The Effectiveness of Weather-Based Index Insurance and Area-Yield Crop Insurance: How Reliable are ex post Predictions for Yield Risk Reduction?

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Abstract

An *ex post* measure of risk reduction is commonly used in the literature to predict the potential reduction of farmers' yield risk due to weather-based index insurance and area-yield crop insurance. In this paper, we evaluate the predictive power of the *ex post* risk reduction for different weather-based index as well as area-yield index and farm yield insurance contracts. We compute an empirical benchmark of potential risk reduction against which the *ex post* estimates are evaluated by distinguishing between a training data set and a test data set. Based on data for 40 wheat producers in Kazakhstan, our empirical analysis shows that the *ex post* approach can overestimate farmers' future risk reductions due to crop insurance schemes based on weather indexes or area yields. Therefore, we argue that the decision about the market launch of index-based insurance instruments should be based on more than just the common *ex post* approach.

Keywords: index-based crop insurance, Kazakhstan, risk analysis, weather-based index insurance, yield risk
JEL: D81, G22, Q14

1 Introduction

There have been many attempts to reduce farm households' exposure to weather risk. Recently, BARNETT and MAHUL (2007), the UNITED NATIONS (2007), the FOOD AND AGRICULTURE ORGANISATION OF THE UNITED NATIONS (2005), and VARANGIS et al. (2002) recommended so-called index-based crop insurance schemes as a promising instrument for managing weather-related risks of farms in developing countries. According to the UNITED NATIONS (UN) DEPARTMENT OF ECONOMIC AND SOCIAL AFFAIRS (2007), as well as BARNETT and MAHUL (2007), pilot projects on weather

index-based insurance have been implemented in India, Ukraine, Ethiopia, Malawi, and China.[1]

Whereas the level of indemnity payments depends on the actual farm yield in the insured period for common farm yield insurance, for index-based crop insurance, the level of indemnity payments depends on the realisation of a particular index, e.g. amount of rainfall, accumulated temperature, or a regional average crop yield. Index-based crop insurance contracts based on weather variables are referred to as 'weather-based index insurance' (SKEES et al., 1999). Additionally, as they are equivalent to a put option based on the same weather variables; they are also called 'weather insurance derivatives' (GAUTAM, 2006) or 'weather derivatives' (e.g. VEDENOV and BARNETT, 2004) in the literature.

An important precondition for the implementation of weather-based insurance instruments is a high sensitivity of farmers' yields to a weather-based index, which indicates a high risk-reducing potential of the respective weather-based insurance scheme. Analogously for area-yield crop insurance, a farmer's yield should be highly correlated with the area yield. Empirical case studies extensively use historical yield and weather data to evaluate the potential risk reduction through index-based crop insurance. In so doing, the studies implicitly assume that the risk reduction, which is measured based on historical data, presents a reliable predictor for future risk reduction (i.e., risk reduction after having purchased insurance). MIRANDA (1991), SMITH et al. (1994), and MAHUL and VERMERSCH (2000) investigated the risk reduction for area-yield crop insurance contracts and compared it with risk reduction due to common farm-yield insurance contracts. SKEES et al. (2001), VEDENOV and BARNETT (2004), and KARUAIHE et al. (2006) evaluated the crop yield risk reduction of risk management tools based on weather indexes.[2] BREUSTEDT et al. (2008) compared the risk reduction of farm yield, area-yield, and weather-based index insurance. The abovementioned studies evaluate the potential risk reduction *ex post*.[3] Accordingly, they implicitly assume that risk reduction, measured by using historical data, presents a reliable predictor for future risk reduction (i.e., risk reduction which the farmer would be able to obtain by purchasing an insurance contact). In our view,

[1] According to the same references, new pilot projects were to be implemented by 2008 (Tanzania, Nicaragua, Thailand, Bangladesh) or are planned for implementation in, e.g., Kazakhstan, Senegal, Morocco, and Vietnam. Most of those insurance schemes are subsidized.

[2] It must be noted that SKEES et al. (2001), VEDENOV and BARNETT (2004), and KARUAIHE et al. (2006) do not investigate risk management of individual farm yields, but rather regional average yields.

[3] All mentioned studies are based on the principle of the so-called burn-rate method, which is often applied in actuarial practice and assumes that future losses will be distributed as in the past.

this assumption is rather restrictive and needs to be tested because it might seriously limit the validity of respective predictions.

We argue that there might be significant deviations between *ex post* predictions and the risk reduction which a farmer would gain actually by purchasing insurance in future periods. This might happen in at least three cases: a) time series are not sufficiently long to enable reliable estimates because they do not adequately represent the true underlying distribution[4]; b) certain changes in technology and production practices cannot be appropriately caught by any trend c) there are serious temporary changes in the joint distribution of relevant variables, e.g. a weather indicator and farm yields due to either technological changes or climatic changes This may simply be because a case study's time period is too short to be representative, e.g. all studies focusing on farm yields are based on periods not exceeding 15 years (except BREUSTEDT et al. (2008)). In this context, evaluating the predictive power of the *ex post* estimated risk reduction constitutes a highly relevant empirical problem. However, the literature has paid only limited attention to this aspect of index insurance and weather derivative assessment to date.

In this paper we evaluate the predictive power of an *ex post*-predicted risk reduction by comparing it with a reference measure of risk reduction called 'empirical benchmark'. To do so, we distinguish between two consecutive periods in the available time series. The data from the first period are used as a so-called training data set to estimate the *ex post* risk reduction. We use the data set from the second period to form a so-called test data set and use it to compute the benchmark risk reduction. The estimates of both *ex post* and benchmark risk reductions are done for each farm separately. Subsequently, the two values of risk reduction are compared to evaluate the estimated *ex post* predictor. Consequently, a calculated *ex post* risk reduction is said to have poor predictive power if its estimates differ substantially from the benchmark risk reduction calculated from the test data set.

