



Weather index-based insurance as a meteorological risk management alternative in viticulture

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Abstract

This article explores the hedging potential of two weather index-based insurance programmes designed for the Rias Baixas Protected Designation of Origin (Spain). The first alternative insures both extreme and non-extreme weather events, while the second instrument covers exclusively extreme meteorological states. Two bioclimatic indicators computed for the period most correlated to grape yields are proposed as underlyings: the Branas, Bernon and Levadoux (BBL) and the Ribéreau-Gayon and Peynaud hydrothermal scale (RGP). Yield-weather dependence is then modelled with two different methodological approaches: copulas and linear regression. To assess the risk reducing potential, a hedging effectiveness analysis based on real and simulated data is carried out. The model uses variance and expected shortfall as risk measures. The results attained point out the high hedging ability of both insurance programmes, especially of the first of them based on RGP. This appraisal also reveals that the copula technique outperforms linear regression. Overall, the study results suggest that the implementation of policies geared to bioclimatic indices able to signal adverse weather events can significantly mitigate weather-related yield variations in viticulture.

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Keywords: Weather index-based insurance; Viticulture; Meteorological risk; Hedging effectiveness; Copula approach

1. Introduction

Fine wine making is extremely sensitive to weather conditions (Cyr and Kusy, 2007, p.146; Zara, 2010, p.222; Ashenfelter and Storchmann, 2016, p.25). Meteorological risk does not only adversely impact the quantity (Lobell et al., 2007; Chevet et al., 2011; Lorenzo et al., 2012) but also the quality (Jones et al., 2005; Storchmann, 2005; Alston et al., 2011; Lorenzo et al., 2012) of the grapes used for wine production.

Different adaptation measures have been suggested and occasionally adopted by wine producers to mitigate the income volatility derived from weather risk exposure and other sources of uncertainty. Some of them are supported by the European Union's and member states' agricultural policies (Castañeda-Vera and Garrido, 2017, p.3). These alternatives are classified into two main groups. The first of them are the so-called self-coping strategies, which involve the use of on-farm resources to change the production strategy (diversification, input intensification, variation in harvest times, geographical shifts in areas planted, substitution of grape cultivars and acquisition of new technologies), the commercial strategy (vertical integration) or the use of business benefits (stabilisation accounts) (Ashenfelter and Storchmann, 2016, p.25; Castañeda-Vera and Garrido, 2017, p.5). The second group comprises those measures that transfer the risk to a third party in return for a fee, such as insurance or mutual funds (Zara, 2010, p.223; Ashenfelter and Storchmann, 2016, p.25;

Abbreviations: PDO, Protected Designation of Origin; CAP, Common Agricultural Policy; IST, Income Stabilisation Tool; WI, Winkler Index; HI, Huglin Index; BBL, Branas Bernon and Levadoux; RGP, Ribéreau-Gayon and Peynaud hydrothermal scale; ENESA, State Agricultural Insurance Entity; AEMET, Spanish National Meteorological Agency; ES, Expected shortfall.

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Castañeda-Vera and Garrido, 2017, p.5). Concerning insurance, two main modalities are usually implemented: specific weather risk policies and multi-peril crop insurance.¹ Both yield indemnities that are not based on transparent criteria but on the subjective assessment and estimation made by the insurance firm's loss assessor (Skees and Reed, 1986, p.658; Smith and Goodwin, 1996, p.437; Coble et al., 1997, p.225; Hess et al., 2002, p.297; Zara, 2010, p.223).

Although less commonly adopted in this sector, there is another insurance alternative, the so-called weather index-based insurance. In contrast to the other two policies, this instrument is based on a weather index instead of on actual yields. Thus, this option not only significantly reduces administrative costs and insurance premiums (Bokusheva et al., 2016, p.200) but also encourages best management practices as there are no asymmetric information and moral hazard issues (Skees and Reed, 1986, p.658; Quiggin et al., 1993, p.95; Smith and Goodwin, 1996, p.437; Coble et al., 1997, p.225; Hess et al., 2002, p.297; Turvey and Kong, 2010, p.18). Despite these advantages, this tool presents some design challenges, such as the selection of a suitable underlying that adequately captures production risk and the availability of reliable historical weather data (Cyr and Kusy, 2007, p.146).

The usual predominance of small farms increases the bureaucracy implied by the specific weather risk and multi-peril crop insurances, which are the most commonly used financial instruments. This often leads to public intervention (Turvey and Kong, 2010, p.18). For instance, in Spain, the Ministry of Agriculture and Fisheries, Food and Environment, through the State Agricultural Insurance Entity (ENESA), subsidises a percentage of the insurance costs faced by farmers. Weather index-based insurance, which carries less management expenses, has consequently arisen as a more effective option, as shown by the increasing interest towards its application in the agricultural sector. In fact, over the last years, several authors have addressed its implementation in viticulture. Such is the case of Turvey et al. (2006) and Cortina and Sánchez (2013), who focused on the relevance of the accurate valuation of this insurance typology. The first of them developed and applied a pricing procedure for situations where returns depend on both the occurrence and timing of the weather event. For their part, Cortina and Sánchez (2013) modelled and valued a temperature weather contract to mitigate late frost risk. Other authors, despite still being interested in the valuation methodology, devoted more attention to the hedging effectiveness issue, such as Cyr and Kusy (2007) and Cyr et al. (2008). These authors concluded on the high risk reducing ability of this insurance modality based on the analysis of the meteorological volatility in the Ontario ice-wine producing region. Some years later, Cyr et al. (2010) designed a rainfall-based weather contract for the Niagara region of Canada. They highlighted the increasing

volatility of this meteorological variable as a determinant for the use of weather derivatives in viticulture. Following a different approach, Zara (2010) designed a temperature risk hedging strategy for the Bourgogne Côte de Nuits Pinot Noir PDO (Protected Designation of Origin) and evaluated its risk reducing potential based on the comparison of the crop's economic value with and without insurance.

This paper aims to contribute to the literature by exploring the hedging ability of different weather index-based insurance programmes designed for the Rias Baixas PDO. This is a small wine-growing area located in the northwest region of the Iberian Peninsula, Galicia (Spain). Despite having a long tradition, it was not until 1988, after the Rias Baixas wine Regulating Council was set up, that this activity began playing a significant role in the regional economy. Nowadays, the Rias Baixas wine-growing industry generates 7600 full-time jobs and 5200 temporary positions, which represent between 7% and 12% of the total area's employment (Denominación de Origen Rías Baixas, n.d.-a).

