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Handling the risk dimensions of wind energy generation

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ABSTRACT

In this paper, we explore two strategies for reducing the cash flow uncertainty of wind energy producers ascribed to variable weather conditions. The first strategy is based on the idea of aggregating the output of geographically-dispersed generating units. The second strategy employs financial instruments that compensate producers for unanticipated declines in the power delivery. Using a blend of advanced weather modeling, time series analysis, simulation and optimization techniques, we empirically access the ability of the two risk management approaches to control volumetric risk in Spain. With the aid of factor analysis techniques, we proceed with the decomposition of the remaining risk levels and assess the exposure of each strategy's revenue to systematic risk factors. Motivated by the results of this analysis, we propose new financial contracts and mixed-style strategies that are better suited to the risk position of each market player.

1. Introduction

The European Union has introduced institutional reforms to deal with climate change risks and reduce the carbon footprint of electricity generation. One of the key goals of the action plan is to increase the share of clean energy in the generation mix of each Member Country through the integration of spatially distributed resources and mixed generation technologies. Industry players warn that the decarbonization of electricity generation will not be possible unless the market provides the essential funds to support large-scale investments on clean energy generation capacity. As government incentives are gradually withdrawn from all Member Countries, private funds are meant to play a key part in this endeavor.

Wind power project developers are exposed to various risks that restrict their access to cheap sources of funding. First and outmost is their inability to accurately forecast the output of the power generator at a future time period, also known as *volumetric* or *production* risk. The level of volumetric risk of a candidate site – in particular the anticipated energy output in adverse weather conditions – is a key input to a project financing plan and determines not only the loan interest rate but also the amount of capital that wind project developers have to hold on side to protect themselves against sharp losses.

Those who participate in the day-ahead electricity market are additionally exposed to a fluctuating selling price per offered MWh as well as other indirect (imbalance) costs, resulting from the deviation between the bidded and the actual power delivery. Wind farm owners have access to power purchase agreements (PPA), a special type of a bilateral contract between a producer and an off-taker (typically a corporate entity) to sell/buy electricity at a fixed pre-determined price for a specific time period. PPAs essentially lock-in the selling price of electricity over a long investment period and are also common between an aggregator (representing many independent producers) and a load entity. This is the so-called *portfolio PPA* version [1].

Specifically for Spain, the number of PPAs signed each year is rapidly increasing. According to survey conducted by Pexapar, 34 deals for a total of 4 GW of installed power were made in 2021 only.[1] Nevertheless, even in business cases where the price risk is neutralized, the income uncertainty from variable wind generation is a concern for asset owners. Key industry actors, such as OffshoreWIND.biz,[2] warn that producers should expect a 30 – 45% variation in the gross seasonal production of a wind farm, with a typical annual production variability of 10%. In parallel, they also encourage asset owners to trade in financial instruments for securing their income.

Traditionally, hedging instruments would be offered by big insurance companies, such as Swiss Re Corporate Solutions, with an expertise on the mitigation of weather risks. The terms of these products would be agreed on a case-by-case basis being tailored to the client needs. Recently, organized exchanges, such as the European Energy Exchange (EEX) and the NASDAQ, have launched standardized instruments against volumetric risk called *wind power futures*. Wind power futures are essentially index futures that are cash-settled. According

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[1] See indicatively https://h2-ccs-network.com/blog/spain-largest-ppa-market-in-europe-last-year-with-almost-4-gw-of-deals/ [accessed on Dec 8, 2022].
[2] See https://www.offshorewind.biz/2017/11/30/wind-industry-meets-hedging-against-volume-risk/ [accessed on Dec 8, 2022].

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to NASDAQ, the two parties of a wind power futures bet on the course of a synthetic underlying index, which is an average of local wind capacity utilization factors,[3] measured at various nodes of a reference national grid. The calculation of the utilization index is typically based on weather re-analysis data assuming a common wind turbine technology across all grid nodes.

Power futures are not the only commercial solution to wind energy producers for securing their income. To increase the coordination of distributed energy resources, regulatory authorities have initiated a new business entity, entitled *renewable energy resources aggregator* or simply aggregator. Aggregators form an array of spatially distributed power plants and trade their energy output as a unified asset. Aggregators are free to select the mixture of generation sites and, for doing so, they take into account the correlation structure of local outputs. Indeed, many research studies have confirmed that wind resources have a spatial balancing property; below average production in one site can be balanced by distant sites that still deliver. If this is the case, the spatial aggregation of resources is expected to offer higher income stability. The idea of aggregation decouples one's ability to sell energy in the wholesale electricity market from the ownership of the power generating asset, thus increasing the coordination of distant generation and the potential for mitigating volumetric risk.

In this paper, we investigate the effectiveness of two risk management strategies for managing the volumetric risk faced by wind power producers and aggregators in Spain. We mainly focus on that type of resource due to the fact that wind has the largest share in the Spanish renewable energy mix (23.28% as of 2021).[4] The wind resource is very delivering (average hourly capacity factors can go up to 25 – 30%) but also extremely volatile, hence the need for advanced risk management strategies to secure the producer's revenue. The first strategy we examine in this study is based on the idea of forming a generation portfolio or mix that distributes capacity among distant geographical areas. The second strategy makes use of financial instruments (wind power futures) that compensate the seller in periods when the actual production falls below a reference level. Both strategies are designed to control volumetric risk but their approach to risk management is fundamentally different. Generation portfolios attempt to smoothen out fluctuations in the local energy output by integrating assets of dissimilar generation profile. The idea of hedging is to offset revenue uncertainty by taking a short position in a financial contract whose payoffs *closely mimic* the fluctuations of wind generation in a particular area. Using a blend of advanced weather modeling, time series analysis, simulation and optimization techniques, we empirically assess the ability of the two risk management approaches to reduce volumetric risk. Furthermore, we perform a decomposition of the remaining risk levels to judge how effective each strategy is in eliminating systematic factors of revenue uncertainty (i.e. factors that shape the generation profile of the entire reference area) or region-specific generation variability. Motivated by the results of this analysis, we move onto proposing new types of financial contracts and mixed-style strategies for the aggregator with the ability to control different systematic dimensions of volumetric risk.

The rest of the text is structured as follows: Section 2 reviews the existing literature on the management of wind volumetric risk and Section 3 discusses the contribution of this study beyond the state-of-the-art. In Section 4, we analyze the two approaches to the management of volumetric risk (diversification and hedging). Section 5 discusses empirical findings and proposes new types of strategies for effectively reducing cash flow uncertainty. Section 6 concludes the paper and points to future research directions.

[3] Analytical definitions are given in Section 4.

[4] See Ref. [2] and [accessed on Dec 8, 2022].

2. Literature review

The management of volumetric risk has received considerable attention in the study of wind energy generation. One literature stream recommends the spatial allocation of wind generation capacity as a cure for the stochasticity of the resource. The performance of this strategy has been evaluated at various terrains and time scales. For the island of Corsica (France), Cassola et al. [3] show that an interconnected array of carefully selected generation sites could have greatly reduced the variability of the wind power that is fed to the island grid. The benefits are tangible despite the fact that wind power harvesting takes place in a relatively small region. Reichenberg et al. [4] apply a computational heuristic to determine the optimal topology of a large wind farm network, covering the Nordic countries and part of Germany, with a view on minimizing the coefficient of variation (CV) of the aggregate supply. In this study, the CV index is calculated as the (temporal) standard deviation of the wind capacity factor divided by the mean utilization of the generators. For the calculation of the utilization index, the authors resort to simulated wind speed data (averaged over three-hour intervals), which are then transformed into equivalent power generation using a variety of commercial power curve models. Optimization results demonstrate the benefits of spatial aggregation in terms of stabilizing the energy production while maintaining an acceptable level of power delivery. The coefficient of variation of the optimal capacity allocation plan is 40% reduced compared to the risk-yield ratio of the network of wind farms already in operation in these countries.

In a regional study, Archer and Jacobson [5] consider different interconnection scenarios for 19 sites located in the midwestern United States. Although those sites had been marked for their rich wind resources, the authors find that as the number of portfolio assets increases, the performance metrics of the aggregate annual output are improved substantially. Still, the marginal gain from including an additional site falls with the cardinality of the portfolio. Roques et al. [6] present a plan for the coordinated production of wind energy in five European countries allowing for the possibility of cross-border energy transfers. Based on a dataset of historical hourly wind production data, the authors derive minimum variance capacity allocations applying concepts and techniques from Markowitz's portfolio theory [7]. Grothe and Schnieders [8] focus on the German wind resources (measured by onshore and offshore weather stations) and propose a fresh capacity allocation plan that is geared towards maximizing the availability of the aggregate energy supply in adverse weather conditions, both in an hourly and daily frequency. A similar capacity allocation plan is explored by Thomaidis [9] for the Netherlands. In a more recent study, Santos-Alamillos et al. [10] apply mean–variance optimization techniques to recommend re-powering actions for wind energy capacity in Spain. Repowering is perceived as the gradual transition to a new capacity allocation plan by upgrading specific locations or removing part of their installed capacity. Portfolio-selection techniques are also popular in the context of PPAs. Gabrielli et al. [1] examine two types of portfolio PPAs, diversifying across locations and across technologies. Conditional value-at-risk (CVaR) is used as a risk measure and a stochastic optimization method is applied to dictate the optimal deal structure. The authors find that the combination of different technologies and locations reduces the financial risk to a great extent and can provide stable energy to the demand side of the contract.

The resurgence of interest in the aggregation of wind energy has coincided with a change of paradigm in the assessment of renewable resources. Traditionally, the deployment of wind farms has been following the average wind speed profile of candidate areas, measured at the hub height of commercial wind turbines (typically at an elevation of 80 – 120 m). As renewable energy resources started taking a larger share of the global generation mix, transmission system operators and energy traders became more and more worried about the stochasticity of clean power in-feeds. This gave researchers the motivation to start looking more deeply into the probability laws governing the evolution of wind energy fields, including the correlation structure of nodal generation. In one of the seminar studies on US wind resources, Kahn [11] reported that aggregating the outputs of dispersed wind farms reduces the variability of the generated power and increases the availability of the mix in weak wind conditions. Ever since, this smoothing or balancing property of wind resources has been studied in different geographical terrains and time scales, see [12], ch. 6; [13]; [5,14]; [15–19], among others.

Almost in parallel to the research on the benefits of the spatial aggregation of wind resources, academics and practitioners have investigated the possibility of managing volumetric risk using financial contracts. This strategy is a way to *financially* control volumetric risk, as these contracts shape the revenue of the energy trader not the output profile of the power generating assets. The research in this area has been popularized after the launching of wind power futures in the NASDAQ and the European Energy Exchange (EEX). Wind power futures are typically written on an aggregate wind production index (also called wind utilization index) and compensate the buyer (seller) in case the value of the index exceeds (or goes below) a predetermined reference production level (the futures market price). The EEX futures use as underlying index the cross-sectional average injection of wind energy produced by German or Austrian power plants over predefined time intervals, while NASDAQ employs the NAREX WIDE index (NASDAQ Renewable Index Wind Germany (DE)) that is built on reanalyzed weather data for all ECMWF grid points in Germany.[5] Due to their special design, EEX and NASDAQ wind power futures are mainly addressed to German or Austrian wind power producers, although they could be easily extended to other markets in the future.

Benth and Šaltytė-Benth [20] and Benth and Pircalabu [21] derive analytical valuation formulae for wind power futures. Any pricing exercise begins with postulating a particular stochastic process for the underlying index dynamics. Despite the recent advances in continuous time modeling and derivatives pricing, this task is challenging for wind utilization indices due to their distinctive statistical properties. We will elaborate on this issue in the following section. Benth and Pircalabu [21] find that an Ornstein–Uhlenbeck (OU) stochastic process can represent some of the stylized facts of utilization index dynamics. This model is then calibrated to a large sample of German wind production measurements spanning a period of 37 years. In a recent study, Hess [22] investigate the pricing of wind power futures under the assumption that the wind utilization index follows a multifactor version of the standard OU model. Kanamura et al. [23] apply econometric techniques to derive an accurate model for the German national wind power production index. Based on a detailed analysis of seasonality patterns and short-memory dynamics, they derive pricing formulae for wind power futures and call options that are written on this underlying. Härdle et al. [24] is another econometric treatment of wind power production dynamics. Starting with a fine-resolution grid of wind power production in Germany, they employ continuous ARMA modes with Lévy increments to address the right-skewness and bimodality of the national aggregate index distribution. The model is calibrated on actual price data on wind power futures covering the period 2016–2018.

In a study that is more related to ours, Christensen and Pircalabu [25] investigate the effectiveness of a single wind power futures contract (written on a national average of local wind capacity utilizations) to reduce the volumetric risk in 31 geographically dispersed generating sites in Germany. Using copula techniques, they explicitly model the dependence structure between the local wind energy production and the national aggregate. Then, they calculate the optimal hedging ratio (i.e. the number of contracts that have to be bought or sold to minimize the total revenue variance) for each local producer. The authors find that the optimal position on the hedging instrument and the effectiveness of the hedging strategy heavily depend on the location of the wind farm. In some sites, a single wind power futures seems to offset a large part of the annual revenue fluctuations, whereas in others the futures does not provide an adequate hedge against income variability. Benth et al. [26] also derive optimal hedging ratios for wind farms in Germany based on a multivariate continuous-time treatment of local wind energy utilization indices.

A microeconomic analysis of the German market for wind power futures is performed by Geresma and Wozabal [27]. The authors derive analytical expressions for the equilibrium price and the risk premium of the futures. Most importantly they provide theoretical arguments for the viability of the market for wind power futures. Taking into account the stochasticity of wind power production and its inverse relationship with electricity prices, they show that wind farm owners would have the inceptive to short-sell wind power futures, while the owners of conventional (fossil-fuel burning) plants would be the main writers of these contracts.

