On the risk efficiency of a weather index insurance product for the Brazilian semi-arid region

by Mateus P. Lavorato and Marcela J. Braga

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Abstract: Weather index insurance (WII) has long been advertised as a viable alternative to crop yield insurance. WII products were firstly developed to assist climate-vulnerable farmers from developing countries where establishing a well-structured crop insurance market is expressively difficult due to the poor transport infrastructure and the prevalence of sparsely distributed small-scale farms. In Brazil, the semi-arid region stands out as the one that concentrates the ideal conditions for the implementation of a WII product since it houses thousands of climate-vulnerable farmers. Seen this, we designed and priced a WII product for farmers from the semi-arid region of Brazil and posteriorly investigated its risk efficiency. To do so, we first investigated crop yield responses to aridity, enabling the selection of locations for which the WII product was posteriorly assessed. Second, we grouped selected locations into specific contracts according to geographical proximity and evaluated each of these contracts to attest the risk efficiency of the proposed WII product using the method of stochastic efficiency with respect to a function (SERF). Our results show that the WII product is indeed effective in protecting farmers from adverse variations in production revenue, being attractive for utility-maximizer farmers that are sufficiently risk-averse.

Keywords: weather index insurance; aridity; risk efficiency; Brazil

JEL codes: D81; G22; Q14

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1. Introduction

Climate change is expected to lead to decreasing rainfall and rising temperature in several parts of the world, including Brazil. As a consequence, the expansion of areas with arid-like climates is identified as one of the main developments of global warming (Pour et al., 2020). In fact, the number of people living in arid lands worldwide may rise by more than 20% in the near future (Park et al., 2018). Therefore, evaluating and monitoring this phenomenon is of very importance, especially for the regions where agriculture and livestock production corresponds to an expressive share of local economy (Pellicone et al., 2019).

Considering the Brazilian territory, the semi-arid region (Figure 1) stands out in terms of the (possible) effects of climate change. Being primarily composed by municipalities from the Northeast region, the Brazilian semi-arid is, among the arid regions of the world, the most densely populated (Marengo, 2008). The region experiences great interannual variability in rainfall, which leads to the periodic occurrence of drought episodes (Marengo and Bernasconi, 2015). These phenomena have severe social, economic and environmental consequences (Silva, 2004), which are mainly driven by declines in the yield of crops.

[Figure 1 here]

In the semi-arid region of Brazil, rainfed cultivation predominates, which surges the risk of crop frustration due to the region's climatic variability. Despite this, many farmers still grow crops primarily for human consumption, but, when plants fail to grow, stover is used as animal feed (Silva and Regitano-Neto, 2019). Ultimately, the residents of the semi-arid, which often exclusively depend on the outcomes of agricultural production for their livelihood, face the challenge of achieving a sustainable rainfed production with an increasingly-limited water supply (Melo and Voltolini, 2019). Therefore, climate aridification poses a serious threat on the livelihood of the semi-arid population.

Accordingly, one can relate the climate of the Brazilian semi-arid region to the prevalence of poverty among its inhabitants, especially those living in rural areas. In fact, data from the 2017 Census of Agriculture show that farmers from the semi-arid region account for only 6.4% of Brazil’s agricultural production value despite operating more than 1/3 of country’s farms. In spite of housing thousands of climate-vulnerable farmers who could benefit greatly from insurance products[1], the Brazilian semi-arid region has long been neglected by the Rural Insurance Premium Subsidy Program (PSR) as its farmers account for only 0.6% of program’s operations (MAPA, 2020).

In this context, weather index insurance products stand out as possible alternatives to protect vulnerable farmers from the semi-arid region of Brazil against adverse events like droughts. These products use a weather parameter as a proxy to crop yields. By conditioning payouts on the realization of an independent and transparent index instead of actual yield losses, key problems related to crop yield insurance schemes are surpassed (Conradt et al., 2015). Farmers cannot influence payoffs due to the randomness of the underlying index, mitigating information asymmetry (Shen and Odening, 2013), whilst, administering costs are minimized as the on-farm assessment of losses are unnecessary (Stoppa and Hess, 2003).

Seen this, we designed and priced a weather index insurance product for farmers from the semi-arid region of Brazil and posteriorly investigated its risk efficiency. To do so, we applied a multistep approach. First, crop yield responses to weather—which is captured by an aridity index—were thoroughly investigated, enabling the selection of locations for which the

[1] It must be stressed that family farmers from the Brazilian semi-arid are currently served by the Garantia Safra Program. It works like an area-based crop insurance as farmers are compensated when crop yields measured at the municipal level fall below the long-term average. Although the participation fee is divided between federal, state and municipal governments, as well as the farmer himself, payouts are standardized to R$850.00, which are paid in five equal installments. This amount, however, is often not able to cover crop losses.

weather index insurance product was posteriorly assessed. Second, selected locations were grouped into specific contracts according to geographical proximity and each of these contracts were evaluated in order to attest the risk efficiency of the proposed weather index insurance product using the method of stochastic efficiency with respect to a function (SERF).

The literature on the potential of weather index insurance products covers a wide variety of crops, geographical locations and methods of evaluation. For Brazil in specific, to the best of our knowledge, Raucci et al. (2019) is the only applied study on the subject. They design a weather index insurance contract for soybean cultivation in selected locations from southern Brazil and evaluate hedging efficiency against lack of rainfall during the growing season. Our analysis, however, significantly differs to theirs. In addition to differences in the crops and the locations analyzed, we contribute to the literature as the insurance product is evaluated in terms of risk efficiency and not only to divergences in expected revenue.

2. Data

In order to design and price a weather index insurance product for the semi-arid region of Brazil, we used information on weather conditions—which were employed in the construction of De Martonne's aridity index—and crop yield. Data on accumulated precipitation and average temperature recorded by automatic weather stations distributed across the Brazilian semi-arid region were obtained from the Meteorological Database for Education and Research (BDMEP) of the Brazilian National Institute of Meteorology (INMET). Yield data were collected from the Municipal Agricultural Production Survey (PAM), which is conducted annually by the Brazilian Institute of Geography and Statistics (IBGE).

