Nonparametric Estimation of Risk Preferences: An application to Dairy Farmers

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Preliminary and incomplete

Abstract

The analysis of risk and risk preferences using Just and Pope (1978, 1979) theoretical model - based on Expected Utility - has been studied and applied extensively in agricultural economics over the past three decades. However, most empirical studies have used parametric specifications for the production, the risk production and the risk preference functions. As shown by Kumbhakar and Tsionas (2010), parametric restrictions on the functions and on errors distributions are not necessary to identify farmers' risk aversion and risk preferences. In this paper, we extend the estimation of the functional approach proposed in three dimensions. First, we use Local Linear Least Squares (LLLS) nonparametric estimators allowing simultaneous estimation of functions and their derivatives. Second, as observational data are composed of both continuous and discrete variables, we use generalized product kernel to allow mixed discrete and continuous regressors in the nonparametric estimation. Third, we use data-driven bandwidth selection (cross-validation) and asses the validity of the structural model through a bootstrap test for the relevance of regressors proposed by Racine, Hart, and Li (2006). Finally, we propose to estimate the production function under shape constraints using the constraint weight bootstrapping proposed by Du, Parmeter, and Racine (2013). We apply this method to compute risk preferences of dairy farmers based on an individual-level data set that covers the period 1996-2006. We investigate the stability of measured risk attitudes over time. Our preliminary results show that the majority of dairy farmers is generally risk neutral or slightly risk averse, and the distribution of dairy farmers' risk aversion is significantly higher when an extreme climatic event occurs.

Keywords: Nonparametric estimation, generalized product kernel, nonparametric significance tests, risk preferences, dairy farmers.

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1 Introduction

Farmers have to take every day's decisions under a wide range of risks including climatic risks. The individual farmers' risk preferences are mostly unknown but drive farmer's decisions in farm operations. Assessing the risk preferences of farmers is thus important when analyzing farmers' choices and to understand how farmers take decisions to cover the risks they are facing. So it is important to develop methods that consistently estimate individual risk preferences.

In the economics literature, there exist two main methods for valuating risk preferences: the revealed preference method (or econometric approach), and the stated preference method (or experimental approach). In the stated preference methods, farmers' risk preferences are assessing from real choices between lotteries (Menapace, Colson, and Raffaelli, 2016; Bocquého, Jacquet, and Reynaud, 2014). In the revealed preference methods, they are deriving from the divergence between observed real decisions made under risk and expected decisions made without risk (see the papers of Saha, Shumway, and Talpaz, 1994, and Antle, 1989 for the presentation of the three main econometric methodologies for estimating farmer's risk preferences; see also the review of literature proposed by Reynaud et al., 2010).

Although these two methods differ in terms of underlying estimation procedure, they are commonly based on the same theoretical framework. They both follow the Expected Utility theory, representing the individual risk preferences as a local measure of the utility function curvature: the Arrow-Pratt coefficient of risk aversion. The theoretical framework for estimating risk preferences is generally based on structural models of production technology and on first-order conditions defining optimal input decisions. The most popular approach among agricultural economists for handling production risk was developed by (Just and Pope, 1978, 1979). The basic concept introduced by Just and Pope is to define the production function as the sum of two components, the first one revealing the output level, and the second one presenting the variability of output. Such a characterization allows us to identify the effect of inputs on output level and risk.

The analysis of risk based on the Just and Pope production function has been studied extensively in the past three decades but most studies use parametric specifications of the production, risk production and risk preference functions. Kumbhakar and Tsionas (2010) have proposed a less restrictive estimation framework relaxing assumptions on the production and risk preference functions specification. In their framework the derivation of the risk preference function depends neither on specific parametric form nor on any assumption regarding the distribution of the error term representing the production risk. This first attempt towards a flexible but tractable estimation process on risk preference has been ignored by practitioners with the notable exception of Czekaj and Henningsen (2013). These authors propose an application in a very general framework introducing nonparametric panel-data estimators (Henderson, Simar et al., 2005). Despite its general modeling embedding three types of risks and quite a complex estimation framework, this paper does not provide some insights for the practitioner and lacks of significance tests and ex-post checks of shape constrains for the production function. Still, these two papers show that nonparametric methods would be useful for the estimation of the technology, risk and risk preferences of producers facing uncertainty in production .