Spain, as a member state, is subject to the Common Agricultural Policy (CAP) of the European Union, which has traditionally supported two main alternatives to reduce income volatility: insurance and mutual funds. However, its last reform (2014–2020) has enlarged the available battery of measures with the introduction of the Income Stabilisation Tool (IST) (El Benni et al., 2015, p.2; Castañeda-Vera and Garrido, 2017, p.4; Trestini et al., 2017a, p.25; Trestini et al., 2017b, p.461). Mutual funds refer to private initiatives that allow farmers or groups of farmers to self-manage their risks by contributing to a common financial reserve. When losses occur, the farmers whose income has been negatively affected are compensated (European Commission, 2017). The new instrument of IST is directly related to the concept of mutual funds, as it covers part of their paid indemnities. Indeed, Article 39 of the EU Regulation No 1305/2013 settles a maximum reimbursement by the IST of 65% of the compensation previously paid by the mutual fund, which can amount up to 70% of the income loss (Trestini et al., 2017a, p.25). Despite promising, this measure presents some challenges, such as the precise definition of income trigger levels per year, farm type and country, which may be refraining its application at European and, specifically, at Spanish level (Meuwissen et al., 2011, p.8). In fact, Castilla y León has been the only Spanish region supporting IST within its Rural Development Programmes (2014–2020) (Castañeda-Vera and Garrido, 2017, p.6; Trestini et al., 2017a, p.25; Trestini et al., 2017b, p.461). Regulation No 1305/2013 also considers in its article 36 the possibility of covering part of the premium of different insurance typologies, mutual funds and IST. However, this measure has already been implemented in several EU countries through State aids. Such is the case of Spain (Castañeda-Vera and Garrido, 2017, p.6), where the Spanish System of Combined Agricultural Insurance, founded in 1978, provides a financially feasible alternative that allows the agricultural sector to cope with the damages caused by non-controllable and unexpected risks. Nowadays, there are policies available for all agricultural products that provide

¹ The first type of policies is mainly used in Europe, whereas the second modality, which insures grape yields against a fixed package of risks, is commonly applied in US (Zara, 2010, p.223).

coverage against almost all natural disasters, such as frost, hail, rain and wind among others. The system is based on the joint participation of private and public institutions: the Spanish national and regional governments, which provide grants that cover part of the insurance premiums; the Professional Agricultural Associations, representative of farmers and ranchers; and the insurance entities, grouped in *Agroseguro* (*Agroseguro*, n.d.).

This insurance structure has enjoyed considerable demand since its launch. In 2017, the number of agreed policies amounted to 240186. Although the public budget devoted to insurance has decreased in comparison to pre-financial crisis times, it has started to rise again since 2014. In fact, in 2017, the grants supplied by the national and regional governments added up to the significant amount of 314.11 million euros. The highest number of agreed policies was registered for arable crops, with 131082 contracts, followed by winery, with 29428 agreements (*Agroseguro*, 2017). These figures emphasise the need of hedging meteorological risk in viticulture and indicate that the launch of weather index-based insurance may actually succeed in Spain. This idea is further reinforced by the positive results of different studies which have analysed the farmers' willingness to pay for weather index-based policies (McCarthy, 2003; Sarris et al., 2006; Turvey and Kong, 2010; Ali, 2013). However, the implementation of this alternative would be subject to a thorough programme design. For instance, given that wine producers generally have a "lack of knowledge about the consequences of climate risk on their financial results and the way to hedge them", the most appropriate distribution vehicle may not be individual firms. Instead, associations of producers able to offer the product in a more understandable way may be required (Zara, 2010, p.234).

Most authors who have addressed the application of this type of insurance in the agricultural sector have used linear regression to model the relationship between yields and weather, assuming thus linear correlation (Vedenov and Barnett, 2004; Breustedt et al., 2008; Pelka and Musshoff, 2013) and treating the yield-index distribution as a multivariate normal (Embrechts et al., 2003, p.342; Bokusheva, 2018, p.3). This assumption is not valid for non-elliptical distributed risks (Embrechts et al., 2003, p.342) and may lead therefore to inaccurate conclusions. Consequently, in the present research, dependence is modelled using copulas and the results are compared to those derived from the linear regression approach. The copula technique has been suggested in some agricultural studies. Goodwin and Hungerford (2015) applied it to price and rate insurance schemes that covered several sources of risk—either low prices, low yields or a combination of these—. Focusing on weather index-based insurance, Bokusheva (2011) proposed this methodology to capture temporal changes in the weather-yield joint distribution, while Bokusheva et al. (2016) and Bokusheva (2018) used copulas to design and rate contracts that provided a hedge against extreme weather events. In this article, this last insurance typology is also addressed and additionally, a hedging modality that covers both extreme and non-extreme adverse

meteorological states is considered. Two different hydrothermal bioclimatic indices are suggested as underlyings.

The remainder of the paper is organised as follows. Section 2 reviews the materials and methods applied to design and value the suggested insurance plans. Then, Section 3 presents the calculations. After that, Section 4 displays the hedging effectiveness analysis and discusses the results attained. Finally, Section 5 summarises the main conclusions of the research.

2. Materials and methods

With a current coverage of 4061 ha spread over different locations of the province of Pontevedra and a small part of A Coruña county, the Rias Baixas PDO produces wines of worldwide renown that share common and unique characteristics derived from the climate, landscape and soil features of this wine-growing area. Regarding meteorology, this Atlantic region is characterised by heavy rainfall in winter. Precipitations are also common in spring and autumn, while infrequent and light during summertime. Temperatures are mild in winter and warm in summer. Concerning the landscape, the sub-zone of Val do Salnés, which accounts for more than 60% of the total yearly production, is mainly characterised by the predominance of low-lying land and the presence of coastal plains. For their part, Condado do Tea and O Rosal sub-zones are better described by the alternation of inter-river areas. In respect of the soil characteristics, granite is the most commonly type of rock found in the Rias Baixas production region (*Denominación de Origen Rias Baixas*, n.d.-b).

Concerning the life cycle of the vineyards of this PDO, three different stages are clearly distinguished and temporally allocated (Lorenzo et al., 2012, p.888): the bud-break, which takes place between April and June; the bloom, which occurs between June and mid-August; and the *véraison*, which materialises between mid-August and September.

