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Designing a whole-farm revenue insurance for agricultural crops in Zanjan province of Iran

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ABSTRACT: The purpose of this article is to design and empirically evaluate the Whole Farm Insurance (WFI) over the conventional insurance programs in Zanjan province of Iran. Historical farm-level and county-level data were used to estimate yield and price density functions. Both parametric and nonparametric methods were applied for predicting the future values and the PQH simulation method was utilized to calculate premium rates. Results revealed that loss ratios of the WFI are lower for farmers who insured more than one crop. Additionally, utilizing WFI reduces premiums. Moreover, premiums obtained from nonparametric method are relatively lower compared to the parametric approachy.

KEYWORDS: Indemnity, Iran, price risk, whole-farm insurance, yield risk, Zanjan.

Diseño de un seguro de ingresos de toda la granja para cultivos agrícolas en la provincia de Zanjan de Irán

RESUMEN: El propósito de este artículo es diseñar y evaluar empíricamente el Seguro Agrario Integral (SAI) con respecto a los programas de seguros convencionales en la provincia de Zanjan de Irán. Se usaron datos históricos a nivel de explotación y de comarca para estimar las funciones de rendimiento y de densidad de precios. Se aplicaron métodos paramétricos y no paramétricos para predecir los valores futuros y se utilizó el método de simulación SAI para calcular las tasas de primas. Los resultados revelaron que los índices de pérdida del SAI son más bajos para los agricultores que aseguraron más de un cultivo. Además, la utilización del SAI reduce las primas. Las primas obtenidas del método no paramétrico son relativamente más bajas en comparación con el enfoque paramétrico.

PALABRAS CLAVE: Indemnización, Irán, riesgo de precio, seguro de granja completa, riesgo de rendimiento, Zanjan.

JEL classification/Clasificación JEL: G22, C15, C53, C63.

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1. Introduction

Agriculture is inherently a risky business. Risk is defined as uncertain adverse consequences, while uncertainty is imperfect knowledge. In mathematical terms, risk is described by the probability distribution function of an outcome variable (Hardaker *et al.,* 2004). There are two main issues on the importance of the risk in agriculture. First, most farmers have some degree of risk aversion when faced with significantly risky returns. A risk-averse farmer is willing to give up some expected return for a reduction in risk. The second issue is the fact that sometimes the nature has a tendency to be unkind to farmers, in the way that what they gain in the good years rarely compensates for the losses in the bad years (Hardaker *et al.*, 2004; Roberts *et al.,* 2004).

Risk management strategies are of great importance in agriculture. Two major risks are significant to the agricultural sector owing to their influence on farmers' financial returns. Price risk is caused by volatility in prices and production risk stems mostly from uncertainty about the levels of production. Enjolras *et al.* (2014) argued that income volatility mainly depends on the production conditions found on the farm and concluded that risk management tools can clearly be counterproductive and should be applied cautiously. Although agricultural risk is inescapable and cannot be totally eliminated, it can be managed and reduced. Among the strategies available for risk management in agriculture, crop insurance is more common and has a long history. But there are some issues in this respect that must be considered. Meanwhile, adverse selection and moral hazard are two ingrained issues in developing a crop insurance product due to the hidden information and unknown behavior of the insured farmers (Skees *et al.*, 2008).

Crop insurance is by far the most popular risk management tool used in Iran. Moreover, it is a topic of interest to farmers, policy makers and Agricultural Insurance Fund. The agricultural insurance fund in Iran, despite many years of experience has not managed to protect all the producers in the sector. For example, only almost 2.12 million out of the 4.5 million farmers have insured their farms in 2013-14 crop year. Similarly, in Zanjan less than 50 percent of the farmers are under the coverage of agricultural insurance fund (Agricultural Insurance Fund, 2014). Furthermore, the value of loss ratio for the agricultural insurance fund is approximately 1.4 that implies the fund is not profitable. On the other hand, the traditional insurance policy has not achieved to meet the projected objectives such as economic security for farmers, attract investment and ensure a proper growth for the sector. One of the most important factors in this regard is the insufficient flexibility in the policies proposed by the Agricultural Insurance Fund. Accordingly, it is necessary to evaluate and adopt the new emerging insurance policies. In this line, the current study posits a new approach to farm insurance named whole farm income insurance (WFI) for Zanjan province in Iran.

Modern risk management in agriculture is rapidly becoming concentrated on whole farm income insurance. The underlying principle of whole farm insurance is to pool all the insurable risks of a farm into a single policy. In the WFI the insurer and the insured must balance a large number of random variables including yield risk, price risk, and their correlations (Turvey, 2012). Since most crop risks do not perfectly

covariate, WFI provides a more efficient coverage than insuring each crop with a specific policy. This is because WFI provides coverage for the whole farm's revenues or margins, which are good proxies of farmers' profitability. Its justification is based on simple diversification and portfolio management (Mahul and Wright, 2003). DiFalco *et al.* (2014) found that crop diversification and financial insurance can both be significant tools for risk management at the farm level, and that the estimated parameters connected to these two variables are very similar for the three-first moments of the distribution of profits. Following Hennessy *et al.* (1997), if a farm grows two crops, a policy insurance based on the farm's total revenue will be cheaper than the sum of the premiums of two individual insurances for the same expected revenue.

