

Fig. 5. Cumulative hedge effects of derivatives by area for volumetric risk.

performance.

Third, the out-of-sample hedging effects remain generally high, implying that a robust hedging model can be constructed without excessive overfitting. As illustrated in Figs. 5 and 6, each additional product (component) helps enhance hedge performance—especially with PC derivatives. From these graphs, employing three or four PC derivatives appears both efficient and sufficient to cover the entire area effectively.

To make the results more intuitive, Figs. 7 and 8 show the cumulative hedging effect up to PC4 on volumetric and multiplicative risk, respectively, as a heat map on a map of Japan. PC derivatives cover a wide range that can be covered by the first principal component alone. In addition, high hedging effectiveness is achieved over almost the entire area with transactions up to about PC3. In other words, it suggests that PC derivatives can respond to a relatively small number of instruments in terms of covering the entire area and can meet a wide range of hedging needs.

Thus, these results underline how traditional instruments—be they wide-area futures or single-region derivatives—often fall short in capturing localized or cross-regional risk structures, particularly in an environment with highly decentralized renewable generation. By isolating principal components, our method better accommodates spatial variations and allows hedgers in different regions to effectively mitigate their risks against each other. This is why PC-based derivatives exhibit superior hedge effectiveness compared to both nationwide and purely local instruments.

4.2. *Trend analysis of trading volumes*

Fig. 9 shows the seasonal trend of the contract volume of Rad PC derivatives, $f_{i,PR,k}(Seasonal_t)$, in the hedging model (7). In PC1, the seasonal changes by regions are well reflected in the trading volumes.

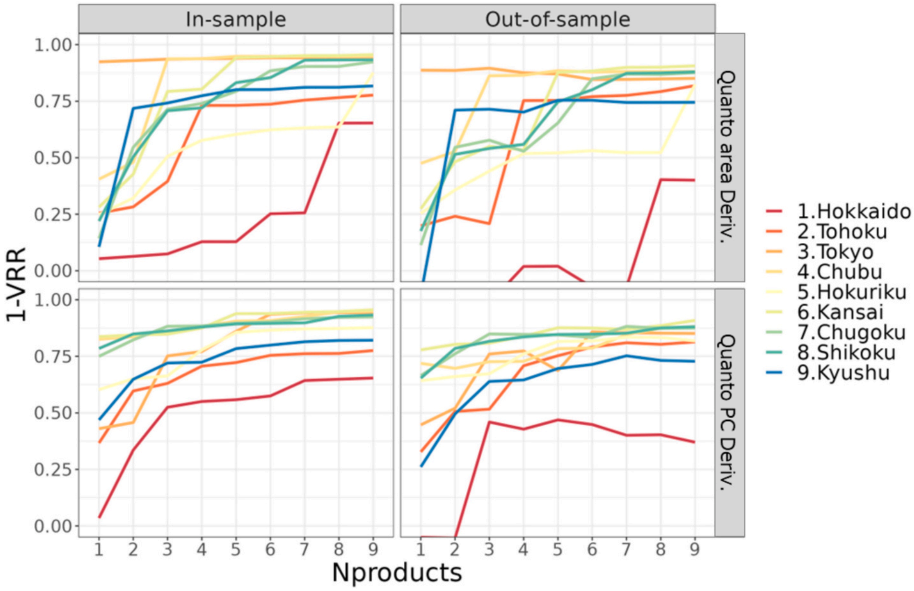

Fig. 6. Cumulative hedge effects of derivatives by area for multiplicative risk.

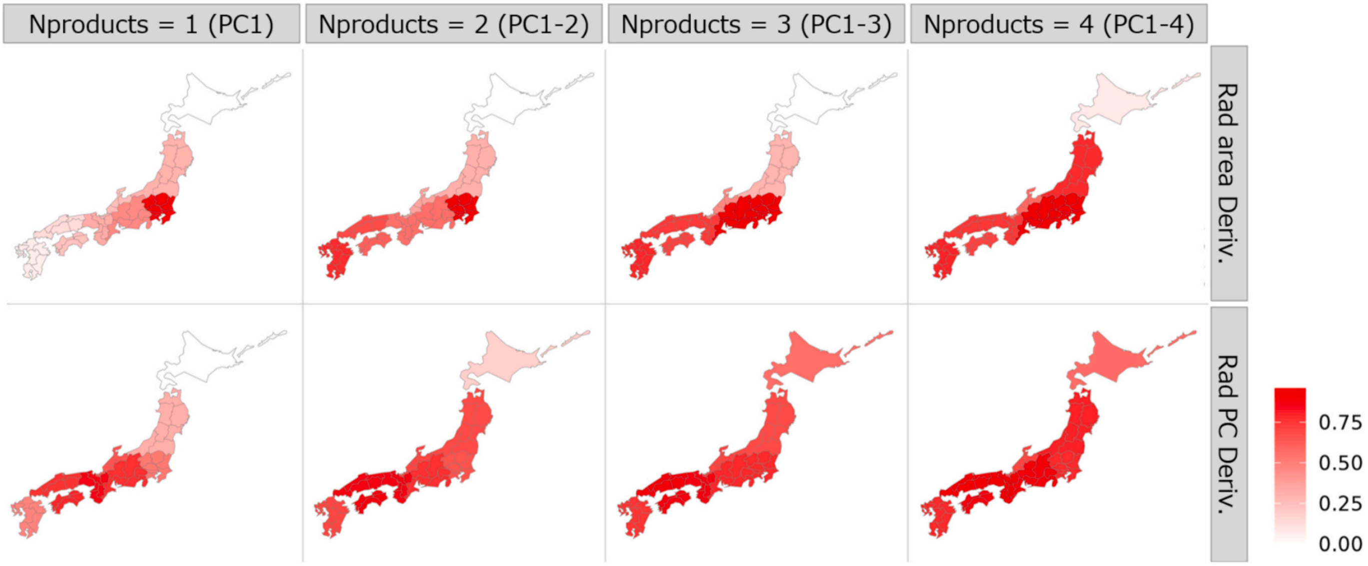

Fig. 7. Mapping of hedge effects for four PCs (for volumetric risk).

For instance, the trading volume is consistently lower throughout the year in Hokkaido, where there is less solar radiation, and the trading volume is lower in winter in Tohoku or Hokuriku, where snow cover is more prevalent. The higher the order of PC, the wider the confidence interval (gray band) tends to be, and the intensity of seasonality tends to be mitigated.

Notably, regions with opposite signs mean that efficient trades can be made between them. For example, PC2 derivatives can be effectively traded between eastern Japan (Hokkaido, Tohoku and Tokyo) and western Japan (Chugoku, Shikoku and Kyushu) to reduce each other's risk. Similarly, PC4 derivatives can be effectively traded between “Chubu or Kansai” and “Tohoku or Kyushu”.

Similar result can be observed for the contract volume of the Quanto PC derivative, $f_{i,PQ,k}(Seasonal_t)$, in the hedging model (9) shown in Fig. 10. As price seasonality affects the multiplicative hedging risk, there is a tendency for the contract volume of Quanto PC derivatives to exhibit more seasonality than that of Rad PC derivatives. However, the overall trends in terms of signs, shapes, confidence intervals, etc., remain consistent with those of the Rad PC derivatives.