In line with the literature, we present a case study on risk reduction due to hypothetical area yield crop insurance schemes and weather-based index insurance schemes. However, in contrast to the previous studies, we evaluate the predictive power of *ex post* risk reductions.

Our empirical analysis draws attention to a serious problem which has been abandoned when developing index-based insurance products. Most of the insurance products introduced on a pilot basis are developed by employing rather short time series of farm yields and weather data and do not evaluate the effectiveness of the developed

[4] E.g. all studies employing farm-level data are based on periods not exceeding 15 years (except BREUSTEDT et al. (2008)).

insurance schemes *ex ante*. Our empirical results demonstrate that such a procedure can lead to serious overestimations of the index-based insurance effectiveness. In our view, such overestimations might be one important explanation for a rather sluggish participation of farmers in index-based insurance programs in most countries where they were introduced on a pilot basis.

The remainder of the paper is organised as follows. Section 2 presents the conceptual framework, as well as limitations of the *ex post* risk reduction analysis, and describes our approach to generating an empirical benchmark. Section 3 provides details on both the data and an empirical application to evaluate yield risk reduction by means of farm yield and area yield insurance schemes as well as weather-based index insurance schemes for 40 wheat farmers in Kazakhstan. Conclusions are drawn in the final section.

2 Conceptual Framework

First, we review the theoretical framework for estimating risk reductions due to hypothetical farm yield and index-based crop insurance, and then discuss the common *ex post* approach and its limitations. We proceed by describing an empirical procedure for evaluating the reliability of *ex post* risk reduction due to crop insurance contracts.

2.1 Theoretical Framework

There is considerable literature on assessing the potential of crop insurance to reduce a farmer's yield risk. For crop insurance, the indemnity payment n (per insurance contract) is defined as $n = p\ \mathrm{Max}[x_s - x, 0]$, where x is defined as follows: for the area (farm) yield insurance, it denotes area (farm) yield, whereas for weather-based index insurance or weather insurance derivatives it denotes a weather index. Indemnity is paid whenever the actual values of x fall below the strike or trigger value x_s; this value is defined as the difference $x_s - x$ times a monetary factor p. If x is based on a variable that is different from the per-hectare farm yield, the resulting insurance is called index-based insurance. In this case, a farmer is free to choose the number of insurance contracts (put options) z that he wants to purchase. For farm yield insurance, z is constrained to be less than one per hectare insured to limit moral hazard.

Under the general setting, MIRANDA (1991), SMITH et al. (1994), and MAHUL and VERMERSCH (2000) evaluated the effectiveness of area yield crop insurance in terms of farmers' (relative) revenue variance reduction.[5] SKEES et al. (2001) focused on

[5] Constant output prices and production costs are assumed in all of these articles; i.e., yield variation is the only source of risk in these analyses.

reducing the coefficient of variation for a portfolio of different crops due to weather-based index insurance, while BREUSTEDT et al. (2008) used two approaches, i.e., the common (unrestricted) variance reduction and a stochastic dominance criterion. VEDENOV and BARNETT (2004) also employed two risk measures – the semi-variance of insured revenue and the concept of Value-at-Risk – to measure weather derivatives' effectiveness. Finally, VEDENOV and BARNETT (2004) and KARUAIHE et al. (2006) applied expected utility (EU) models based on explicit utility functions, including an assumption about the farmer's level of risk aversion. All in all, the cited empirical studies work analogously in the sense that they either maximise EU or minimise a risk measure (*RM*) for one harvesting year with respect to the number of insurance contracts (or put options) z.[6] For simplicity, in the following we only refer to minimising an *RM* such as variance or the coefficient of variation. The (absolute) effectiveness of index-based insurance is measured by determining the difference in the *RM* without insurance, i.e., $RM(0) = RM(z = 0)$, and with insurance, i.e., $RM(z^*)$, if the optimal number of contracts (put options) z^* is chosen:

$$(1) \qquad \Delta RM = RM(0) - RM(z^*)$$

2.2 *Ex post* Risk Reduction

To define an index-based insurance contract or a weather derivative and assess its effectiveness for a farmer, the empirical analysis must consider historical time series for farm and regional yields, as well as historical weather data. Most of the abovementioned studies are conducted in two steps. In the first step, they construct a series of hypothetical indemnity payments by determining insurance contract parameters (i.e., the index strike level or the weights of different weather variables in a weather index). In the second step, they use these hypothetical indemnities to determine the optimal number of insurance contracts by

$$(2) \qquad \min_z RM_{t_0}^T \middle| \Omega_{t_0}^T$$

The minimisation of the risk measure *RM* is conditioned on the information $\Omega_{t_0}^T$, i.e., historical yields and weather data from year t_0 to T, i.e., the *RM* minimisation is performed *ex post*. The *ex post* optimal number of insurance contracts is denoted as $z_{t_0,T}^*$. The ex-post risk reduction is computed by assuming that the optimal number of insurance contracts $z_{t_0,T}^*$ does not change over the whole period from t_0 to T; the same

[6] Both approaches can be considered equivalent under certain restrictions, e.g. minimizing the variance can maximize EU if the insurance contracts are actuarially fair and the random variables follow the so-called location-scale condition (MEYER, 1987).

assumption holds true for the insurance contract parameters $\mathbf{w}_{t_0,T}$.[7] The risk reduction becomes

(3) $$\Delta RM_{t_0}^{T} = RM_{t_0}^{T}(0) - RM_{t_0}^{T}\left(\mathbf{w}_{t_0,T}, z_{t_0,T}^{*} \middle| \Omega_{t_0}^{T}\right).$$

Next we pose the decisive question: is $\Delta RM_{t_0}^{T}$ a good predictor of risk reduction in a future period of a (arbitrary) length $L \geq 1$ after year T?