Whole farm insurance is frequently proposed as a theoretically effective alternative to commodity specific insurance. It is attractive to policy makers and farmers because can pool all price and yield risks of a farm into a single insurance policy and provide insurance more cheaply as compared to commodity-specific revenue insurance or any individual price and yield insurance products (Coble and Miller, 2006). In addition, it overcomes most of the major impediments to existing policies. Another important issue is indemnity payments to farmers during the studied years were more than received premiums. In other words, loss ratio for Iranian Agricultural Insurance Fund has been greater than one during the period 2002-2014. Despite a downward trend in the loss ratio and a comparative improvement in performance of the fund, it is not efficient enough to cover all the producers in the sector. On the other hand, the current insurance program has not managed to assure farmers economically, stabilize investment and ensure the country's agricultural growth. One of the most important factors in this context is not enough variety in the programs offered by the Agricultural Insurance Fund.

Traditional agricultural insurance program is subject to deviate from Pareto optimality due to lack of full information. Two different sources of deviations from Pareto optimality are moral hazard and adverse selection. Moral hazard is an alteration in input use which deviates from social optimality and occurs because the insured can take actions which affect the probability of losses and cannot be observed by the insurer. Quiggin *et al.* (1993); Smith and Goodwin (1996); Babcock and Hennessy (1996); Coble *et al.* (1997) and Goodwin and Smith (2003) have shown that moral hazard exists with respect to crop insurance. Adverse selection occurs when due to information asymmetry, farmers with higher risk of loss incline to insure their crops than the general population (Nelson and Loehman, 1987). As a result the contract is priced too high to the producers with below average risks of loss, but too low for those with above average risks. In such a case, losses and premium rates eventually increase and more farmers drive out from the insurance market. Santeramo *et al.* (2016) argued that the expected loss ratio plays a significant role in the farmer's participation to insurance program and demonstrated that contrary to prior expectations, higher expected loss ratios correspond to a lower likelihood of participation and to a more probability of exit. Although these two problems and correlated risks are not unique to crop insurance but addressing these issues for crop insurance is more costly due to the high costs of monitoring agricultural production (Goodwin and Smith, 1995).

The primary objective of this study was to introduce and then estimate the premium rate, sum insured and aggregate limit of indemnity for the whole farm insurance contracts of wheat, barley and alfalfa in Zanjan province of Iran. The contribution of this study is to present a new farm insurance product and also a suitable model to simulate prices and yields of crops in the region in addition to evaluate its performance over the traditional insurance program. Additionally, to provide a stepping stone for policy makers to consider the proposed insurance plans or indemnity funds for implementation in order to better address the farming risks.

2. Literature review

Since whole farm insurance is a new policy, so only a few studies are available in this topic. Hennessy *et al.* (1997) noted that the whole-farm revenue insurance is advantageous for farmers than other insurance products because it leads to lesser risk and hence lower premiums. Stokes *et al.* (1997) also found that whole farm revenue insurance is more efficient than the summation of crop-specific revenue insurance. Also Skees and Nutt (1988) used Monte Carlo simulation to examine the influence of crop insurance premium rates and demonstrated that the cost of crop insurance becomes an important issue as yield risk and initial debt levels increase. Meuwissen *et al.* (2000) stated that whole-farm insurance is more attractive to the producers in comparison to other insuring products because it is convenient for optimizing the welfare of the farm family.

Hart *et al.* (2006) designed whole farm revenue insurance programs and estimated the probability density function of the prices and yields using the Monte Carlo simulation method. Their results indicated that at coverage levels of 95 % or lower, the fair insurance premiums for this type of insurance, are far lower than the fair premiums for corn alone on the same farm. Coble and Miller (2006) mentioned that the whole farm insurance up to 70 percent coverage level falls under the WTO Amber box; therefore it is WTO-compliant as well. Zhu *et al.* (2008) noted that the premium of WFI is not as much of the combination of the two crop-specific revenue insurance. Bielza and Garrido (2009) compared separated multi-peril crop-specific insurance policies with whole farm insurance and concluded that loss ratios are lower for farmers who insure more than one crop. Moreover, premiums are reduced by 20 percent and farmer's certainty equivalents are slightly larger.

Turvey (2010) studied Whole Farm Income Insurance in a Canadian agriculture. His results indicated that farmers will alter farm plans significantly in response to the type of insurance offered and the level of subsidy. Chalise (2011) designed a customizable area whole farm insurance (CAWFI) model and tested on representative farms in four states including Kansas, North Dakota, Illinois, and Mississippi, producing three crops, corn, wheat and soybean and concluded that the optimal CAWFI outperforms both no insurance and restricted CAWFI programs. In addition, it results in a risk reduction roughly equal with 90 % farm-level whole-farm insurance though the expected indemnities in it are at least three fold.

Coble *et al*. (2013) developed a customizable area whole farm insurance (CAWFI) as a possible alternative to existing insurance designs and found that an optimal CAWFI design generates higher certainty equivalents than the current products. Chalise *et al*. (2017) developed a customizable area-based whole-farm insurance (CAWFI) model for four states of the USA. Their results revealed that a restricted CAWFI design generates significant risk reduction at much lower cost than the Farm-level Whole-Farm Insurance (FWFI).

Whole-Farm Insurance allows farmers to insure all products on the farm under one insurance policy, rather than each individual commodity. It is designed for farms to insure between 50 to 85 % of their gross revenue, up to $ 8.5 million of revenue guaranteed and is available in all 50 states and all counties within each state in the United States.

In general, studies concerning the WFI have indicated that it is superior to crop-specific insurance. But like other policies this product has some disadvantages, too. For example, it is complex to design because it covers price, yield, and price-yield interaction of all the crops grown in a farm. In addition, verifying revenue losses and indemnity payments is very laborious in this policy. In other words, the transaction costs in this program are higher relative to other insurance policies.