Data on daily weather conditions for the period 1990–2017, which were used for the construction of the underlying indices, were extracted from the Spanish National Meteorological Agency (AEMET) and the regional meteorological agency of Galicia, *MeteoGalicia*. Pontevedra station was chosen for the analysis as weather data at this location correlate significantly to those from the main regions of production of the Rias Baixas PDO: O Rosal (As Eiras station), Pontearas (A Granxa station) and Vilanova de Arousa (Tremoedo station). Concretely, Spearman correlation values over 0.97 ($p < .01$) and 0.86 ($p < .01$) were found regarding temperature and rainfall respectively. Fig. 1 shows the location of these meteorological stations in the region of Galicia and of the Rias Baixas PDO in Europe. The shaded areas correspond to the production sub-zones.

Grape yield data (in kg/ha) for the timespan 1990–2017 were provided by the Regulating Council of the Rias Baixas PDO.

In order to evaluate the hedging effectiveness of the weather index-based insurance programmes suggested, a

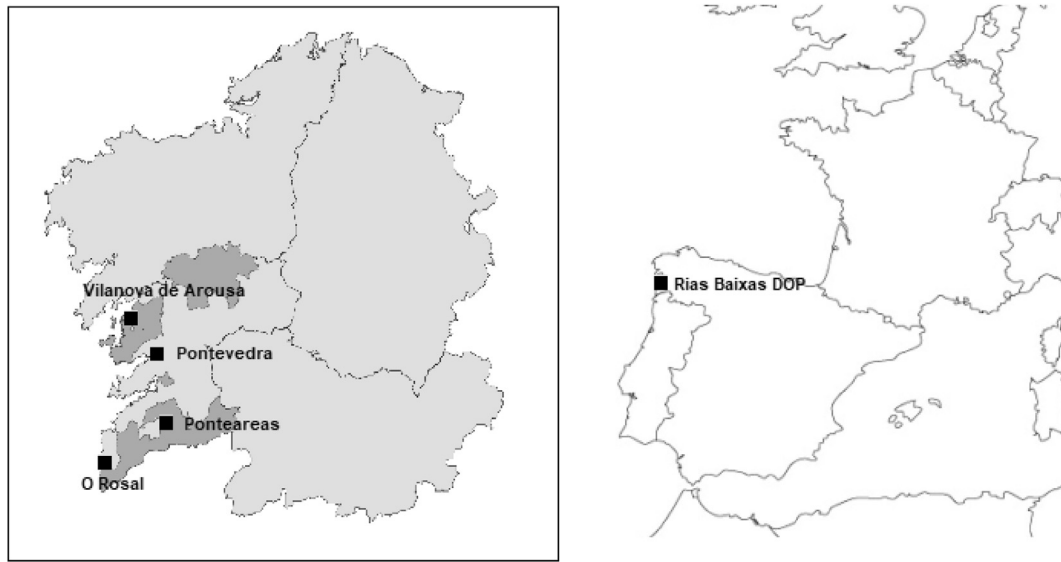


Fig. 1. Location of the Rias Baixas PDO production area and of the meteorological stations considered in the analysis.

stepwise process was followed. First, indices that are strongly and significantly correlated to grape yields were chosen. Then, the relationship between yields and the weather indicators selected was examined. After that, and before the hedging effectiveness could be quantified, the insurance policies were priced based on the results derived from the previous step. The elements of this analysis are summarised in Fig. 2.

2.1. On the selection of weather indices

Bioclimatic indicators have been generally used for viticulture zoning. Some of them include only one factor, such as the Winkler (WI) and Huglin (HI) indices, which account for the accumulated heat over the growing period. Other available indicators compile both temperature and rainfall factors, such as the Branas, Bernon and Levadoux (BBL) and the Ribéreau-Gayon and Peynaud hydrothermal scale (RGP).

The WI and HI may be suitable underlying variables for weather index-based insurance when there is a substantial level of basis risk for rainfall (Zara, 2010, p.235). However, given the high correlation in terms of precipitation between the main Rias Baixas PDO producing areas and the meteorological station of Pontevedra, the BBL and RGP indicators were selected as underlyings. Indeed, they showed higher levels of correlation to grape yields.

The BBL index is computed as:

$$BBL = \sum_{j=1}^J T_j R_j \quad (1)$$

where j denotes the month, which ranges between April and August; T_j is the mean monthly temperature on month j ; and R_j is the cumulative monthly rainfall on month j .

The RGP index is calculated as:

$$RGP = \sum_{i=1}^I \max\{T_i - 10; 0\} - R_i \quad (2)$$

where i denotes the day and is comprised between April 1 and October 30; T_i is the mean daily temperature on day i , which is given by $\frac{T_{i(\min)} + T_{i(\max)}}{2}$; and R_i is the cumulative daily rainfall on day i .

The design of an effective weather index-based insurance programme relies on the selection of a measure as correlated as possible to the yield. Thus, both hydrothermal indicators were not only calculated for their standard periods but also for different timespans. Regarding BBL, the Kendall rank correlation coefficient increased from -0.40 ($p < .01$) to -0.56 ($p < .01$) when the calculation period was April–June instead of April–August. Concerning RGP, this correlation coefficient raised from 0.41 ($p < .01$) to 0.63 ($p < .01$) when the computation timespan was April–August instead of April–October. Therefore, these modified indicators were used as underlyings.

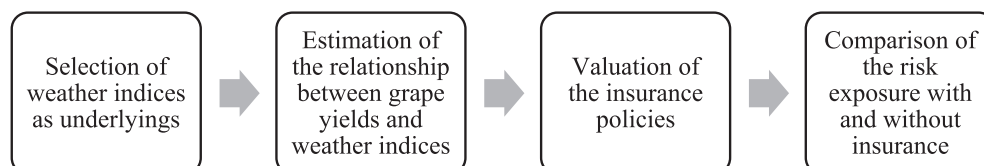


Fig. 2. Steps of the hedging effectiveness analysis of weather index-based insurance.

Figs. 3 and 4 depict the evolution of the grape yield and meteorological indices data over the period 1990–2017. Summary statistics of these three variables can be found in Table A1 of the Appendix.

Fig. 3 shows a clear increasing trend for grape yields, which is verified by the results of the non-parametric Mann-Kendall test ($p < .01$). This may be explained by the technological development that winery has experienced over the last decades. However, before concluding this, the evolution of the meteorological indices needs to be considered, as climate change could have also had some effect on their development. In that case, this phenomenon might be related to a certain extent to the grape yields' upward trend.