We propose here to adapt this nonparametric framework using up-to-date nonparametric estimation procedures and significance tests. We extend Kumbhakar and Tsionas (2010) functional framework in four dimensions. First, we use Local Linear Least-Square (LLLS) nonparametric estimators (Henderson and Parmeter, 2015) allowing a simultaneous estimation of functions and their derivatives. Second, since the production function must be increasing with inputs, we provide ex-post tests and propose to introduce a nonparametric estimation under shape constrains (Du, Parmeter, and Racine, 2013). Third, many empirical application, including ours, involve mixed continuous and discrete data, we use nonparametric estimators with generalized product kernels (Racine and Li, 2004). Finally, we propose an empirical framework with significance testing based on data-driven cross validated bandwidths for both categorical and continuous variables (Racine, Hart, and Li, 2006). Despite its apparent complexity, this approach is computationally tractable using up-to-date estimators and a clear step-by-step procedure.[1]

We apply this method for first assessing risk preferences of dairy farmers, and second, for analyzing the stability of dairy farmers' risk preference estimations across time under climatic risk. We also propose an analysis of the stability of dairy farmers' risk preference estimations in a changing climate environment. Dairy farmers' risk preferences are measured using observational data. This analysis uses data on French dairy production farmers covering the 1996-2006 period. The data encompass years both before and after the extreme heat wave which has strongly affected the targeted region in 2003. For the whole period, we observe annual farm-level information on type

[1] We use several R packages and take advantage of its parallel computing features to alleviate the computational burden of the cross-validation procedure. We also propose to use a *trick* mentioned in (Li and Racine, 2006) and avoid as much as possible the computation of these bandwidth over the whole sample in the empirical application.

of structure, performance (as dairy and feed productions), system control variables, the technical and economic data and on the forage system. The sample used in the analysis covers farms in the Southwestern France's main milk production regions with six particular soil and weather conditions. The farm-level data were complemented with weather data for each region from the French Meteorological Institute. The data is a panel of 2589 farmers over the 1996-2006 period with a total of 28479 observations. Empirical analysis over many years allow us to investigate the stability of measured risk attitudes over time, and to show the impact of extreme climate events on farmers' risk preference estimations. Results show that the majority of dairy farmers is generally risk neutral or slightly risk averse, and the distribution of dairy farmers' risk aversion is significantly higher when an extreme climatic event occurs.

The rest of the paper is structured as follows. Section 2 presents the theoretical framework for defining farmers' risk preferences. Section 3 describes the nonparametric estimation procedure for assessing risk preferences. Section 4 provides one empirical application of the proposed procedure. Section 5 concludes.

2 Theoretical framework

We adopt a structural approach that allows us to describe the problem of the dairy farmer in terms of production and input decisions under risk. We focus on production risk, which is the dominant source of risk in our context. Indeed, dairy farmers may generally face several types of risk, principally affecting price and yield variability. The impact of price risk is reduced in our context due to price support by EU; therefore yield volatility dominates price volatility. We assume that dairy farmers only face climate risk impacting production, and therefore farmers' wealth.

The usual way of investigating the production risk into a stochastic production function is to consider a Just and Pope (Just and Pope, 1978, 1979), production function given by:

$$y = f(x, z) + g(x, z)\epsilon \tag{1}$$

where y is the observed output quantity, x is a vector of variable input quantities $(x_1, ..., x_J)$, z is a vector of quasi-fixed input quantities $(z_1, ..., z_K)$, $f(.)$ is the mean production function, $g(.)$

is the production risk function. The random term ϵ represents a weather shock that may affect output, exogenous to farmer's action, with zero mean and a variance of one (Just and Pope 1978, 1979). The production risk function $g(x, z)$ is used to analyze the marginal influences of inputs on the variance of production.