In our opinion, $\Delta RM_{t_0}^{T}$ can be a poor predictor of future yield risk reduction, first, if the joint distribution of yields and the underlying index variables change between the period t_0 to T, and the period $T + 1$ to $T + L$, or within the period from $T + 1$ to $T + L$, respectively. These changes may cause over- or underestimation of the risk reduction. Second, $\Delta RM_{t_0}^{T}$ may persistently underestimate potential risk reduction over a period of several future years, because there is no option that allows for updating either the optimal number of insurance contracts or the insurance contracts' parameters within this period. Such updating can improve predictions considerably, however, because they utilise additional information about the joint distribution of yields and index values.

There are various ways to deal with the abovementioned problems. VEDENOV and BARNETT (2004) analysed the stability of the joint distribution of (regional) yields and payments based on weather derivatives by means of out-of sample calculations, which they compared with the in-sample risk reduction. These authors defined their in-sample risk reduction according to (3) based on $z_{t_0,T}^{*}$, which is calculated in-sample as described in (2). To assess risk reduction out-of-sample in equation (4), they used the years after T only, viz.;

(4) $$\Delta RM_{T+1}^{T+L} = RM_{T+1}^{T+L}(0) - RM_{T+1}^{T+L}\left(\mathbf{w}_{t_0,T}, z_{t_0,T}^{*} \middle| \Omega_{t_0}^{T}\right).$$

Accordingly, VEDENOV and BARNETT (2004) assume that neither the parameters of the derivatives $\mathbf{w}_{t_0,T}$ nor the optimal number of derivatives $z_{t_0,T}^{*}$ change between in- and out-of-sample analyses.

Based on their empirical results, VEDENOV and BARNETT (2004: 398) state that there "appears to be no consistent relationship between contract performance in- and out-of-sample". In the case of cotton production, they found that the weather derivatives reduced (regional) yield risk in-sample, but increased it out-of sample. The authors

[7] The insurance contract parameters provide a formal description of the underlying index, the strike level, the insurance premium, and so on.

concluded that this "inconsistency … creates a potential problem in marketing and designing the contracts" (p. 399).

Though VEDENOV and BARNETT (2004) evaluated the predictive power of the *ex post* designed weather derivatives, they did not consider the possibility of updating the derivative parameters and the optimal number of derivatives for individual years in the period after *T*.

Recently, OZAKI et al. (2008) attempted to improve the forecasting of crop yields. Hence, they predicted actuarial fair premiums for area yield crop insurance more precisely by applying hierarchical Bayesian models. Their analysis captured spatio-temporal dynamics underlying crop yields and took into account uncertainty related to the trend parameter estimations. The authors evaluated different model specifications by minimising a posterior predictive criterion defined as a minimum mean squared prediction error. However, in view of a rather short time series, potential risk reductions could not be studied in their analysis.

2.3 Benchmark for *ex post* Risk Reduction

The expected risk reduction generated from the data of the period from t_0 to T represents a reasonable predictor for the risk reduction in year $T+1$. However, evaluating the predictive power after the outcome of year $T+1$ is impossible because one cannot assess yield risk from a one-year-observation. Consequently, the calculation of the corresponding risk reduction must consider a period that spans a reasonably large number of years after *T*. Thus, we proceed similarly to VEDENOV and BARNETT'S out-of-sample risk reduction (2004) according to (4). However, we extend (4) to allow for updating the insurance contract parameters and the optimal number of insurance contracts for each year in the test data set, i.e from $T+1$ to $T+L$. Consequently, our benchmark risk reduction is defined by

$$\Delta RM_{T+1}^{T+L} = RM_{T+1}^{T+L}(0) - RM_{T+1}^{T+L}\left(\mathbf{w}_{T+l}, z_{T+l}^{*} \middle| \Omega_{t_0}^{T+l-1}\right), \tag{5}$$

with $l = 1,\ldots,L$. To this end, based on the information from t_0 to $T+l-1$, we first estimate for each farm the vector of the insurance contract parameters $\mathbf{w}_{T+l}$ for every year $T+l$, and then compute for each farm separately the optimal number of insurance contract z_{T+l}^{*} for year $T+l$ as

$$\min_{z_{T+l}} E\left[RM_{t_0}^{T+l-1}\left(\mathbf{w}_{T+l} \middle| \Omega_{t_0}^{T+l-1}\right)\right] \middle| \Omega_{t_0}^{T+l-1} . \tag{6}$$

Equation (6) determines z^*_{T+l}, which minimises the farmer's expected risk for each year $T+l$. The expected risk reduction is expressed by the *ex post* reduction in the period from t_0 to $T+l-1$. Thus, for each year in the test data set, historical information prior to $T+l$ is used to build the corresponding weather or area yield index and to choose the optimal number of insurance contracts (put options). We suppose that (5) represents a reasonable benchmark for examining the predictive power of the *ex post* risk reduction.

Predictions of yields and insurance indemnities must account for trends in the variables. To separate the impact of uncertainty following from the trend estimation we account for trend by two different approaches. First, we estimate the underlying trend parameters based on the same information as insurance parameters, i.e. trend parameters are treated like elements of vector **w.** Hence, the trend parameters differ between the *ex post* (3) and the benchmark estimations (5). Accordingly, for (5), yield predictions for $T + l$ are estimated from observations t_0 to $T + l - 1$. Consequently, the predicted yield for $T + l$ is calculated based on the parameters of the trend estimation for the period from t_0 to $T + l - 1$. For the *ex post* risk reduction (3), trend parameters are estimated based on t_0 to T.