Rodríguez et al. [28] examine more sophisticated derivative contracts for controlling volumetric risk. The so-called up-and-in European wind put barrier options use as underlying a synthetic wind utilization index, calculated over the Colombian territory. Bartlett [29] presents a review of futures, options and other hedging instruments available to wind power producers in the US. Benth et al. [30] address the case of a wind power producer with active participation in the day-ahead electricity market. In this set-up, the producer has to control not only volumetric risk but also a fluctuating selling price for each generated megawatt-hour (market risk). Deriving a strategy that can mitigate market risk is a demanding task in the light of the empirical properties of electricity price series and its inverse relationship with wind power in-feeds. For this reason, the authors propose a complex type of a derivative contract (aka quanto option) to hedge against weather and market risks.

Another stream of literature deals with the problem of optimizing the layout of a wind farm with a view on controlling on-site the stochasticity of the output and improving the production levels. For example, Marmidis et al. [31] employ Monte Carlo simulation on a hypothetical square site that is sub-divided into 100 square cells (individual turbine locations), in order to find the optimal position of wind turbines and increase the expected annual generation output. The final solution selects over 30 wind turbines and in comparison with other studies on the same problem it manages to increase the total mean annual production by approximately 20%. Perez et al. [32] use nonlinear mathematical programming techniques to optimize the layout of an existing German offshore wind farm located in the North Sea. The authors conclude that adopting the optimal configuration one can improve the mean annual production by 3.52%.

3. Contribution to the state-of-the-art

As witnessed from the bulk of studies reviewed in the previous section, the research on the management of volumetric risk moves in two, often parallel, directions. The opponents of spatial diversification see this strategy as a way to stabilize the aggregate wind power production, but in the absence of a revenue model, they overlook the ability of hedging instruments to reduce revenue exposure to weather shocks. Most of the studies on hedging instruments explore the effectiveness of financial contracts to offset part of the revenue risk. Still, they fail to acknowledge that these contracts are written on an aggregate wind utilization index and hence they are unable to reproduce the entirety of the local generation profile.

In this paper, we make an attempt to close the existing literature gap and evaluate the relative benefits of each approach on a common

[5] More details on the specification of EEX and NASDAQ wind power futures can be found at https://www.eex.com/fileadmin/EEX/Downloads/Trading/Specifications/Key_Information_Documents/02_Energiewende_Products/20171213-eex-kid-futures-wind-power-en-data.pdf and https://www.nasdaq.com/solutions/wind-power-futures [accessed on Dec 8, 2022].

dataset. We employ state-of-the-art numerical weather forecasting models to generate wind utilization scenarios for the 47 provinces of the Spanish mainland. In the first set of experiments, we compute optimal national mixes of regional wind resources with a view on minimizing the aggregator's revenue risk, which is measured by the standard deviation of the monthly portfolio proceeds. At second stage, we make use of wind power futures to hedge the position of regional producers, whose generating assets are located within the administrative borders of each province. In both exercises, we go a step further and analyze the revenue variance in order to get a deeper understanding of the risk dimensions that each strategy is effective in controlling. Motivated by this analysis, we propose a new set of financial contracts whose underlying mimics the course of the principal risk components. Finally, we propose synthetic strategies that combine diversification with hedging and thus help the aggregator offset systematic risk components that cannot be eliminated though pooling of resources.

Our formulation of the capacity allocation problem draws on earlier literature on the spatial diversification of volumetric risk [4,6,8,9]. Roques et al. [6] derive optimal portfolios with generating assets extending national borders, while our study focuses on the exploitation of national wind resources, where regional installations take the place of an asset. Despite the national-level aggregation scheme, the cardinality of our asset universe is much larger compared to [6], a feature which theoretically increases the opportunities for risk pooling. Most of the studies mentioned above are confined to a derivation of the optimal capacity allocation and an empirical assessment of its superiority over the existing harvesting plan. In this paper, we provide intuition for the selected portfolio constituents and weights using factor analysis techniques. Through factor analysis, we are able to perform an explicit decomposition of the revenue variance into systematic and idiosyncratic components and propose the right strategy for each market player.

Archer and Jacobson [5,14] and Handschy et al. [16] make an attempt to derive empirical relationships between the size of the smoothing effect and the cardinality of the asset universe or the size of the geographical area that power generating plants cover. Still, they fail to recognize that the ability of the mix to reduce production variations depends not only on the size of the interconnected array but also on the correlation structure of local energy outputs. Weak correlation allows us to diversify away a great deal of risk even in an asset universe of low cardinality. Further assuming that the variability of the regional energy outputs is largely attributed to a reduced set of risk factors, a large portfolio of power plants dispersed over a wide region would be unable to diversify away the entirety of volumetric risk, if all production sites are positively loaded by at least one factor.

Studies on the optimal design of a wind farm, such as [31] and [32], present methods to control the volumetric risk and improve the productivity of the wind farm on a local scale. This approach though is only relevant to independent producers and not aggregators, who by definition can form portfolio of wind power generators located many kilometers apart. Our empirical results indicate that local features are less important to the enhancement of the aggregator's revenue as those can be diversified away in an optimal mix.

Most of the literature on wind power derivatives focuses on the valuation of these contracts under a certain set of assumptions for the probability law of the underlying index. Christensen and Pircalabu [25] are an exception to the rule and move onto gauging the hedging effectiveness of a wind power futures across an array of wind production areas in Germany. The authors consider a single futures contract that is written on a simple average of wind productivity indices across grid points. In our study, factor analysis techniques show that the national aggregate index is a proxy for the first systematic risk component, which is one of the many sources of co-variability in the Spanish wind energy generation. The loadings of additional risk factors vary significantly in terms of size and sign across areas, implying that a single futures contract is an inadequate hedge for most of the Spanish provinces. The extent at which it manages to stabilize the revenue variance of a regional producer depends on the exposure of the region to the first risk component.

Another point of deviation from most of the studies employing financial contracts is in our modeling of the underlying dynamics. Empirical research revealed that the mean wind speed as well as its time variability depend strongly on the season of the year and the diurnal cycle. The sample distribution of wind speeds is right-skewed and bounded away from zero. Wind utilization data have additional elements of complexity due to the technological features of wind power generation (see also [24] for a discussion). Commercial wind turbines start producing energy when the speed of the wind measured at the hub height exceeds a lower limit, the so-called cut-in speed. This is usually between $3-5$ meters per second (m/s) depending on the turbine model. Beyond that point, power production increases monotonically (though nonlinearly) with the wind intensity and reaches its peak at the cut-out speed, which typically lies in the range 25–30 m/s. If the wind is stronger, an emergency shutdown protocol is activated to avoid potential wind turbine damaging. This implies a sigma-shaped power curve with an abrupt zeroing of energy production beyond cut-out-speed. Still, in an interconnected array of wind turbines the aggregate production slowly diminishes to zero as the wind speed increases to levels beyond the cut-out limit. The peak of the power production coincides with the nominal rating (installed capacity) of the wind turbine, so that the wind utilization index ranges between 0 and 1.

An additional feature that increases the complexity of the wind field dynamics is the high degree of spatial dependence, which is also observed between distant generation sites (see e.g. [12], ch. 6, and [26]). In the light of these empirical findings, continuous-time stochastic processes are often proven inadequate modeling devices, whereas multivariate econometric techniques, such as copulas or factor analysis (employed in this study), manage to capture most of the patterns of seasonality and cross-dependency. Härdle et al. [24], Kanamura et al. [23] and Rodríguez et al. [28] do acknowledge the advantages of the latter approach and perform an econometric analysis of the underlying wind power production indices. Nevertheless, their modeling efforts are directed towards deriving a faithful representation of the dynamics of the aggregate utilization index, measured on a national basis. This approach does not allow us to evaluate the hedging effectiveness of the standard wind power futures on a local basis, which is more relevant for wind farm owners whose assets are typically located at certain parts of the grid. Christensen and Pircalabu [25] deviate from this trend and employ copulas techniques to model generation cross-dependencies between selected harvesting areas.

In summary, the novelty of our paper can be outlined in the following points:

- We implement, evaluate and benchmark two strategies (diversification and hedging) for the management of the wind volumetric risk in the Spanish Iberian Peninsula, a large geographical area of great topographic and climatic variety.
- We employ state-of-the-art numerical weather forecasting models to generate hourly wind utilization scenarios for the 47 Spanish mainland provinces and model the variance–covariance structure of the domestic wind resources.
- We apply factor analysis techniques to decompose the revenue variance into systematic and non-systematic components. This way, we provide guidance to independent producers and aggregators on the choice of the optimal risk management strategy, which in many instances turns to be a combination of diversification and hedging.
- We propose a new series of wind power futures contracts (factor contracts) that are specifically designed for offsetting systematic components of wind power generation risk.
- We discuss hybrid risk management strategies (following the principles of diversification and hedging) that offer a better control on all risk dimensions (systematic and region-specific), greatly enhancing the revenue profile of wind energy traders.

4. Risk management strategies

4.1. Setting the scene

When devising a risk management strategy, it is of major importance to clarify the viewpoint, i.e. whom the risk management tool is designed for. As in conventional financial markets, energy markets have different participants each of whom has to deal with different sources of risk, sets different priorities and obviously has different needs for risk management tools. Many studies on clean energy harvesting attempt to quantify the benefits of distributing generation capacity across space. These are tailored to the needs of policy makers, whose concern is to increase the utilization of clean energy resources by reducing the stochasticity of the aggregate supply. Transmission system operators, on the other hand, focus on more operational issues such as how to serve load with the most economical and reliable dispatch. The terms *investor* and *trader* are interchangeably used in studies of financial markets but in the context of an electricity market one needs to be careful about the selection of terms, as different physical or business entities qualify to each description. Project developers who invest in generating capacity are obvious candidates. Their objective is to pick locations of high productivity. No reallocation of capacity is possible during the project lifetime, unless new turbines are installed (capacity upgrading) or old turbines are replaced by modern ones (capacity downgrading). Aggregators differ from all the above market players in that they do not own the power generating units, instead they act as brokers of multiple, typically small, independent producers. This provides them with the essential flexibility not only to determine the optimal share of each location in the mix but also to rebalance portfolio weights from time to time. This paper addresses the stand of independent power producers, whose generating assets fall within the administrative borders of a Spanish province, and of aggregators, who are free to adjust their generation portfolio by pooling regional resources.

4.2. Power portfolios

Portfolio theory was developed by Harry Markowitz in the 50's and is based on the idea of combining heterogeneous assets to minimize investment risk [7]. The theory was originally applied to financial assets with uncertain payoffs (e.g. stocks) assuming a single-period investment framework. In this set-up, investors make their choices based on the current value of the assets (which is known at the beginning of the investment period) and on the future value (assumed to be governed by a probability law). The building block of the Markowitz's analysis is the *single-period return*, which is defined as the net profit over the invested capital. Transferring these concepts to power generating assets is not a straightforward task and requires a modification of some of the base elements of the analysis, including the very definition of the return. As a measure of the ability of a power producing asset to deliver, we adopt the *capacity utilization factor* or *capacity factor*, which is translated to revenue if one specifies the terms of energy trading. The (daily) capacity factor is defined as:

$$r_t \equiv \frac{Energy\ generation\ at\ day\ t}{Nominal\ production\ at\ day\ t} \equiv \frac{G_t}{h_t C}$$

The generated energy is the actual cumulative output of a unit (e.g. a wind farm) at operational day t. This is measured in megawatt-hours (MWh). The nominal production refers to the maximum possible output under ideal circumstances. This is equal to the installed capacity C, measured in megawatts (MW), times the hours in day t at which the unit is set in operation (typically $h_t = 24$). A wind turbine produces near nominal rates at very high wind speeds (typically between 20 and 30 m/s). If we assume that the unit operates in multiple time periods, $t = T_1,\ T_1+1, \dots, T_2$, and for each generated MWh the investor receives a fixed payment of F Euros, the revenue is given by the expression:

$$\tilde{R} = C\,F\left(\sum_{t=T_1}^{T_2} h_t r_t\right) \tag{1}$$

Contemporary energy companies typically have under their possession multiple power stations placed at distant sites, even outside national borders. Motivated by this trend, we extend the above definitions to the case of a portfolio of power generating assets indexed by $i = 1, 2, \dots, N$, where each asset i represents a generation site or region. Let C_P be the installed capacity of the portfolio, measured in MW. The total proceeds from the investment are simply

$$\tilde{R}_p = \sum_{i=1}^{N} \tilde{R}_i$$
$$\Rightarrow C_p F\left(\sum_{t=T_1}^{T_2} h_t r_{tp}\right) = \sum_{i=1}^{N} C_i F\left(\sum_{t=T_1}^{T_2} h_t r_{ti}\right)$$

where r_{tp} is the portfolio utilization factor, $\tilde{R}_i$ is the revenue from asset i and r_{ti} is the ith-asset's capacity utilization. Dividing both sides of the equation by the total capacity, we get

$$F\left(\sum_{t=T_1}^{T_2} h_t r_{tp}\right) = \sum_{i=1}^{N} \frac{C_i}{C_p} F\left(\sum_{t=T_1}^{T_2} h_t r_{ti}\right)$$

or

$$R_p = \sum_{i=1}^{N} x_i R_i \tag{2}$$

where $R_{\cdot} \equiv \tilde{R}_{\cdot}/C_{\cdot}$ is the revenue per MW of installed capacity (*standardized revenue*) and $x_i \equiv C_i/C_p$ is the percentage of the total capacity absorbed by asset i (the portfolio "weight"). Eq. (2) holds for any value of F, hence, to simplify the presentation of the results, we can assume that aggregators/producers are remunerated at $F = 1$ Euro per delivered megawatt-hour. Our perception of the portfolio weight is conceptually different from the definition routinely applying to portfolios of financial assets, where the weight is the percentage of the investment capital absorbed by an asset. Even in this new setup, we can still derive a formula expressing the standardized portfolio revenue as a linear combination of the proceeds from each asset. This linear relationship greatly simplifies the probabilistic treatment of the portfolio selection problem. In particular, we can coin a measure of *yield* (the equivalent to the Markowitz's mean return on the investment) as follows:

$$\mu_p = \sum_{i=1}^{N} x_i \mu_i = \boldsymbol{x}'\boldsymbol{\mu}$$

where $\boldsymbol{\mu} = (\mu_1, \mu_2, \dots, \mu_N)'$, $\boldsymbol{x} = (x_1, x_2, \dots, x_N)'$ and μ_i is the expected Euro revenue from asset i (per MW of installed capacity). The investment risk can be measured by the variance of $\tilde{R}_p$, i.e.

$$\sigma_p^2 \equiv E\left(\tilde{R}_p - \mu_p\right)^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j \sigma_{ij} \equiv \boldsymbol{x}'\boldsymbol{\Sigma}\boldsymbol{x}$$

where $\boldsymbol{\Sigma} = (\sigma_{ij})_{i,j}$ is the covariance matrix of standardized revenues from assets i and j.