5. Discussion on the validity of hedging instruments

As outlined in the preceding sections, our proposed PC derivatives offer numerous advantages, notably high hedging effectiveness and efficient cross-trading capabilities. It is imperative, however, that the process of calculating PC derivatives is transparent and interpretable, ensuring their robustness and reliability in real-world applications. In other words, we need to verify that the loading matrices, which can be considered as the core formulation for PC derivatives, is intuitively understandable. Moreover, it is noteworthy that our derivatives are designed to have an expected (or average) payoff of 0, enhancing the flexibility of combining with other financial instruments without requiring premium payment at the time of contracting. In this section, we aim to validate our proposed PC derivatives as effective hedging instruments. Additionally, we conduct further empirical analysis of the PCA calculation outcomes and payoff biases to provide comprehensive

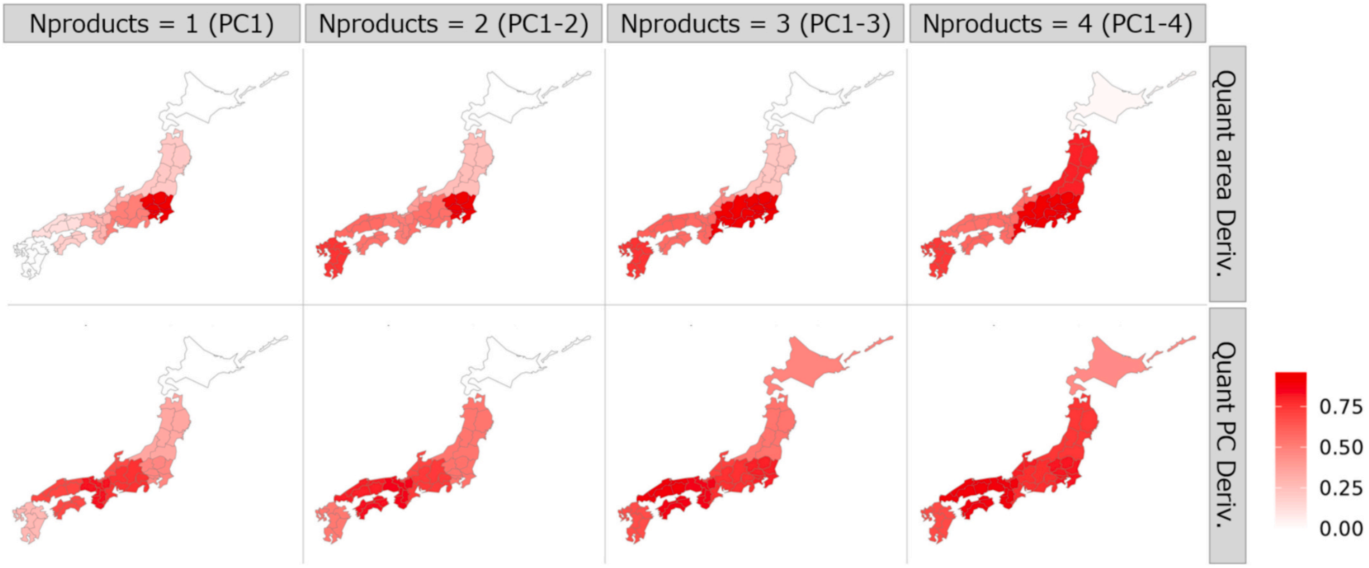

Fig. 8. Mapping of hedge effects for four PCs (for multiplicative risk).

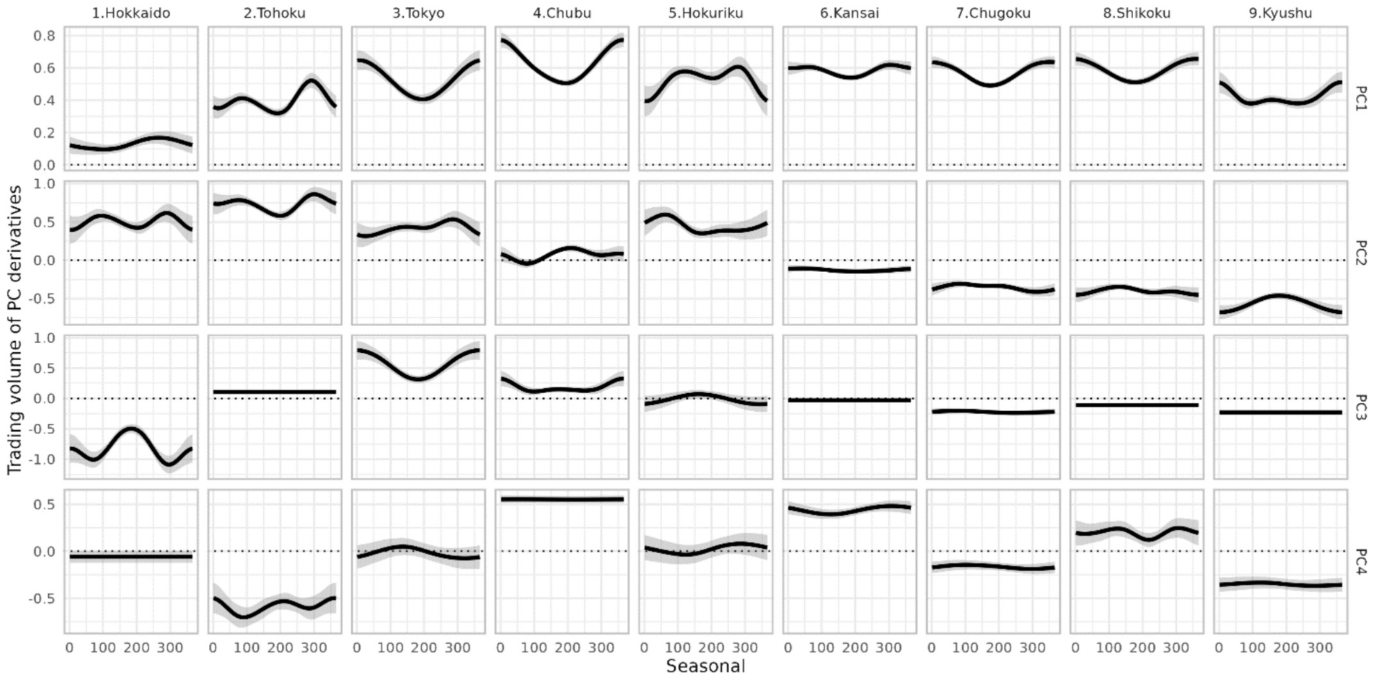

Fig. 9. Seasonal contract volume of Rad PC derivatives for each area.

insights into the validity and advantages of the proposed hedging instrument.

5.1. Applications of principal component analysis

Fig. 11 shows the first four components (i.e., $V_{R:,(1:4)}$ and $V_{Q:,(1:4)}$ of PC1–4) of the estimated loading matrix for both the Rad PC derivatives and the Quanto PC derivatives as a heat map in Japan. Note that these are the loading matrices obtained by PCA for the standardized series as described in Section 3.2, so these values indicate the correlation matrices between the original series and the principal component scores (Wold et al., 1987). It is confirmed that the components of both loading matrices have characteristic properties that can be easily distinguished geographically. The principal component (PC1) has the same sign in all areas, indicating the general direction of the nationwide solar radiation. PC2 through PC4 exhibit a gradation from north to south, a mountain-like shape with the Tokyo area at the top, and a stripe pattern, respectively. In such cases, it would be useful to label the loading matrices with interpretable instrument labels. That is, for example, PC1 could be referred to as a “whole area” type product, PC2 as a “north-south” type product, PC3 as a “radial” type product, PC4 as a “wave” type product, etc., to facilitate trading decisions.