In the second approach, the data are detrended over the whole period from t_0 to $T + L$. In this case, the *ex post* and the benchmark risk reduction are based on the same detrended yields. Consequently, evaluating the predictive power of the *ex post* approach is no longer affected by the uncertainty related to trend estimations. Furthermore, in line with BREUSTEDT et al. (2008), we use third-degree and second degree polynomials for trend estimations and control for historical precipitation when estimating yield trends, thereby reducing potential bias in the trends due to extreme weather conditions in the available time series.

3 Empirical Application

In this section, we first present our data, and then we describe the empirical procedures employed for evaluating the performance of the *ex post* approach in predicting the risk reduction of index-based insurance schemes for crop farmers. We then turn to the empirical results.

3.1 Data

In our empirical analysis we employ wheat yield data for 40 large grain producers from six rayons in 3 most important agricultural regions of Kazakhstan. The total

wheat crop area of the study farms account for 407,000 ha[8] as in 2002. The yield data were collected from *rayon*[9] statistical offices and covered the period from 1980 to 2002. Our data include the transition period of Kazakhstan's agricultural sector; therefore, we excluded yield time series with a statistically significant structural break.[10] In 2002, the surveyed farms' wheat areas varied from 672 to 23,800 hectares, with a mean of around 10,500 hectares. The expected farm yields for 2002 (table A1 in the appendix) varied from 0.71 t/ha in central Kazakhstan (*rayon* Atbasar) to 2.93 t/ha in eastern Kazakhstan (*rayon* Glubokoje).

In addition to farm data, we used official statistics on *rayon* yields, as well as weather data from seven weather stations, one in each of the considered *rayons*.[11] The weather data (daily rainfall and average daily temperature as reported to the regional meteorological offices) covered the same period as the yield data. The average cumulative precipitation (table A1) during the summer months (June to August) was between 103 mm (standard deviation of 45 mm) and 153 mm (standard deviation of 61 mm).

3.2 Empirical Procedure

In the empirical procedure, we employ two risk measures: the mean squared prediction error (MSPE) and the mean squared negative prediction error (MSPEN). Although these measures are very similar to variance and semivariance, respectively, there are two differences: first, MSPE and MSPEN take into account a non-zero mean prediction error. Second, for MSPEN the sum of squared negative prediction errors is divided by the number of observations with negative errors only. Because farmers are primarily concerned about downside risk, MSPEN (corresponding to semivariance) presents a more empirically relevant measure of risk than MSPE (corresponding to variance). We employ MSPE in addition to MSPEN to get estimates analogous to those, which can be found in the literature and rely on variance or standard deviation calculations (e.g. MIRANDA, 1991; Smith et al., 1994; MAHUL and VERMERSCH, 2000; BREUSTEDT et al., 2008).

For uninsured yields, MSPE is defined as the average squared deviation of the farm observed yield from the predicted yield. MSPEN is calculated as the average squared negative deviation of the farm observed yield from the predicted yield. For insured yields, MSPE (MSPEN) denotes the average squared (negative) deviation of the farm

8 i.e. four percent of the wheat crop area in Kazakhstan.

9 *Rayons* are administrative districts similar to counties.

10 The initial data set contained data for 84 farms. By applying Chow-test we detected a statistically significant structural break in the yield time series for 44 farms.

11 Weather stations belong to Kazhydromet – Kazakhstan's national meteorological service.

observed yield plus indemnities (minus insurance premium)[12] from the predicted yield. The yield risk reduction due to insurance was measured for each farm in terms of relative and absolute risk reduction by employing MSPE and MSPEN.

Next, we compared the risk reduction calculated *ex post* as defined by (3) with the risk reduction as determined by our benchmark (5). Based on these differences, we were able to evaluate predictive power of *ex post* risk reductions. Consequently, we argue that the *ex post* risk reduction has poor predictive power for the future risk reduction if it differs considerably from our benchmark.

Finally, we evaluated three crop insurance types: weather-index based insurance (WII), area-yield insurance (AYI) based on the national and the rayon yields (NYI and RYI, respectively), and – as a reference – farm yield insurance (FYI). WII were based on two drought indices developed for the climatic conditions of Kazakhstan by SELYANINOV (1958) and PED (1975) (quoted in SHAMEN, 1997).

Accordingly, the Selyaninov drought index is defined as:

$$(7) \qquad Sel_t = \frac{10 * R_t^{June-August}}{30 * Temp_t^{June} + 31 * Temp_t^{July} + 31 * Temp_t^{August}}$$

and the Ped drought index is determined as follows:

$$(8) \qquad Ped_t = \frac{R_t^{June-August}}{\sigma_R} + \frac{R_t^{September-May}}{\sigma_R} - \frac{Temp_t^{June-August}}{\sigma_{Temp}},$$

where t denotes different years. The variables R and $Temp$ are the cumulative precipitation in millimetre and average daily temperature in degree Celsius in an indicated sub-period, respectively, while σ_R and σ_{Temp} are the respective long-term standard deviations. The strike levels for AYI and WII were assumed to be the expected value of the respective index. For the FYI, the strike level was set to 75% of the expected farm yield.

The relevant years for the *ex post* prediction (3) and for the benchmark (5) were set as follows: $T = 1991$ and $T + L = 2002$. Accordingly, we distinguished between the training data set covering the period of 12 years from 1980 to 1991[13] and the test data

[12] We assume fair insurance premium.

[13] Only BREUSTEDT et al. (2008) used a considerably longer time period than 12 years for their risk reduction analysis of index-based crop insurance. The other above cited farm-level analyses used farm yield data of 10 to 15 years.

set corresponding to the period from 1992 to 2002. For our benchmark risk reduction, the strike levels, indemnities, and premiums were updated for each year in this data set based on each farm's data. The optimal z^* was determined numerically from a set {0.00, 0.01, …, 0.99} and {0.00, 0.01, …, 7.00} for FYI and index-based insurance schemes, respectively.