In this paper, portfolios are selected with a view on risk minimization (as measured by the standard deviation of the standardized portfolio revenue), although a second performance criterion on yield (as measured by mean scaled portfolio revenue) could be considered, in the style of Markowitz. Our elaboration on variance minimization facilitates comparisons with the hedging strategy, which also aims at offsetting the variability of revenue albeit from a different viewangle. Optimal portfolios are obtained as the solution of the following mathematical programming problem:

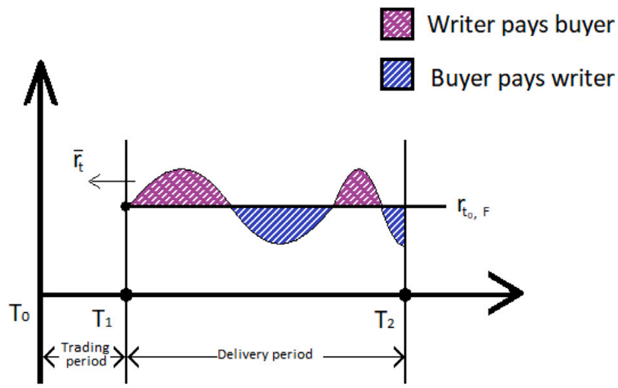

Fig. 1. The wind power futures payoff scheme.

$$\underset{x=(x_1,x_2,\ldots,x_N)'\in\mathbb{R}^N}{\text{minimize}} \quad \sigma_P^2(\boldsymbol{x}) = \boldsymbol{x}'\boldsymbol{\Sigma}\boldsymbol{x} \tag{3a}$$

subject to

$$\boldsymbol{x}'\mathbf{1} = 1 \tag{3b}$$

$$x_i^L \leq x_i \leq x_i^U, \qquad i = 1, 2, \ldots, N \tag{3c}$$

The decision variables are $\boldsymbol{x} = \left(x_1, x_2, \ldots, x_N\right)'$, where x_i is the proportion of available capacity allocated at asset i and $\mathbf{1} = (1, 1, \ldots, 1)'$ is the N-dimensional unit vector. Our formulation of the portfolio selection problem is equipped with two types of constraints: the full allocation constraint and the floor/ceiling constraint. These constraints are common in the financial literature but their significance needs to be re-assessed in the context of power portfolios. The full allocation constraint (3b) makes sure that no capacity is withheld. This would be the case for instance if the investor decided to reserve a certain percentage of the capacity in thermal power plants and she was left with the rest to distribute in variable generation units (e.g. a mixture of wind and solar technologies). The set of inequalities (3c), where x_i^L, x_i^U are two constants satisfying $0 \leq x_i^L, x_i^U \leq 1$, place a lower and upper limit on the amount of nominal power that can allocated at each asset. Choosing a tight ceiling constraint (e.g. choosing a value of x_i^U much less than 1) imposes more balanced capacity allocations and also restricts the size of the installation in particular areas (this is relevant for densely populated or environmentally sensitive areas). On the other hand, a value of x_i^L greater than 0 would make sure that no tiny amounts of capacity are wasted in single assets unless their contribution to the portfolio objectives is significant. This is an indirect way of reducing the geographical coverage of the portfolio and the unnecessary reservation of particular sites.

4.3. Hedging

The use of derivative contracts to hedge the revenue risk in wind energy trading has become a trend in the latest years. Of all possible contract designs, the *wind power futures* has attracted the attention of most researchers, as it is available for trading in organized exchanges. The mechanics of the wind power futures is illustrated in Fig. 1.

At time T_0, the two parties agree on a reference capacity factor that will apply throughout the delivery period $[T_1, T_2]$. This is denoted by $r_{t_0,F}$ and taken as the contract's current price. If for some future day $T_1 \leq t \leq T_2$ the average national wind utilization $\bar{r}_t$ exceeds the predetermined reference index r_{t_0F}, the writer of the contract pays the buyer the amount $\frac{X}{T_2-T_1+1}\left(\bar{r}_t - r_{t_0F}\right)$, where X is the tick size. To facilitate comparative analysis, we assume as in [25] that $X = 100$ Euros per index unit step, although the exact value of the tick size is not important as revenue scales linearly with X and most of the performance metrics are invariant to X. If $\bar{r}_t < r_{t_0F}$, cash flows from buyer to writer. The total revenue from a long position on the contract is given by

$$R_C^L = \frac{X}{T_2 - T_1 + 1}\sum_{t=T_1}^{T_2}\left(\bar{r}_t - r_{t_0F}\right) = X\left[\left(\frac{1}{T_2 - T_1 + 1}\sum_{t=T_1}^{T_2}\bar{r}_t\right) - r_{t_0F}\right]$$

while the revenue from a short position is

$$R_C^S = -R_C^L$$

As illustrated in Fig. 1, a long position on the wind power futures provides insurance to the buyer in the case of rich wind conditions. On the contrary, the short position is beneficial when the average national production $\bar{r}_t$ is anticipated to stay below the reference generating capacity r_{t_0F} for most of the delivery time period. Aggregators and owners of wind farms would naturally go short in such a contract to protect themselves against underproduction events. Later in this paper, we will assume that more contracts (in total $K > 1$) are available in the market, so the revenue from a synthetic (hedged) position on a wind power generating asset i is calculated as follows:

$$R_{H,i} = R_i + \boldsymbol{\gamma}'\boldsymbol{R}_C^L$$

where R_i are the proceeds from the baseline position (energy generation), $\boldsymbol{R}_C^L = (R_{C,1}^L, R_{C,2}^L, \ldots, R_{C,K}^L)' \in \mathbb{R}^K$ and $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \ldots, \gamma_K)' \in \mathbb{R}^K$. The element $R_{C,k}^L$, $k = 1, 2, \ldots, K$, represents the buyer's revenue from a long position on contract k (as stated in formulae (1)) and γ_k is the number of k-type contracts bought/sold ($\gamma_k < 0$ implies a short position on contract k).

The objective of hedging is to determine the optimal basket of contracts ($\boldsymbol{\gamma}^*$) that minimizes the revenue risk of the baseline position. For the variance of $R_{H,i}$ we have

$$Var\left(R_{H,i}\right) = Var\left(R_i\right) + \boldsymbol{\gamma}'Cov\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right)\boldsymbol{\gamma} + 2\boldsymbol{\gamma}'Cov\left(\boldsymbol{R}_C^L, R_i\right)$$

where $Cov\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right)$ denotes the variance–covariance matrix of the array of contract payoffs

$$\left(R_{C,1}^L, R_{C,2}^L, \ldots, R_{C,K}^L\right)$$

and

$$Cov\left(\boldsymbol{R}_C^L, R_i\right) = \left[Cov\left(R_{C,1}^L, R_i\right), Cov\left(R_{C,2}^L, R_i\right), \ldots, Cov\left(R_{C,K}^L, R_i\right)\right]'$$

is the vector of covariances between the revenues from a long position in each contract and the baseline position. Applying the first-order condition for optimality

$$\frac{\partial Var(R_{H,i})}{\partial \boldsymbol{\gamma}} = \mathbf{0}$$

and assuming that $Cov\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right)$ is positive definite, we get the solution

$$\boldsymbol{\gamma}^* = -\left[Cov\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right)\right]^{-1} Cov\left(\boldsymbol{R}_C^L, R_i\right) \tag{4}$$

The Hessian of $Var(R_{H,i})$ is

$$\frac{\partial^2 Var(R_H)}{\partial \boldsymbol{\gamma}\partial \boldsymbol{\gamma}'} = 2Cov\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right)$$

which is positive definite for all $\boldsymbol{\gamma} \in \mathbb{R}^K$, hence the variance of the hedged position revenue attains a global minimum at $\boldsymbol{\gamma} = \boldsymbol{\gamma}^*$. In practice, the optimal hedging position $\boldsymbol{\gamma}^*$ can be computed as the ordinary least-squares (OLS) estimator of the slope coefficients in the following regression

$$R_i = \theta_i + \boldsymbol{\gamma}'\boldsymbol{R}_C^L + e_i$$

where θ_i is a constant and e_i is the disturbance term.

In the case of a single contract being traded in the market (as is currently the situation in NASDAQ), Eq. (4) simplifies to

$$\gamma^* = -\frac{Cov\left(R_C^L, R_i\right)}{Var\left(R_C^L\right)} = -\rho_{R_C^L, R_i}\sqrt{\frac{Var\left(R_i\right)}{Var\left(R_C^L\right)}} \tag{5}$$

where R_C^L is the payoff from a long position on the contract and $\rho_{R_C^L, R_i}$ is the Pearson correlation coefficient between R_C^L and R_i.

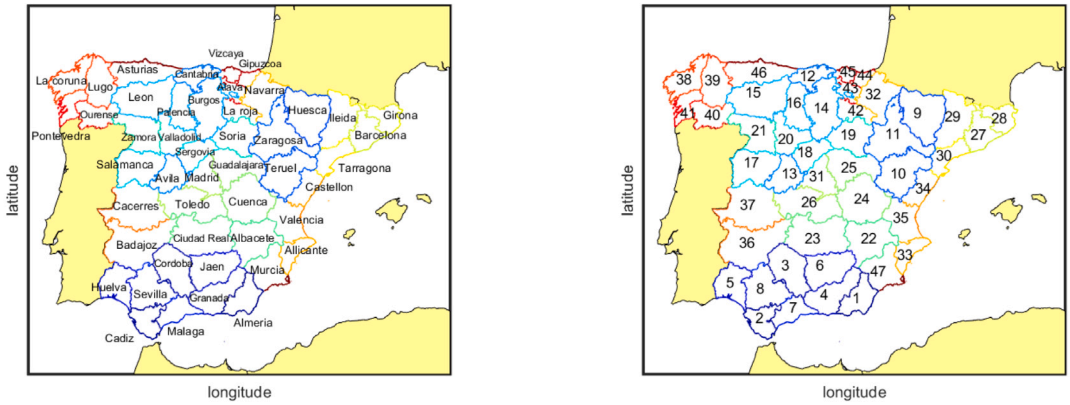

Fig. 2. The reference area for our empirical study.

5. Empirical study

5.1. Sample data

As a reference area for our empirical study, we chose the Spanish Iberian Peninsula. The wind resources of this area have been explored in previous studies [10,33] and were also selected here as a test bed for our methodologies. The Iberian Peninsula is quite rich and variant in its wind resources, as it is exposed to Mediterranean, Atlantic and Continental weather systems. This level of spatial variability is proven beneficial in terms of reducing volumetric risk.

The generation profile of the Continental Spain has been assembled following a physical approach.[6] Using the Weather Research and Forecasting (WRF) model [34], we simulated paths of hourly wind speeds at 80 m above ground level for the period 2008 – 2010. The WRF model emulates the dynamical and physical processes that take place in the atmosphere and with the aid of numerical techniques it provides meteorological fields of high spatial and temporal resolution for preselected areas. We chose to use modeled data as a viable alternative to historical observations because the latter are not often available for the typical hub height of modern wind turbines. Furthermore, the network of operational wind power plants is quite sparse and the generation output includes many zero production records attributed to a number of factors (malfunctions, emergency shutdown, scheduled maintenance works etc.) not related to the actual wind input. Based on the Climate Forecast System Reanalysis (CFSR) data [35], we modeled the aforementioned wind field in a 5 km spatial resolution grid covering the entire Iberian Peninsula. The gridded wind speed from the WRF simulations was vertically adapted to the reference altitude of 80 m using a cubic splines interpolation scheme. Two popular wind farm power curves were then used to estimate the capacity factors in all the WRF's grid cells in Spain depending on the terrain altitude [10]. To bring the portfolio selection problem down to a manageable size, we estimated hourly capacity factors on a province level by taking spatial averages of all gridded data within the administrative borders of each province. These are shown in Fig. 2. As a final step, we derived an equivalent panel of daily utilization indices by consolidating hourly increments. The final form of the estimation sample is $\{r_{ti}\ ,\ t = 1, 2, \ldots, T;\ i = 1, 2, \ldots, N\ \}$, where $T = 1096$ (number of calendar days in the period 2008–2010) and $N = 47$ (number of provinces in the Spanish mainland).

[6] Due to space restrictions, we provide a brief exposition of the data-generation process skipping most of the technicalities. More details are given in [10].

5.2. Modeling the wind utilization indices

Both the portfolio selection and the hedging exercise require estimators of the first two moments of the joint (unconditional) probability distribution of revenues. To obtain a faithful representation of distribution moments beyond the estimation sample, we resorted to bootstrap techniques. Sample wind utilization indices take values in the open real interval $(0, 1)$ and their distribution is right-skewed. To derive equivalent utilization indices whose statistical properties are closer to normality, we applied the logit transformation:

$$\tilde{r}_{ti} \equiv \text{logit}\left(r_{ti}\right) \equiv \ln\left(\frac{r_{ti}}{1 - r_{ti}}\right)$$

which maps from $(0, 1)$ onto $\mathbb{R}$. Fig. 3 shows two typical sample paths of the transformed wind utilization index for the case of the Almeria and Vizcaya province.