It is also noteworthy that Japan's archipelago is roughly linear from northeast (Hokkaido) to southwest (Kyushu). If we approximate this shape by a single coordinate x, then:

- PC1 can be viewed as an almost “constant term,”
- PC2 resembles a linear function of x (capturing a smooth north–south gradient),

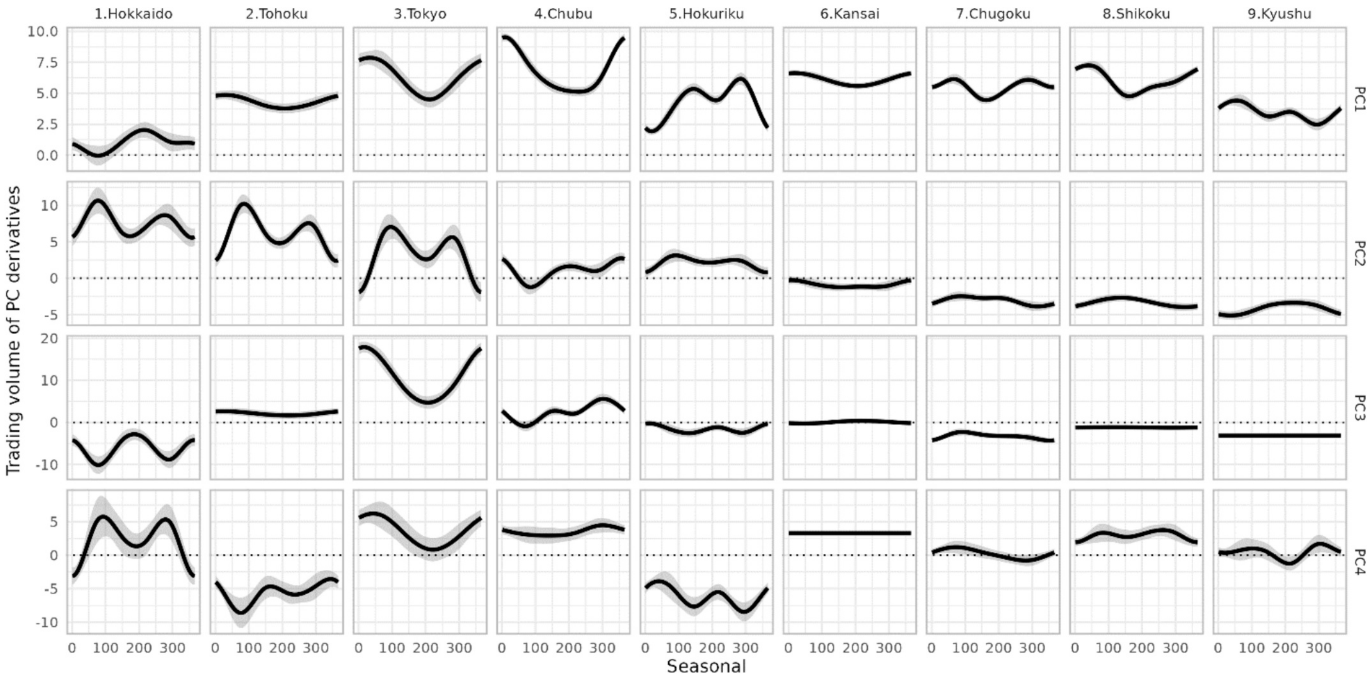

Fig. 10. Seasonal contract volume of Quanto PC derivatives for each area

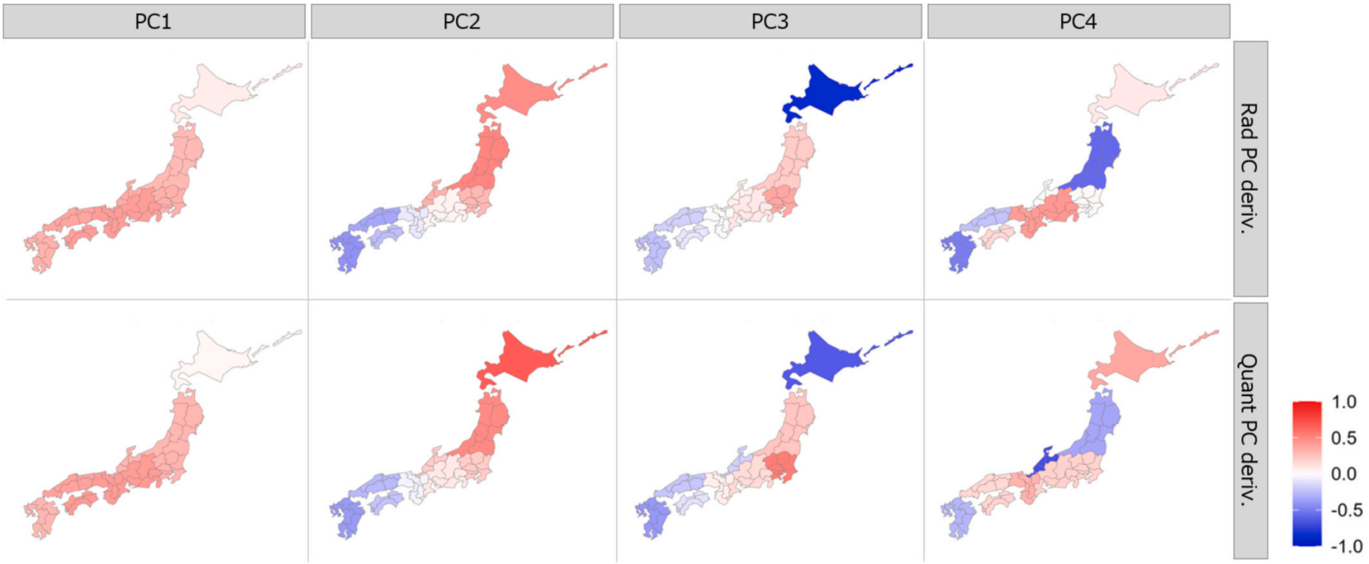

Fig. 11. Mapping of loading vectors for four principal components.

- PC3 corresponds to a quadratic term x^2 (highlighting a peak around Tokyo), and
- PC4 might reflect a cubic term x^3 (manifesting in a stripe-like pattern).

These polynomial-like interpretations help clarify why each principal component exhibits the geographical loadings seen in Fig. 11[15].

Furthermore, it is interesting to note that the sign and magnitude of the PC loading matrix also align with the optimal trading volume for each PC as described in Figs. 9 and 10. It can be understood that the loading matrix represents the correlation between the principal component scores and each area's solar radiation residuals, whereas the trading volumes reflects the model coefficients mapping those PC series onto the area's PV output, Hence, they show similar tendencies in both sign and magnitude.

If PC derivatives are allowed to be traded continuously over a long period of time, the loading matrix could be reviewed and updated, for example annually, to maintain the trader's hedging effectiveness. In such cases, it is desirable for the loading matrix not to fluctuate with the usage sample (estimation period). In other words, the robustness of the loading matrix, as well as the interpretability mentioned earlier, may influence the exchanges' decision to commoditize. Therefore, Fig. 12 shows the