The analysis of the evolution of the bioclimatic indices displayed in Fig. 4 shows that neither BBL nor RGP seem to follow a trend. This was further explored by applying the Mann-Kendall test, whose outcomes supported the graphical findings for both indices ($p > .05$). For their part, the Augmented Dickey-Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were used to analyse the presence of a unit root and stationarity. For both series, results led to rejection of the existence of a unit-root ($p < .01$) and non-rejection of stationarity ($p > .05$). Autocorrelation was also assessed graphically through the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Figs. A1 and A2 of the Appendix display the correlograms for

estimated with the algorithm introduced in Bai and Perron (2003) and their optimal number was computed following the Bellman principle. This assessment did not reveal the presence of any structural break.

At the light of these results, there is no evidence that the increasing trend in grape yields is related to the effect of climate change or any particular behaviour of the bioclimatic indices. Thus, this study considers that the upward trend is mainly explained by technological development. Accordingly, the relationship between yield and weather evaluated in the next section was estimated using detrended yield data.

2.2. On the estimation of the relationship between yield and weather

The computation of insurance payoffs requires the accurate characterisation of the relationship between the detrended yield and weather. This allows the estimation of the expected detrended yield conditioned on the occurrence of adverse weather events. In this article, two insurance modalities were suggested.

The Insurance Type I covers both extreme and non-extreme weather conditions and was designed to provide a different indemnity for certain ranges of the bioclimatic index. The expected detrended yield ($\mu_{p,p+0.1}^*$) is expressed as follows for each of the ranges considered:

$$\check{\mu}_{p,p+0.1}^* = \check{\mu}_{p,p+0.1|q_p(W) \leq W < q_{p+0.1}(W)} = E(Q^{det} | q_p(W) \leq W < q_{p+0.1}(W)) \quad (3)$$

BBL and RGP respectively, which indicate that no autoregressive or moving average terms are needed. Finally, the presence of structural breaks was also tested. The breaks were

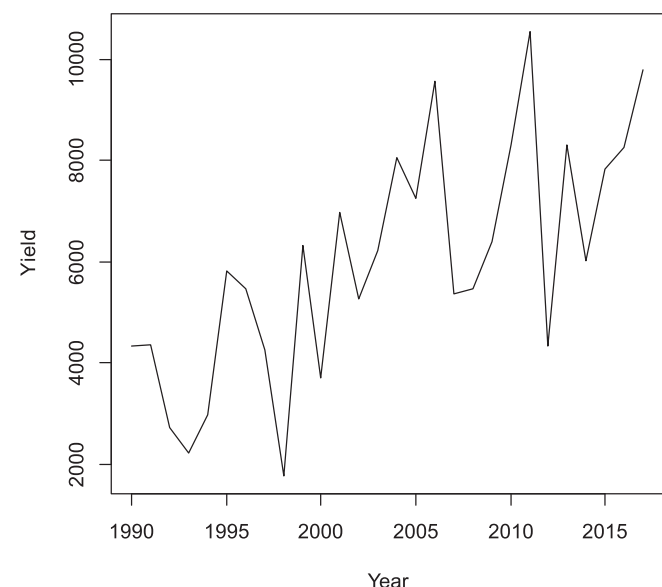


Fig. 3. Yield evolution (1990–2017).

where Q^{det} denotes detrended yield, W is the weather index, E corresponds to the expectation operator and q_p denotes the p -quantile, with $0 \leq p \leq 1$.

The Insurance Type II offers hedge against extreme meteorological events. Thus, it makes necessary the computation of the expected detrended yield when extreme weather states are recorded. If the correlation between the detrended yield and weather is positive, this measure is derived as:

$$\check{\mu}_{0,p}^* = \check{\mu}_{0,p|W \leq q_p(W)} = E(Q^{det} | W \leq q_p(W)) \quad (4)$$

On the contrary, if the correlation is negative, it is computed as:

$$\check{\mu}_{p,1}^* = \check{\mu}_{p,1|W \geq q_p(W)} = E(Q^{det} | W \geq q_p(W)) \quad (5)$$

As mentioned in Section 1, two methodologies were applied to capture yield-weather dependence and consequently, to derive the expected detrended yields of the insurance modalities proposed: copulas and linear regression.

The application of copulas has been extensively contemplated in Integrated Risk Management as a method to deal with deviations from the normal distribution behaviour and the existence of heavy tails (Embrechts et al., 2003, p.331). Recently, this methodology has been considered in some

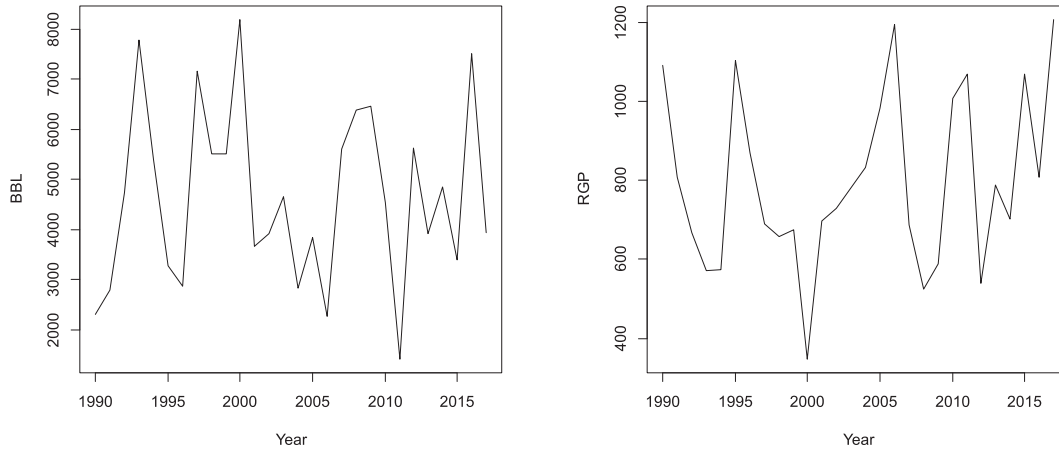


Fig. 4. BBL (left-hand side) and RGP (right-hand side) evolution (1990–2017).

agricultural applications (Bokusheva, 2011, 2018; Goodwin and Hungerford, 2015; Bokusheva et al., 2016).