A preliminary analysis of the $\{\tilde{r}_{ti}\}$ time series revealed substantial seasonality and autocorrelation both in mean and variance. These features are also apparent in Fig. 3. To be able to reproduce these properties in the bootstrapped samples, we employed a combined AR-GARCH model with exogenous variables, in the spirit of [23,25]. Information criteria and extensive diagnostic checking on the residuals and standardized residuals showed that an AR(2) model for the conditional mean combined with a GARCH(1,1) specification for the conditional variance are adequate for the dynamic properties of the transformed daily generating capacities. The final specification of the models is given below:

$$\tilde{r}_{ti} = \beta_{i0} + \beta_{i1}\tilde{r}_{t-1,i} + \beta_{i2}\tilde{r}_{t-2,i} + \boldsymbol{c}_i'\boldsymbol{d}_t + e_{ti} \tag{6a}$$

$$\upsilon_{ti} = a_{i0} + a_{i1}\upsilon_{t-1,i} + a_{i2}e^2_{t-1,i} + \boldsymbol{\delta}_i'\boldsymbol{d}_t \tag{6b}$$

where $\boldsymbol{d}_t$ is a 11×1 vector of monthly dummy variables (January is excluded to avoid multicollinearity with constant terms β_{i0} and a_{i0}), $\upsilon_{ti} \equiv E(e^2_{ti}|\Omega_{t-1})$ is the conditional variance of $\tilde{r}_{ti}$ based on the information Ω_{t-1} available up to day $t-1$ and e_{ti} is the disturbance term, for which we assume $E\left(e_{ti}|\Omega_{t-1}\right) = 0$. Model coefficients $\beta_{i\cdot}$, $a_{i\cdot}$, $\boldsymbol{c}_i$ and $\boldsymbol{\delta}_i$ are estimated independently for each province $i = 1, 2, \ldots, N$ using the quasi maximum-likelihood method (under the assumption of normally distributed errors). All calculations were conducted in MATLAB.

Based on the panel of the estimated standardized residuals $\left\{\hat{z}_{ti} = \hat{e}_{ti}/\sqrt{\hat{\upsilon}_{ti}}\right\}$, we generated $B = 5000$ bootstrap samples of the form $\left\{z^{(b)}_{ti}\right\}$, where $b = 1, 2, \ldots, B$; $i = 1, 2, \ldots, N$ and $t = T + 1, T + 2, \ldots, T + 365$, to replicate the wind power production over the following (out-of-sample) calendar year 2011. An equivalent set of simulated paths for daily wind utilization indices $\left\{r^{(b)}_{ti}\right\}$ across all provinces was created by passing the $\left\{z^{(b)}_{ti}\right\}$ time series through

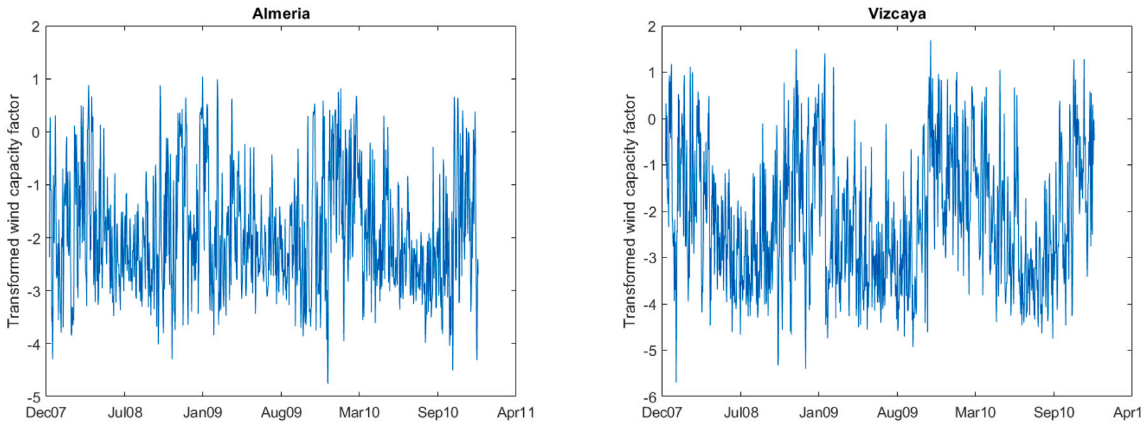

Fig. 3. Transformed wind capacity factors for the Almeria and Vizcaya provinces.

the estimated AR(2)-GARCH(1,1) filter presented in Eq. (6) (with a proper adjustment of the monthly dummies for the year 2011 and the application of the inverse logit transformation). To be able to preserve higher order dependencies across time, we generated standardized residual $\left\{z_{ti}^{(b)}\right\}$ scenarios using the stationary bootstrap technique of Politis and Romano [36] and not any other resampling scheme that assumes temporal independence of observations. The idea of the stationary bootstrap is to create an artificial dataset by sequentially resampling strings of observations, whose string length is a random variable following a geometric distribution. Bootstrap techniques are known to provide robust estimates of population moments even for a small sample of observations and do not rest on stringent assumptions on the underlying probability law.

Another property that requires special attention in the design of the resampling scheme is the cross-dependence of regional wind utilization indices. Wind power generation is determined by mesoscale weather systems with a typical geographical range of thousands of kilometers. Due to the span of these systems, we expect high correlation in daily wind power production that extends far beyond neighboring provinces. This is confirmed by an inspection of Fig. 3, which shows significant similarity between the daily capacity factors in Almeria and Vizcaya, although the two provinces are almost 1000 km apart. The spatial dependence of wind energy fields has been dealt in the literature using copula techniques [25] and multivariate continuous-time stochastic models [26], which are well suited for skewed-distributed data. However, both approaches pose numerical challenges, hence they are not recommended for a large-cardinality asset universe. Besides, as we demonstrate in Sections 5.7 & 5.8, a factor model of the transformed wind generating capacities is able to reproduce many of the features of the cross-dependence structure with significantly less computational effort. In scenario generation, we chose not to make any parametric assumption on the correlation structure of daily utilization indices. Instead, we coined a simple multivariate extension of the stationary bootstrap to reproduce wind energy production dependencies across provinces. This amounts to resampling the same subset of observation indices across all panel units.

5.3. Deriving inputs for strategy design

The dataset of simulated capacity factors $\left\{r_{ti}^{(b)}\right\}$, where the day index t takes values in $\{T+1, T+2, \ldots, T+365\}$, provides the essential input to the selection of minimum variance portfolios and the design of the optimal hedging strategy. For this reason, we henceforth refer to this sample as the *strategy design sample*, which should not be confused with the *estimation sample* originally used in the specification of models (6). Note that the portfolio optimization exercise requires estimators of the mean and the variance–covariance matrix of revenue across provinces. Strategies involving wind power futures additionally require information on the covariance structure between the contract payoffs and the proceeds from the baseline position (energy selling). Wind power futures have different delivery periods, which are in principle a fraction of the year. To facilitate performance comparisons across various strategies, we will also adopt this convention in the selection of the optimal capacity distributions and assume that the aggregator can periodically change the portfolio weights depending on the starting date and the duration of the power delivery agreement.

The inputs to the design of the risk management strategies were derived based on the following procedure. First, for each province $i = 1, 2, \ldots, N$, we calculated revenue scenarios based on the standardized payoff formula:

$$R_i^{(b)}(T_1, T_2) = \sum_{t=T_1}^{T_2} h_t r_{ti}^{(b)}$$

where $[T_1, T_2]$ is the power delivery period and, as in Section 4.2, we assumed $C_i = 1$ MW and $F = 1$ Euro/MWh. Energy selling takes place out-of-sample, so $T < T_1 \leq T_2 \leq T + 365$. An estimator for the mean (standardized) revenue in each province is derived from simulation paths based on the formula

$$\hat{\mu}_i \equiv \hat{\mu}_i(T_1, T_2) \equiv (1/B) \sum_{b=1}^{B} R_i^{(b)}(T_1, T_2)$$

and the (standardized) revenue covariance between two provinces i and j is estimated by

$$\hat{\sigma}_{ij} \equiv \hat{\sigma}_{ij}\left(T_1, T_2\right) \equiv -\hat{\mu}_i \hat{\mu}_j + (1/B) \sum_{b=1}^{B} R_i^{(b)}\left(T_1, T_2\right) R_j^{(b)}\left(T_1, T_2\right) \tag{7}$$

where $i, j = 1, 2, \ldots, N$ and i can be equal to j. Similarly, we estimated the covariance matrix of the proceeds on an array of contracts using the formula

$$\widehat{Cov}\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right) \equiv \widehat{Cov}\left(\boldsymbol{R}_C^L, \boldsymbol{R}_C^L\right)(T_1, T_2)$$
$$\equiv -\hat{\boldsymbol{\mu}}_C \hat{\boldsymbol{\mu}}_C' + (1/B) \sum_{b=1}^{B} \boldsymbol{R}_C^{L,(b)}\left(T_1, T_2\right)\left[\boldsymbol{R}_C^{L,(b)}\left(T_1, T_2\right)\right]'$$

where $\hat{\boldsymbol{\mu}}_C \equiv \hat{\boldsymbol{\mu}}_C\left(T_1, T_2\right) = (1/B) \sum_{b=1}^{B} \boldsymbol{R}_C^{L,(b)}\left(T_1, T_2\right)$ and $\boldsymbol{R}_C^{L,(b)}\left(T_1, T_2\right)$ is the revenue from a long position on contracts at scenario $b = 1, 2, \ldots, \boldsymbol{B}$. The final input to the calculation of the optimal hedge is an estimator of the covariance matrix between the revenue from the baseline position and the contracts. This is also derived based on simulation data as follows

$$\widehat{Cov}\left(\boldsymbol{R}_C^L, R_i\right) \equiv \widehat{Cov}\left(\boldsymbol{R}_C^L, R_i\right)(T_1, T_2)$$

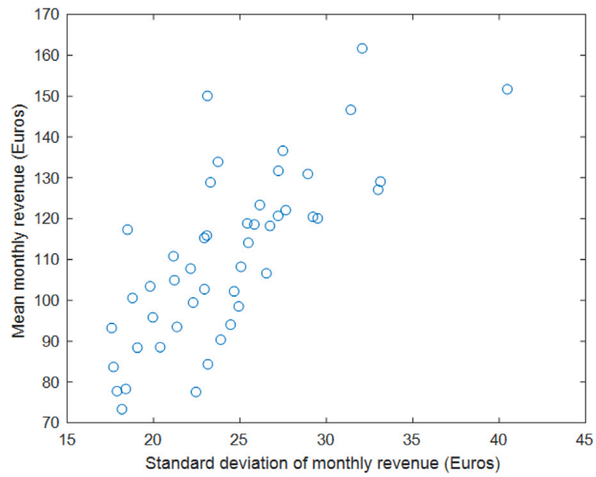

Fig. 4. The monthly $\sigma - \mu$ revenue profile of regional producers.

$$\equiv -\hat{\boldsymbol{\mu}}_C \hat{\mu}_i + (1/B) \sum_{b=1}^{B} \boldsymbol{R}_C^{L,(b)} (T_1, T_2)\, R_i^{(b)} (T_1, T_2)$$

5.4. Risk-reward relationship

Financial theory dictates that in equilibrium (liquid) assets should reward investors for taking additional (systematic) risk. If an asset offers excessively higher return compared to its risk levels, investors will seek to acquire it, pushing its price up and its return down. On the other hand, if the risk levels of a poorly-delivering asset suddenly increase, market players will no longer consider it an attractive investment. Increasing selling pressure will drive its price down, aligning its return with the new risk levels.

The key factors preserving the risk-reward balance described above are the investors attitude towards risk and the extent at which market permits the instant correction of mispricings. When it comes to power portfolios, equilibrium arguments do not apply because both the risk and the reward levels are determined by nature. It would thus be interesting to investigate how much nature compensates wind energy producers relatively to the volumetric risk of their generation mix. Although the strategies employed in this paper are designed for minimizing the revenue variance, in this subsection we make a slight deviation to shed light to the empirical risk-reward relationship implied by the Spanish wind resources. This is illustrated in Fig. 4. As was explicitly stated in Section 5.3, the revenue statistics depend on the length of the delivery period. To avoid any complications from varying delivery horizons and be in line with the design of commercial wind power futures, we base our presentation on monthly gross revenues.

Fig. 4 shows the relationship between the mean and the standard deviation of the monthly revenue per unit of installed capacity and selling price. Monthly statistics are averaged over the year, so that each circle in the $\sigma - \mu$ plane corresponds to one of the 47 sample provinces. Despite the increased levels of dispersion, the formation of the cloud of points is indicative of a positive correlation pattern. Wind power producers are, in principle, compensated for increasing levels of risk (as measured by the standard deviation of monthly revenue across generation scenarios). From a different perspective, this empirical observation is the equivalent to the “no-free-lunch” hypothesis in power markets. An investor cannot increase the revenue from wind energy trading without accepting higher levels of risk. Although this remark should not take an economist by surprise, the astonishing feature of Fig. 4 is that no-free-lunch carries over to renewable energy harvesting, bringing a sense of equilibrium to this market. The fact that maximization of yield and minimization of risk turn out to be two contradicting investment targets increases the practical relevance of risk management strategies (especially spatial diversification).

5.5. Diversification

As discussed in Section 1, aggregators have enough flexibility to rebalance their mix from time to time, just because they are not the owners of the wind power stations. Among the many possible rebalancing rates that an aggregator can implement in practice, we assume that the spatial allocation of generating capacity can only be changed once in a month. This is in accordance with the design of the wind power futures being traded in EEX and NASDAQ, which assume that delivery takes places in subperiods, typically each calendar month starting from January. Christensen and Pircalabu [25] evaluate the performance of the hedging strategy based on the gross annual result. However, as Benth et al. [30] note, the seasonality of wind intensity and variability is so intense that the payoff of a wind power futures strongly depends on the delivery month. This is why in this paper we chose to monitor the performance of risk management strategies on a monthly basis. To facilitate comparisons between the two strategies, we report only minimum variance (MV) capacity allocations calculated based on the covariance matrix of the monthly gross revenue in each province. The covariance structure is estimated with reference to formula (7) by bootstrapping generation scenarios.