2.1. Yield data

Annual yield data, which are measured in kilograms per hectare, were gathered specifically for beans and maize. Data from the 2017 Census of Agriculture show that these are the crops most cultivated in the semi-arid region of Brazil—at least in terms of the number of farms in which they are grown. In fact, out of the more than 1.3 million rural establishments existing in the analyzed region, approximately 0.8 million cultivated beans or maize. Moreover, it must be highlighted that both beans and maize are temporary crops, being harvested up to three and two times in the same year, respectively. However, we only consider the first harvest, as it concentrates most of the regional production of beans (~80%) and maize (~85%).

Figure 2 depicts the average yield of beans (left-hand side) and maize (right-hand side) for the semi-arid region of Brazil during the period ranging from 2003 to 2018. Only the municipalities in which these crops were grown during all years of analysis are considered, totaling 602 municipalities for beans and 591 for maize. Both crops follow a relatively similar pattern in terms of the geographic distribution of mean yields since the lowest values are concentrated predominantly in the northern portion of the Brazilian semi-arid. Moreover, the highest means of crop yields are achieved in municipalities located in the southwest region of the investigated territory.

[Figure 2 here]

2.2. Weather data

Monthly data on accumulated precipitation and average temperature from 71 automatic weather stations distributed across the semi-arid region of Brazil (Figure 3) were spatially interpolated. We used three methods: inverse distance weighting (IDW), ordinary kriging (OK) and thin plate spline (TPS). IDW estimates the value for unsampled points as the weighted average of the actual points in its vicinity, where weights are a decreasing function of distance (Lu and Wong, 2008). OK estimates the value of a variable over a given region for which a variogram is known, assuming stationarity (Wackernagel, 2003). TPS smooths a scatter plot by fitting a nonparametric regression model that uses penalized least squares (Wood, 2003).

[Figure 3 here]

The accuracy of interpolation methods was evaluated using the mean absolute error (MAE) and the root mean square error (RMSE) obtained by k-fold cross-validation. As depicted in Table 1, IDW generated more accurate data than OK and TPS for both precipitation and temperature. This result is in line with Xavier et al. (2016), who investigated Brazil as well. However, it should be noted, especially for precipitation, that the accuracy of spatial interpolation was relatively low, i.e., both the mean absolute error and the root mean square error were quite high. This is possibly due to the sparse distribution of weather stations within the Brazilian semiarid and the high spatiotemporal variation of precipitation in the region.

[Table 1 here]

Precipitation and temperature data were extracted for the centroid of each of the municipalities analyzed, being used to construct the aridity index proposed by De Martonne (1926). This is one of the most used indicators of the degree of local water deficiency. In fact, despite being one of the oldest indexes developed to assess aridity levels, De Martonne's aridity index is still applied worldwide due to its efficiency and relevance in classifying regions in arid/humid climates (Pellicone et al., 2019). One of the main advantages of such aridity index regards data requirement, since it only demands information on precipitation and temperature. Specifically, growing season values for De Martonne's aridity index were calculated as

$$I_{DM} = \frac{P \times \frac{12}{d}}{\bar{T} + 10} \tag{X}$$

where I_{DM} is the aridity index; P is the growing season accumulated rainfall; d is the duration of the growing season in months; and $\bar{T}$ is the growing season average temperature. Precipitation is multiplied by $12/d$ in order to annualize the values and 10 is added to the temperature in order to avoid a negative denominator.

We followed the schedule presented by the National Food Supply Company (Conab, 2019) to define that maize growing season ranges from January to August ($d = 8$), while beans growing season goes from December to June ($d = 7$). Taking the average for the period between 2003 and 2018, Figure 4 shows the spatial distribution of De Martonne's aridity index for the growing season of (a) beans and (b) maize in the Brazilian semi-arid. Local climate is classified based on Araghi et al. (2018). It is worth noting that arid-like climates ($I_{DM} < 20$) are more prevalent during maize growing season since it has a longer duration, reaching July and August, which are some of the driest months of the year in the Brazilian semi-arid.

[Figure 4 here]

3. Methodology

The approach employed in this study to evaluate the risk efficiency of a weather index insurance product for the semi-arid region of Brazil is composed of three steps. First, considering the values of De Martonne's aridity index obtained for the municipalities analyzed, we used the Geographically Weighted Panel Regression (GWPR) model to examine crop yield responses to the degree of aridity and selected the locations where basis risk is possibly minimum. Second, we applied actuarial tools to design and price a weather index insurance product. Third, we assessed product's risk efficiency by the utilization of the Stochastic Efficiency with Respect to a Function (SERF) method.

3.1. Choosing the municipalities to be analyzed

It is of key importance to correctly identify the municipalities to be analyzed since it makes no sense to implement a weather insurance product in locations where the correlation between index realizations and crop yields are weak or even nonexistent. Recognizing that crop yield responses to weather conditions vary across locations, we estimated the Geographically Weighted Panel Regression (GWPR) model proposed by Yu (2010). This approach allowed the identification of municipalities for which the correlation between index realizations and crop yields are sufficiently strong through the estimation of a single model that takes into account the spatial non-stationarity of the weather-yield relationship.

Specifically, the GWPR model is expressed as

$$Y_{it} = X_{it}\beta_i + \varepsilon_{it} \tag{X}$$

where Y denotes the dependent variable; X denotes independent variables; and ε denotes idiosyncratic errors. The parameters to be estimated are denoted by β, and its estimates, which vary across space but not in time since the spatial relationship between locations is time-invariant, are given by

$$\hat{\beta}_i = (X'W_iX)^{-1}X'W_iY \tag{X}$$

where W_i denotes a n-by-n spatial weighting matrix whose diagonal elements indicate the weight assigned to each of the n observations for the regression point i.

The regression model presented in the Eq. X was calibrated via Weighted Least Squares (WLS), which assumes that the closer an observation is to the regression point i, the greater its influence on the estimation of β_i. The spatial weighted matrix, in specific, was calculated by an adaptive bi-square kernel, which allows the bandwidth to adjust to data density. Taking d_{ij} as the distance between locations i and j, the bi-square kernel is specified as

$$\begin{aligned} w_{ij} &= \left[1 - \left(d_{ij}/d_{ik}\right)^2\right]^2 && \text{if } j \in Z_i(k) \\ &= 0 && \text{otherwise,} \end{aligned} \tag{X}$$

where w_{ij} denotes the weight assigned to j when calibrating the model for i; and $Z_i(k)$ denotes the set of kth nearest neighbors of i.