3.3 Results

We first compare the *ex post* with the benchmark yield risk estimates for both risk measures. According to the *ex post* estimations, the MSPEN (MSPE) of the farms' yields amounts to 13.2 (12.9) on average. The benchmark estimates are 17.2 and 19.7, respectively. This clearly indicates that the common *ex post* approach underestimates yield risks for the investigated farms. In addition, Pearson's and Spearman's rank correlation between *ex post* and benchmark MSPE estimates are rather low, with both equal to 0.37. For the MSPEN, we cannot find any substantial correlation: both coefficients are below 0.08. Hence, we conclude that the yield risk can be underestimated if the uncertainty related to trend predictions is not taken into account. In particular, downside risk cannot be predicted well enough by means of the *ex post* approach (at least, if based on rather short time series).

We now turn to the risk reduction analysis. Table 1 shows the relative risk reductions averaged over farms for different insurance schemes. We found that the average *ex post* risk reduction assessed by means of the MSPE is the highest for the rayon yield insurance: it amounts to 55% (first row, third column). In this case, all 40 study farms can benefit from risk reduction. The results are less favorable for the farm yield insurance. In contrast to the previous case, only 38 farms can benefit from risk reduction.[14] The average MSPE reduction for the FYI amounts to 34%, a level that is slightly higher than the risk reduction due to the WII schemes (i.e., based on the SELYANINOV and PED drought indices) in this approach. Considering our benchmark risk reduction, the average MSPE reduction due to FYI is quite similar to its corresponding *ex post* estimate (second row, first column). By contrast, it decreases by 18 percentage points for the rayon yield insurance. The outcomes for the WII schemes are less promising. According to our benchmark, the WII schemes cannot provide substantial risk reduction because their respective averages are below 10%.

[14] This means that there are two farms for which observed yields do not fall below 75% of the expected yield, i.e., the strike yield.

Table 1. Risk reductions with yield prediction uncertainty

sample means (40 farms)	farm insurance	national yield insurance	rayon yield insurance	weather-index insurance (Selyaninov)	weather-index insurance (Ped)
mean squared prediction error (MSPE)					
ex post approach (eq. 3), %- reduction	34	40	55	30	29
benchmark (eq. 5), %- reduction	35	16	37	6	4
mean squared negative prediction error (MSPEN)					
ex post approach (eq. 3), %- reduction	48	51	65	39	40
benchmark (eq. 5), %- reduction	46	14	39	-18	-21

Source: authors' estimates

The relative reduction of MSPEN is given in the third and fourth rows of table 1. According to the *ex post* approach, all insurance schemes reduce MSPEN by a higher percentage than MSPE. This is not surprising because insurance aims to downside risk. Altogether, the rayon yield insurance offers the highest ex-post risk reduction on average: the respective MSPEN is reduced by two-thirds. In addition, it is higher than FYI by 17 percentage points. Again, FYI's *ex post* and benchmark risk reductions are quite similar (46% compared to 48%), while the latter is substantially lower than the *ex post* MSPEN for rayon yield insurance (by 26 percentage points, i.e., 39% compared to 65%). Even worse, the benchmark estimates of risk reduction for the WII schemes turn negative on average. Only about one-third of the farms would have experienced downside risk reduction due to WII contracts.

What do these results imply for our research questions? First, the predictive power of *ex post* risk reductions (averaged across farms) is high for farm yield insurance for both risk measures. Second, the predictive power is worse for index-based insurance schemes: e.g. for the rayon yield insurance, the difference between the average *ex post* and benchmark risk reductions amounts to at least 26 percentage points for the downside risk measure MSPEN and 18% for the variance-like measure MSPE. Third, there is no risk reduction due to WII contracts in the benchmark. According to the benchmark estimates, both WII schemes are ineffective (on average over farms). Measured *ex post*, the respective risk reductions look much more promising (on average, ranging between 29% and 40%).

Considering the aforementioned results, we conclude that *ex post* estimates may provide poor predictions for future risk reduction due to yield risk management

instruments with basis risk. This implies that one should not rely on *ex post* estimates as a sole instrument for assessing the effectiveness of an index-based insurance contract. In fact, *ex post* predictions tend to overestimate the relative risk reduction calculated for the test data set for all considered insurance types. In all scenarios, the *ex post* risk reduction (averaged across farms) is higher than the benchmark risk reduction (except once for FYI). This is in agreement with the aforementioned conclusion, indicating that one should be very careful when predicting risk reductions of yield insurance by means of *ex post* risk estimates.

Moreover, looking at relative risk reduction reveals a different ranking of insurance schemes between the *ex post* and benchmark approaches: for all *ex post* measures, rayon yield insurance outperforms national yield insurance, which in turn performs better than farm yield insurance. With respect to the benchmark approach, however, the farm yield insurance is much more competitive. Consequently, recommendations on which particular insurance scheme should be launched should not be derived based on the *ex post* evaluation of risk reduction only.[15]

The reasons behind the poor performance of the *ex post* estimates seem to emphasise the role of uncertainty. In fact, the different trend specifications show that uncertainty over yield predictions explains, to a large extent, the low predictive power of the *ex post* approach. The *ex post* risk reduction measures are quite similar under both trend procedures (see table 2). However, the sample average benchmark risk reduction of index-based insurance schemes turns out to be substantially lower for the trend procedure based on the same information as the farmers' and insurance companies' decisions. Consequently, estimating the trend over the whole period of 23 years produces a clearly smaller difference between the *ex post* measures and the benchmark.[16] Thus, eliminating uncertainty over yield predictions in the common literature studies is likely to cause an overestimation of the relative risk reduction due to the index-based insurance. Nevertheless, the main results from above remain valid when employing the second trend procedure: (i) the average relative risk reductions are higher for the *ex post* approach than for our benchmark, particularly for index-based insurance schemes; (ii) the ranking of insurance schemes according to the relative risk reductions differs between the *ex post* approach and the benchmark. Besides trend uncertainty, there remains a substantial overestimation in the *ex post* approach that

[15] Our results are confirmed by sensitivity analyses. In these analyses the time periods for the ex post prediction and the benchmark risk reduction are changed. The results are given in the appendix tables A2 to A4.