In Fig. 5, we illustrate the spatial allocation of capacity in minimum-variance portfolios. To save space, we present seasonal averages of portfolio weights, as these seem to be relatively stable in each quarter. The tone of the color reflects the share of each province in the optimal mix. The approximate value of weights can be found on the colorbar shown to the right of each panel. Despite seasonal variations, a standard pattern of spatial allocation seems to prevail all portfolios. The key to the diversification of the generation risk is to combine a northeastern province[7] (especially Girona) with a region located in the south of the Iberian Peninsula (Cadiz is the common candidate). Spring and Autumn portfolios also make use of the wind resources of western provinces, which occasionally receive considerable weight. The rate at which the portfolio selection algorithm indicates re-allocation of capacity highlights the importance of dynamic portfolio selection as opposed to a static diversification strategy, according to which the aggregator keeps the portfolio shares constant across seasons.

An interesting aspect of the dynamic portfolio selection strategy is the limited engagement of provinces. As shown by the allocation schemes, MV formations use small bundles of assets to control volumetric risk. This finding has two important implications for the wind energy business: firstly, it is possible to improve the stability of the aggregate production using a much less intensive capacity allocation plan that focuses on a smart blend of wind energy resources rather than a large-scale commitment of generation sites. Secondly, despite the topographic and climatic variety of the Spanish Iberian Peninsula, there is a great deal of redundancy in wind resources. Contrary to what other studies recommend [5,14,15], in our case the aggregator would see no benefit from incorporating more provinces in her portfolio. With a smart combination of sites, she can improve her risk profile beyond what she could get with any other capacity allocation plan.

5.6. Hedging

Fig. 6 shows the seasonal development of the hedging strategy. Each province is colored according to the number of contracts that a regional producer has to hold to optimally hedge her baseline position. To facilitate comparisons with the aggregator’s strategy, we assume that the baseline position is an installation of 1 MW remunerated at the fixed rate of 1 Euro per generated MWh. In line with the theoretical reasoning presented in Section 4.3, the optimal γ is negative across all provinces implying that producers have to go short on the standard wind power futures to minimize their revenue risk. Surprisingly, their

[7] See the maps of Fig. 2.

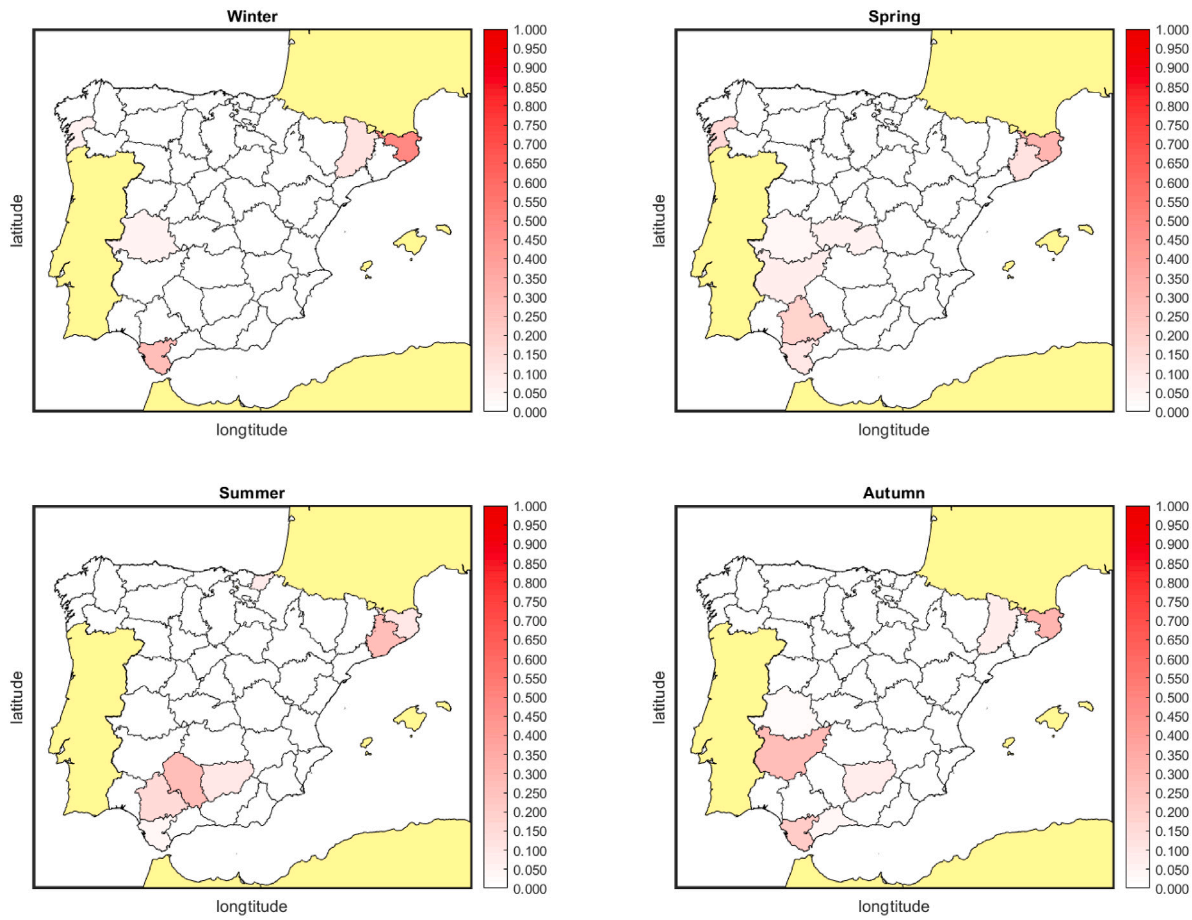

Fig. 5. The minimum-variance capacity allocations.

derivative position is relatively stable across the year, implying that they do not need to rebalance the financial leg of their strategy too often. The range of the monthly optimal hedge ratios is -14.2967 to -2.0581, the largest value being reported for Cadiz (ID 2) and the smallest for Castellon (ID 34). With reference to formula (5), large (absolute) values of γ^* can arise if the correlation of revenues from the two legs of the strategy is high (again in absolute terms) or the risk of the baseline position is considerable. The latter issue will be re-examined in Section 5.7 with the aid of factor analysis techniques.

5.7. Factor analysis

The seasonal capacity allocations presented in Fig. 5 generally indicate as optimal risk mitigation strategy the dispersion of generating capacity across the Iberian Peninsula. However, in most cases, capacity allocation plans are polarized assigning a non-zero weight to a relatively small number of provinces. As far as the hedging strategy is considered, the optimal number of contracts to be held in each season varies significantly with the geographical location of the wind farm. Still, in Fig. 6, one can discern groups of provinces with comparable values of γ^*. Being confronted with these positions, the producer finds it hard to understand why optimization algorithms indicate them as optimal and in what sense they safeguard her income. Modern portfolio theory dictates that in order to understand the opportunities for risk reduction we have to differentiate between systematic and non-systematic risk sources in our generation data. Mixtures are effective as long as risk is primarily diversifiable. This is equivalent to saying that asset returns are not mainly driven by common risk factors, such as the market, which positively load all assets. On the other hand, if the market is the main driver of asset returns, this factor could be hedged away by a suitably designed derivative contract whose underlying asset is a market aggregate, such as a stock index. In other words, hedging is more beneficial in investment environments where systematic risk dominates. In the context of renewable energy generation, the systematic risk components are perceived as factors that jointly determine the wind energy generation in a group of provinces. The non-systematic component represents the region-specific volumetric risk, which can be attributed to local weather effects and can be diversified away in a large portfolio. This component should not matter as we expand the capacity allocation incorporating more and more provinces. Before we recommend the use of any risk management strategy it is of paramount importance to explore the signature of volumetric risk. Of course, such an analysis has to be made separately on each province. Still, even if the generation risk is systematic to a large extent, then comes the question of whether a single power futures (written on a spatial average of capacity factors) constitutes an adequate hedge. The latter question is related to the dimensionality of the common factors space. This section attempts a quantitative treatment of these research questions.

For the extraction of the systematic risk components, we resort to the advancing literature on approximate factor models (see e.g. [37]). Standard factor analysis is not suitable for wind generating capacities as, by definition, they are restricted to $(0,1)$ and deviate from normality. Therefore, it makes more sense to base any factor decomposition exercise on the series of transformed wind generating capacities $\{\tilde{r}_{ti}\}$ defined in Section 5.2. In particular, we assume that the panel of time series $\left\{\tilde{r}_{ti}\right\}$ has a common factor structure that reads as follows

$$\begin{aligned}\tilde{r}_{ti} &= \alpha_i + \lambda_{i1} f_{t1} + \lambda_{i2} f_{t2} + \cdots + \lambda_{iK} f_{tK} + e_{ti} \\ &= \alpha_i + \lambda_i' \boldsymbol{f}_t + e_{ti}, \qquad i = 1,2,\ldots,N; \quad t = 1,2,\ldots,T\end{aligned}$$

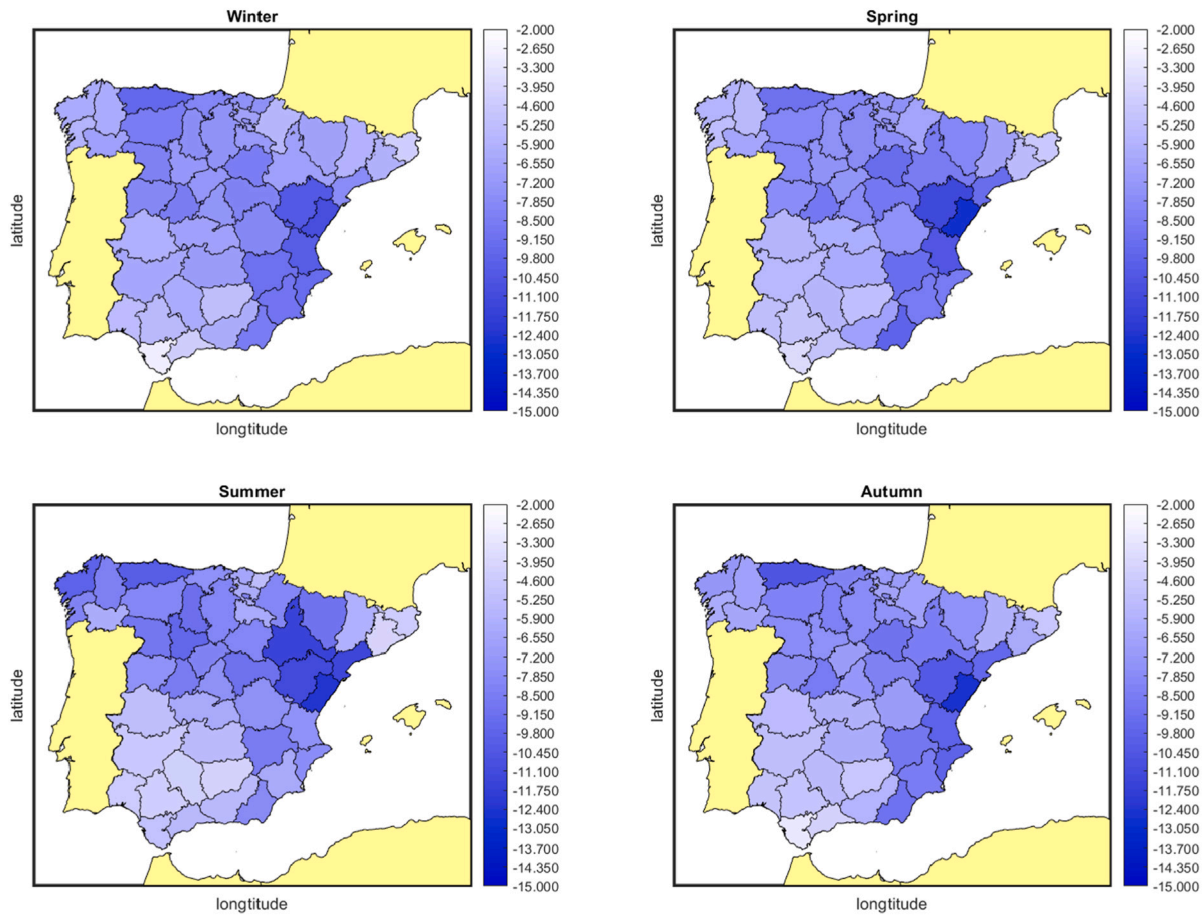

Fig. 6. The optimal hedging position per province (standard contract).

where α_i is the constant term, $\boldsymbol{f}_t = (f_{t1}, f_{t2}, \ldots, f_{tK})'$ is the vector of common factors and e_{ti} is the idiosyncratic part of the wind capacity factor of region i. Both $\boldsymbol{f}_t$ and e_{ti} are unobserved and need to be estimated. The common factors can be perceived as different sources of systematic risk, in the sense that every shift in the value f_{tk} affects the generating capacity of all provinces i for which $\lambda_{ik} \neq 0$. The λ_{ik} coefficient, which is also known as the loading of factor k to region's i generating capacity, measures the exposure of $\tilde{r}_{ti}$ to time variations in factor k. The term $s_{ti} = \lambda_i' \boldsymbol{f}_t$ is the systematic component of $\tilde{r}_{ti}$ and captures common variations in wind generating capacities (dictated by the common sources of risk). In our study, we used principal components analysis (PCA) to estimate the factor model components under the following set of assumptions:

A.1: $(1/T)\sum_{t=1}^{T} \hat{\boldsymbol{f}}_t = \mathbf{0}_K$
A.2: $(1/T)\sum_{t=1}^{T} \hat{\boldsymbol{f}}_t \hat{\boldsymbol{f}}_t' = \mathbf{I}_T$
A.3: $(1/T)\sum_{t=1}^{T} \hat{\boldsymbol{f}}_t' \hat{e}_t = \mathbf{0}_T$
A.4: $(1/N)\sum_{k=1}^{K} \hat{\lambda}_k \hat{\lambda}_k'$ is diagonal

where symbol ^ denotes PCA-estimated quantities. Assumptions A.1 & A.2 impose zero mean and orthonormality to the estimated factors. A.3 ensures that the vector $\hat{\boldsymbol{f}}_t$ (and thus the systematic component of the transformed capacity factor) is uncorrelated with the residual term $\hat{e}_t$. A.4 is used to complete the number of restrictions so that the factor model is identifiable. The triplet of assumptions A.1–A.3 permits the following convenient in-sample decomposition of the generation risk of each province:

$$\widehat{Var}\left(\tilde{r}_{ti}\right) = \widehat{Var}\left(\hat{s}_{ti}\right) + \widehat{Var}\left(\hat{e}_{ti}\right) = \hat{\lambda}_{i1}^2 + \hat{\lambda}_{i2}^2 + \cdots + \hat{\lambda}_{iK}^2 + \widehat{Var}\left(\hat{e}_{ti}\right)$$

The ratio $\hat{\lambda}_{ik}^2/\widehat{Var}\left(\tilde{r}_{ti}\right)$ is the percentage of (transformed) revenue variance attributed to k-factor variations. This is a measure of the relative importance of the kth systematic component to the shaping of the volumetric risk.