In spite of evidence showing that crop yields respond nonlinearly to the weather, only the linear term of the weather proxy was considered in the present study. Schlenker and Roberts (2009), for instance, found that nonlinearity is expected to occur only when temperature varies more than 10ºC across observations. Cai et al. (2014), however, argue that an expressive spatial variation is highly unlikely when applying a GWPR model since coefficients are estimated using geographically close subsets of data. Moreover, investigating only the linear aspects of the weather-yield relationship facilitates the discussion of results in an insurance context.

Ultimately, the following model was estimated:

$$yield_{it} = c_i + \beta_{1i} aridity_{it} + trend + \varepsilon_{it} \tag{12}$$

where $yield_{it}$, and $aridity_{it}$ respectively denote crop yields and the aridity index of location i in year t; c_i denotes location-specific, time-invariant fixed effects[2]; $trend$ denotes a linear time trend[3]; and ε_{it} denotes the error term.

As an exercise of robustness check, GWPR results are compared to those obtained from a non-spatial fixed effects (FE) model. Additionally, two statistical tests for spatial non-stationarity are also applied. Under the null hypothesis that GWPR and FE models describe the data equally well, the first statistic (F_2) evaluates GWPR goodness of fit using analysis of variance. The second statistic (F_3), on the other hand, considers the null hypothesis that all local coefficients estimated via GWPR are statistically equal, testing if spatial non-stationarity indeed holds for the analyzed sample. These tests are demonstrated and explained in depth by Leung et al. (2000).

3.2. Designing and pricing a weather index insurance product

We divided the semi-arid region of Brazil in three subregions according to geographical proximity[4] and a different contract was designed and priced for each of them. In order to minimize basis risk, we chose the municipalities for which the aridity coefficient estimated by the GWPR model was positive and statistically pseudo-significant[5] at the level of 5%.

[2] As some time-invariant aspects specific to each unity of analysis can interfere in the relationship between crop yields and the degree of aridity, the use of a fixed effects specification is readily justified. Among such aspects, one could highlight both altitude and soil quality. The spatial rigidity of altitude is straightforward. For soil quality, in turn, this consideration is not so simple. However, for not-so-long time spans one could expect soil quality to remain relatively constant as both the degradation or correction of soil take some time to occur.

[3] The time trend is used to control for technological advances that can influence crop yields.

[4] Specifically, subregions are determined by k-means clustering, using latitude and longitude as inputs.

[5] Pseudo-significance, in this case, refers to the t-statistic for the coefficient of each regression point (Kusuma et al., 2018).

Additionally, we followed Stoppa and Hess (2003) and defined annual degree of aridity as a weighted average of growing season's monthly values of De Martonne's aridity index, as follows

$$A_t = \sum_{i=1}^{n} \omega_i DM_{it} \tag{1}$$

where A_t is the degree of aridity for year t; n is the total number of months in the growing season; ω_i is the weight assigned to the month i; and DM_{it} is De Martonne's aridity index for the month i of year t.

The weights were chosen to maximize the sample correlation between the degree of aridity and crop yields:

$$\max_{\omega_i} corr(A, Y) = \frac{\sum_t (A_t - \bar{A})\,(Y_t - \bar{Y})}{[\sum_t (A_t - \bar{A})^2]^{1/2}[\sum_t (Y_t - \bar{Y})^2]^{1/2}} \tag{2}$$

$$\text{subject to } 0 \leq \omega_i \leq 1 \text{ and } \sum \omega_i = 1.$$

where Y_t denotes crop yield for year t, and $\bar{Y}$ denotes average yield.

Among contract parameters, the trigger and the exit point are the most important ones as they define indemnity payments according to the payout structure. In a simple zero/one contract, indemnity is paid in full once the trigger is surpassed. A layered scheme, in turn, has a set of triggers and exit points. In a proportional payment schedule, which is the one considered here, payouts are defined as a fraction of the insured amount. Indemnity starts to be paid when the index falls below the trigger, increasing until the exit point is reached. At this point, the payment received by the farmer is maximum, equaling total liability. In particular, the payout is governed according to the following scheme

$$Payout = \begin{bmatrix} 1 \quad \text{if } A_t \leq A_E \\ \dfrac{A_T - A_t}{A_T - A_E} \text{ if } A_E < A_t \leq A_T \\ 0 \quad \text{if } A_T < A_t \end{bmatrix} \times Liability \tag{3}$$

where A_T denotes the trigger and A_E denotes the exit point.

The values of A_T and A_E were empirically determined in the same fashion as Choudhury et al. (2016) as we employed a model-base clustering to identify two heterogeneous groups regarding the degree of aridity and crop yields. Focusing on the cluster with the lowest values for the degree of aridity and crop yields, the trigger (A_T) was defined as the average value of the degree of aridity, whilst the exit threshold (A_E) was defined as the lowest value observed for aridity. The model-based clustering built on parameterized finite Gaussian mixture models was estimated by the expectation-maximization (EM) algorithm. Detailed information about this method can be found in Bouveyron et al. (2019).

The insurance product was priced via burning cost analysis, a method that uses the empirical distribution of insurance losses to calculate the premium (Heimfarth and Musshoff, 2011). As observed by Parodi (2015), burning cost analysis is essentially a multi-step procedure. Accordingly, we followed four steps to calculate the risk premium rate. First, payouts were retrospectively calculated from 2018 to 2003. Second, both liability[6] and payout values were forwardly discounted at a 5% rate. Third, annual loss cost ratios were obtained by averaging the ratio of payouts to liabilities over locations. Fourth, the risk premium rate was computed by averaging the loss cost ratio over the analyzed years.

3.3. Assessing product's risk efficiency

[6] Liability is calculated as the expected yield times the coverage level. In order to account for operational costs, a deductible of 15% is considered and thus coverage level is set at 85%.