Copula theory dates back to Sklar (1959), who demonstrated that a n -dimensional distribution function can be decomposed into two parts: the marginal distributions and a dependence function. Thus, according to Sklar's theorem, considering two random variables X and Y with marginals $F_X(x)$ and $F_Y(y)$, the joint distribution $F_{XY}(x, y)$ is:

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)) \quad (6)$$

where $C(F_X(x), F_Y(y))$ is a copula that captures the dependence between X and Y (Reboredo, 2011, p.949).

There are several advantages to using copulas to analyse yield-weather dependence (Reboredo, 2011, p.949). First, they model the marginal behaviour of the random variables separately and thus, allow for flexibility in the description and estimation of margins. Second, the copula function not only captures the level but also the structure of dependence. Therefore, this methodology is expected to improve the results attained using simple linear correlation, which analyses how random variables “move together on average across marginal distributions assuming multivariate normality” (Reboredo, 2011, p.949).

In this study, parametric copulas were examined, which consist of elliptical and Archimedean classes. Elliptical copulas, such as the Gaussian and t -copulas, do not have a closed form and are restricted to have radial symmetry, whereas Archimedean copulas have a close form and allow for a number of different dependent structures (Embrechts et al., 2003, p.2, p.365). This last typology comprises families such as Frank, Joe, Clayton and Gumbel.

According to the copula approach, the joint distribution of Q^{det} and W can be described by a parametric copula $C(u, v; \theta)$, where $u = F_{Q^{det}}(q^{det})$, $v = F_W(w)$ and θ is the copula parameter. This definition allows the computation of $\mu^*_{p,p+0.1}$, and $\mu^*_{0,p}\mu^*_{p,1}$, which were derived in this article from the marginal expected shortfall expression introduced in Jiang (2012, p.13) and Eckernkemper (2018, p.91).

The results obtained from this method were compared to those generated using simple linear regression. The payoffs were conditioned on the same thresholds of the hydrothermal indices as in the copula approach.

2.3. On the valuation of weather index-based insurance

The methodology introduced in Section 2.2 allows the estimation of the expected detrended yield value conditioned on a hydrothermal index and thus, the calculation of the insurance payoff.

The indemnity of the Insurance Type I based on BBL was computed as:

$$I^I_{t, BBL} = \begin{cases} K - \check{\mu}^*_{0.9,1t} & \text{if } BBL_t \geq q_{0.9}(BBL) \\ K - \check{\mu}^*_{p,p+0.1t} & \text{if } q_p(BBL) \leq BBL_t < q_{p+0.1}(BBL) \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where t denotes the year and p takes the values 0.5, 0.6, 0.7 and 0.8.

Equivalently, the indemnity of this insurance typology based on RGP was derived as follows:

$$I^I_{t, RGP} = \begin{cases} K - \check{\mu}^*_{0.0,1t} & \text{if } RGP_t < q_{0.1}(RGP) \\ K - \check{\mu}^*_{p,p+0.1t} & \text{if } q_p(RGP) \leq RGP_t < q_{p+0.1}(RGP) \\ K - \check{\mu}^*_{0.4,0.5t} & \text{if } q_{0.4}(RGP) \leq RGP_t \leq q_{0.5}(RGP) \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where p takes the values 0.1, 0.2 and 0.3.

The payoff of the Insurance Type II based on BBL was calculated in the following form:

$$I_{t, BBL}^{II} = \begin{cases} K - \check{\mu}_{p, 1t}^* & \text{if } BBL_t \geq q_p(BBL) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where p takes the value 0.7.

While the indemnity of the insurance based on RGP was derived as:

$$I_{t, RGP}^{II} = \begin{cases} K - \check{\mu}_{0, pt}^* & \text{if } RGP_t \leq q_d(RGP) \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where p takes the value 0.3.

The fair premium (π) was calculated as the expected value of the insurance payoff.

2.4. On the estimation of the hedging effectiveness

The risk-reducing effectiveness of both insurance modalities was evaluated based on two different criteria: variance and expected shortfall (ES). These measures were computed for the insured and uninsured detrended yield. The price effect was not considered as it might distort results. Thus, this research examined the risk reducing ability purely derived from the implementation of weather index-based insurance.

The insured detrended yield (Q_t^{det}) for each year t was calculated by adding the indemnity to the uninsured detrended yield and subtracting the insurance premium.

The expected shortfall was calculated in the following form for the insured and uninsured detrended yield:

$$ES_{\alpha}(Q_t^{det}) = \frac{1}{\alpha} \int_0^{\alpha} q_p(Q^{det}) dp \quad (11)$$

$$ES_{\alpha}(Q_t^{det}) = \frac{1}{\alpha} \int_0^{\alpha} q_p(Q^{det}) dp \quad (12)$$

where $0 \leq \alpha \leq 1$ and q_p is the p -quantile.

The hedging effectiveness analysis was applied to the real detrended yield samples. Additionally, 10000 simulated values of the detrended yield were generated from the copula and linear regression approaches.

3. Empirical procedure

Five different copula models were employed to estimate yield-weather dependence: Gaussian, Frank, Joe, Gumbel and Clayton.² Regarding the Archimedean classes, 90° and 270°

² Gaussian and Frank classes require the same degree of dependence in both corners of the copula, meanwhile Joe, Gumbel and Clayton are used to model asymmetric joint distributions.

rotated versions were considered to capture dependence between the detrended yield and BBL, while non-rotated and survival copulas were tested to describe the relationship between the detrended yield and RGP. The marginals were modelled using empirical distributions, thus following a non-parametric approach.

The copula parameter was estimated through the inversion of Kendall's tau technique and the most appropriate copula was then selected using the Cramer-von-Mises criterion. As explained in Genest et al. (1995), the Kendall's tau inference procedure requires significantly lower computational effort than the maximum likelihood technique and produces consistent results in the bivariate case. The specific assumptions under which it can be applied hold here (Brahimi and Necir, 2012, pp.476–477).

Table 1 displays the estimated dependence parameters of the copula models considered as well as the p -values of the Cramer-von-Mises test statistic. The results indicate the Frank as the most suitable copula to capture dependence between the detrended yield and each of the bioclimatic indices under study.

Figs. 5 and 6 show the densities and contour plots of the Frank copulas modelling dependence between the detrended yield and the BBL and RGP indices respectively.

Regarding the linear regression methodology, the relationship between the detrended yield and weather was captured through the following model:

$$Q_t^{det} = c + bW_t + e_t \quad (13)$$

where W is the bioclimatic index and t denotes the year.