In this paper, factor analysis was deployed in three directions:

- in the decomposition of the regional wind power generation risk
- in the performance assessment of risk management strategies
- in the design of a new hedging strategy

The first step in principal component analysis is to estimate the dimensionality of the common factor space. In our study, this parameter was determined using a mixture of state-of-the-art statistical criteria and computational methods on the initial (1096 × 47) sample of observations (estimation sample). Bai and Ng [38]'s information criterion (IC) suggested $K = 7$ common factors, while the data-driven approach of Alessi et al. [39] indicated a common factor space of smaller dimensionality ($K = 4$). The first four principal components explain 84.33% of the total in-sample data variance and if one adds three more common factors, this index climbs up to 91.03%. Bai and Ng's IC is known to deliver estimates of K that are upward biased in finite samples. This makes us more confident about the results of the Alessi et al. [39]'s approach. Besides, the estimate provided by the latter method coincides with the position of the elbow point in the scree plot (not shown here). The collective empirical evidence presented above gives

Table 1
Decomposition of the total (transformed) revenue variance.

Estimated factor	Percentage of variance explained (%)	Cumulative sum (%)
1	56.28 (4.49)	56.28 (4.49)
2	11.24 (1.18)	67.52 (3.71)
3	9.22 (0.94)	76.74 (2.98)
4	5.22 (0.69)	81.96 (2.49)

us reasons to believe that the true cardinality of the common factor space is 4. This value was adopted in all experiments presented in this paper.

5.8. Risk decomposition

Once we estimated the dimensionality of the systematic risk space, we applied PCA in the strategy design sample to extract the common risk factors. The process was repeated for each of the $B = 5000$ bootstrapped samples of dimensionality 365×47. Table 1 shows the decomposition of the total (transformed) revenue variance $\left[\sum_{i=1}^{N} \widehat{Var}\left(\tilde{r}_{ti}\right)\right]$ per principal component. The main entries are averages across simulation paths, while in parentheses we show bootstrap estimates of the standard deviation. Principal components are ordered by the percentage of the total variance explained.

As numbers in the second column show there is a great deal of commonality in wind energy generation profiles. The first principal component (PC) is responsible for almost 56% of the out-of-sample total generation variability. The contribution of the second and third PC is smaller yet significant (11.24 and 9.22%, respectively). Four components in total make up for 81.96% of the variability, while as much as $1 - 0.8196 = 18.04\%$ of the total production uncertainty is of non-systematic (region-specific) nature. A 95% central confidence interval for the level of non-systematic risk in simulated data is $[13.43, 23.10]\%$.

Fig. 7 shows the spatial distribution of out-of-sample factor loadings, in an attempt to intuitively explain the composition of optimal portfolios. Each region is colored according to the average loadings estimate available from each simulation scenario. Squared dots mark the provinces participating in any of the aggregator's portfolio. As the upper-left panel shows, all areas admit on average a positive loading from PC-1 implying that the first common factor represents a prominent risk source (possibly related to the climatic background of the Iberian Peninsula). Since PC-1 loads all areas with the same sign it cannot be offset in a properly formed portfolio; almost 56% of the overall production uncertainty is non-diversifiable. Inspecting the loading maps of less eminent principal components, we detect *dipolar* regional zones across which loading estimates change sign. From the perspective of principal components 2–4, the MV optimization strategy holds positions in regions of positive and negative loading, which gives the aggregator the opportunity to offset the production variability caused by these risk sources. Although PC-2 represents a common risk source accounting for almost 11% of the production uncertainty, this part of the variability can be diversified away. Whether it will actually be depends on the overall risk profile of each region and the ratio of systematic to diversifiable risk. We will elaborate on this issue in Section 5.9, where we evaluate the performance of risk management strategies.

5.9. Performance evaluation

5.9.1. Risk reduction ability

The performance of each risk management strategy is assessed along two axes. A first metric of superiority, which is also adopted by [25] in the case of a single wind power futures, is the extent at which the strategy manages to reduce the total risk. A second aspect that we consider here and is equally important to investors is the composition of *residual* risk. This is determined by whether the fluctuations of the strategy's revenue are region-specific or can be attributed to shifts in systematic factors. In order to avoid benchmarking strategies on the sample where they were parametrized, we generated a new bunch of simulated wind generating capacities, which we call *strategy evaluation sample* to separate it from the sample where strategies were designed (termed earlier in this paper as the strategy design sample). The evaluation sample is also composed of $B = 5000$ scenarios.

Before we report results on performance metrics, we provide an indication of the starting risk levels. Fig. 8 shows the revenue risk level of each province, which is of particular concern for regional producers. The revenue risk is defined as the bootstrapped standard deviation of the monthly revenue (averaged across the year). Risk levels vary between 17.53 and 40.54 Euros per MW of installed capacity (assuming that all local producers receive 1 Euro for each MWh of energy they supply to the system). The minimum risk is reported for Girona (ID 28) in the North East and the maximum for Castellon (ID 34) further to the South along the Mediterranean coastline.

The aggregator's portfolios depicted in Fig. 5 combine several provinces to exploit the correlation structure of regional wind resources. How advantageous is this tactic compared to placing all available capacity in a single province, possibly Girona characterized by the lowest levels of generation risk? The out-of-sample statistical analysis of generation revenue showed that the average risk level associated with the diversification strategy is 13.18 Euros, which is an improvement in the risk exposure of the Girona producers by more than 4 Euros per MW of installed capacity assuming a flat selling price of 1 Euro per generated MWh. Fig. 9 shows the spatial distribution of the risk-reduction (RR) index defined by

$$RR_i = 1 - \frac{\hat{\sigma}_P}{\hat{\sigma}_i} \tag{8}$$

where $\hat{\sigma}_i$ denotes the standard deviation of the monthly gross revenue of province i. We only report monthly averages of the RR index on the strategy evaluation sample. Some of the provinces admit a value of $RR_i > 0.5$ implying that a dynamic spatial allocation strategy is able to diversify away much of the province-specific generation risk. This significantly reduces the aggregator's exposure to volumetric risk compared to how vulnerable to generation variability regional producers are. The actual range of the RR index's out-of-sample values is 23.10 to 68.29%, the former being attained for Badajoz (in the South-West) and the latter for Castellon (in the East). Assuming an installed capacity of $C = 1$ MW and a feed-in-tariff of $F = 1$ Euro/MWh, we estimated that wind farm owners located in Badajoz would experience an average standard deviation of monthly revenue equal to 17.93 Euros (in the strategy evaluation sample). The dynamic capacity allocation strategy manages to bring it down by almost 1/4 (the risk level of the aggregator is 13.18 Euros). The improvement in the risk position is much more considerable for a producer in Castellon, who starts with an average standard deviation of monthly gross revenue equal to 40.54 Euros.

The per province risk reduction in the case of the standard hedging strategy is given in Fig. 10. In this case, the RR index is calculated using formula (8) after replacing $\hat{\sigma}_P$ with $\hat{\sigma}_{H,i}$, the standard deviation of the gross monthly hedged revenue received by a regional producer in province i. The out-of-sample values for the RR index range from 6.00 to 71.71%, the two extremes being attained for provinces Cadiz and Soria, respectively. The average standard deviation of the monthly revenue of a producer based in Cadiz (unhedged position) is 27.32 Euros. Going short on the standard wind power futures, she manages to reduce the average standard deviation to 25.66 Euros, thus experiencing a minor improvement in her risk exposure. In the case of Soria, the wind farm owners start with a revenue risk level of 25.56 Euros, which after the application of the hedge goes down to 7.30 Euros. Apparently,

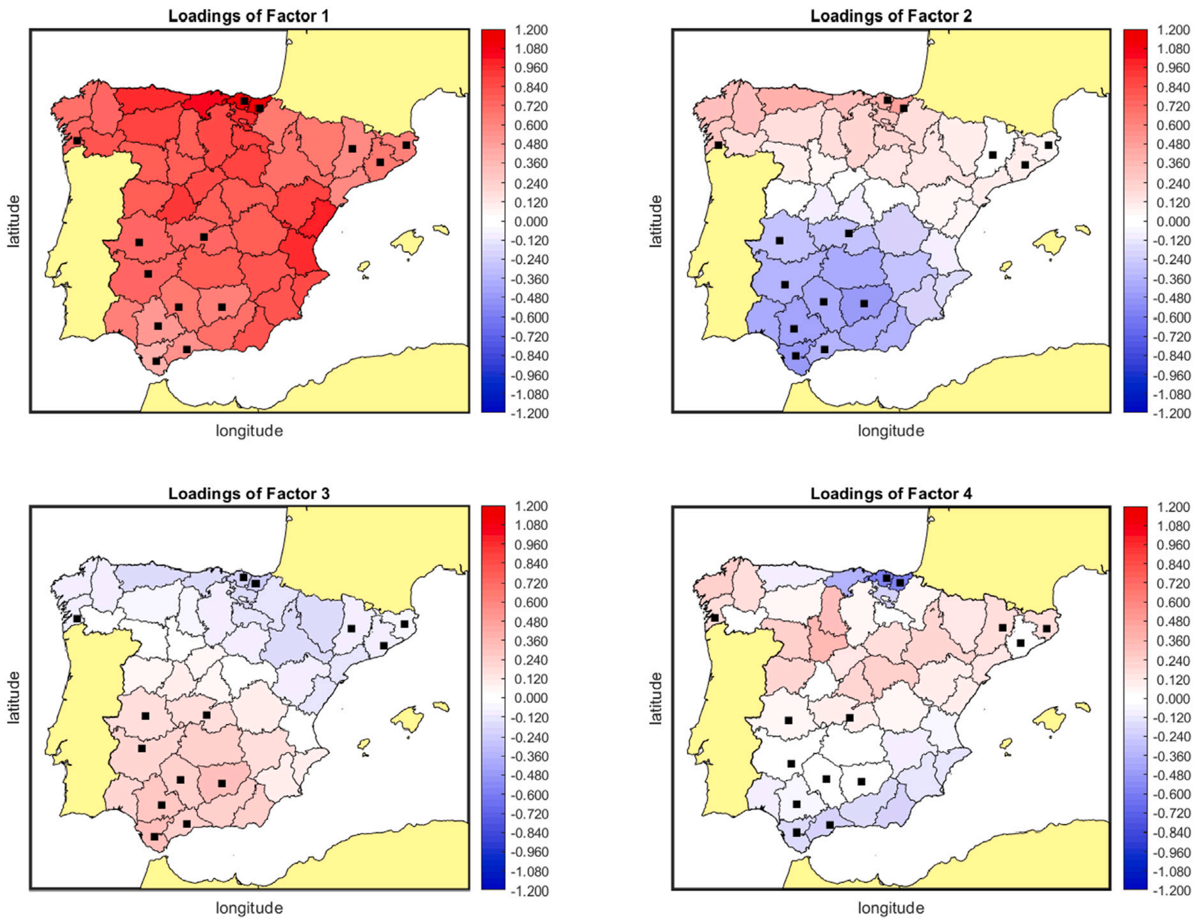

Fig. 7. The loadings of the common factors on the Spanish mainland provinces.

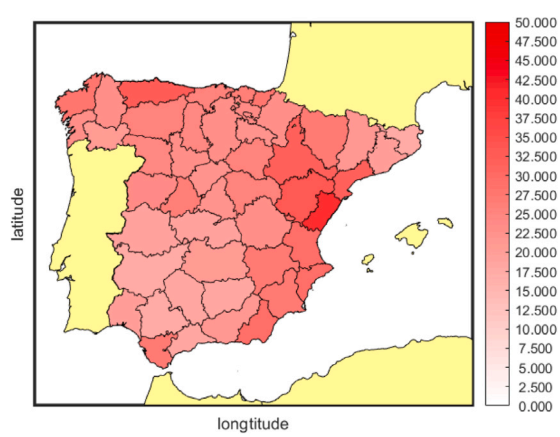

Fig. 8. The out-of-sample revenue risk per province.

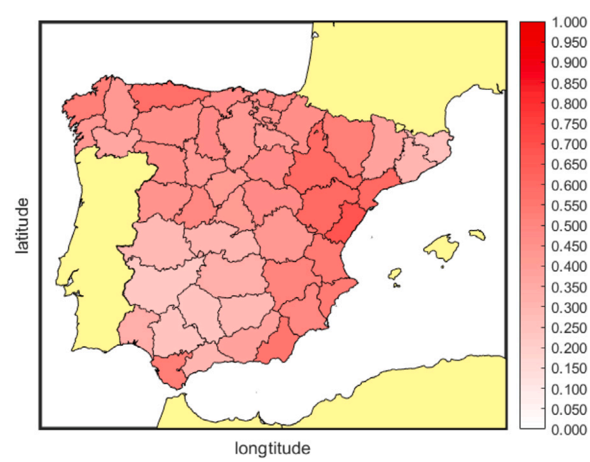

Fig. 9. The out-of-sample risk reduction ability of the diversification strategy.

the standard contracting strategy provides a better hedge for Soria producers because the wind generation risk profile of this province matches the payoff of the strategy revenue. The similarity in revenue profiles is less noticeable for Cadiz.