The effectiveness of the weather index insurance product proposed in this study in guaranteeing farmers against climate risk is evaluated through the comparison of crop revenues with and without insurance adoption. When no insurance is contracted, per hectare revenue corresponds to the multiplication of crop yield (kg ha^{-1}) by postharvest crop price (R$ kg^{-1}). For the case where index insurance is contracted, in turn, the premium is subtracted and the (possible) payout is added to the per hectare revenue previously presented. Specifically, we compared these alternatives in terms of risk efficiency through the use of the Stochastic Efficiency with Respect to a Function (SERF) method.

The SERF method was firstly proposed by Hardaker et al. (2004). This method identifies utility efficient alternatives for a range of risk attitudes as the assessed alternatives are ordered in terms of the certainty equivalents (CEs) calculated for a set of risk aversion coefficients. A certainty equivalent corresponds to the sure sum that yields the same utility as the expected utility of a given alternative. Following the subjective expected utility hypothesis, the utility of an individual depends on the degree of risk aversion, r, and the distribution of returns, R, as follows:

$$U(R,r) = \int U(R,r)f(R)\mathrm{d}R \approx \sum_{j=1}^{m} U\big(R_j,r\big)P\big(R_j\big), \tag{6}$$

where $U(\cdot)$, which denotes the utility function, is evaluated for risk aversion values ranging from r_{L} to r_{U}. The second term of (6) represents the continuous case, whilst the third term provides the discrete approximation, in which $P\big(R_j\big)$ denotes the probability of state j among the set of the m states for each alternative.

Partial ordering alternatives by CEs yields the same results as partial ordering through utility values since the former is given by the inverse of the utility function (Hardaker et al., 2015). Only the alternatives with the highest CEs for some coefficient in the $[r_{\mathrm{L}}, r_{\mathrm{U}}]$ interval are utility efficient (Hardaker et al., 2004). The difference between the CE of a utility efficient alternative and any other alternative yields the utility weighted risk premium (UWRP), which corresponds to the minimal amount one should receive for not choosing the utility efficient alternative (Wang et al., 2020). In mathematical terms,

$$UWRP(a, b, r_k) = CE(a, r_k) - CE(b, r_k), \tag{7}$$

where UWRP for a risk aversion level of k is obtained by subtracting the CE of the utility efficient alternative a from the CE of alternative b.

Under SERF, the calculation of CEs can be done using any type of utility function for which the inverse can be obtained (Hardaker et al., 2004). As farmers are assumed to be risk-averse (Lien et al., 2007; Fathelrahman et al., 2011), we used the following monotonic concave $(U' > 0$ and $U'' < 0)$ power utility function

$$U(R) = \frac{R^{(1-r_r(R))}}{1 - r_r(R)} \tag{8}$$

where r_r denotes the coefficient of relative risk aversion. According to Anderson and Dillon (1992), the degree of (relative) risk aversion varies from 0.5 (hardly risk-averse) to 4 (extremely risk-averse). Therefore, we considered that the relative risk aversion coefficients vary within that interval, i.e., $r_{\mathrm{L}} = 0.5$ and $r_{\mathrm{U}} = 4$.

4. Results

First, we present the results obtained by the GWPR model, which we use to select the municipalities to be considered for the development of the weather index insurance product. Considering that the GWPR model estimates one coefficient for each municipality analyzed, we present the aridity estimates by quantiles (Table 2). As supposed, the magnitude of local coefficients varies considerably across the region. In fact, the interquartile range of GWPR estimates is considerably larger than the standard errors of the global coefficient obtained by the FE model. This is an indication that crop yield responses are characteristically non-stationary in space[7], endorsing the validity of estimating local coefficients.

[Table 2 here]

The median value of the coefficients estimated by the GWPR model is quite similar to the global coefficient estimated by the FE model, providing evidence in favor of the robustness of the GWPR model in estimating crop yield responses to the degree of aridity. Moreover, GWPR estimates are also validated by the results of Leung's tests (Table 3). We were able to reject both null hypotheses at the 1% significance level. Therefore, we can state that, in the context of the present study, the GWPR model describes the data analyzed better than the FE model, whilst local coefficients estimated for the degree of aridity are not statistically equal, i.e., different locations indeed present distinct yield responses to the weather.

[Table 3 here]

[7] Following Fotheringham et al. (2002), spatial non-stationarity refers to the case where the investigated process is not constant over space. In other words, the estimate of the relationship of interest depends on where the measurement is taken.

The proportion of municipalities for which aridity estimates were pseudo-significant at the 5% level is 94% for beans and 74% for maize. The vast majority of the coefficients estimated are positive, with the magnitude of crop yield responses to the degree of aridity varying across the territory as depicted in Figure 5. The municipalities for which estimates were not pseudo-significant are primarily located in the southern part of the territory, the same area where the locations with negative coefficients are concentrated. On the other hand, the locations for which the largest coefficients were estimated are agglomerated in the western portion of the semiarid region of Brazil.

[Figure 5 here]

As previously explained, we selected only the municipalities for which the aridity coefficients estimated by the GWPR model were positive and statistically pseudo-significant at the 5% level. Subsequently, we calculated the weights to be assigned to each of the months of beans and maize growing seasons. Table 4 presents the solution to the maximization problem, which considered average values of each subsample. Weights are highly heterogenous between crops as well as between contracts of a same crop. This result can be related to two facts. First, different growing seasons lead to different responses to aridity. Second, distinct climatic regimes and yield levels are observed among the analyzed subregions.

[Table 4 here]

After generating weighted values for the degree of aridity, we determined the values of the trigger and exit parameters via model-based clustering and applied burning cost analysis to determine the premium rate—as well as the payouts—related to each of the contracts designed for beans and maize. The information presented in Table 5 shows how parameters vary between the crops analyzed. Averaging across contracts, the premium rate estimated for maize is higher than that calculated for beans, indicating that it is riskier to grow the former than the latter in the Brazilian semi-arid as the premium rate is expected to be directly proportional to crop's risk exposure.

[Table 5 here]

Unlike for maize, the premiums calculated for beans vary considerably between its contracts. This is an indication that the analyzed subregions have different levels of risk exposure, which may be connected to the distinct weather patterns experienced by the municipalities in these areas. Both trigger and exit points also vary substantially, especially for maize. This is due to differences in weight assignment and, consequently, to differences in the values used for the aridity index. For instance, August dominates index weighting for maize's contract of subregion 1, leading to weighted aridity values comparatively lower than those of the other subregions.