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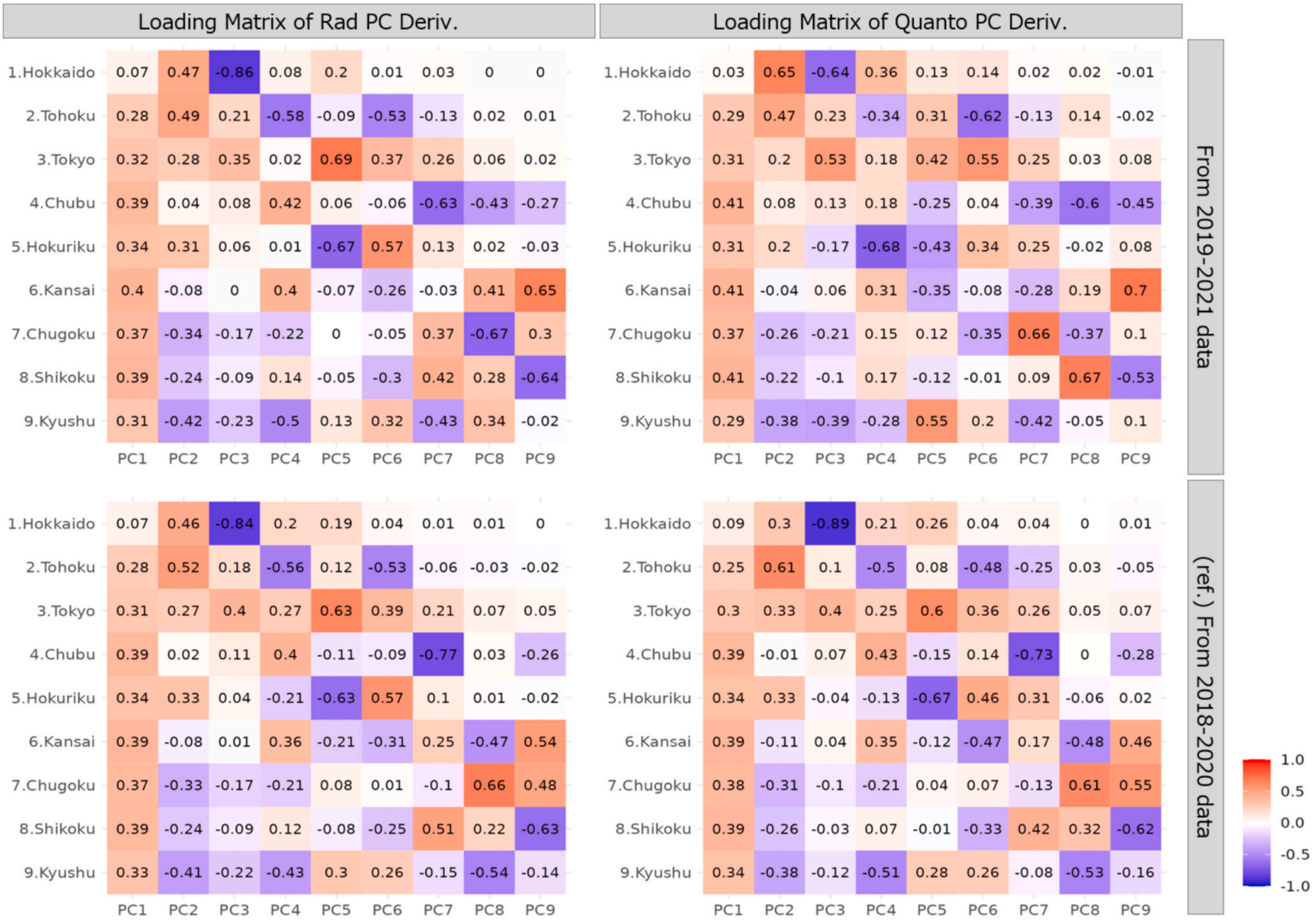
[15] We acknowledge that not all regions (countries) have this linear shape. In more “two-dimensional” geographies, principal components may exhibit more complex patterns or require different interpretations. Our study focuses on Japan to exploit its relatively one-dimensional shape for clearer interpretability as a first step toward commoditizing PCA-based derivatives. Extending these ideas to broader regions remains an important topic for future work.



Loading Matrix of Rad PC Deriv. — From 2019-2021 data

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
1.Hokkaido	0.07	0.47	-0.86	0.08	0.2	0.01	0.03	0	0
2.Tohoku	0.28	0.49	0.21	-0.58	-0.09	-0.53	-0.13	0.02	0.01
3.Tokyo	0.32	0.28	0.35	0.02	0.69	0.37	0.26	0.06	0.02
4.Chubu	0.39	0.04	0.08	0.42	0.06	-0.06	-0.63	-0.43	-0.27
5.Hokuriku	0.34	0.31	0.06	0.01	-0.67	0.57	0.13	0.02	-0.03
6.Kansai	0.4	-0.08	0	0.4	-0.07	-0.26	-0.03	0.41	0.65
7.Chugoku	0.37	-0.34	-0.17	-0.22	0	-0.05	0.37	-0.67	0.3
8.Shikoku	0.39	-0.24	-0.09	0.14	-0.05	-0.3	0.42	0.28	-0.64
9.Kyushu	0.31	-0.42	-0.23	-0.5	0.13	0.32	-0.43	0.34	-0.02

Loading Matrix of Quanto PC Deriv. — From 2019-2021 data

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
1.Hokkaido	0.03	0.65	-0.64	0.36	0.13	0.14	0.02	0.02	-0.01
2.Tohoku	0.29	0.47	0.23	-0.34	0.31	-0.62	-0.13	0.14	-0.02
3.Tokyo	0.31	0.2	0.53	0.18	0.42	0.55	0.25	0.03	0.08
4.Chubu	0.41	0.08	0.13	0.18	-0.25	0.04	-0.39	-0.6	-0.45
5.Hokuriku	0.31	0.2	-0.17	-0.68	-0.43	0.34	0.25	-0.02	0.08
6.Kansai	0.41	-0.04	0.06	0.31	-0.35	-0.08	-0.28	0.19	0.7
7.Chugoku	0.37	-0.26	-0.21	0.15	0.12	-0.35	0.66	-0.37	0.1
8.Shikoku	0.41	-0.22	-0.1	0.17	-0.12	-0.01	0.09	0.67	-0.53
9.Kyushu	0.29	-0.38	-0.39	-0.28	0.55	0.2	-0.42	-0.05	0.1

Loading Matrix of Rad PC Deriv. — (ref.) From 2018-2020 data

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
1.Hokkaido	0.07	0.46	-0.84	0.2	0.19	0.04	0.01	0.01	0
2.Tohoku	0.28	0.52	0.18	-0.56	0.12	-0.53	-0.06	-0.03	-0.02
3.Tokyo	0.31	0.27	0.4	0.27	0.63	0.39	0.21	0.07	0.05
4.Chubu	0.39	0.02	0.11	0.4	-0.11	-0.09	-0.77	0.03	-0.26
5.Hokuriku	0.34	0.33	0.04	-0.21	-0.63	0.57	0.1	0.01	-0.02
6.Kansai	0.39	-0.08	0.01	0.36	-0.21	-0.31	0.25	-0.47	0.54
7.Chugoku	0.37	-0.33	-0.17	-0.21	0.08	0.01	-0.1	0.66	0.48
8.Shikoku	0.39	-0.24	-0.09	0.12	-0.08	-0.25	0.51	0.22	-0.63
9.Kyushu	0.33	-0.41	-0.22	-0.43	0.3	0.26	-0.15	-0.54	-0.14

Loading Matrix of Quanto PC Deriv. — (ref.) From 2018-2020 data

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
1.Hokkaido	0.09	0.3	-0.89	0.21	0.26	0.04	0.04	0	0.01
2.Tohoku	0.25	0.61	0.1	-0.5	0.08	-0.48	-0.25	0.03	-0.05
3.Tokyo	0.3	0.33	0.4	0.25	0.6	0.36	0.26	0.05	0.07
4.Chubu	0.39	-0.01	0.07	0.43	-0.15	0.14	-0.73	0	-0.28
5.Hokuriku	0.34	0.33	-0.04	-0.13	-0.67	0.46	0.31	-0.06	0.02
6.Kansai	0.39	-0.11	0.04	0.35	-0.12	-0.47	0.17	-0.48	0.46
7.Chugoku	0.38	-0.31	-0.1	-0.21	0.04	0.07	-0.13	0.61	0.55
8.Shikoku	0.39	-0.26	-0.03	0.07	-0.01	-0.33	0.42	0.32	-0.62
9.Kyushu	0.34	-0.38	-0.12	-0.51	0.28	0.26	-0.08	-0.53	-0.16

Fig. 12. Estimated loading matrices.

loading matrices for all PC derivatives, including the top four components shown in Fig. 11, which also represents the estimation results when the estimation period is shifted by one year along with their numerical values. Overall, the changes with different estimation periods are small from the first to the fourth components. This suggests that the estimation results of the loading matrices, i.e. the instrument specifications of the PC derivatives of the prediction errors, are robust for the upper principal components. Note that the quanto derivatives show relatively large changes around and beyond the fourth component, due to differences in the estimation period. This is likely attributed to the relatively large impact of annual price changes. Given this, it may be realistic for exchanges to commoditize quanto derivatives up to the third component. However, assuming that trading decisions could be fully algorithmic rather than made by humans, there might not be a necessary to limit the number of instruments. It is worth noting that Rad PC derivatives exhibit relatively robust characteristics, and stable results have been confirmed up to approximately the fourth component, even with a one-year in-sample period rather than the three-year period of the default case (although the figures are not shown here).