By assumption, dairy farmers maximize the expected utility of profit. Then the dairy farmer's optimization program is written as follows:

$$Max_x \;\; EU(\pi) = EU\Big(pf(x,z) + pg(x,z)\epsilon - wx\Big) \tag{2}$$

where p denotes the milk production price, w the vector of variable input prices.

We get the following first-order conditions (FOC):

$$E\Big[U'(\pi)\big(pf_j(x,z) + pg_j(x,z)\epsilon - w_j\big)\Big] = 0 \quad \forall j = 1, ..., J \tag{3}$$

where $U'(.)$ is the marginal utility of profit, f_j and g_j denote the first derivatives of the mean production function and the risk production function, respectively, with respect to the j-th variable input.

To derive the risk preference function, we can rewritten (FOC) in the following way:

$$pf_j(x,z) - w_j + \theta(.)pg_j(x,z) = 0 \quad \forall j = 1, ..., J \tag{4}$$

where $\theta(x, z, p, w) = \frac{E[U'(\pi)\epsilon]}{E[U'(\pi)]}$ is the risk preference function. A positive (negative) value of θ indicates risk averse (risk seeking) farmers and $\theta = 0$ indicates risk neutral farmers.

Under the assumption that $U(\pi)$ is continuous and differentiable, $U'(\pi)$ can be approximated at $\epsilon = 0$ by a first-order polynomial (Kumbhakar and Tsionas, 2010).Then the risk preference function $\theta(.)$ takes the following form:

$$\theta(.) = -AR(\pi)\sigma_\pi \tag{5}$$

where $AR(\pi) = \frac{-U''(\pi)}{U'(\pi)}$ is the Arrow-Pratt measure of absolute risk aversion and $\sigma_\pi^2 = var(\pi) = p^2(g(x,z))^2$.

3 Nonparametric estimators

The theoretical framework is based on three functions namely the mean production function, the risk production function and the risk preference function that we estimate nonparametrically. Nonparametric regression estimators are mostly based on Local Constant Least-Squares (LCLS) estimators, also known as Nadaraya-Watson estimators. They are defined as a weighted average, with weights that depends on the covariates. One can also express that estimator as the solution of a distance minimization problem. Let y be the variable of interest (production) and w the vector of covariates. Following Henderson and Parmeter (2015), the local constant kernel estimator estimator for the (production) function $f()$ is $\widehat{f()}$ defined as the solution of:

$$Min_{f(w)} \sum_{i=1}^{n} [Y_i - f(w)]^2 \ K\left(\frac{w_i - w}{h}\right)$$

Treating $f(w)$ as locally constant$(= a)$ leads to the FOC:

$$-2\sum_{i=1}^{n} [Y_i - a] \ K\left(\frac{w_i - w}{h}\right) = 0$$

giving:

$$a = \widehat{f}(w) = \frac{\sum_{i=1}^{n} Y_i \ K\left(\frac{w_i - w}{h}\right)}{\sum_{i=1}^{n} K\left(\frac{w_i - w}{h}\right)}$$

which is the usual Local constant or Nadaraya-Watson estimator, where $K()$ is a multivariate kernel function and h is a vector of bandwidths associated to the set of explanatory variables w.

Here, we are interested in the estimation of the derivatives of the functions, and so we prefer using Local Linear Least-Squares (LLLS) nonparametric estimator allowing simultaneous estimation of both the function and its derivatives $f_j(w)$ for $j = 1, \ldots, J$ (see Li and Racine, 2006). The local linear estimator is defined also as a local approximation of $f(w)$:

$$\begin{aligned} y_i &= f(w_i) + u_i \\ &\approx f(w_i) + (w_i - w)\beta(w) + u_i \end{aligned}$$

Treating $f(w)$ and $\beta(w)$ as parameters (a and b), the minimization problem becomes:

$$Min_{a,b} \sum_{i=1}^{n} [Y_i - a - (w_i - w)b]^2 \; K\left(\frac{w_i - w}{h}\right) \tag{6}$$

leading to the local linear estimator providing both and estimation of $f(w)$ and of its local derivative $\beta(w)$. In the empirical application, we are facing a mix of discrete (unordered and ordered) and continuous variables, so we use a generalized product kernel estimator proposed by Li and Racine (2004) for the kernel $K(\cdot)$. A least-squares cross validation approach, also proposed by Li and Racine (2004), is used to select the bandwidths.