Having defined contract parameters and the distribution of crop revenues, we were able to evaluate the risk efficiency of the weather index insurance product. In order to complement the results of the SERF method, which will be exhibited ahead, we explore the notion of mean-semivariance[8] to compare the insurance and no insurance scenarios in terms of mean crop revenue and its deviations below the mean (downside risk). The results of the mean-semivariance approach, depicted in Table 6, show that no dominance is identified as the introduction of the

[8] Under the mean-semivariance approach, dominance implies that an insured farmer has a higher expected revenue and at least an equal risk exposition or a lower risk exposition and at least an equal expected revenue than a farmer that is uninsured.

weather index insurance product leads to declines in both risk and return. This is true for all contracts analyzed for both crops.

[Table 6 here]

Finally, we used the SERF method to rank insurance and no insurance alternatives in terms of farmer's attitude towards risk. Figure 6 depicts the UWRP curve for risk aversion coefficients ranging from 0.5 to 4.0. Regardless of the contract analyzed, the insurance scenario becomes utility efficient as the level of risk aversion increases. In fact, the UWRP becomes positive when the risk aversion coefficient is around 1.5. From such point on, the CE calculated for the insurance scenario exceeds that of the no insurance alternative, with the opposite being true for risk aversion coefficients below this threshold. The CEs calculated for risk aversion coefficients ranging from 0.5 to 4 are found in the Appendix.

[Figure 6 here]

5. Discussion

Crop yield responses to weather conditions considerably fluctuate across the semi-arid region of Brazil. Accordingly, so do the parameters governing the payouts of the weather index insurance product designed in this study. Trigger and exit thresholds, as calculated through a model-based clustering algorithm, vary expressively among the different contracts designed for beans and maize. This is, therefore, another piece of evidence on the spatially non-stationary nature of risk exposure to the weather, which corroborates the idea of offering different contracts to different parts of the Brazilian semi-arid.

With the payout parameters in hand, we were able to calculate the premium rate of each contract by means of a burning cost analysis. Except for the region for which Contract 1 was designed, which comprises municipalities from the states of Piauí, Bahia and Minas Gerais, an expressive divergence regarding the premium rate was observed between the crops analyzed. In fact, maize premiums calculated for Contract 2 and 3 are approximately twice as high as those computed for beans. For Contract 1, in turn, beans premiums are slightly higher.

As premiums are estimated in order to capture the risk faced by farmers, which ultimately are transferred to insurers, they provide an approximation of how much the farmers of a given crop in a given region are exposed to risk. According to the findings of this study, beans and maize farmers located in the southernmost part of the semi-arid do not have, between them, major differences in risk exposure. For the remainder of the region, however, maize production is much more susceptible to weather variations. In fact, as shown by Guerra et al. (2003), in certain parts of Brazil, beans require comparatively less water than maize during the growing season, with emphasis on the flowering stage of the plants.

In regard of the effectiveness of the proposed weather index insurance product in protecting farmers against revenue variability, interesting features of the results achieved in this study worth highlighting. The mean-semivariance analysis showed that neither alternative dominates the other. In fact, the introduction of the insurance product leads to decreases in both downside risk and mean revenue. This result can be interpreted in light of the risk-return tradeoff defined by Markowitz (1952), which says that higher returns are obtained at the expense of a greater exposure to risk. Conversely, farmers should sacrifice some fraction of expected return in search of a lower level of risk.

The results of the mean-semivariance analysis are better understood when compared to those obtained through the application of the SERF method. For all the contracts analyzed, the insurance alternative becomes utility efficient as the relative risk aversion coefficient increases.

For lower levels of risk aversion, on the other hand, the utility efficient alternative is the one with no insurance. As the introduction of this risk management tool leads to declines in both the mean and the semivariance of revenues, a less risk-averse farmer would not acquire the WII product developed here, thus guaranteeing a higher expected return.

6. Conclusion

In this article, we designed, priced and evaluated a weather index insurance product for beans and maize farmers from the Brazilian semi-arid region. Municipalities were chosen according to the results obtained by a Geographically Weighted Panel Regression (GWPR) model in order to mitigate basis risk. Subsequently, locations were divided in three groups and one contract was designed for each of them. The parameters of a proportional payment schedule were estimated by a model-based clustering algorithm, contracts were priced via burning cost analysis and the risk efficiency of the insurance product was evaluated using mean-semivariance analysis and the Stochastic Efficiency with Respect to a Function (SERF) method.

Reflecting the greater water requirement and, consequently, the greater production risk, the premiums calculated for maize were, on average, higher than those of beans. Averaging across contracts, the premium rate for beans (maize) was set at roughly 10.6% (15.7%). Ultimately, these figures may help explaining the incipience of crop insurance in the Brazilian semi-arid as the region accounts for only 0.2% (2.1%) of subsidized policies contracted by beans (maize) farmers countrywide (MAPA, 2020). The risk exposure may be such that insurers may be intimidated to operate in the region. In this case, government subsidies may play a crucial role even for a weather index insurance product.

Based on the results of the mean-semivariance analysis, it can be concluded that the weather index insurance product proposed for beans and maize farmers from the Brazilian semiarid would indeed be effective in protecting them from adverse variations in production revenue. Moreover, the results obtained through the application of the SERF method suggest that utility-maximizer farmers that are sufficiently risk-averse would prefer to adopt the insurance product than to do not use this risk management tool. Assuming that farmers are generally risk-averse[9], we can ultimately conclude, based on our results, that the weather index insurance product designed here would be commercially competitive.

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[9] Farmers that face extreme resource-poor situations, like most of the smallholders from the semi-arid region of Brazil, may reach relative risk aversion coefficients as high as four (Dillon and Scandizzo, 1978). In other words, many smallholders may be classified as extremely risk-averse according to Anderson and Dillon (1992).