In addition, Table 1 shows the contribution ratio and the cumulative contribution ratio of each component by PCA: both Rad PC derivatives and Quanto PC derivatives explain more than 50 % of the variance in the first principal component, and more than 10 % in the second and third components. The cumulative contribution ratio up to the fourth component shows that these components together explain about 85 % of the variance. Comparing the Rad PC derivatives and the Quanto PC derivatives, the contribution of the first principal component is smaller for the latter. This may reflect the fact that the latter includes price fluctuations that tend to disperse the factors (features). Since this result is derived only from solar radiation and price data, it does not immediately indicate the hedging effect on the cashflow fluctuation for solar power generators. However, the fact that the top three or four components account for most of the variation in the underlying assets provides valuable insights for exchanges to assess the importance of commoditization.

Table 1
Cumulative contribution ratio of principal component analysis results.

Principal components	Rad PC deriv.		Quanto PC deriv.	
	Explained variance	Cumulative sum	Explained variance	Cumulative sum
PC1	57.1 %	57.1 %	53.4 %	53.4 %
PC2	15.0 %	72.1 %	13.3 %	66.7 %
PC3	10.1 %	82.1 %	10.6 %	77.2 %
PC4	5.3 %	87.4 %	7.3 %	84.5 %
PC5	4.6 %	92.0 %	5.6 %	90.1 %
PC6	3.0 %	95.0 %	3.9 %	94.0 %
PC7	2.2 %	97.2 %	3.0 %	97.0 %
PC8	1.7 %	98.9 %	2.0 %	99.0 %
PC9	1.1 %	100.0 %	1.0 %	100.0 %

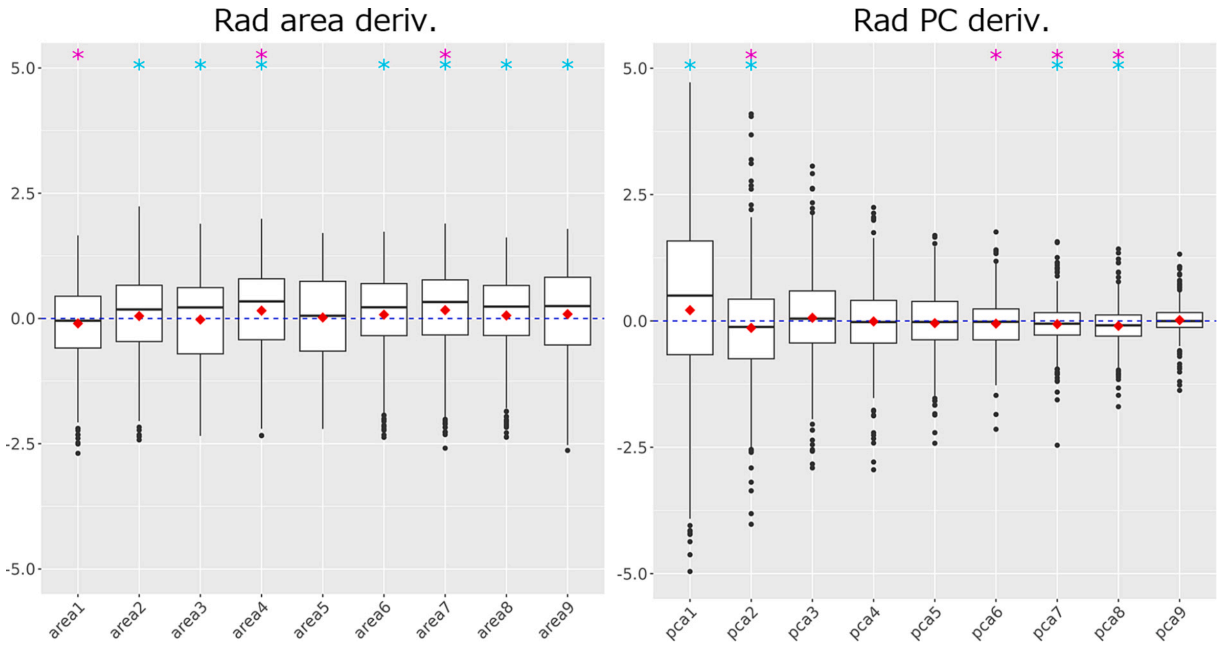


Fig. 13. Out-of-sample payoff of Rad area/PC derivatives (boxplot).

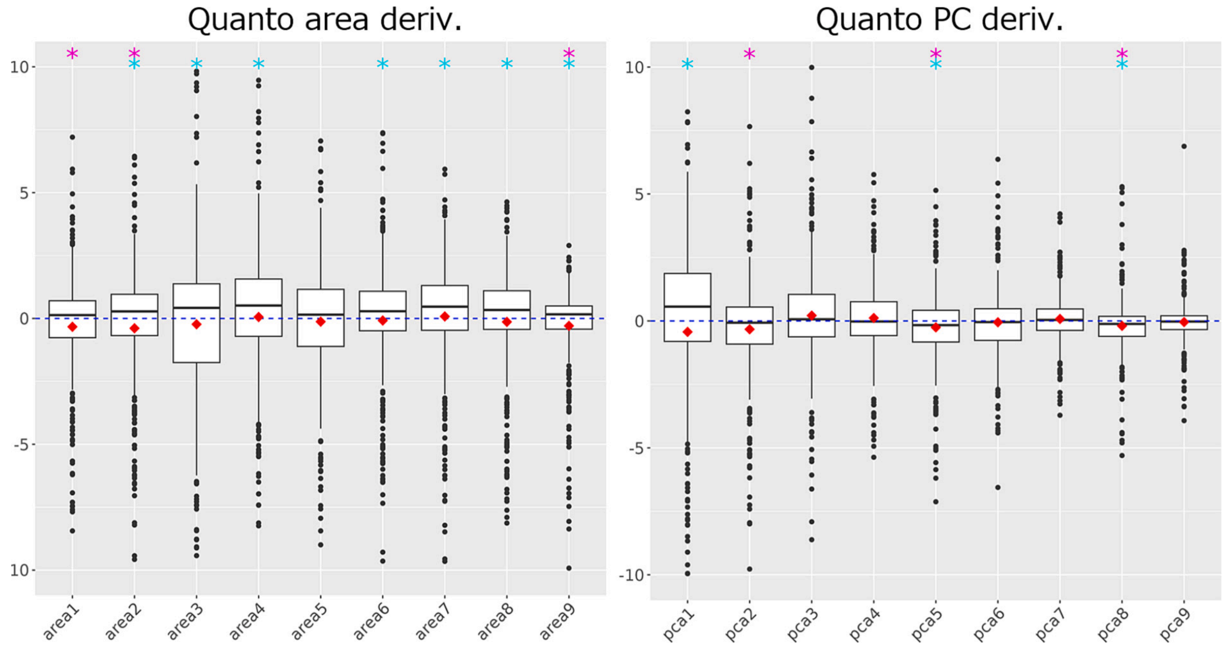


Fig. 14. Out-of-sample payoff of Quanto area/PC derivatives (boxplot).