Table 2 shows the parameter estimates and the explanatory power of model (13) when W takes the form of BBL and RGP.

Hedging effectiveness was evaluated based on both real and simulated detrended yield data. Concerning the copula approach, random values of u and v were first generated from the selected copula (in this case the Frank) and its estimate, using the R command `rCopula()` of the package “copula”. Next, it was checked that the correlation between the simulated values was preserved. Finally, they were transformed as $F_{Q^{det}}^{-1}(u)$ and $F_w^{-1}(v)$, applying the R command `qemp()` of the package “EnvStats”.

Regarding linear regression, random paths were drawn from (13). Values of both hydrothermal indices were first generated based on their empirical distributions, using the R command `remp()`. The driving noise process was then modelled with normally distributed random variables, applying the Excel command `INV.NORM()` with the mean and standard deviation of the residuals and a random generated probability. The Jarque-Bera test results of the residuals are displayed in Table A2 of the Appendix.

4. Results and discussion

This section compares the hedging effectiveness ability of the insurance modalities suggested based on real and simulated data.

Table 1
Copula dependence parameter estimates.

Detrended yield-BBL								
	Normal	Frank	Clayton (r90)	Clayton (r270)	Gumbel (r90)	Gumbel (r270)	Joe (r90)	Joe (r270)
Param.	−0.77 (0.29020)	−6.97 (0.43407)	−2.55 (0.23626)	−2.55 (0.01349)	−2.28 (0.33217)	−2.28 (0.32617)	−3.39 (0.09241)	−3.39 (0.4001)
Detrended yield-RGP								
	Normal	Frank	Clayton	Clayton (surv.)	Gumbel	Gumbel (surv.)	Joe	Joe (surv.)
Param.	0.84 (0.34316)	8.78 (0.58791)	3.4 (0.08541)	3.4 (0.02647)	2.7 (0.34416)	2.7 (0.34715)	4.22 (0.16434)	4.22 (0.36713)

Notes: Param. stands for the copula dependence parameter, surv. for survival and r for rotated. P-values of the Cramer-Von-Misses test are given in parenthesis.

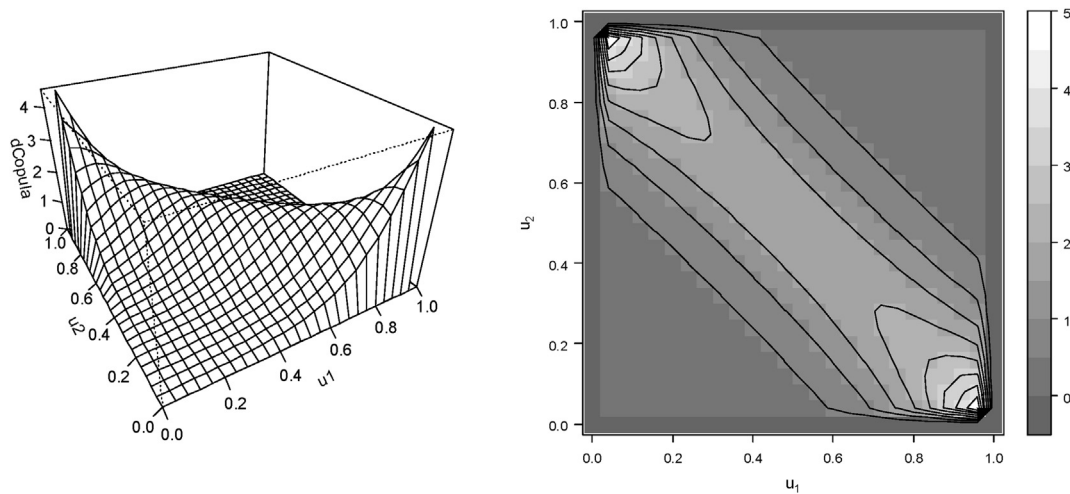


Fig. 5. Density (left-hand side) and contour plot (right-hand side) of the Frank copula modelling detrended yield-BBL dependence.

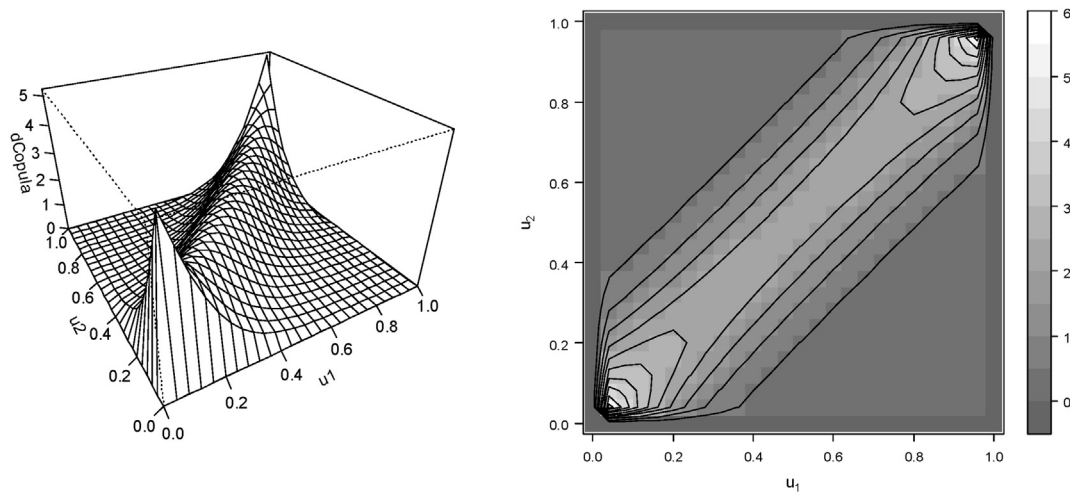


Fig. 6. Density (left-hand side) and contour plot (right-hand side) of the Frank copula modelling detrended yield-RGP dependence.

Table 3 displays the risk reducing effects as measured by variance as well as the p-values of the Fligner-Killeen test for homogeneity of variances. Our results suggest the high hedging effectiveness potential of both insurance modalities, especially when the copula approach is used to model yield-weather dependence. Based on the real sample, this methodology provides risk reductions of up to 34% and 38% for BBL-

based policies and of up to 43% and 35% for RGP-based contracts regarding the Insurance Types I and II respectively. These positive conclusions in terms of hedging potential are somewhat impaired by the test results, as only the RGP-based Insurance Type I leads to significant non-homogeneous variances ($p < .05$). The other typologies, modelled with the copula technique, yield significant results at the 10% level.