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Figures

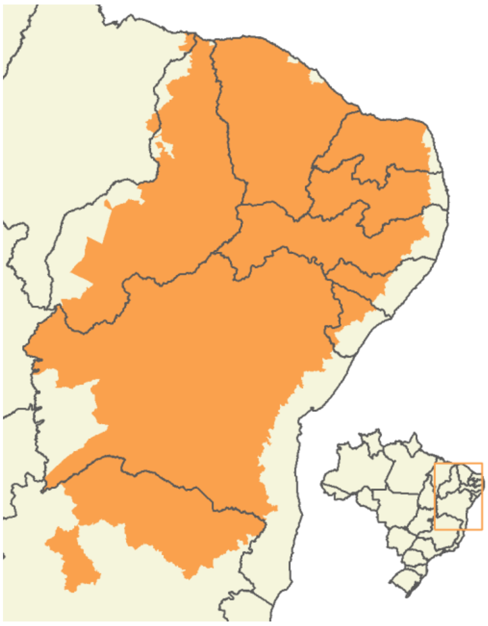

Figure 1. The semi-arid region of Brazil.

Source: Elaborated by the authors.

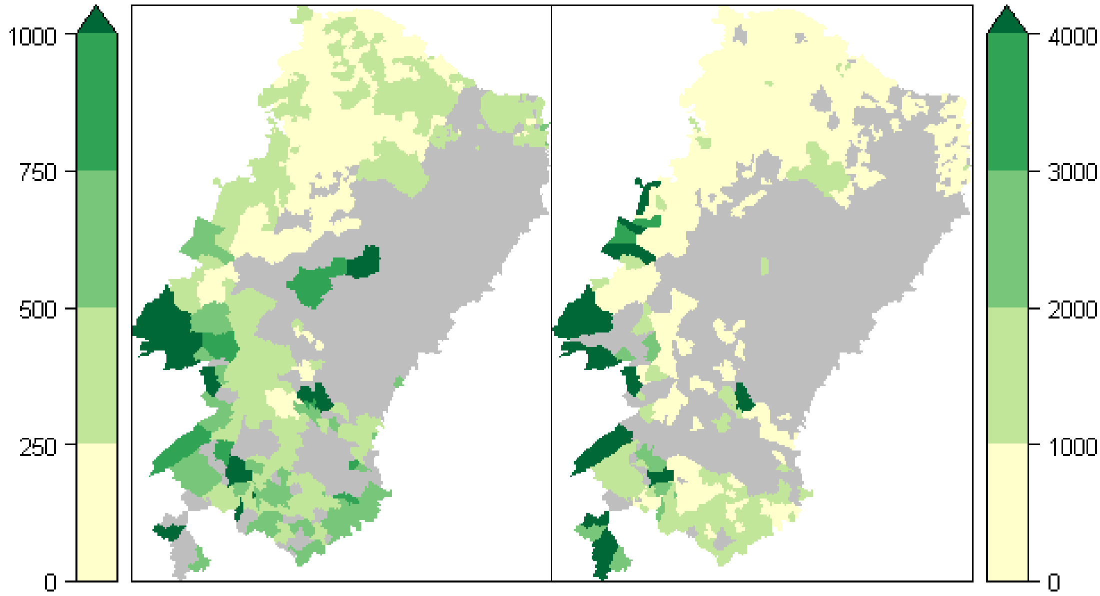

Figure 2. Average yields (kg ha^{-1}) for beans (left-hand side) and maize (right-hand side), Brazilian semi-arid, 2003-2018.

Source: Elaborated by the authors based on data from IBGE (2020).

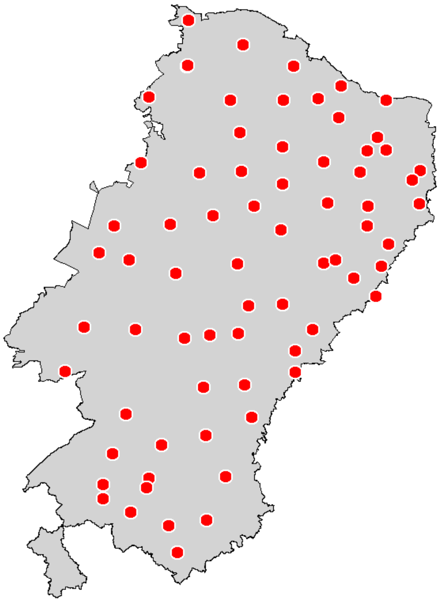

Figure 3. Geographical distribution of INMET's automatic weather stations across the semi-arid region of Brazil.

Source: Elaborated by the author based on data from INMET (2020).

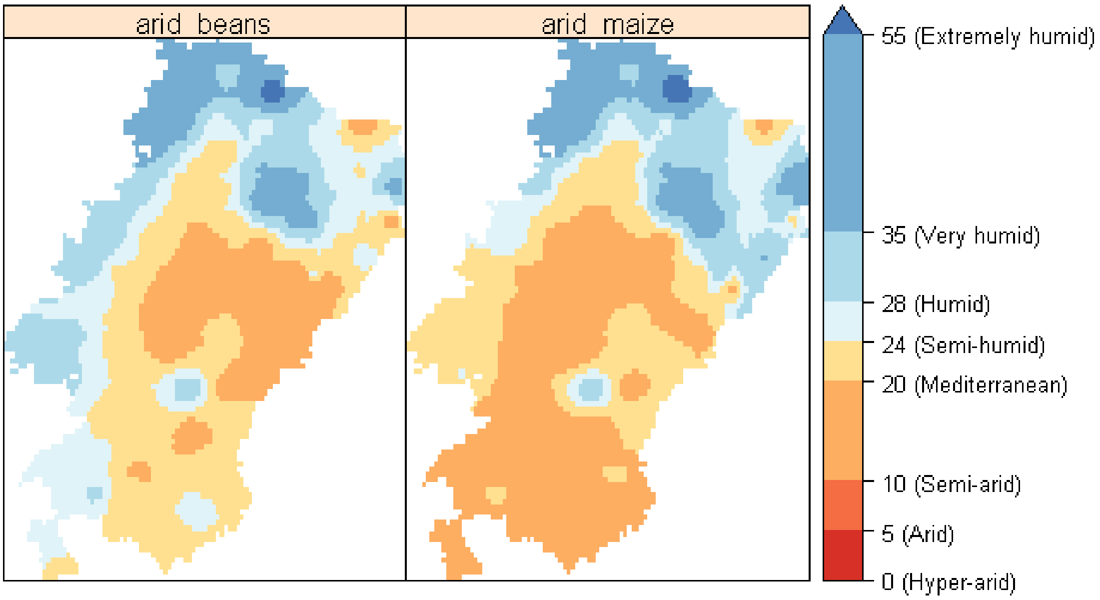

Figure 4. Average of De Martonne's aridity index for beans (left-hand side) and maize (right-hand side), Brazilian semi-arid, 2003-2018.