5.2. *Verifications of payoff bias*

We mentioned earlier that our PC derivatives incorporate the concept of prediction error derivatives, so that the premium at the time of contracting can be treated as zero. To verify this, Figs. 13 and 14 show box plots of the out-of-sample payoffs for the solar radiation and quanto derivatives, respectively. The payoffs for the Rad area derivatives are the solar radiation residuals [MJ/m^2], and the payoffs for the quanto area derivatives are the product of the solar radiation residuals [MJ/m^2] and the average daytime price [JPY/kWh]. Note that for ease of comparison, the area-type derivatives are also standardized using the in-sample mean and standard deviation, as is the PC derivative, and the payoffs are plotted here in this case. In addition, to more objectively capture payoff bias and distributional distortion, results that are significant at the 5 % level from the bootstrap test (testing the null hypothesis that the mean is 0) are indicated with a magenta *, and results that are significant at the 5 % level from the sign test (testing the null hypothesis that the median is 0) are indicated with a cyan * in each figure.

PC derivatives are characterized by larger variation in PC1 payoffs (reflecting the larger variance of the first principal component score).

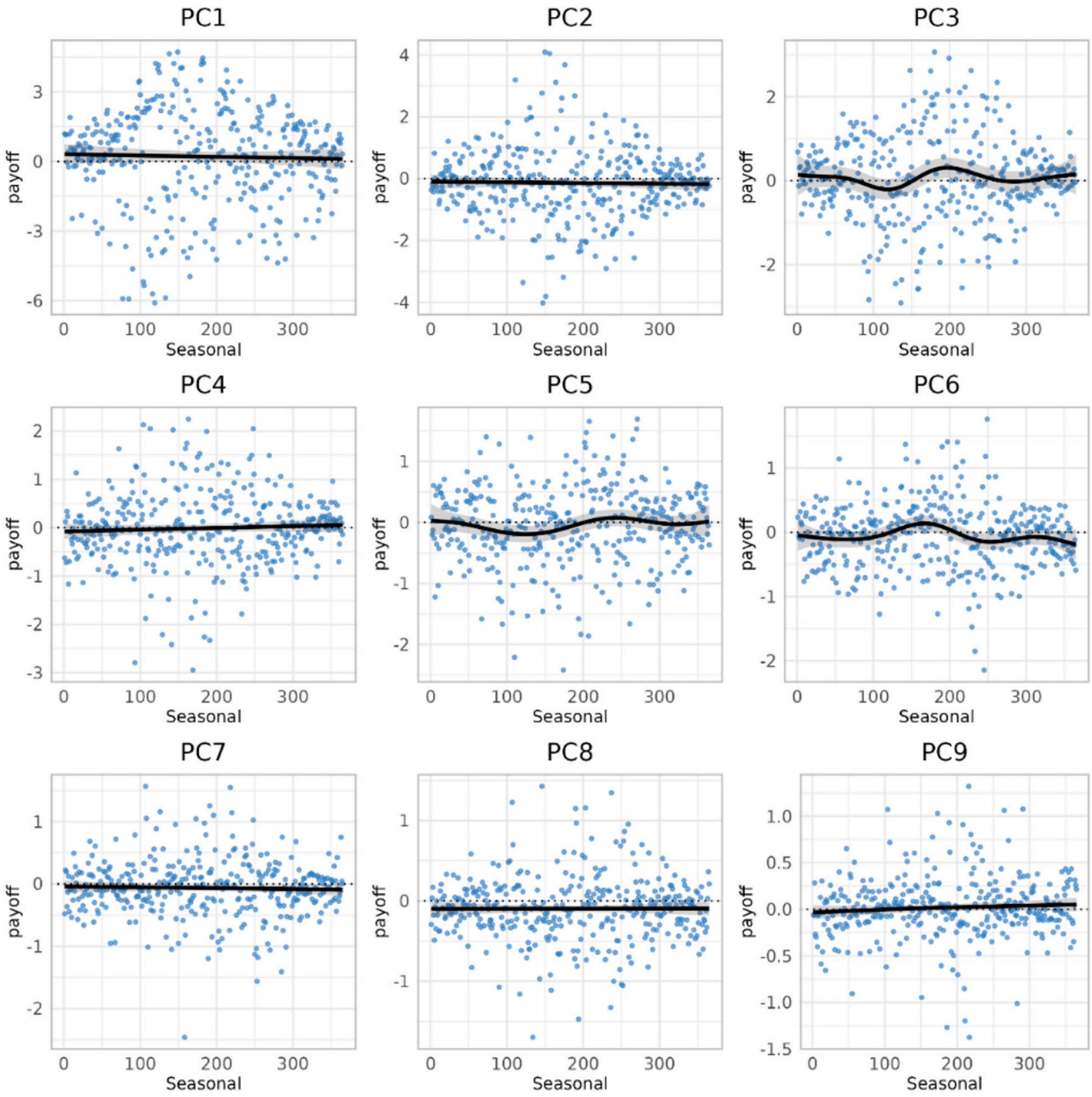


Fig. 15. Out-of-sample payoff of Rad PC derivatives (full year trend).

Overall, PC derivatives tend to have smaller distributional distortions and mean biases than area derivatives. In particular, with the exception of the first principal component, the medians (centerline of the box plot) are close to zero, and if we focus on the top four components, all but the second component can be statistically considered to have a mean of zero. While it is a natural consequence that the mean of the payoffs is not necessarily zero due to the out-of-sample results, the overall proximity to zero would provide a straightforward guide to determining the premium for contracting our proposed derivatives.

Figs. 15 and 16 show the out-of-sample payoffs for the Rad PC derivative and the Quanto PC derivative plotted over the course of a year. The out-of-sample data shows that the payoffs for the PC derivatives fluctuate around 0 for all periods, and there is some validity in contracting a premium of 0 for any given period. The first principal component derivative (PC1) of the Quanto PC derivative shows a slight seasonal variation, for which it may be useful to remove the seasonal trend derived from the seasonal correlation between solar radiation and prices from the underlying asset (PC score) $T_{Q_{t,k}}$. Although we do not explore this in detail in this study, it should be considered in the trade-off with the complexity of the specification in the case of practical commoditization.

While minor seasonal variations are evident, the overall advantage of having average payoffs consistently close to zero remains pivotal when utilizing the seasonal trend elimination method inherent in prediction error derivatives. Absent this process, pricing PC derivatives would present a considerable challenge, necessitating highly complex computation such as Monte Carlo simulations, even when the loading matrices are disclosed and the computational process is clarified. Additionally, attaining consensus among traders on such pricing and ensuring liquidity in the trading of these instruments would present further challenges. Our approach addresses these issues by mitigating the complexity of pricing PC derivatives and enhancing their market tradability. A significant implication arising from our efforts to commoditize PC derivatives is the recognition that designing them with average payoffs (associated with premiums) close to zero could prove highly advantageous, despite the potential oversight, in bolstering their