3. Materials and Methods

3.1. Customizable Area Whole Farm Insurance (CAWFI) Model

The actual farm revenue based on planted acres under CAWFI is the same as it appears under whole farm insurance computation except that the CAWFI replaces farm yield with county level yield. The expression to estimate CAWFI actual farm revenue is:

$$CAWFI_{\mathrm{R}} = \sum_{i} A_{i,f} \times Y_{i,c} \times P_i \qquad [1]$$

where $CAWFI_{\mathrm{R}}$ represents actual farm revenue under CAWFI. $A_{i,f}$ denotes planted acres of crop i on farm f; P_i is output price of crop i, $Y_{i,c}$ is output quantity per acre of crop i in county c. Guaranteed revenue under CAWFI is estimated as:

$$CAWFI_G = E(CAWFI_{\mathrm{R}}) \times CL \qquad [2]$$

Expectation of price and expectation of county yield are used to determine expected revenue under CAWFI, which are also customized by appropriate weight. Therefore, this equation can be extended as:

$$CAWFI_G = \sum_i \mu_{i,f} \times E(P_i) \times E(Y_{i,c}) \times CL \quad [3]$$

where is guaranteed revenue under CAWFI, $\mu_{i,f}$ is appropriate weight for the planted acres of crops i in the farm f, CL is coverage level, $E(P_i)$ is expected output price for crop i, and $E(Y_{i,c})$ is expected output of crop i in county c. The equation used by Skees *et al.* (1997) to estimate indemnity payout for area yield product GRP is:

$$GRP_{Indem} = Max\left[\left(\frac{GRP_G - GRP_{Yield}}{GRP_G}\right) \times E(GRP_{Yield})(scale), 0\right] \quad [4]$$

where GRP_G is critical area yield in GRP, GRP_{Yield} is area yield in group risk plan (GRP), $E(GRP_{Yield})$ is insurer's forecast of the area yield in GRP (Chalise *et al.*, 2017).

In the GRP model, farmers are restricted to a scale ranging from 0.9 to 1.5 and allowed to select a different scale at that range and are also allowed to select different coverage levels ranging from 0.70 to 0.90. Scale is a multiplier that adjusts the magnitude of the indemnity. The optimal scale in this equation is derived as β_1 from the following equation:

$$y_i = \beta_0 + \beta_1(y_c - E(y_c)) + \varepsilon_i \quad [5]$$

where y_i is the county yield for crop i, $E(y_c)$ is expected county yield for the same crop i, ε_i is the error term. The indemnity is paid only when $y \prec y_c$. The above equations are used here with some extensions. Basically, CAWFI replaces the area yield by area revenue. The indemnity under CAWFI is paid only when CAWFI revenue falls below the guaranteed CAWFI revenue, otherwise indemnity paid would be zero. The equation to estimate indemnity is

$$CAWFI_{Indem} = Max\left[\left\{\frac{CAWFI_G - CAWFI_R}{CAWFI_G}\right\}(ECAWFI_R)(Scale), 0\right] \quad [6]$$

where $CAWFI_{Indem}$ is indemnity under CAWFI model.

The optimal scale is obtained as a beta coefficient, which is a response of county revenue deviation from its mean to farm revenue deviation from its mean. This beta coefficient measures the linear relationship between the county revenue and farm revenue. The error term reflects the basis risk associated with this farm's revenue variability. The scale in the form of β_1 is estimated from the following equation:

$$CFWFI_R - E(CFWFI_R) = \beta_1(CAWFI_R - E(CAWFI_R)) + \varepsilon_i \quad [7]$$

where $CFWFI_R$ is the revenue under whole farm insurance based on farm level yield, $E(CFWFI_R)$ is the expected revenue in CAWFI from multiple crops and $E(CAWFI_R)$ is the expectation of revenue in the farm level.

3.2. Whole Farm Insurance Based on Farm Level Yield (CFWFI) Model

To evaluate the performance of CAWFI, a hypothetical farm-level whole farm policy is also modeled. Farmers are assumed to have the option to buy whole farm insurance based on farm-level yield. The actual farm revenue, guaranteed revenue, and indemnity in whole farm insurance were estimated using the following equation:

$$CFWFI_{\mathrm{R}} = \sum_i A_{i,f} \times P_i \times Y_{i,f} \qquad [8]$$

where, $CFWFI_R$ is actual whole farm revenue, $A_{i,f}$ is planted acres of crop i in the farm f, P_i is output price of crop i, $Y_{i,f}$ is the output of crop i in farm f. The guaranteed revenue in whole farm insurance was estimated as:

$$CFWFI_G = A_{i,f} \times E(P_i) \times E(Y_{i,f}) \times CL \qquad [9]$$

where, $CFWFI_G$ is guaranteed revenue in whole farm insurance, $E(P_i)$ is the expected output price of crop i, $E(Y_{i,f})$ is the expected farm yield for crop i in the farm f, and CL is the insurance coverage level. The indemnity pay out in the whole farm insurance was estimated using the equation:

$$CFWFI_{Indem} = Max\{(CFWFI_G - CFWFI_R), 0\} \qquad [10]$$

Where, $CAWFI$ is the indemnity payout in the whole farm insurance. The indemnity is paid only when the actual farm revenue falls below the guaranteed farm revenue, otherwise indemnity would be zero (Chalise *et al.*, 2017).