Source: Elaborated by the authors based on data from INMET (2020).

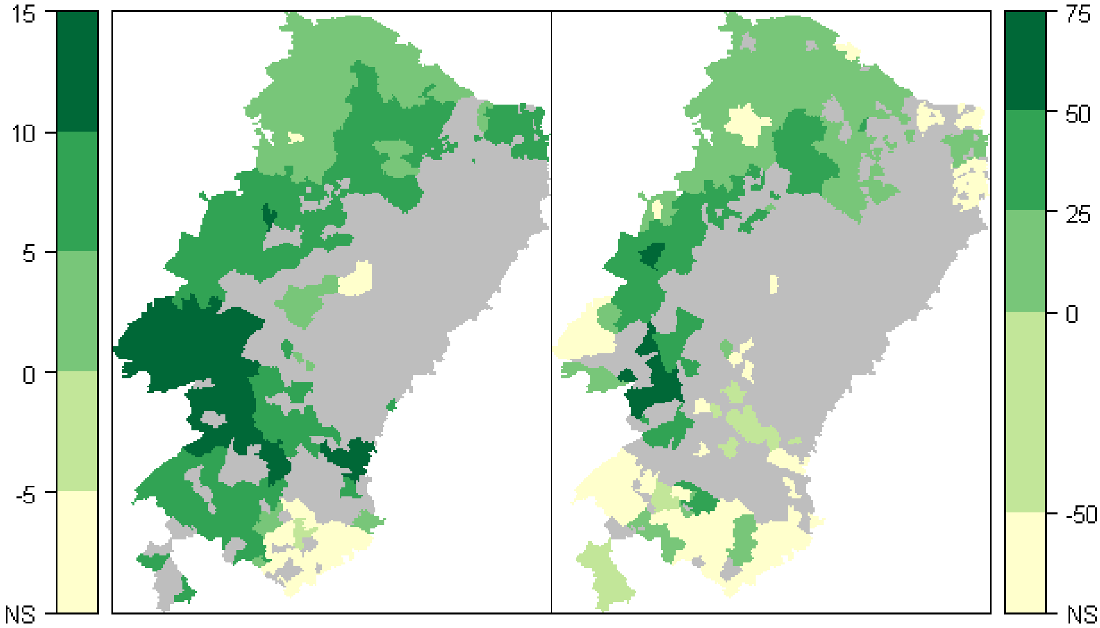

Figure 5. Aridity estimates for beans (left-hand side) and maize (right-hand side), Brazilian semi-arid.

Note: NS represent not significant at the 5% level.

Source: Research results.

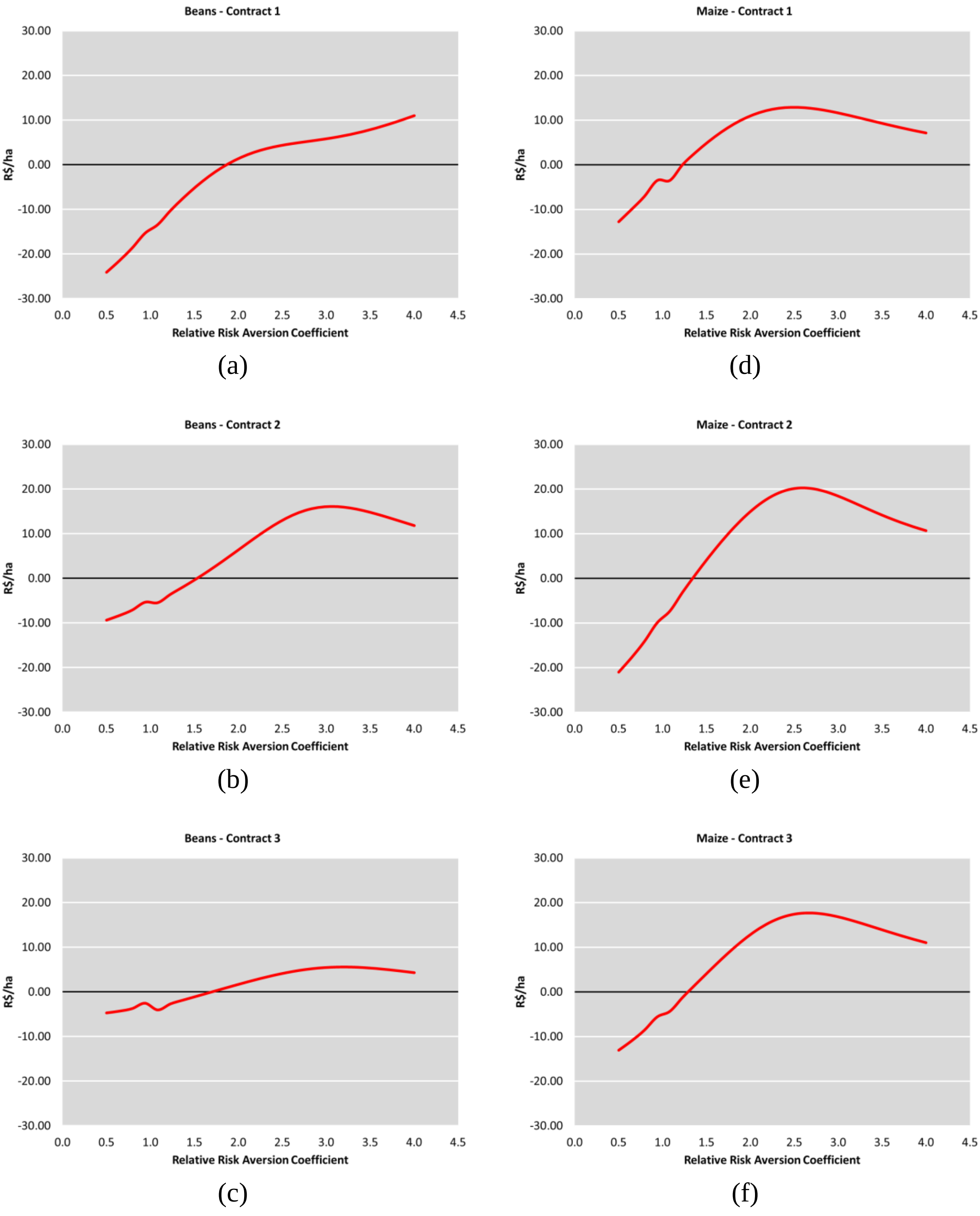

Figure 6. Utility Weighted Risk Premiums calculated for (a, b, c) beans and (d, e, f) maize, Brazilian semi-arid.