Table 2
Values of the coefficients and statistical results of the regression models.

	BBL	RGP
C	6328.473 (0.00000)	−947.8221 (0.2585)
B	−0.644600 (0.00000)	5.377860 (0.00000)
Adjusted R2	0.470128	0.511023
Prob (F-statistic)	0.000034	0.000012

Notes: P-values are given in parenthesis. The constant term of the yield-RGP model is not significant, which can be explained by the fact that the yield cannot be negative. However, it was not removed as it helps checking the sensitivity to RGP.

The test outcomes might be affected by the sample size as observations are only available for the period 1990–2017. The reliability of the hedging potential and the test results are thus expected to improve with the simulated samples, which are based on 10000 values. Indeed, more favourable hedging effects are attained with simulated data, as measured by the risk reducing extent and its significance. With the copula technique, figures of up to 41% and 34% are derived regarding BBL-based policies ($p < .01$ and $p < .05$) for the Insurance Types I and II respectively, while values of up to 47% and 40% ($p < .01$) are reached for RGP-geared contracts.

In line with the previous findings, Table 4 shows the high hedging ability of the insurance modalities suggested. Concretely, it demonstrates their strong downside risk reducing potential as evaluated by expected shortfall, especially the lower the value of α . As with the variance criterion, this measure indicates the copula as a superior method to capture and model dependence. Based on the simulated sample and on this methodology, the Insurance Type I is favoured for both BBL and RGP-based contracts, with expected shortfall increases over 300 and 500 units respectively based on real data and over 450 and 550 regarding simulated data.

The analysis of the risk reducing potential of both insurance typologies, displayed in Tables 3 and 4, points at the Insurance Type I as the most suitable option. The appropriateness of this modality is further explored through its loss-indemnity correlation in Table 5. Significant and strong Spearman's rank coefficients are derived for both BBL and RGP-geared policies, either based on real or simulated data. However, the RGP-based typology, for which correlation decreases with the simulated sample but still remains at the substantial level of 0.77, is revealed as superior.

Table 3
Downside risk reduction estimates of weather index-based insurance as measured by variance.

Index	Insurance Type I		Insurance Type II	
	Copula	LR	Copula	LR
Real data				
BBL	34% (0.08305)	24% (0.24048)	38% (0.07789)	36% (0.08451)
RGP	43% (0.03529)	38% (0.06509)	35% (0.09484)	30% (0.13345)
Simulated data				
BBL	41% (0.00911)	30% (0.08338)	34% (0.03035)	30% (0.10074)
RGP	47% (0.00132)	33% (0.0671)	40% (0.00728)	26% (0.17228)

Notes: LR stands for linear regression. P-values of the Fligner-Killeen test are given in parenthesis.

The outcomes of Tables 3–5 point unequivocally at the Insurance Type I based on the RGP indicator and dependence modelled with the copula approach as the most suitable alternative. The RGP, computed for the period April–August, is actually the index most strongly and significantly correlated to the detrended yield of those considered. Our results highlight thus the importance of choosing the right underlying to accurately mitigate basis risk,³ which is one of the main concerns refraining the development of a market for weather index-based insurance.

This article demonstrates that the use of the relative recent methodology of copulas in agricultural insurance practises may outperform linear regression. Specifically, our outcomes show that the application of the insurance policies proposed with dependence modelled through this approach may be highly beneficial for the Rias Baixas PDO wine-growing industry. These results become even more favourable taking into account that the indices proposed as underlyings are simple and effortless to construct. In fact, both BBL and RGP have been generally used for viticulture zoning. Furthermore, this research overcomes one of the main difficulties of the hedging strategy building process suggested by other authors, which is the need of selecting the optimal number of contracts, which may even render these instruments unfeasible. In fact, the programmes designed in this study are significantly simpler and only require the acquisition of the policies that cover the most sensitive production period.

Despite the positive results here attained, it should be noted that this study has not been based on individual farms data but on the whole Rias Baixas PDO average yield. Thus, the actual risk reducing ability may vary as the risk exposure at an individual firm might differ from the effect experienced at the county level. Accordingly, further research based on disaggregated data would be needed before stating policy implications for the insurance sector and concluding about the risk hedging ability of the suggested insurance modalities. This research validates two relevant methodological approaches, linear regression and copulas, and makes special emphasis on the high value of the second technique. In fact, it is shown that copulas allow for greater flexibility and capture yield-weather dependence more precisely. Thus, this article represents a valuable example on their promising potential for insurance design and valuation applications in viticulture.

5. Conclusion

This article explored the applicability of two weather index-based insurance modalities to cover grape yield losses of the Rias Baixas PDO. The first alternative was designed to provide a hedge against both extreme and non-extreme adverse meteorological states, while the second instrument was planned to insure exclusively extreme weather events.

³ Basis risk can be defined as “the risk that payoffs of a given hedging instrument do not correspond to shortfalls in the underlying exposure” (Woodard and García, 2008, p.99).

Table 4

Downside risk reduction estimates of weather index-based insurance as measured by Expected shortfall (ES).

Index	No insurance	Insurance Type I				Insurance Type II			
		Copula	Change	LR	Change	Copula	Change	LR	Change
Real data									
ES0.3									
BBL	1386.17	1726.99	340.83	1587.97	201.81	1781.00	394.83	1768.26	382.10
RGP	1386.17	1921.86	535.70	1890.68	504.519	1813.52	427.36	1801.46	415.30
ES0.2									
BBL	1032.13	1354.25	322.13	1165.69	133.56	1403.90	371.77	1398.29	366.16
RGP	1032.13	1575.54	543.41	1536.27	504.15	1471.99	439.86	1448.99	416.86
ES0.1									
BBL	386.46	687.37	300.91	392.68	6.22	973.86	587.40	926.75	540.29
RGP	386.46	982.30	595.84	927.61	541.15	1008.99	622.54	891.95	505.50
Simulated data									
ES0.3									
BBL	1386.17	1842.97	456.81	1692.92	306.75	1734.74	348.57	1756.04	369.87
RGP	1386.17	1954.24	568.08	1793.07	406.90	1821.07	434.90	1693.54	307.37
ES0.2									
BBL	1032.13	1539.01	506.88	1374.93	342.80	1392.05	359.92	1430.86	398.73
RGP	1032.13	1685.12	652.99	1493.02	460.90	1517.37	485.25	1377.65	345.52
ES0.1									
BBL	386.46	1093.16	706.71	911.40	524.94	963.85	577.39	960.16	573.70
RGP	386.46	1272.96	886.50	1060.27	673.81	1095.35	708.90	917.32	530.86

Notes: LR stands for linear regression. Higher (lower) ES corresponds to lower (higher) risk exposure.