We follow and extend the multi-step procedure proposed by Kumbhakar and Tsionas (2010) for estimating the mean production function $f(\cdot)$, the production risk function $g(\cdot)$ and their derivatives. The functions estimated using nonparametric estimators are then plugged in the analytic formulas of section 2, providing estimates of the risk preferences functions at the observed (farm-level) values.

In the first step, we estimate of mean production function $f(w)$ of the Just and Pope technology using nonparametric kernel regression. In the second step, the residuals of the production model estimation are regressed on the same set of explanatory variables. These are the estimates of the mean risk production function. Once nonparametric estimates of the mean production function and the mean risk production function have been obtained, the risk preference functions can be computed following the theoretical model. The sequence can be described as follows:

- The Just and Pope model, as defined in (1), can be rewritten:

$$\begin{aligned} y &= f(x,z) + g(x,z)\epsilon \\ &= f(w) + \nu \end{aligned}$$

  where w denotes the vector of all variable inputs, and ν is an error term. The production function $f(\cdot)$ is estimated by $\widehat{f}(\cdot)$, using the local linear kernel estimator defined by the equation (6), using cross-validated bandwidths.

- We then compute the sample residuals $\widehat{e_i} = Y_i - \widehat{f}(W_i)$ using the first stage regression model. Recalling that ν is defined from the Just and Pope (1979) model (equation 1 as $g(x,z)\epsilon$, we regress the residuals squared on the set of explanatory variables w. We use again a local linear nonparametric estimator of $|e_i|$ on w. We use least-squares cross validation (LSCV) to compute the bandwidths associated with each covariate. We then compute the estimator of the mean risk production function $\widehat{g}(w)$ and its derivatives $\widehat{g_j}(w)$ for $j = 1, \ldots, J$.

- Once the mean production function and the mean risk production function and their derivatives have been estimated, we compute the risk preference function $\theta(\cdot)$ using the FOC in equation (4).

$$\hat{\theta}(\cdot) = \frac{1}{J}\sum_{j=1}^{J}\Big[\frac{\hat{f}_j(X) - c_j/p}{-\hat{g}_j(X)}\Big] \tag{7}$$

That approach follows closely the parametric approach, except that the functions are not specified here.

A variant of this approach would involve a functional form for the production function in the first stage (e.g. a Cobb-Douglass specification) and estimating the risk function $g()$ and its derivatives as proposed above. This semi-parametric approach would probably make the estimation easier. However, estimating the production function is of prime importance in this setting since any misspecification would directly affect the residuals and thus have an effect on the risk production estimation function $g()$ and its derivatives.

A second improvement consists in estimating the production function under shape constraints using the constraint weight bootstrapping (CWB) proposed by Du, Parmeter, and Racine (2013). One of the advantages of this method, compared to other nonparametric estimators under shape constraints proposed in the literature (see Parmeter et al., 2014, or Henderson and Parmeter, 2009 for a survey), lies in its simplicity and its low computational burden. It applies to a wide class of kernel regression smoothers that can be written as linear combinations of the response variable Y. In particular, one can rewrite the production function estimator as:

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} A_i(x)Y_i, \tag{8}$$

where $A_i(x)$ is a local weighting matrix. Imposing constraints on the estimates of $\hat{f}(.)$ resumes in imposing constraints on any partial derivative. We denote by s the order of the partial derivative corresponding to each element of x. Since the vector of regressors X is of dimension r, $s = (s_1, s_2, \ldots, s_r)$. Thus $s = (0, 0, \ldots, 0)$ represents the function itself, while $s = (1, 0, \ldots, 0)$ represents $\partial f(x)/\partial x_1$. Imposing monotonicity on $\hat{f}(\dot{)}$ can be written as:

$$0 < \hat{f}^(s)(x) \tag{9}$$

for $s = (1, 1, \ldots, 1, 0, \ldots, 0)$, the number and positions of ones corresponding to the inputs in the production function. Rewriting (3) in a more general way:

$$\hat{f}(x) = \sum_{i=1}^{n} p_i A_i(x) Y_i, \tag{10}$$

The Nadaraya-Watson estimator mentioned above can be seen as a special case of equation 3 with $A_i(x) = \frac{nK(X_i - x)}{\sum_{j=1}^{n} K(X_j - x)}$ and $p_i = 1/n, i = 1, \ldots, n$. The approach proposed by Du, Parmeter, and Racine (2013) is based on the fact that we can rewrite the production function derivative estimator as:

$$\hat{f}^s(x) = \sum_{i=1}^{n} p_i A_i^s(x) Y_i \tag{11}$$

with $A_i^s(x) = \partial^{s_1} A_i(x)/\partial x_1^{s_1}, \ldots, \partial^{s_r} A_i(x)/\partial x_r^{s_r}$.

Imposing constraints on $\hat{f}(x)$ resumes in imposing linear constraints on the system of weighting vectors p_i. The constrained nonparametric estimator therefore allows different points to contribute differently to the overall average. By letting the weights differ from the uniform $1/n$, one can manipulate the p_i to ensure that the constraints imposed on $\hat{f}^s(x)$ are preserved. Note that the Du, Parmeter, and Racine's approach allows the p_i's to be positive or negative (while satisfying $\sum_{i=1}^{n} p_i = 1$).

4 Empirical application

4.1 Data

The model presented in the preceding sections is applied to France dairy farmer data. The sample consists of 2588 dairy farmers from six regions in the Southwestern of France. The period covered is from 1996-2006. Thus total number of observations is 28458. Details on the data can be found in Sautier (2013).

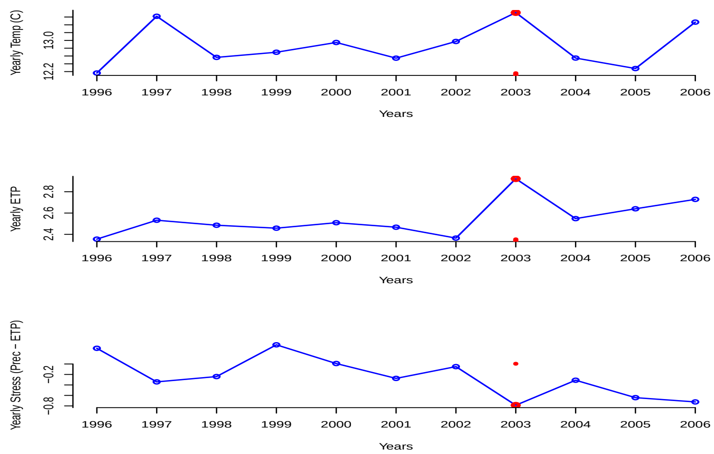

Figure 1: Mean meteorological variables [1996-2006]

The farm-level data were complemented with weather data for each region from the French Meteorological Institute. The year 2003 has been exceptionally hot and dry and has been a shock for Farmers. The grass and the hay have been quite scarce and some farmers may have switched to grain. In Figure 1 we see an increase in the mean temperature in 2003 (upper panel) as well as for evapo-transpiration, (ETP, middle panel). As a consequence, the hydric stress, computed as the difference between precipitation and ETP, is negative and shows a sharp increase in absolute value.[2]

Descriptive statistics of the key variables are presented in Table 1. The dependent variable is the milk production. The main variable inputs are: hectares of land (area) used, livestock (Heads), the quantity of purchased feed (kg/cow) and surface irrigated Land (ha) for pasture. We introduce in the production some control variables (Milk Quota) and temperature (C). We use prices collected either at the national or regional level (grain). The milk price is the price received by the farm.

4.2 Nonparametric estimation

We use up-to-date nonparametric estimation techniques to compute the ingredients needed for estimating $\theta(\cdot)$ according to equation (7).