Source: Research results.

Tables

Table 1. Accuracy of spatial interpolation methods

Evaluation metrics	Interpolation method		
	IDW	OK	TPS
Precipitation (mm)			
Mean absolute error	40.0170	46.0752	44.4311
Root mean square error	55.4365	60.2441	57.4798
Temperature (ºC)			
Mean absolute error	1.5945	1.9051	1.7966
Root mean square error	2.1029	2.3508	2.3313

Source: Research results.

Table 2. Estimation results for the Geographically Weighted Panel Regression model, semi-arid region of Brazil, 2003-2017.

Crop yield (kg ha^{-1})	GWPR					FE
	Min	Q1	Median	Q3	Max	
			Beans (N = 9,632)			
Aridity	-3.8228	2.8194	5.5232	7.3921	14.9515	4.4463*** (0.1984)
Trend	-2.3394	-0.8261	0.2011	1.3008	3.9194	0.2058 (0.2391)
			Maize (N = 9,456)			
Aridity	-49.5818	7.4768	11.6032	19.9774	63.0053	11.2879*** (0.6452)
Trend	-9.9721	-2.7182	0.1751	4.1529	47.3939	2.0209*** (0.7504)

Note: *** represent significance at the 1% level. Standard errors are shown in parentheses.

Source: Research results.

Table 3. Results for Leung's tests of spatial non-stationarity

Test	F statistic	p-value
	Beans	
F_2	3.9852	0.0000
F_3	10.4396	0.0000
	Maize	
F_2	2.5852	0.0000
F_3	6.3928	0.0000

Source: Research results.

Table 4. Weights assigned to each month of crop's growing season

Contract	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
					Beans				
1	0.54	0.00	0.19	0.26	0.00	0.00	0.00	-	-
2	0.54	0.00	0.05	0.18	0.14	0.00	0.09	-	-
3	0.22	0.24	0.26	0.06	0.19	0.03	0.00	-	-
					Maize				
1	-	0.00	0.04	0.02	0.00	0.02	0.00	0.00	0.92
2	-	0.02	0.27	0.33	0.34	0.04	0.00	0.00	0.00
3	-	0.03	0.04	0.02	0.01	0.08	0.20	0.62	0.00

Source: Research results.

Table 5. Parameters of weather index insurance for the Brazilian semi-arid

Contract	Average liability (R$ ha^{-1})	Trigger (index points)	Exit (index points)	Average payout (R$ ha^{-1})	Premium (%)
			Beans		
1	1,324.29	33.15	7.68	167.80	14.93
2	541.51	30.53	4.09	42.04	9.90
3	649.78	21.14	1.66	39.41	6.83
			Maize		
1	436.68	48.14	13.84	34.47	12.79
2	713.60	4.71	1.21	90.86	16.77
3	397.46	4.58	0.62	52.59	17.57

Source: Research results.

Table 6. Results of mean-semivariance approach for revenues of the contracts designed for beans and maize

Contract	Mean (R\$ ha^{-1})			Semivariance (R\$ ha^{-1})		
	Insurance	No insurance	Difference	Insurance	No insurance	Difference
			Beans			
1	1,528.03	1,557.98	-29.95	847.45	869.43	-21.98
2	625.52	637.07	-11.56	317.08	327.31	-10.23
3	759.48	764.44	-4.96	352.26	358.12	-5.86
			Maize			
1	492.36	513.74	-21.38	288.84	310.55	-21.72
2	810.72	839.53	-28.80	465.56	497.54	-31.97
3	450.36	467.60	-17.25	253.79	273.74	-19.95

Source: Research results.
Notes: Revenue is averaged across space and time and standard deviation is shown in parenthesis.

Appendix

Table A1. Certainty equivalents for beans and maize, Brazilian semi-arid region

RRAC[1]	Contract 1		Contract 2		Contract 3	
	Insurance	No insurance	Insurance	No insurance	Insurance	No insurance
			Beans			
0.50	1,254.26	1,278.34	551.58	560.94	684.18	688.91
0.89	1,056.53	1,073.10	467.69	473.78	545.11	548.26
1.28	927.08	936.34	470.66	473.65	676.67	679.06
1.67	777.07	779.65	404.88	403.12	596.03	596.23
2.06	647.56	645.70	344.23	337.04	538.80	536.83
2.44	537.09	532.94	284.12	271.72	484.28	480.39
2.83	446.18	440.85	227.61	211.98	429.78	424.61
3.22	373.72	367.15	179.37	163.45	376.02	370.45
3.61	317.11	308.65	141.91	127.71	325.44	320.29
4.00	273.18	262.20	114.44	102.60	280.67	276.38
			Maize			
0.50	409.99	422.73	663.36	684.40	367.67	380.74
0.89	298.08	303.00	545.26	556.80	295.66	302.42
1.28	347.62	346.61	483.40	485.15	280.60	280.85
1.67	271.60	264.30	386.55	378.40	225.88	218.63
2.06	214.57	203.20	296.45	280.58	177.59	163.99
2.44	167.39	154.55	214.35	194.44	134.94	117.77
2.83	130.21	117.97	148.38	128.83	100.43	83.01
3.22	102.40	91.81	102.79	86.24	74.83	59.23
3.61	82.23	73.47	74.01	60.74	56.79	43.58
4.00	67.70	60.57	56.10	45.43	44.28	33.27

Note: [1] Relative Risk Aversion Coefficient.

Source: Research results.