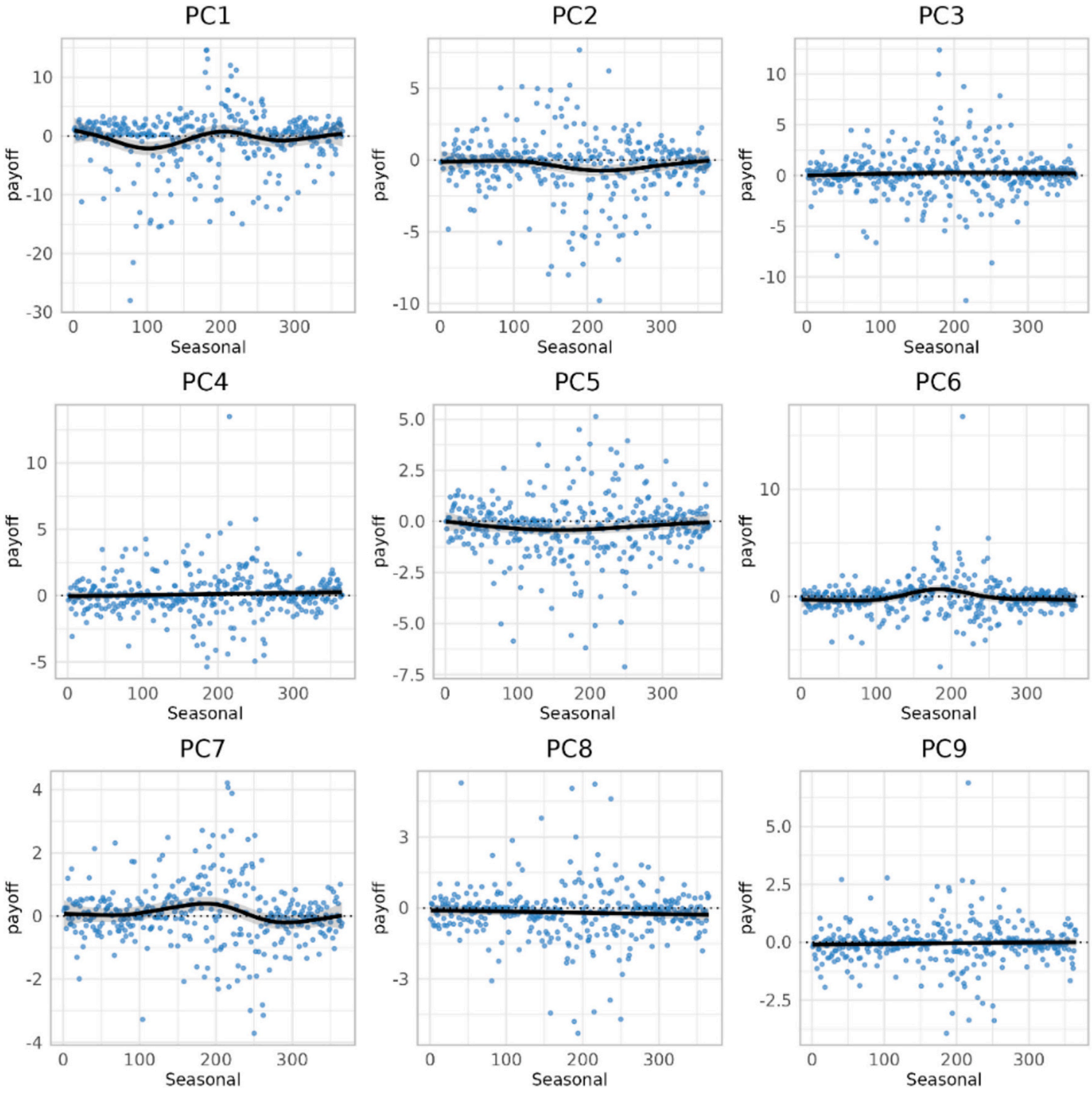


Fig. 16. Out-of-sample payoff of Quanto PC derivatives (full year trend).

tradability in real world markets.

In conclusion, despite the natural variations observed in out-of-sample results, the consistent proximity of payoff means to zero across different components provides strong empirical support for our proposed zero-premium contracting approach. This finding not only simplifies the practical implementation of PC derivatives but also significantly enhances their potential for market adoption and liquidity.

6. Conclusion

In this study, we extended the concept of PCA-based derivative contracts, as initially proposed by Thomaidis et al. (2023), to the solar PV sector and investigated its applicability to actual market transactions from various perspectives. Leveraging the idea of weather prediction error derivatives introduced in our previous studies for PC derivatives, we developed an intuitive and easy-to-trade methodology for PC derivatives. Moreover, in response to recent diversified needs, we constructed the "Quanto PC Derivative" based on the product of solar radiation and price, clarifying its effectiveness and improving transparency in pricing and product design.

Our empirical results demonstrate, similar to Thomaidis et al. (2023), that the utilization of PC derivatives significantly enhances hedging effectiveness compared to existing wide area derivatives. For both volumetric and multiplicative risks, it is worth noting that hedging effectiveness improved with three to four PC derivatives across the entire area by approximately 20 %, relative to multiple area-specific derivatives. While PC derivatives require additional computational complexity, the benefits of commoditization are deemed to be significant, even considering this factor. Moreover, in many jurisdictions transitioning from FIT to FIP, renewable energy producers face heightened price exposure; hence, the introduction of Quanto PC derivatives may also carry policy implications by mitigating these newly emerging risks in a transparent, market-oriented manner.

If PC derivatives are to be listed in the market, exchanges would need to specify loading matrices. Regarding this matter, we have confirmed that the loading matrices remains relatively unchanged with the estimation window for the first 3—4 components, indicating the feasibility of trading. In addition, when the loading matrices are visualized on a map, it is evident that semantic labeling of each PC derivative product up to about the fourth component (in the Japanese case, "whole area" type, "north-south" type, "radial" type, and "wave" type) is possible, helping avoid the issue of black boxing of instruments. In addition, by applying the seasonal trend elimination idea of prediction error derivatives in previous studies, the loading matrix required for the derivative contract can be computed robustly and used throughout the year. Furthermore, the average payoffs remain close to zero in our out-of-sample tests, which supports setting a near-zero premium in practice. While slight biases may arise on certain days or components, these deviations are small enough that the overall pricing framework remains both transparent and tractable.

PC derivatives can be traded simultaneously by players in multiple areas, which naturally facilitates higher liquidity compared to instruments limited to a single region. Moreover, by allowing hedgers in different areas to offset each other's risk in the second and subsequent principal components (PC2, PC3, etc.), these products may eliminate the need for a dedicated "risk taker," thereby reducing or even removing additional risk premiums. This mechanism has not been monetarily quantified in our empirical results, but it does imply lower overall transaction costs and thus supports more active trading. In addition, because the first principal component (PC1) reflects the nationwide or system-wide risk factor, it becomes a universal product for all generators, further enhancing liquidity and price discovery. Compared to designing separate derivatives for each area—where trading volume can disperse—PC derivatives effectively pool demand into a smaller number of well-defined instruments, potentially improving both efficiency and market reliability.

Finally, while we have demonstrated the feasibility and utility of PC derivatives for practical solar PV risk management in Japan, further validation with data from other countries or regions will help solidify their role in promoting cost-effective, liquid hedging solutions in renewable-dominated markets. In particular, a more detailed analysis of investor risk preferences, liquidity constraints, and market microstructure lies beyond the current scope but represents a promising direction for future research[16]. Pursuing these directions will build on the insights offered here and foster the broader adoption of PC derivatives as a versatile risk-management tool in the global energy transition.

CRediT authorship contribution statement

Takuji Matsumoto: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yuji Yamada:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and DeepL Write in order to improve readability and language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declared no potential conflicts of interest.

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Appendix A. "Quanto-only" scenario vs. two-layer approach

As discussed in Section 3.5, our multiplicative model relies on standard electricity futures to hedge linear price risk, followed by Quanto PC derivatives for the residual volume–price exposure. A natural question is whether one could simply use Quanto derivatives alone, ignoring electricity futures. In previous studies, including Yamada and Matsumoto (2021, 2023), it was assumed that Quanto derivatives would be used in conjunction with power futures; here, we revisit this "Quanto-only" approach by excluding power futures from our hedging model.