[2]All climatic variables are provided at the sub-region level by the French national meteorological service, Météo-France. Mean per year is computed as the average over the year of the mean per day. Temperatures are in Celsius degree.

	Variable	mean	sd	min	max
y	Milk. Prod.(1000 L)	251.78	123.34	17.01	1407.11
x_1	Irrigated Land (ha)	4.30	7.53	0.00	80.00
x_2	Purchased feed (kg/cow)	1420.60	424.65	0.00	8294.00
z_1	Farm Land (ha)	65.12	42.42	0.10	997.00
z_2	Forage crop (ha)	42.62	26.87	0.00	300.10
z_3	Livestock (Heads)	64.04	29.77	6.90	367.40
z_4	Milk Quota (1000 L)	214.65	121.69	0.00	2102.74
c_1	Temp (C)	13.23	0.85	10.26	14.76
c_2	Evapotranspiration	2.56	0.27	2.09	3.32
c_3	Hydric Stress	-0.32	0.65	-1.70	0.91
p	Milk price (euros)	138.52	150.38	0.00	609.77

Table 1: Descriptive statistics, (1996-2006)

As in any nonparametric estimation the choice of the bandwidth a is a crucial element in the practical implementation. For both the computation of $\widehat{f}(\cdot)$, $\widehat{g}(\cdot)$ and $\widehat{\sigma^2}(\cdot)$, we opted for the computation of cross-validated (CV) bandwidths for each each year so that the local linear estimators are automatically balanced between bias and variance. We choose higher order continuous kernels implemented in the R package *np* (Hayfield and Racine, 2008)

We use another interesting feature of the recent development in nonparametric estimation technique by using Kernel Regression Significance Tests. We run this test based on the work by Racine, Hart, and Li (2006) for each year and derive significance of each explanatory variable (399 bootstraps). Hence, we confirm the significance observed in running a linear regression (t-test).

Finally, we also check *ex-post* whether the risk production function estimated where satisfying classical production function features ($f' > 0$ and $f'' < 0$). One possible extension would be to estimate $f(\cdot)$ under shape constrains (see Du, Parmeter, and Racine, 2013). Estimation of economic relationships as functional forms in the production context often requires imposition of constraints (such as monotonicity or concavity) or restrictions provided by economic theory (for example, production functions are monotonic in input quantities).

4.3 Dairy farmers' risk attitudes: Preliminary results

We discuss results concerning dairy farmers' risk attitudes. To obtain an insight into the risk attitudes and the differences therein, we computed the predicted values of the absolute risk aversion

(AR) functions for each farm and for each year. We examine risk preferences for each farmer based on the predicted values of the risk preference function, θ calculated from equation (7).

In Figure 2 we represent the distribution of the estimated AR over the whole period. Estimated AR coefficients vary substantially among years. The AR values are both farmer- and year-specific. This result of heterogeneous risk preferences among farmers is in line with previous studies (see Reynaud et al., 2010 for a review).