[16] Removing the uncertainty related to trend estimations is expected to increase the predictive power of the ex post risk reduction substantially. This uncertainty can be especially high for countries in economic transition.

might be explained by temporal changes in the joint distribution of farm yields and index variables.

Table 2. Risk reductions without yield prediction uncertainty

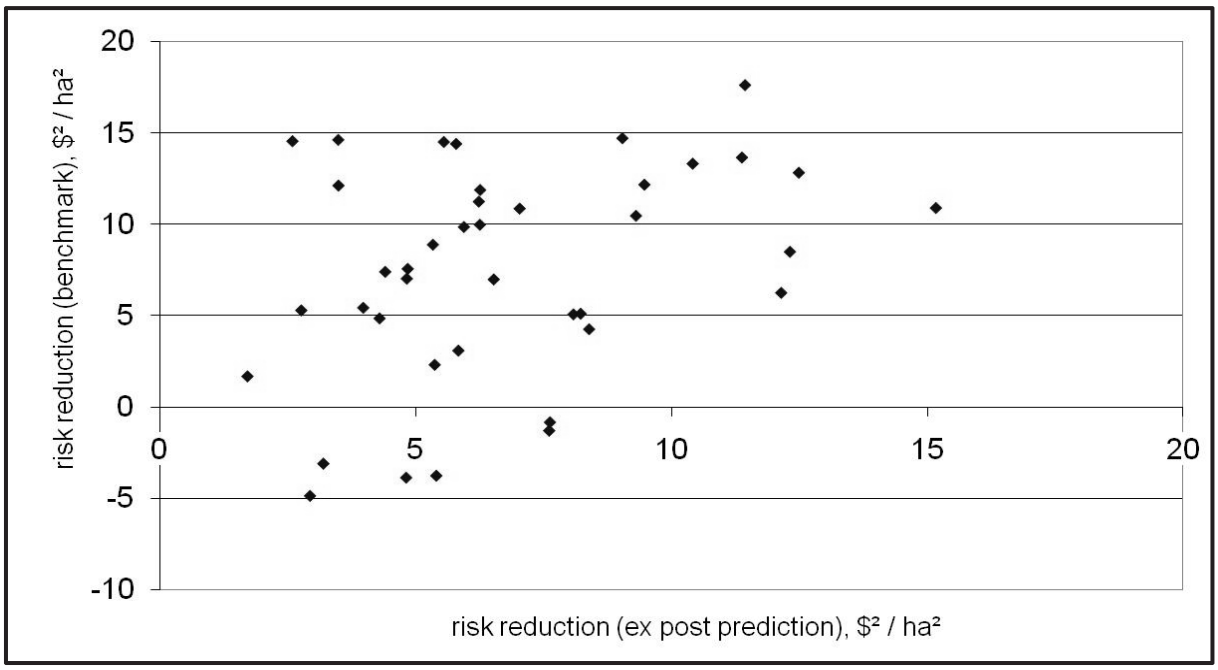
sample means (40 farms)	farm insurance	national yield insurance	rayon yield insurance	weather-index insurance (Selyaninov)	weather-index insurance (Ped)
mean squared prediction error (MSPE)					
ex post approach (eq. 3), %- reduction	28	37	54	29	26
benchmark (eq. 5), %- reduction	26	26	41	18	26
mean squared negative prediction error (MSPEN)					
ex post approach (eq. 3), %- reduction	46	52	66	35	32
benchmark (eq. 5), %- reduction	40	19	49	-2	20

Source: authors' estimates

Although the *ex post* measures cannot provide a good prediction of either the farms' yield risk or the relative risk reduction, it might be argued that *ex post* measures can predict the absolute risk reduction sufficiently well. However, our estimations do not confirm this. For individual farms, we find only a low correlation among absolute risk reduction estimates measured *ex post* and by our benchmark, respectively: for the farm yield insurance, the Pearson's (Spearman's rank) correlation between the MSPEN absolute reduction estimates amounts to 0.17 (0.20); regarding MSPE absolute reduction estimates, this figure increases to 0.29 (0.35). The correlation between the MSPEN absolute reduction estimates is lower than 0.07 for the remaining insurance schemes. The highest correlations between *ex post* and benchmark absolute MSPE reductions are obtained for FYI and RYI: the corresponding correlation coefficients range from 0.32 to 0.35.