Table 5

Loss-indemnity correlation of the Insurance Type I as measured by the Spearman's rank coefficient.

Index	Real data	Simulated data
BBL	0.7545866 (0.00000)	0.7158559 (0.00000)
RGP	0.8136685 (0.00000)	0.7689534 (0.00000)

Notes: P-values of the correlation test are given in parenthesis.

Two hydrothermal indices, the BBL and RGP, were suggested as underlyings and computed for the periods with higher yield dependence.

Two different methodologies were applied and compared to estimate the relationship between weather indices and yield: linear regression, which has been the most commonly used in the related agricultural literature; and the most recent technique of copulas, which allows the accurate modelling of the degree and structure of dependence. Regarding this last approach, the Frank copula was selected as the alternative that better captured both the BBL and RGP-yield dependencies. The hedging effectiveness was then evaluated based on real and simulated data.

Our analysis revealed that the application of weather index-based insurance policies in the Rias Baixas PDO wine-growing area may be very beneficial and efficiently reduce weather risk exposure, as measured by grape yield variance and expected shortfall. The insurance modality designed to cover both extreme and non-extreme adverse weather states based on the RGP indicator yielded better results in terms of risk reducing ability. Furthermore, the copula approach outperformed linear regression.

In conclusion, the results of this article suggest the high potential for the use of weather index-based insurance in winery through an empirical application to the Rias Baixas PDO. Before its implementation, the institutional framework as well as other design issues, such as the most appropriate distribution vehicle, should be thoroughly considered. Future lines of research may explore farmers' willingness to pay as well as attitudes and impressions towards this insurance instrument. It would also be interesting that the copula approach, as a method to design and rate policies, was further explored by applying it to other regions and appellations of origin.

Conflict of interest

This research is funded by a grant awarded to Andrea Martínez Salgueiro by “la Caixa” Foundation in its “Doctoral Scholarship Programme 2016”. This institution, which encourages the publication of research results, had no other involvement in the development of this study.

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Appendix.

Table A1

Summary statistics of detrended grape yields, BBL (April–June) and RGP (April–August).

	Yield	BBL (April–June)	RGP (April–August)
Mean	3329.516	4652.433	795.3607
Median	3391.726	4598.025	755.7500
Std. Dev	1638.803	1779.202	221.6664
Skewness	−0.120353	0.279695	0.273775
Kurtosis	0.518633	2.281322	2.282065

Table A2

Jarque-Bera test results of the regression models residuals.

	BBL	RGP
Test statistic	2.270308	0.294742
P-value	0.321363	0.862974

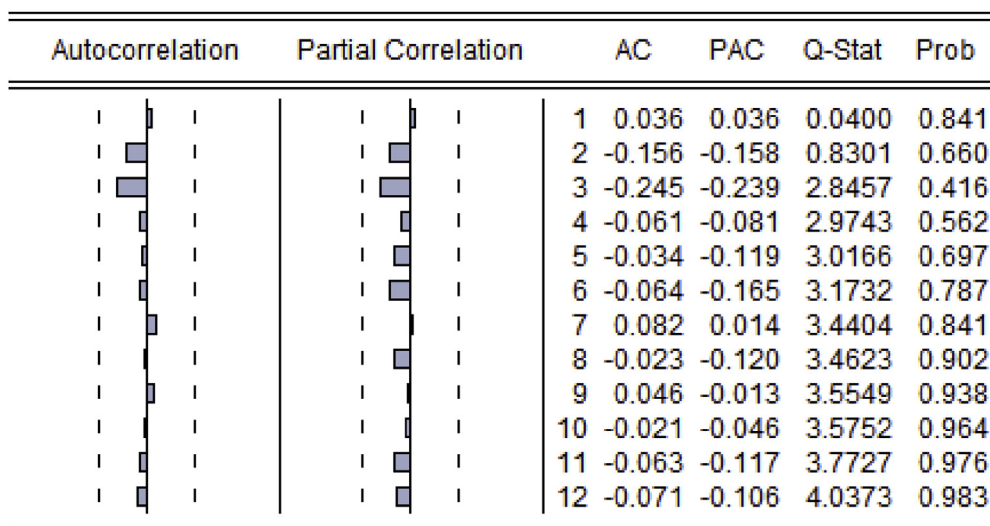


Fig. A1. BBL correlogram.

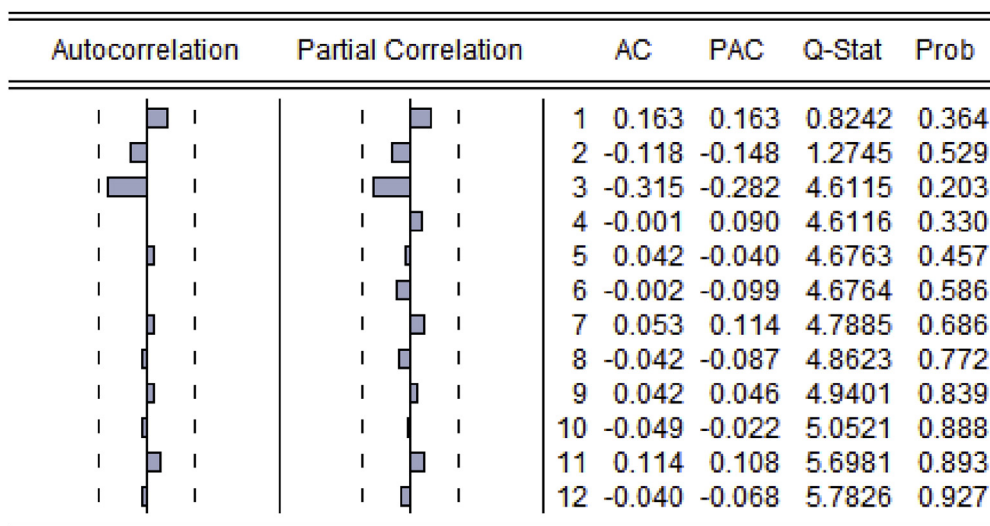


Fig. A2. RGP correlogram.

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