5.9.2. Risk decomposition

Both strategies attain a satisfactory level of risk reduction, as judged by the relatively high values of the RR indices for some provinces. In this sense, they are consistent with the principle upon which they were designed. Still, it is important to understand that the RR metric is an indicator of the total risk profile improvement and does not provide any information on the composition of the remaining risk, i.e. whether it is of systematic or diversifiable nature. To address this issue, we applied PCA to estimate the factor structure of the transformed wind generating capacities in the strategy evaluation sample. For each simulation path, we regressed the daily revenue from each strategy on the estimated factors and a constant. Based on the slope coefficient estimates and the sample properties of principal components, we were able to quantify

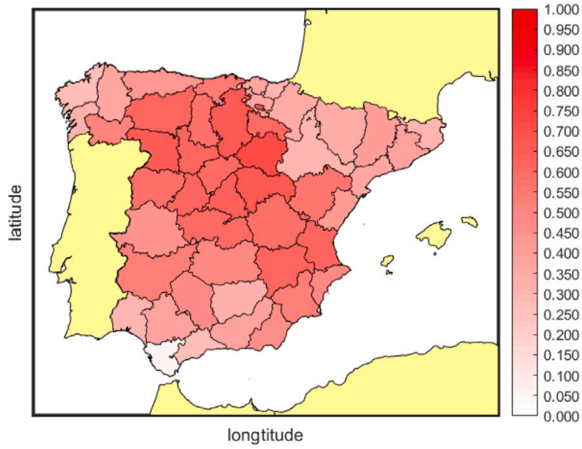

Fig. 10. The out-of-sample risk reduction ability of the hedging strategy (standard contract).

the contribution of each factor to the revenue risk. In particular, the risk share of factor k is measured by the ratio

$$RS_{p,k} = \frac{\widehat{b}_{pk}^2}{\widehat{Var}(\tilde{r}_p)}$$

where $\widehat{b}_{pk}$ is the estimate of the k-factor slope coefficient and $\widehat{Var}(r_p)$ is the sample variance of the daily revenue.[8] To decompose the revenue risk of the hedging strategy, we applied a slightly different procedure. First, we derived estimates for the slope coefficients of a multivariate regression of the daily hedged revenue in each province on the estimated common factors and a constant. Based on the estimates of the slope coefficients, we computed the share of factor k to the revenue risk of province's i hedged position as follows:

$$RS_{i,k} = \frac{\widehat{b}_{ik}^2}{\widehat{Var}(\tilde{r}_i)}$$

Similarly, we estimated the revenue variance share of starting (unhedged) positions.

Fig. 11 shows the contribution of systematic and idiosyncratic risk sources to the revenue variance experienced by regional producers. The plot's input data are bootstrap averages of the $RS_{i,k}$ estimates for each province i and factor k. We see that a great deal of regional revenue risk is due to PC-1 fluctuations. The variance shares of PC-1 range from 13.44% to 77.27%, the lower limit being attained for the Cadiz province (ID 2) and the upper limit for Avila (ID 13). As far as the contribution of PC-2 is concerned, this is less pronounced than PC-1 but still important for some regions in the southern part of the Iberian Peninsula and the North of Spain (especially provinces with IDs 3–9). Wind generation in the Girona region, located at the northeastern tip of the Iberian Peninsula, is the least exposed to systematic risk factors (see entry with ID 28). More than half (53.68%) of the total revenue variability is attributed to local weather effects. Girona is an exception and in most provinces the level of systematic risk exposure is quite high, ranging from 60 to 82% of the total revenue variability.

The second row of Table 2 shows the revenue variance decomposition for the diversification strategy. Reported figures are averages across bootstrap samples; also shown in parentheses is the standard deviation of the corresponding estimate. The results of Table 2 are in accordance with the loading maps and the risk decomposition of provinces. Above all, they highlight the weakness of the diversification strategy to control systematic risk exposure.

[8] No correction to the degrees of freedom was made to the variance estimator so that it matches the assumptions of the factor analysis.

The average contribution of common factors to the revenue variance of the pure diversification strategy is as high as 65%. The strategy's revenue is largely governed by fluctuations in systematic risk factors. Clearly, of all risk factors, PC-1 is the major source of non-diversifiable risk, accounting for more than half of the portfolios' out-of-sample revenue variance. This result is expected as according to the in-sample estimates of Fig. 7, all provinces are positively loaded by PC-1, which makes it impossible to diversify away this dimension of systematic risk. Table 2, second row, shows that the share of less prominent risk components is negligible (and not statistically significant) compared to that of PC-1, implying that factors 2–4 have been almost neutralized. Overall, the results of Table 2 are supportive of a multidimensional risk structure which cannot be diversified away through the spatial distribution of generating capacity.

How effective is the hedging strategy in offsetting systematic risk components? Fig. 12 shows the variance decomposition for the hedging strategy. We perform this decomposition on a province level, as the common assumption underlying the wind power derivatives literature is that local producers select independently the optimal hedging ratio according to the regional wind profile.

As the area plot dictates, hedging manages to offset much of the PC-1 related risk, as opposed to how determinant this risk source is for the daily revenue of the aggregator. The variance share of PC-1 stays below 24% in all provinces and goes above 15% in only three regions (13, 37 and 43). This result can be interpreted on the grounds of the loading maps presented in Fig. 7. The underlying index of the standard wind power futures is an equally weighted average of wind capacity factors across provinces. Due to the positiveness of loadings from PC-1, the equally-weighted portfolio unavoidably carries a great deal of PC-1-risk and since in all hedging strategies producers take a short position in the future, this risk source is largely neutralized. Because of its special design, the standard futures is effective in controlling the systematic risk stemming from factor 1 but not from others. Most important, the ability of the standard futures to reduce region-specific risk is questionable. The levels of idiosyncratic risk exposure vary from 26.39 to 90.88% across provinces, the latter figure being attained for Guadalajara (id 25). In this respect, the standard futures is a suboptimal hedge. Several options on how to design a superior hedging strategy are considered in the following section.

5.10. Composite strategies

The results of the performance evaluation highlight the key features of the two strategies often proposed in the literature for controlling volumetric risk. Diversification can reduce idiosyncratic risk and eliminate some of the systematic components but it is unable to offset any source of systematic risk (such as the PC-1) that loads all areas with the same sign. Taking a short position in the standard futures contract reduces exposure to factor-1 risk at the expense of infusing systematic variation (from other principal components) as well as idiosyncratic risk. Whether the risk budgeting is to the benefit of the producer really depends on the significance of the variance source. For instance, as Fig. 11 shows, wind generation in Cadiz (id 2) has relatively little exposure to systematic risk factors (especially PC-1). For this reason, if a wind farm owner established in Cadiz goes short on the standard futures would only see her risk profile being improved by 6% compared to the baseline (see the end of Section 5.9.1). In this section, we examine variations of the basic risk management schemes with the intention of improving their risk reduction performance.

5.10.1. Factor contracts

The wind power futures designs encountered in EEX and NASDAQ assume as underlying index a simple average of regional capacity factors. Judging from the spatial distribution of PC-1 loadings, this design is likely to succeed in offsetting exposure to PC-1 variations but not to other sources of systematic risk, which have a mixed effect on

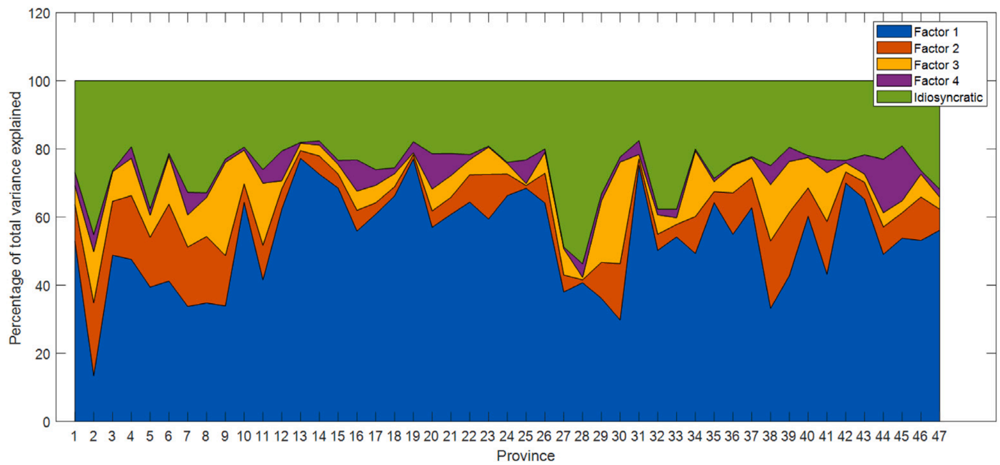

Fig. 11. The decomposition of the out-of-sample revenue risk per province.

Table 2
The (%) decomposition of the out-of-sample risk of the diversification strategy.

	Factor 1	Factor 2	Factor 3	Factor 4	Common component	Idiosyncratic component
Diversification	59.38 (5.30)	3.34 (2.29)	1.96 (1.67)	0.30 (0.43)	64.98 (5.33)	35.02 (5.33)
Diversification and standard contract	12.55 (3.93)	2.61 (2.40)	1.70 (1.77)	3.25 (2.67)	20.11 (4.92)	79.89 (4.92)
Diversification and factor contracts	11.86 (4.21)	0.96 (1.45)	1.19 (1.40)	6.77 (4.33)	20.77 (4.59)	79.23 (4.59)

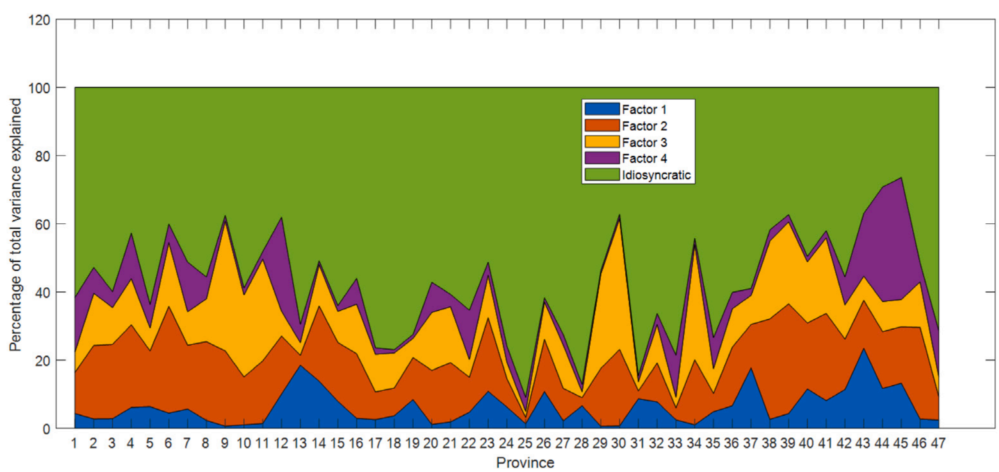

Fig. 12. The decomposition of the out-of-sample revenue risk of the hedging strategy (standard contract).

regional generating capacities. Instead of arbitrarily fixing the mixing weights to $1/N$, our idea is to launch K new futures contracts whose underlying mimics fluctuations in each of the estimated principal components. This way we are able to cover all the dimensions of systematic risk.

To derive underlying indices for the new type of futures contracts, we performed an eigenvalue decomposition of the sample variance–covariance $\widehat{\boldsymbol{\Sigma}}$ of the actual (transformed) capacity factors

$$\widehat{\boldsymbol{\Sigma}} = \frac{1}{T}\sum_{t=1}^{T}\left(\widetilde{\boldsymbol{r}}_t - \widehat{\boldsymbol{\alpha}}\right)\left(\widetilde{\boldsymbol{r}}_t - \widehat{\boldsymbol{\alpha}}\right)'$$

where $T = 1096$, $\widetilde{\boldsymbol{r}}_t = (\widetilde{r}_{t1}, \widetilde{r}_{t2}, \ldots, \widetilde{r}_{tN})'$ and $\widehat{\boldsymbol{\alpha}} = (\hat{\alpha}_1, \hat{\alpha}_2, \ldots, \hat{\alpha}_N)'$ is the sample mean of $\widetilde{\boldsymbol{r}}_t$. Let $\widehat{\mathbf{L}}$ be the diagonal $K \times K$ matrix whose entries are the K-largest eigenvalues of $\widehat{\boldsymbol{\Sigma}}$ and $\widehat{\mathbf{W}}$ the $N \times K$ matrix of the corresponding eigenvectors. Based on PCA theory, we can reconstruct the principal components by properly weighing initial data. The matrix $\widehat{\mathbf{M}}$ of weighting coefficients is given by $\widehat{\mathbf{W}}\widehat{\mathbf{L}}^{-1/2}$.