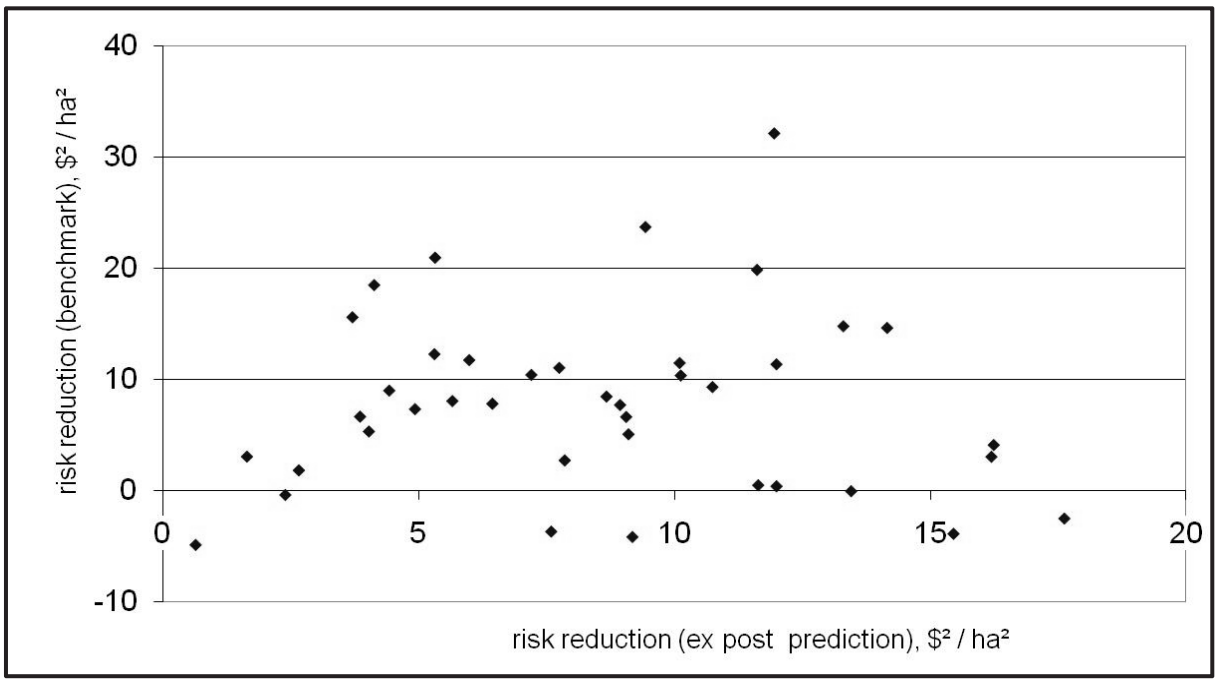
Although the correlation between the absolute *ex post* and benchmark risk reductions is low, for the rayon yield insurance we can identify some farms for which a high MSPE reduction *ex post* coincides with a high MSPE reduction in the benchmark. These farms belong to the third of the sample farms with the highest *ex post* MSPE reductions (figure 1). However, we cannot prove any relationship among *ex post* and benchmark MSPEN reductions for rayon yield insurance (figure 2). The FYI exhibits a clearer relationship between *ex post* and benchmark MSPEN. There are only two farms with an increased risk due to FYI in the benchmark.

Figure 1. Ex post and benchmark MSPE reductions due to rayon yield insurance



Note: The benchmark risk reduction refers to equation (5) while the ex post prediction refers to equation (3).
Source: authors' estimates

Figure 2. Ex post and benchmark MSPEN reductions due to rayon yield insurance



Note: The benchmark risk reduction refers to equation (5) while the ex post prediction refers to equation (3).
Source: authors' estimates

4 Conclusions

To evaluate the potential risk reduction due to index-based insurance instruments, including area-yield crop insurance, weather-index insurance, and weather derivatives, most empirical analyses apply an *ex post* approach, which implicitly assumes that risk reduction, measured on the basis of historical data, presents a reliable predictor for future risk reduction. Consequently, previous studies did not account for uncertainty related to predicting farm yields and insurance contract parameters. Moreover, the *ex post* approach implicitly assumes that the joint distribution of farm yield and index variables estimated from the past will be valid for future periods. In our view, this assumption may be too restrictive and may cause a substantial overestimation of potential risk reduction.

In this paper, we evaluate the predictive power of the *ex post* risk reduction by comparing it with a benchmark risk reduction. To this end, we separate the available time series in two consecutive periods and thus conduct our analysis based on two data sets: a training data set and a test data set. We estimate the *ex post* risk reduction for the training data set and compare it with the benchmark risk reduction computed for the test data set. To measure the benchmark risk reduction, we update the insurance contract parameters and a farmer's optimal number of contracts (put options) annually, thus simulating annual decisions made by both the insurance company and the farmer.

Our estimation results for 40 wheat producers in Kazakhstan show that the *ex post* approach might seriously overestimate the risk reduction of index-based insurance instruments. This is valid for reduction measures of downside risk as well as full risk. For the majority of sample farms, index-based insurance schemes – in particular, weather-based index insurance schemes – do not prove to be a reliable risk management instrument. This is not only true for the relative risk reduction measures but also for the absolute risk reduction.

Moreover, the *ex post* ranking of insurance schemes in terms of relative risk reduction also is not reliable. In summarizing the results, we must state that *ex post* risk reductions cannot reliably govern decisions on insurance products in our sample. Moreover, the insurance companies are not sufficiently advised on selecting the most effective insurance scheme for a market launch, nor are the farmers supported in determining the optimal number of index-based insurance contracts to purchase.

In this context, if farm yield time series are sufficiently long, an analysis such as ours may complement a common *ex post* analysis. Furthermore, analyses as in BREUSTEDT et al. (2008) and OZAKI et al. (2009) that simulate confidence intervals of the *ex post* risk reduction and insurance premiums, respectively, may also provide some additional

information on the predictive power of *ex post* estimates. This approach might be particularly useful if time series are too short to separate data into a trainings data set and into a test data set.

For our data, a decisive source of the poor predictive power of ex post estimates stems from the uncertainty over the yields' predictions. Yet, our estimations also suggest that there must be further factors for poor performance of *ex post* predictions. We suppose that the reliability of ex-post predictions might be affected by temporal changes in joint distributions of yield and index variables over time, as well as by the extent to which available time series represent the true distributions of the underlying variables. Thus, further research is needed to distinguish between the different sources of bias in *ex post* predictions of risk reduction due to index-based crop insurance.

From a practical point of view, the predictions are mostly stable for the farm yield insurance among the evaluated insurance products, with a strike level of 75%. Given this stability, traditional farm yield insurance might present a more reliable instrument of yield risk management than index-based crop insurance. Therefore, farm yield insurance with high coinsurance and deductibles to combat moral hazard and adverse selection might still be more effective than index-based insurance schemes. Finally, the development of remote sensing monitoring techniques may contribute to a drought insurance that neither faces considerable basis risk nor is prone to moral hazard. By documenting plant growth on specific plots over several months, these satellite-based techniques allow for precise detection of drought-driven yield shortfalls.