3.3. Yield Estimation Approaches

Since WFI intends to stabilize farm revenue then future values of both yields and prices are supposed to be estimated. Crop yields indicate growing trends owing to technological advancements over the years, which implies that data generating process is not stable. Thus, it is not reasonable to compare the yields observed over different periods of time. To address this issue a variety of methods for detrending or normalizing yield data have been proposed. According to Zhu *et al.* (2011), the frequently applied method is a two-stage estimation procedure. In this procedure at first step, the yields are predicted by using parametric or non-parametric models. In the second step the crop yields are detrended. For this purpose a variety of regression models such as linear (Goodwin and Mahul, 2004; Ozaki *et al.,* 2008; Adhikari *et al.*,

2012), quadratic (Lu *et al.,* 2008; Adhikari *et al.*, 2012), and polynomials (Ramirez *et al.*, 2003) have been used in the literature. In addition, Deng *et al.* (2008) and Vedenov and Barnett (2004) applied log-linear model. While Harri *et al.* (2011) and Adhikari *et al*. (2012) applied bilinear spline and knot methods. On the other hand, Ker (1996), Goodwin and Ker (1998), and Ker and Goodwin (2000) used stochastic model such as autoregressive integrative moving average (ARIMA) for the yield prediction.

There are two common methods applicable for yield detrending. These two methods are based on the assumptions of constant and non-constant errors. If the researcher believes the size of the errors is not affected by the level of yields, he/she would add all of the residuals to the reference year (last year of the observation). But if one believed that the deviations from the trend are proportional to the level of yields, one might consider constructing normalized yields as:

$$y_t^{\det} = \frac{y_t}{\hat{y}_t}\hat{y}_T \qquad t = 1,2,....T \qquad [11]$$

where $y_t^{\det}$ is the detrended yield at year t, y_t and $\hat{y}_t$ are the observed and predicted values of the yields respectively; and $\hat{y}_T$ is the predicted value of the yield in the base year. By doing so, the potential heteroscedasticity problem will be corrected as well.

In the context, yield distribution modeling is classified to three broad categories; parametric, semi-parametric and non-parametric methods.

3.4. Parametric Methods

This method is set up on the supposition that the stochastic behavior of the interest variables can be represented by the particular parametric distribution function. Parameters of specified distributions are estimated to describe the probability density or distribution function. The strong point of this approach is that it can perform relatively well even in the small sample size. However, its potential weakness is its less flexibility to model the crop yields precisely. In this method, a particular distribution is presumed to yield distribution and parameters of the specified distribution are estimated using the maximum likelihood method. The commonly applied parametric distributions for the yield distribution modeling are Normal (Goodwin and Mahul, 2004; Sherrick *et al.,* 2004; Ozaki *et al.*, 2008), Weibull (Sherrick *et al.,* 2004) Gamma (Gallagher, 1986), Beta (Nelson and Preckel, 1989; Goodwin and Mahul, 2004; Sherrick *et al.*, 2004; Ozaki *et al.*, 2008; Zhu *et al.*, 2011) , Lognormal (Day, 1965; Sherrick *et al.*, 2004), and logistic (Sherrick *et al.*, 2004).

3.5. Non-Parametric Methods

Another actuarial method to estimate the probability density function of a random variable is the nonparametric analysis. In this case, the researcher lets the data reveal

the shape of the density without giving any prior specification to define the shape of the distribution (Ozaki *et al.*, 2008).

Advantages and disadvantages of this method are contrary to the parametric methods. It is free from functional form assumption and more flexible compared to parametric method. But it is less strong in estimation of small sample size. In addition, this approach is not applicable for prediction outside the sample size. Most non-parametric density estimation applications utilize the kernel method to fit a distribution to the available observations. Kernel density procedures provide flexible means to approximate the unknown underlying distribution with sparse data (Richardson *et al.*, 2010). Kernel distribution is the frequently used non-parametric distribution for modeling crop yields in the literature for example by Goodwin and Ker (1998); Ker and Goodwin (2000), Goodwin and Mahul (2004) and Ozaki *et al.* (2008).

Goodwin and Ker (1998) and Turvey and Zhao (1999) utilized the Kernel estimator to estimate the shape of the conditional yield density and pricing a crop insurance contract. Under the kernel approach, each observation is surrounded by asymmetric weighting function *K* which satisfies the following condition:

$$\int_{-\infty}^{+\infty} K(t)dt = 1 \qquad [12]$$

Usually, the weighting function will be asymmetric probability density function although a variety of alternatives may also be used. There are 10 density functions used in the kernel procedure including Cauchy, cosinus, double exponential, Epanechnikov, Gaussian, Parzen, quartic, triangle, triweight, and uniform (Richardson *et al.*, 2010). Among the mentioned density functions, Gaussian kernel density estimator has been frequently used by the researchers. The Gaussian kernel density places a kernel (or bump) at each yield realization, and then the sum of the densities of the kernels forms the shape of then on-parametric curve. The PDF of the Gaussian kernel density estimator is:

$$f_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad [13]$$

where $K\left(\frac{x - x_i}{h}\right) = 1/\sqrt{2\pi}\, e^{-(x-x_i)^2/2h^2}$ is the Gaussian kernel function and *h* is called the bandwidth or window-width parameter. This parameter specifies the weight to assign to bordering observations in constructing the density and thus corresponds to the amount of smoothing to be done. A larger bandwidth will smooth more and thus will result in a flatter, smoother density function while a small bandwidth will yield a rough and irregular density. Choosing the proper bandwidth parameter is an important step in nonparametric kernel density estimation. A variety of methods

are available in this regard, but Silverman's "rule-of-thumb" is the mostly used in the literature (Goodwin and Ker, 1998; Ozaki *et al.*, 2008).

3.6. Modeling Price Distribution

In revenue insurance, the insurer protects the policy holder from declines in income that is combination of the crop yields and prices. Hence revenue insurance entails forecasting yields and prices at harvest-time in order to construct a premium rate. Crop prices incline to increase over time, especially in developing countries. In such circumstances, it is not reasonable to compare the prices of different periods. In other words, in such a case the residuals are subject to heteroskedasticity. So prior to modeling, it is necessary to segregate the random component in the price series.