Although we omit the detailed numerical results here, the hedge effect ($1 - VRR$) in the out-of-sample period was negligible or even negative in most cases. Essentially, the unhedged portion of linear price fluctuations overshadowed any benefit from addressing volume–price interactions. These findings confirm that two layers of hedging—electricity futures plus Quanto derivatives—are needed to effectively capture both primary and secondary risk components.

This outcome supports our main proposition: price futures already offer substantial hedging power for renewable energy operators (as demonstrated by Yamada and Matsumoto (2021)), and the Quanto instruments introduced in this study fill the gap left by these conventional derivatives. While such a two-layer structure may appear more complex, it is consistent with real-world market practices and ultimately achieves stronger risk reduction than a "one-instrument" approach.[17]

Appendix B. Overview of empirical data

For spot price and solar generation, data from the following nine areas are used for each: 1.Hokkaido; 2.Tohoku; 3.Tokyo; 4.Chubu; 5.Hokuriku; 6. Kansai; 7.Chugoku; 8.Shikoku; 9.Kyushu (see Fig. B1). On the other hand, for solar radiation, data from one major city in each area is used (1.Sapporo; 2.Sendai; 3.Tokyo; 4.Nagoya; 5.Toyama; 6.Osaka; 7.Hiroshima; 8.Takamatsu; 9.Fukuoka). Fig. B1 shows an overview of Japan's Electric Power Company (EPC) areas and the percentage of PV power generation installed by area at the end of 2021. Fig. B2 shows the correlations between areas for each dataset. Note that the data for solar radiation "Rad" and solar power generation "PV" are residual series after removing the seasonal trend, while the data for "Price" are based on the original series. The correlations are generally positive throughout the area, but there is almost no correlation in the northernmost area (Hokkaido) and the southernmost area (Kyushu). Prices have a strong positive correlation throughout the area. The correlation matrix for the product of solar radiation residuals and prices ("Rad*Price") shows the same tendency as that for solar radiation.

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[16] As part of this broader line of inquiry, market-impact effects, which are closely related to market microstructure, may also influence pricing dynamics (Kumar and Chakrabarti, 2025).

[17] Even though our hedging strategy—particularly the multiplicative model—may appear somewhat complex, all procedures (trend removal and principal component analysis) rely solely on observable solar radiation and price data, making them amenable to automation in practical settings. We acknowledge that there is still room to simplify the framework and enhance its implementability for real-world applications, which we leave as a promising avenue for future work.

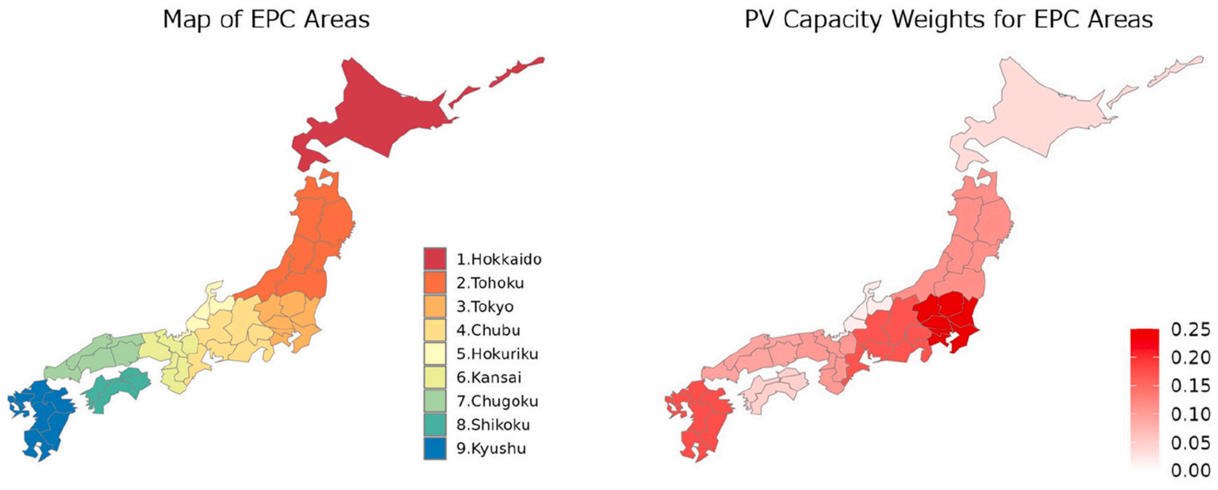

Fig. B1. Overview of Electric Power Company (EPC) areas and share of installed solar power capacity per area.

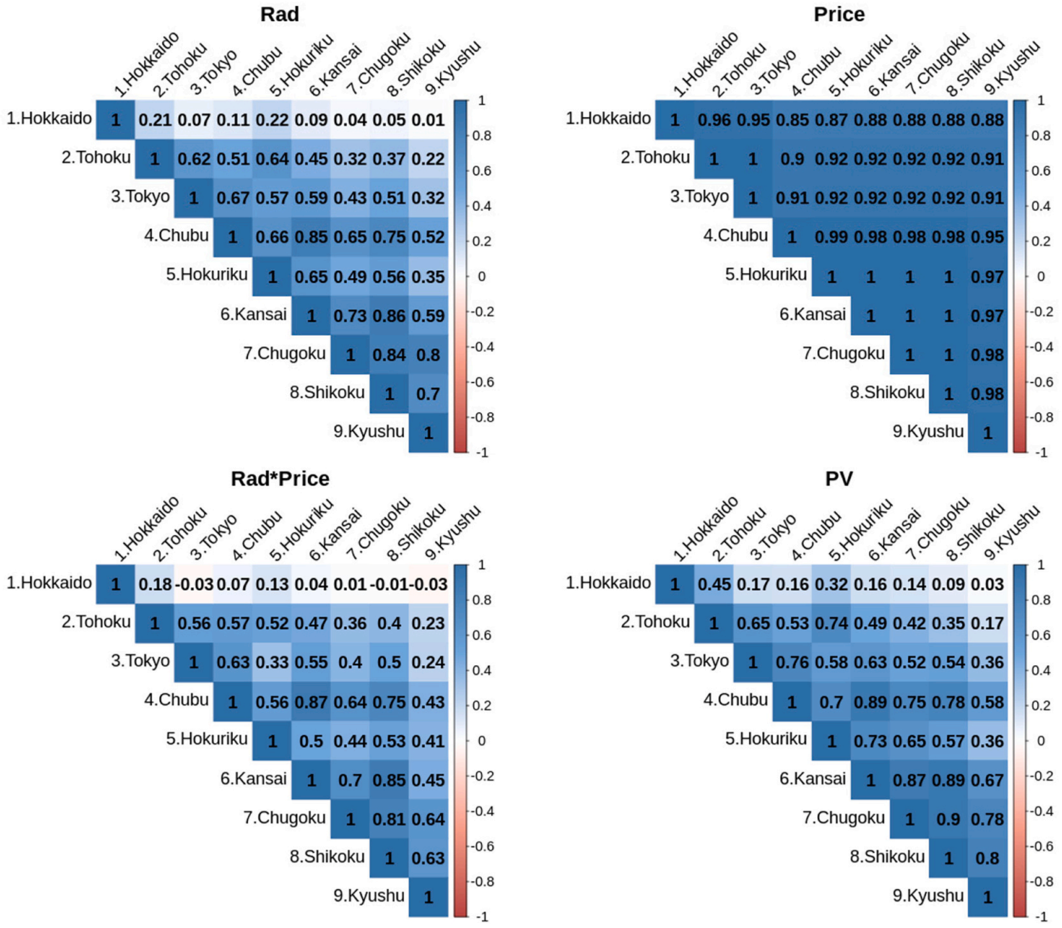

Fig. B2. Inter-area correlation for each time series data.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108821.

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