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Appendix

Table A1. Descriptive statistics for 40 farms selected for risk reduction analysis (1980-2002)

Rayon	expected yield (2002), 0.1t/ha	yield STD, 0.1t/ha	cumulative precipitation in June-August, mm		average daily temperature in June-August, °C	
			mean	STD	mean	STD
Atbasar	10.46 7.09	3.33 4.58	117	49	19.1	1.2
Esil	8.68 11.13	2.90 4.31	103	45	19.6	1.3
Zelinograd	8.86 9.13	2.93 3.96	118	49	19.6	1.1
Novoishim	9.14 10.05	3.58 4.19	112	50	19.5	1.1
Denisov	9.14 14.43	3.86 5.27	153	61	18.9	1.5
Glubokoje	29.32 24.64	3.68 5.13	134	41	19.0	0.7

Note: For each *rayon*, the farms with the highest and the lowest standard deviation (STD) of the detrended farm yield were selected; the weather data come from the weather stations located in the respective rayon.

Source: authors` estimates

Sensitivity Analyses

In the above analyses we divided the 23-year time series of yields and weather variables into a training data set covering 1980 to 1991 and a test data set covering 1992 to 2002. We conducted two sensitivity analyses to test whether these results hold for other data fragmentations. For the first sensitivity analysis we did not change the training data set (1980 to 1991) but we did chose a different time period for the test data set, i.e. 1992 to 1997. For the second sensitivity analysis we extended the training data set (1980 to 1996) and used the remaining years for the test data set (1997 to 2002). The results of both sensitivity analyses confirm our major conclusions with only minor exceptions.

According to the main results above, we start with the specifications that allow for trend uncertainty. For the first sensitivity analysis, the average *ex post* MSPEN (MSPE) of yield risk amounts to 13.2 (12.9) while the benchmark MSPEN (MSPE) is 15.8 (19.6). The second sensitivity analysis also confirms the main results: the *ex post* yield risk (MSPEN = 11.1, MSPE = 14.6) is considerably smaller than the benchmark measures (MSPEN = 17.3, MSPE = 18.5).

Tables A2 and table A3 confirm that the predictive power for the FYI is higher, in general, than for the index-based instruments. Table A2 also confirms that there is no risk reduction due to weather-based index insurance contracts – on average among farmers – while table A3 reveals some potential for these instruments. However, the results in table A3 also suggest that the risk reduction potential for the weather-based index insurance is smaller than for the FYI and RYI (on average). The sensitivity analyses also confirm that the ranking of FYI, NYI, and RYI differs between the *ex post* and the benchmark approach. The low predictive power concluded from the sample correlation between the absolute *ex post* risk reduction and the respective benchmark measure is also confirmed by the two sensitivity analyses.

Table A2. Yield risk reduction for test data set 1980–1991 and training data set 1992–1997 (with yield prediction uncertainty)

sample means (40 farms)	**farm insurance**	**national yield insurance**	**rayon yield insurance**	**weather-index insurance (Selyaninov)**	**weather-index insurance (Ped)**
mean squared prediction error (MSPE)					
ex post approach (eq. 3), %- reduction	34	40	55	30	29
benchmark (eq. 5), %- reduction	37	9	43	-7	-9
mean squared negative prediction error (MSPEN)					
ex post approach (eq. 3), %- reduction	48	51	65	39	40
benchmark (eq. 5), %- reduction	41	18	34	-48	-51

Source: authors' estimates

Table A3. Yield risk reduction for test data set 1980–1996 and training data set 1997–2002 (with yield prediction uncertainty)

sample means (40 farms)	farm insurance	national yield insurance	rayon yield insurance	weather-index insurance (Selyaninov)	weather-index insurance (Ped)
mean squared prediction error (MSPE)					
ex post approach (eq. 3), %- reduction	24	34	50	21	22
benchmark (eq. 5), %- reduction	34	11	35	19	22
mean squared negative prediction error (MSPEN)					
ex post approach (eq. 3), %- reduction	41	43	59	26	26
benchmark (eq. 5), %- reduction	49	-0.5	46	10	25

Source: authors' estimates

Table A4 is based on the same time periods for the training and test data sets as for table A3 but without trend uncertainty. The comparison with table A3 confirms that the trend uncertainty reduces the benchmark measures as we have already shown by comparing table 1 and table 2. So, table A4 also gives some indications that trend uncertainty of yield prediction is a source for the small predictive power of the *ex post* risk reductions.

Table A4. Yield risk reduction for test data set 1980–1996 and training data set 1997–2002 (without yield prediction uncertainty)

sample means (40 farms)	farm insurance	national yield insurance	rayon yield insurance	weather-index insurance (Selyaninov)	weather-index insurance (Ped)
mean squared prediction error (MSPE)					
ex post approach (eq. 3), %- reduction	25	32	51	23	23
benchmark (eq. 5), %- reduction	33	33	21	30	31
mean squared negative prediction error (MSPEN)					
ex post approach (eq. 3), %- reduction	42	42	60	28	27
benchmark (eq. 5), %- reduction	45	14	46	17	41

Source: authors' estimates

The most substantial differences in the sensitivity analyses are the higher benchmark estimates for the weather-based index insurance contracts in tables A3 and A4. The explanation might be that the years 1997 and 1998 were extremely dry in Kazakhstan, so the weather insurance instruments may have done a good job in the two most extreme years of a six-year period in the test data set. Consequently, they may have compensated for much yield variation in that short period. In the main analysis' longer test data set they fail to compensate for yield shortfalls in moderately dry years.