In this study, nominal harvest prices received by farmers during the 1983-2014 were obtained from the agricultural ministry website. Then price data series were converted to real data using producer price index (PPI) deflators obtained from the Central Bank of Iran. Because deflated nominal data do not explain the direct impacts of changes in technology and market structure, it is necessary to detrend the data in order separate the random component in the price series. In this study, detrending of price time series were carried out via linear, quadratic, polynomial and Log-linear regression in addition to autoregressive integrated moving average (ARIMA) models. Then residuals were examined for being normal and white noise. Finally the best distribution for each prices series was specified.

3.7. Measurement of Revenue Risk

As mentioned earlier, revenue risk is a combination of the uncertainty in both prices and yields.

On the whole, revenue insurance programs protect producers against any revenue-reducing combination of low prices and/or low crop yields. If revenues are below the guaranteed level due to any combination of poor yields and/or low prices, insured farmers get an indemnity payment equal to the difference between realized and guaranteed revenues. Revenue insurance is dependent on predicting the yields and harvest-time prices. Furthermore, a measure of the uncertainty connected to the price forecast is required to form a premium rate revealing the risk of opposite movements in prices. Generally in revenue insurance plans, futures prices are used to forecast harvest-time prices. For the reason that futures prices are not yet available for all the crops in Iran, it is necessary to project prices as well.

In measuring revenue risk for the purposes of insurance ratemaking, we are concerned to determine the probability of the both prices and yields. For this purpose, in the first step yield and price risk should be estimated accurately. However, the price and yields densities are not often independent (Goodwin and Ker, 2002; Hart *et al.*, 2006). The premium rates for the whole farm revenue insurance are determined by drawing yield and price deviates from appropriately specified distributions.

In order to measure or simulate of revenue risk, at first marginal distributions of yields and prices should be estimated and the degree of correlation between them calculated. If yields and prices are drawn from a common parametric family, a joint PDF can be applied to generate correlated draws for simulation. However, if the marginals are expected to be from different parametric families, some technique for drawing correlated random variables from different marginal distributions is required.

Two main procedures have been utilized in the literature to achieve random sampling of correlated random variables from specified marginal distributions. The first is the Weighted Linear Combination (WLC) approach, developed by Johnson and Tenenbein (1981).The WLC procedure has a major restriction so that it is applicable only for two variables and is not extended beyond the bivariate case (Babcock and Hennessy, 1996). The second is simulating the multivariate random variables. In the case of a multivariate distribution with more than two correlated random variables like the current study, the latter approach is appropriate. In this procedure, if one supposed to analyze farm that has three enterprises for example wheat, barley and alfalfa; then he has to simulate six variables: three yields and three prices. Meanwhile, Cholesky decomposition is employed to estimate and simulate multivariate probability distributions. This procedure has four attractive properties. First, the procedure works well with any distribution function. Most of the correlation techniques are designed directly at standard distribution functions and are not applicable with other distribution functions. Second, the mathematics behind the procedure is not complicated. Third, the procedure is applicable under any sampling method. Fourth, the moments of the marginal distributions are not influenced by the procedure (Hart *et al.*, 2006).

According to Richardson *et al.* (2008) in order for implementing this procedure, one is supposed to follow five steps. The first step is to segregate the random and non-random components from each other for the stochastic variables. In the second step the random component of each stochastic variable should be calculated. The third step is to convert the residuals to relative deviates about their respective deterministic components. In the fourth step the relative deviates are sorted and pseudo minimums and pseudo-maximums are generated for each random variable.

3.8. Simulating a Mixed Multivariate Probability Distributions

In recent years, simulation is growingly used to deal with agricultural risk management (Richardson *et al.*, 2000). In general, historical multivariate simulation has repeatedly been carried out by supposing a normal distribution for multivariate distributions. However, Harri *et al.* (2009) discovered evidences that normality on the marginal distribution of crop yields and prices is rarely supported by empirical data. They argue that marginal price and also marginal yield distributions are potentially correlated, then the interaction between price and yield should be taken into account. This necessitates the researcher to employ a procedure that is capable of modeling and simulating multivariate distributions (Ramirez, 2000).

In recent years agricultural economists have repeatedly applied the Iman and Conover (1982) procedure to simulate agricultural risks (Mildenhall, 2005). But recently the PQH (2004) procedure has received more attention in the empirical literature and has to a great extent been substituted for IC (1982). The PQH describes a procedure for simulating correlated stochastic variables from mixed marginal distribution. This process is based on Eigen decomposition of the rank correlation matrix. The PQH (2004) procedure presents a more precise connection between interdependent random variables relative to the IC. Furthermore, it is easy to understand and distribution free simulation technique, applicable for multi-crop revenue and whole farm insurance policy instruments. In addition, the data simulated by the PQH have comparatively small bias (Anderson *et al.*, 2009). In this study, 10,000 sample data for prices and yields were generated through PQH simulation technique to stabilize the results.

Multivariate probability distributions are for two or more random dependent variables and frequently used in economic analysis models because most of the economic variables are correlated to each other. Moreover, in the case that the correlation of the two correlated random variables is ignored in simulation, the model will either over or under state the variance and mean of the output variables. Richardson and Condra (1978) suggested the following steps for simulation the parameters of a Mixed Multivariate Probability Distributions. These steps are available in the Simulation for Excel to Analyze Risk (SIMETAR) software (Richardson *et al.*, 2008).