The values $\breve{\boldsymbol{f}}_t^{(b)} = \left[\breve{f}_{t1}^{(b)}, \breve{f}_{t2}^{(b)}, \ldots, \breve{f}_{tK}^{(b)}\right]'$ for the underlying indices of the factor contracts $k = 1, 2, \ldots, K$ in each bootstrap scenario $b = 1, 2, \ldots, B$ are derived from

$$\breve{\boldsymbol{f}}_t^{(b)} = \mathrm{logit}^{-1}\left[\widehat{\mathbf{M}}'\left(\widetilde{\boldsymbol{r}}_t^{(b)} - \widehat{\boldsymbol{\alpha}}\right)\right]$$

where $t = 1, 2, \ldots, T$. The application of the inverse logit transformation $\mathrm{logit}^{-1}(z) = \frac{e^z}{1+e^z}$ ensures that $\breve{\boldsymbol{f}}_t^{(b)}$ takes values in the open interval $(0, 1)$. The payoff of a long position on a single k-factor contract with

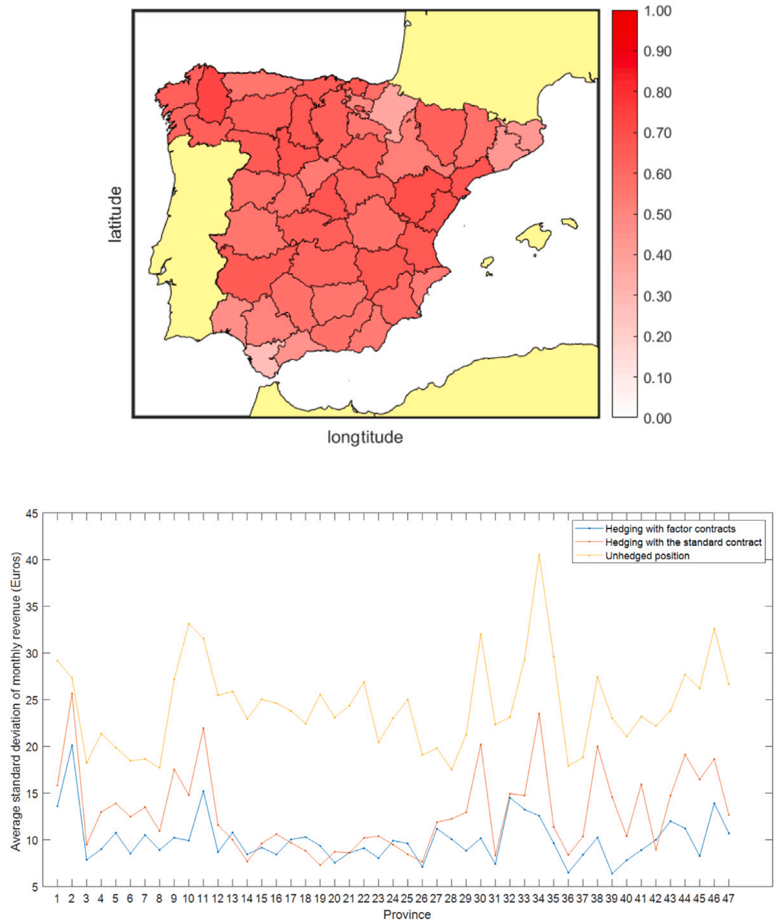

Fig. 13. The out-of-sample risk reduction ability of the hedging strategy (factor contracts).

delivery period $[T_1, T_2]$ is given by

$$R_{C,k}^{L} = \frac{X}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} (\check{f}_{tk} - f_{t_0 k,F})$$

where

$$f_{t_0 k,F} = \frac{1}{B} \left[\frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} \check{f}_{tk} \right]$$

is the neutral price of each instrument.

Fig. 13, top panel, illustrates the risk reduction ability of the composite hedging strategy. To facilitate comparisons, we also report in the bottom panel the absolute risk levels of each position taken by regional producers (unhedged, hedged with a standard contract and hedged with factor contracts). As the displays indicate, of all wind farm owners those based on the northwestern province of Lugo (ID 39) would benefit the most from the adoption of a composite hedging strategy. The average RR ability for this province is 72.91%. The risk anatomy of regional generation, displayed in Fig. 11, sheds light on this finding. As much as 86.33% of the generation capacity variability in Lugo is of systematic nature, hence it can be offset by futures contracts whose underlying index is designed to track the evolution of systematic risk factors. Factor contracts are not so efficient in controlling the overall revenue risk of producers in other provinces, such as Cadiz (ID 2). In Cadiz, systematic risk factors take a smaller share (54.86%) of the total revenue risk. Yet, the composite hedging strategy manages to offset 54.86−18.25 = 36.61% of this share, while the systematic risk exposure of the hedging strategy with a single (standard) contract is 41.02%.

As seen by the variance decomposition diagram of Fig. 14, hedging with factor contracts is quite effective in neutralizing systematic risk components. By taking positions in factor futures, regional producers manage to reduce the exposure to all systematic risk components below what they can achieve with a standard contract design. The benefits from the adoption of a composite hedging strategy are not equal across provinces. In some provinces, the reduction in revenue risk is marginal compared to the comfort zone provided by a standard futures. An explanation for this finding can be sought in model estimation error (bear in mind that common risk factors are estimated on the initial dataset and then applied out-of-sample) or in the contract design. Factor contracts are constructed to control systematic risk exposure, while a simple average of wind generating capacities across provinces accidentally eliminates part of the idiosyncratic risk as well.

Fig. 15 shows the relationship between the risk reduction ability of each strategy and the percentage of the remaining systematic risk per province. To facilitate comparison between the two variables, we measure the systematic risk as the standard deviation of monthly revenue. Also shown are the least-square lines (which include both a slope coefficient and an intercept). Fig. 15 clearly illustrates that the effectiveness of the hedging strategies to reduce the overall revenue variability is increased with the systematic risk exposure. The correlation between those variables is higher in the case of the composite hedging strategy. The R^2 coefficient of the regression line is 0.60, as opposed to 0.24 attained by the hedging strategy with a single contract.

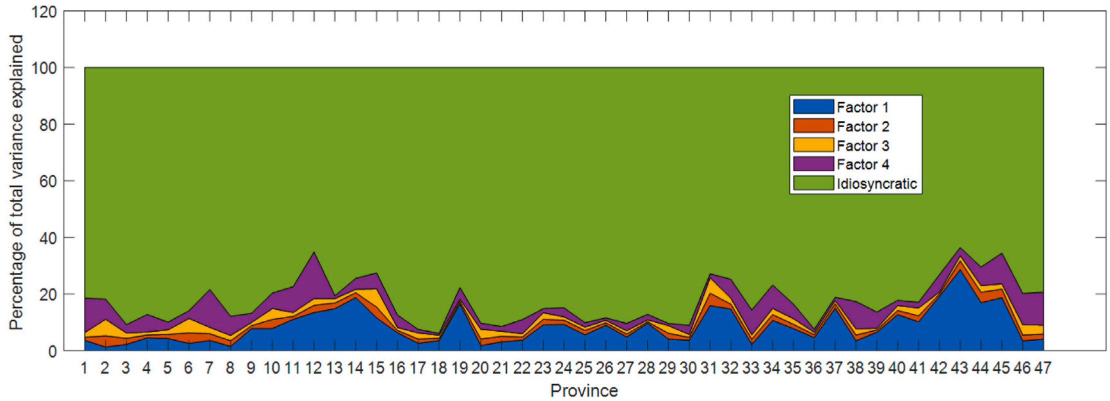

Fig. 14. The decomposition of the out-of-sample revenue risk of the hedging strategy (factor contract).

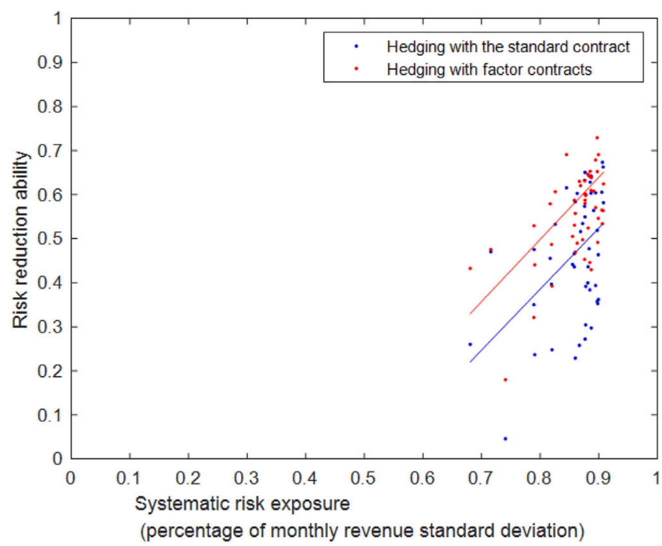

Fig. 15. Risk reduction ability of each hedging strategy vs. the percentage of systematic risk in each province (also shown are the least-square lines which include both a slope coefficient and an intercept).

The difference in the estimated intercepts $-0.63 - (-0.72) = 0.09$ reflects the unconditional superiority of the composite strategy in terms of reducing the total revenue risk (independently of the systematic risk exposure of each province). Still, the slope of the two lines is comparable (the difference in the estimated slope coefficients is only $1.41 - 1.38 = 0.03$ in favor of the composite hedging strategy). Hence no clear advantage can be claimed for each strategy.

5.10.2. Mixed-style strategies for the aggregator

Hedging with factor contracts is suitable for regional producers, as it helps them offset a larger part of systematic variations in wind generation. The aggregator is in a more advantageous position, as she can apply composite strategies to further dampen revenue variations. In Section 5.9, we empirically assessed the ability of spatial capacity allocation to tackle generation risk. Judging from its risk decomposition, we concluded that spatial balancing can control idiosyncratic variations and systematic risk components with loadings of mixed sign. If the aggregator also has access to wind power futures, she might be tempted to take parallel positions in these contracts to eliminate persistent sources of risk. In this section, we discuss two mixed-style strategies available for aggregators. Both of them take as a starting point the minimum variance portfolios and apply different hedging instruments. In the first variant, termed MDS, the aggregator uses a standard contract to offset systematic variations in the aggregator's revenue and, in the second variant, bearing the acronym MDF, the hedging instrument is the set of four factor contracts. In each case, the optimal hedging position γ^* is calculated by (4) after replacing R_i with R_P, the monthly revenue of the portfolio strategy. Fig. 16 shows the monthly (out-of-sample) risk levels attained by the aggregator's risk management strategies. The blue line corresponds to the baseline position and the rest refer to the mixed strategies.

The undertaking of futures positions helps the aggregator offset much of the revenue variability. The percentage risk reduction over the baseline position ranges from 45 to 66% and is equally pronounced in all delivery periods. The out-of-sample evidence shows that through the adoption of the composite hedging strategy, the aggregator manages to further secure her revenue. The marginal gains over the standard hedging strategy seem less sound in the graph, but in percentage terms they can be substantial. E.g. in August and September, factor contracts are able to improve the risk profile of the standard hedging strategy by more than 20%.

The true advantage of using a mixed strategy is illustrated in Table 2 (last two rows). The average contribution of common factors to the hedged revenue risk is at the order of 20%, significantly reduced compared to the systematic risk exposure of the pure diversification strategy. Hence much of the revenue risk being removed from the baseline position is of systematic nature. The largest benefit is observed in the variance contribution of PC-1. In the mixed strategy, this is less than 13% on average, meaning that wind power contracts manage to largely offset persistent variations in power generation. These variations could not have been eliminated through diversification, as all provinces are exposed to PC-1 with the same sign.

6. Conclusions and future research

The objective of this study was to evaluate the performance of various strategies for handling the volumetric risk of wind energy generation in the Continental Spain. These strategies roughly fall in two categories that represent fundamentally different views to risk management. The first approach amounts to interconnecting power generation plants in an attempt to balance the variability in the production of individual components. The second approach makes explicit use of wind power futures to secure the trader's income in periods when the wind farm's production falls below a predetermined level.

The results of the portfolio-selection exercise show that the key to the diversification of the aggregator's revenue risk is to make deals with wind farm owners in northeastern provinces (especially Girona) with producers in the southern part of the Iberian Peninsula (especially

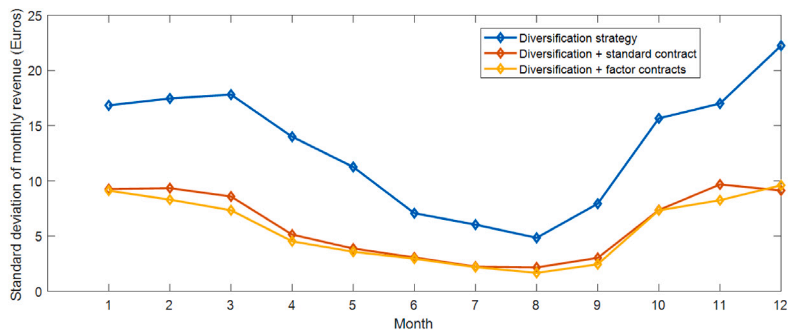

Fig. 16. The out-of-sample revenue risk of the aggregator's strategies.

those located in Cadiz). This capacity allocation pattern seems to repeat itself across all seasons. In general, optimal portfolios are sparse and polarized. Exploring the correlation structure of wind capacity factors, they use a small mix of assets to reduce cash flow uncertainty and avoid large-scale commitment of generation sites. Another important result of our analysis is that not all strategies are suitable for all regions, simply because the volumetric risk is Spain is multifaceted. Factor analysis techniques detected four common factors that collectively forge the generation profile of each region on top of local weather effects. The first factor makes up for a significant part of the national generation variability and loads all areas with the same sign. This means that it cannot be diversified away through the pooling of power plants. The exposure of regional generation to other common components is mixed in terms of sign and size. These risk sources can be diversified away in properly designed capacity allocations but not in an arbitrary aggregation scheme.

The richness and diversity of wind generation profiles raises a cautionary note on policy acts that strongly recommend spatial aggregation of resources as a cure to the stochasticity of wind. It equally questions the hedging effectiveness of EEX and NASDAQ wind power futures, simply because their underlying indices are calculated as a simple average of local wind capacity factors, unable by construction to cover all risk dimensions. Motivated by these empirical findings, we propose a new type of futures contracts (factor futures) whose underlyings are aligned with the four systematic risk axes. We show that these contracts can enhance the revenue profile of regional wind energy producers by eliminating a great deal of systematic variations. They can also be used by the aggregator to neutralize persistent sources of generation risk, i.e. sources that could not be removed through diversification. Of course, any claims on optimality of the new contract design are premature and more empirical research is needed to quantify the benefits. Still, our study highlights an important property of the factor contracts. A basket of four contracts can sufficiently replicate the underlying sources of revenue co-variability thus adding to the completeness of the market for hedging instruments. It turns out that the aggregator can further secure his/her revenue by adopting a hybrid risk management strategy that combines diversification with hedging (using standard or factor contracts). This plan is capable of eliminating the largest part of the wind generation stochasticity, as hedging tackles the systematic risk components (causing country-wide distortions in wind energy generation) while diversification deals with regional variability factors.

Another direction in which this study could be extended in the future is the joint consideration of different clean generation technologies (not only wind farms). Past studies have demonstrated that solar energy generation is less variable and has the ability to smoothen wind intermittencies [29,40–43]. An interesting research question is whether a portfolio of solar and wind generating assets could adequately maintain revenue or new types of derivative contracts need to be devised to remove systematic sources of cash flow uncertainty.

CRediT authorship contribution statement

Nikolaos S. Thomaidis: Conceptualization, Methodology, Software, Resources, Writing – review & editing, Supervision. **Theodoros Christodoulou:** Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Francisco J. Santos-Alamillos:** Methodology, Resources, Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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