At first step, Independent Standard Normal Deviates (ISND) are generated for the variables. In the second step, the correlation matrix is created based on the number of variables in the model. In the third step, the correlation matrix created in the previous stage is factorized using the Cholesky decomposition. The Cholesky decomposition is an algorithm for the square root method of factoring a positive definite matrix into an upper triangular matrix T_{nxn} such that $S = TT$. To correlate random deviates a factored correlation matrix T is multiplied with an n x n column vector of independent standard normal deviates yielding an n x 1 column vector of correlated standard normal deviates. A mathematical description of this procedure is as follows:

$$CSND_{n\times 1} = T_{n\times n} ISND_{n\times 1} \qquad [14]$$

$$\begin{bmatrix} c_1 \\ c_2 \\ . \\ . \\ . \\ c_n \end{bmatrix} = \begin{bmatrix} t_{11} & t_{12} & . & . & . & t_{1n} \\ 0 & t_{22} & . & . & . & t_{2n} \\ . & & & & & \\ . & & & & & \\ . & & & & & \\ 0 & 0 & . & . & . & t_{nn} \end{bmatrix} \times \begin{bmatrix} i_1 \\ i_2 \\ . \\ . \\ . \\ i_n \end{bmatrix}$$

where CSND is an *n* x 1 column vector of correlated standard normal deviates distributed N(0,1); T is an *n* x 1 factored correlation matrix, ISND is a column vector of independent standard normal deviates. The row number of each of the correlated standard normal deviates corresponds to the row number of the correlation matrix and must be applied to the random variable associated with that row in the correlation matrix. The correlated standard normal deviates can be converted to uniform deviates and used to simulate any distribution by applying the inverse-transform method (Richardson *et al.*, 2000).

3.9. Study site and data

Iran, with a total area of 1,648,195 square kilometers, lies between 25 to 40 north latitude and between 44 and 63 east longitude. It is located in the northwest Asia and has about 80 million of population. Its capital is Tehran. Zanjan province with an area of 22164 km² is one of the 31 provinces of Iran, located in northwest of Tehran connected to it via a freeway. Agriculture is a major sector in the province's economy that contributed about 27 percent of the Gross Domestic Product (GDP) in 2015-2016. In addition, more than 35 percent of rural income is dependent on the agriculture sector. Wheat, barley and alfalfa are among the main crops of the province and account for about 65 percent of the total cultivated agricultural lands (AJOZP, 2016).

This study utilizes both farm-level and county-level yield data of the crops to establish expected yields and prices that were obtained from the organization of the Jihad e Agriculture (AJOZP) in addition to farm-gate price series of the selected crops that collected from the AJO's website. In Zanjan province farm-level yield data are available for a 7-year period from 2007 to 2013, while historical county-level yields are existing from 1981 to 2015, in kilograms per hectare. Prices are in Iranian currency (IRR) per kilogram of the products (AJOZP, 2016).

4. Findings and Discussion

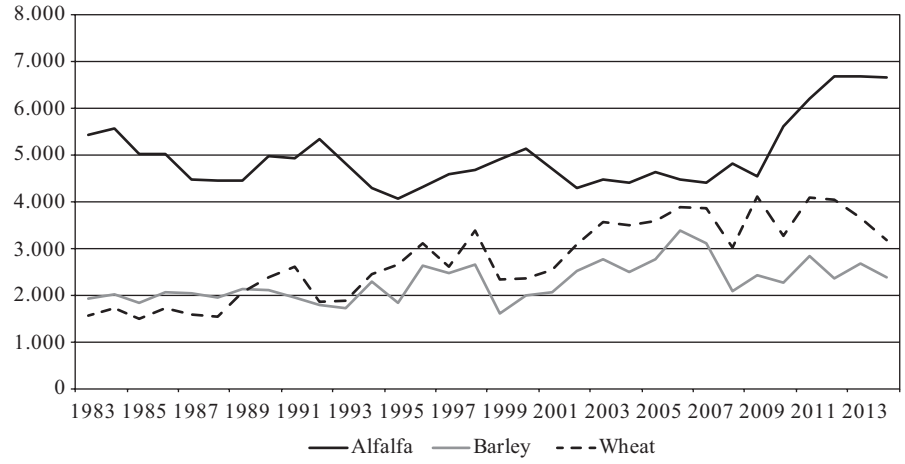
4.1. Variability and statistical properties of crop production

Zanjan is one of the 31 provinces of Iran, located in Iranian Azerbaijan and northwest of Tehran. Agriculture is a major sector in the province economy. Wheat, barley and alfalfa are among the main crops of the province and account for about 65 percent of the cultivated area.

Graphs are beneficial to facilitate data analysis and provide a visual illustration. Figure 1 displays the trends of the wheat, barley and alfalfa yields over the period 1982-2014. As shown in Figure 1, yields of the crops have experienced high fluctuations during the period. Meanwhile, wheat and barley yields had drops in year 1999 due to drought in the region.

FIGURE 1

Trends of wheat, barley and alfalfa actual yields in Zanjan during 1982-2014

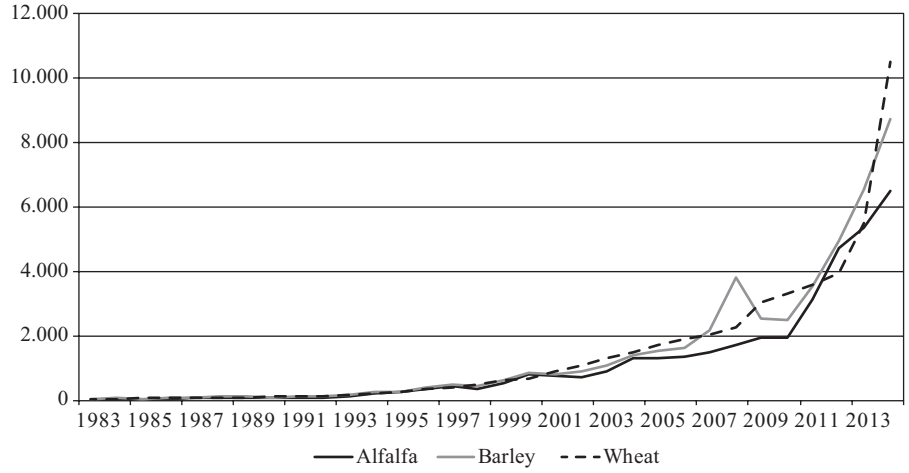


Source: Made by authors from Ministry of Agriculture-Jihad data.

Figure 2 illustrates the trend of the values for the harvest price for alfalfa and guaranteed price for wheat and barley. As it shows prices had growing trends and display a noticeable increase in recent years.

FIGURE 2

Trends of wheat, barley and alfalfa actual prices in Zanjan during 1982-2014



Source: Made by authors based on the data obtained from Ministry of Agriculture-Jihad.

The descriptive statistics of yields and prices time series before detrending is presentedin Table 1. It describes mean, standard deviation, coefficient of variation, maximun, minimum, scenes and kurtosis values of data set.

TABLE 1

Summary statistics of yields and prices prior to detrending

Variable	Yields (kg/ha)			Prices (Rials/kg)		
Summary Statistics	**Wheat**	**Barley**	**Alfalfa**	**Wheat**	**Barley**	**Alfalfa**
Mean	2,770	2,285	4,970	1,448	1,443	1,142
SD	850	420	720	2,163	2,064	1,626
CV	30.7	18.4	14.5	149.3	143	142.4
Max	4,114	3,390	6,683	10,500	8,741	6,498
Min	1,485	1,612	4,057	35	42	32
Skewness	0.014	0.670	1.329	2.747	2.161	2.122
Kurtosis	1.275	0.113	1.016	9.393	4.778	4.139

Source: Authors' calculations.

As Table 1 shows among the three crops, alfalfa has a higher yield but lower price mean values with respect to the other crops. While its coefficient of variation for both yield and price is a smaller amount than the other crops, implying that alfalfa producers have been faced with fewer fluctuations compared to wheat and barley growers. Additionally, prices had more volatility than the yields.

As mentioned earlier, prior to project the probability distribution of the random variables it is needed to detrend the times series with the purpose of setting apart the stochastic and deterministic components. In this study, detrending the yields and prices were implemented using the polynomial linear regression and ARIMA models. Meanwhile, Box-Cox transformation was employed to choose the appropriate model among the linear, logarithmic and log-linear forms. The descriptive statistics of yields and prices after detrending and adjusting to year 2014 have been shown in Table 2 which describes mean, standard deviation, coefficient of variation, maximum, minimum, skewness and kurtosis values of the data.

As shown in Table 2, alfalfa has a higher yield mean while mean price of barley is higher compared with other crops. Coefficient of variation for alfalfa yield is less than other crops while in prices the least CV belongs to wheat which gives explanation for guaranteed price of wheat.

TABLE 2

Summary statistics of the detrended yields and prices

Variable	Yields (kg/ha)			Prices (Rials/kg)		
Summary Statistics	**Wheat**	**Barley**	**Alfalfa**	**Wheat**	**Barley**	**Alfalfa**
Mean	3,828	2,802	6,137	8,332	8,612	6,800
SD	530	403	547	1,512	1,936	1,324
CV	13.8	14.4	8.9	18.2	22.5	19.5
Max	4,702	2,970	7,194	12,547	13,035	10,544
Min	3,006	1,993	5,312	6,100	6,158	4,522
Skewness	0.156	-0.101	0.368	0.631	1.06	0.887
Kurtosis	-1.294	0.094	-0.910	0.408	0.106	0.924

Source: Authors' calculations.

4.2. Stationary Tests

The starting point for any time series analysis is to check the data for stationarity, because the use of non-stationary data can lead to spurious regressions (Brooks, 2014). So the first task is to determine the integratedness of the series in question. In this study, the Augmented Dickey-Fuller (ADF) test was employed for examining the series for stationarity. In the ADF test, rejection of the null hypothesis indicates that the series in question is I(0). Applying the Augmented Dickey–Fuller (ADF) test for each of the series implicitly indicated that the yield series are trend stationary (TSP), while prices are difference stationary (DSP).Therefore, the price series are I(1).

4.3. Forecasting the Future Values of Prices and Yields

In order to determine the guaranteed revenue for each product, the future price and yield of the product was estimated. For this purpose, both parametric methods including polynomial regression, exponential smoothing and ARIMA models were employed. The predicted future values of the variables are depicted in Table 3.

As Table 3 shows, predictions obtained from different methods are not the same. The best model has been selected according to the normality of the errors. Furthermore, Breusch-Godfrey test confirmed the white noise characteristics of the residuals obtained from ARIMA models that imply the residuals are not serially autocorrelated.

TABLE 3

Forecasted future values for yields and prices

	Yields			Prices		
Forecasting Method	**Wheat**	**Barley**	**Alfalfa**	**Wheat**	**Barley**	**Alfalfa**
ARIMA	6,240	2,790	5,600	12,410	9,507	7,837
Exponential Smoothing	4,094	2,727	6,703	12,410	8,507	7,616
Linear Regression	4,400	2,723	6,752	8,880	8,507	6,860

Source: Calculated by authors.

4.4. Calculating the Aggregate Limit of Indemnity and Premium Rate

To calculate Premium rates, the first step is to estimate the probability distribution function of the yields and prices for crops and predicting the future values of the interest variables. The next step is to generate farm guaranteed revenues and associated insurance indemnities. Subsequently, correlated pseudo-random data are generated from the yields and prices using the inverse distribution method. The Cholesky decomposition of the covariance matrix is used to induce correlation in the individual marginal distributions. Next, the simulated prices and yields are passed through at the necessary coverage levels to obtain the simulated indemnity. The actuarially fair insurance rate is defined as the ratio of expected indemnity to liability, where expected indemnity is the level of insurance payment that the insurer expects to pay out to the insured at the time the insurance contract is signed and liability is the maximum payout that can be made (Woodard, 2009). Table 4 reports the premium rates for the crops at different coverage levels.

TABLE 4

Percentage of premium rates for the crops at different coverage levels

Coverage Level	**Wheat**	**Barley**	**Alfalfa**	**Aggregated Crops**
65 %	0.28	0.44	0.03	0.45
70 %	0.33	0.48	0.04	0.49
75 %	0.38	0.51	0.10	0.52
80 %	0.42	0.54	0.16	0.55
85 %	0.45	0.57	0.21	0.58
90 %	0.48	0.59	0.25	0.60

Source: Authors' calculations.

According to Table 4 premium rates in a certain coverage level, for example 75 % for wheat, barley and alfalfa are 38, 51 and 10 % respectively; while it is 52 % for aggregate crops that is less than the summation of the individual crops.

Table 5 compares the guaranteed and simulated revenues, expected indemnities and premium rates of the whole farm revenue insurance for the crops at different coverage levels in Zanjan.

TABLE 5

Guaranteed and simulated revenues, expected indemnities and premium rates for the crops

Coverage Level	Premium Rate	Guaranteed Revenue	Expected Indemnity
Percent	**Percent**	**1000 Rials***	**1000 Rials**
65 %	0.042	96,103	567
70 %	0.079	103,495	2,538
75 %	0.126	110,888	6,878
80 %	0.196	118,280	13,529
85 %	0.234	125,673	21,025
90 %	0.285	133,065	28,833

* Rial is Iranian currency (1$=37000 IRR).
Source: Calculated by authors.

As Table 5 shows premium rates in the whole farm revenue insurance program is lower than the premium rates in the case of crop specific revenue insurance program. Also the table values indicate that in the WFI the minimum and maximum amount of the rates are 0.042 and 0.285 percent, respectively. While their counterparts in the crop specific revenue insurance program are respectively 45 and 60 percent.

As mentioned before, the Gaussian kernel density was used for non-parametric estimation of the premium rates in case of the whole farm revenue insurance for the crops at different coverage levels. The values obtained from this procedure for premium rates are reported in Table 6.

The data presented in Table 6 indicate that premium rates obtained from the non-parametric procedure are slightly less than compared to parametric method. While the estimated guaranteed revenues are lower relative to the parametric method in all of the coverage levels. In addition, expected indemnities calculated by the kernel density method have smaller amounts in comparison to the parametric method. Furthermore, both parametric and non-parametric methods confirm that the premium rates of the whole farm revenue insurance are lower than the case of the insuring the crops separately at different coverage levels.

TABLE 6

Guaranteed and simulated revenues, expected indemnities and premium rates for the crops

Coverage Level	Premium Rate	Guaranteed Revenue	Expected Indemnity
Percent	**Percent**	**1000 Rials**	**1000 Rials**
65 %	0.016	79,456	226
70 %	0.044	85,568	745
75 %	0.096	91,680	1,939
80 %	0.168	91,192	4,020
85 %	0.220	103,904	7,008
90 %	0.280	110,016	10,914

Source: Authors' calculations

5. Conclusions

In this article we examined the efficiency of whole farm insurance when the crop producers face joint yield and price risks and discussed the application of both parametric and nonparametric methods to model the whole farm revenue insurance in Zanjan province of Iran. For do this, both farm-level and county-level crop yield data in addition to price series of the crops were collected for the period 1983-2014. The obtained data were utilized to establish the expected yields and prices by applying both parametric and nonparametric methods to calculate insurance premium rates and to measure the loss risks. In this study we found that yields follow beta distribution while both beta and lognormal are the best distributions to model prices that supports results obtained in the majority of the previous studies including Nelson and Preckel (1989); Tirupattur *et al.* (1996), Stokes *et al.* (1997), Roberts *et al.* (1998), Turvey and Zhao (1999), Zanini *et al.* (2001), Goodwin and Mahul (2004); Sherrick *et al.* (2004); Ozaki *et al.* (2008) and Zhu *et al.* (2011). However our findings disagree with the results of Zhang and Wang (2010) that introduced the Johnson SU and SB distributions along with Burr distribution as the most appropriate approach to model the wheat yield risk in Beijing province of China.

The empirical analysis in this study revealed that premium rates obtained from the parametric and nonparametric methods are significantly different from the currently in use insurance program in the country. In other words, the whole farm contracts are more efficient as a risk management tools than the combination of the crop-specific contracts. This confirms the results of Hart *et al.* (2006) that concluded the sum of the premiums for individual commodity revenues exceeds the premium for the combined coverage. It also supports the results of Bielza and Garrido (2009) that concluded applying whole farm insurance significantly reduces premiums, in addition to findings of Chalise *et al*. (2011) and Chalise *et al.* (2017) which found that whole farm insurance generates significant risk reduction at much lower cost than the other programs.

According to the findings, applying the whole farm revenue insurance can improve accuracy in the measurement of loss risks and may thus promote the actuarial performance of the Agricultural Insurance Fund in Iran. Therefore, it is recommended to the policymakers and planners of the agricultural sector to take this into consideration when the crop insurance program is designed as well as to crop producers to switch from purchasing the crop-specific revenue insurance contracts to whole farm insurance contract. This would result in better risk management and production stability and economic security for the agricultural sector. Finally, further work is needed to examine a wider set of distributional choices including nonparametric analysis and to evaluate the performance of whole farm insurance over the existing insurance programs in other regions.

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