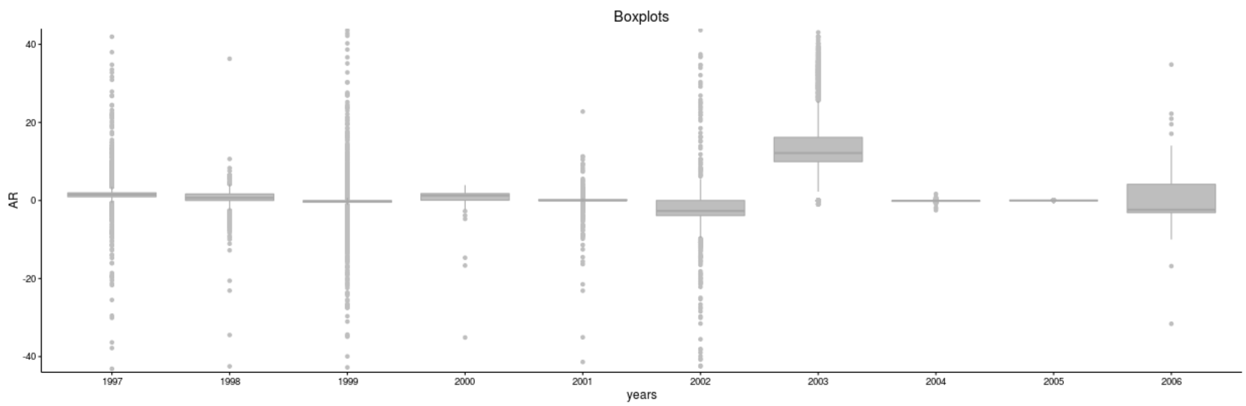

Figure 2: Risk aversion distribution [1996-2006]

Year	Median	AR First quartile	Third quartile	Risk Behavior
1997	1.50	0.94	1.98	Risk-averse
1998	0.67	0.00	1.70	Risk-averse
1999	-0.27	-0.46	0.00	Risk-prone
2000	1.28	0.07	1.79	Risk-averse
2001	0.01	0.00	0.22	Risk-neutral
2002	-2.69	-3.89	0.02	Risk-prone
2003	12.16	9.95	16.19	Risk-averse
2004	-0.09	-0.15	-0.06	Risk-prone
2005	0.00	0.00	0.00	Risk-neutral
2006	-2.37	-3.11	4.15	Risk-prone
Mean	1.02			Risk-averse

Table 2: AR mean values by year (1997-2006)

In Table 2 we report the mean AR values by year. The predicted farmer mean AR values range from -2.69 to 12.16, with a sample mean of 1.02. We find that dairy farmers are meanly risk averse but this trend is not always observed depending on the considered year. We can note risk-averse behavior but also risk-prone behavior depending on the climate year characteristics.

Now we assess the stability over time of the estimated individual risk aversion parameters, and the effect of the climatic event on these parameters. The shift in the distribution of the farmer's adverse risk parameter in 2003 can formally be tested, even if there is no doubt that it is significant. As shown in Figure 2, there is still a great variability in the estimated risk aversion parameter among farmers. This may be due either the estimation framework that allows for heterogeneity in the estimation process, or to the nature of individual risk aversion. We use a new data visualization method, representing each of the 2588 farmers in a single graph. In Figure 3, we represent each farmer's AR parameter over time and link these points for the 11 years through a grey line.

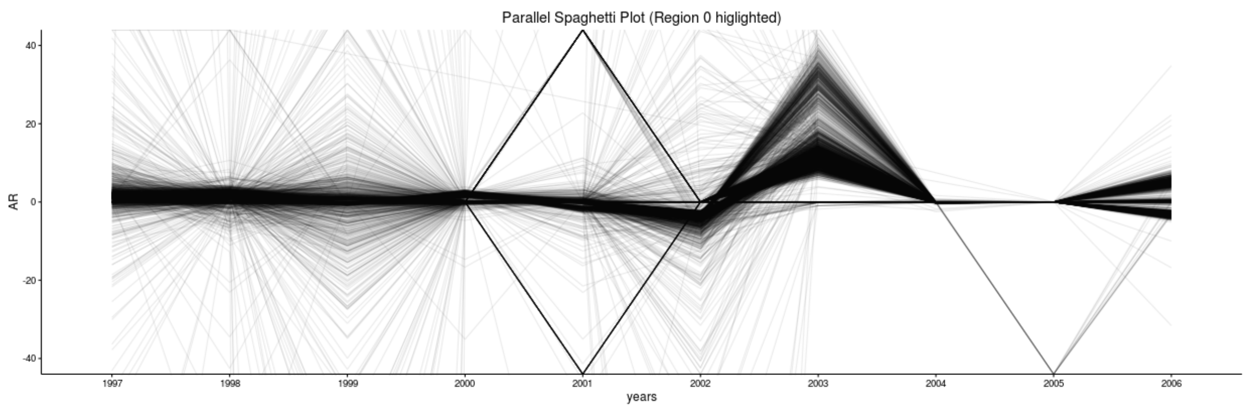

Figure 3: Risk aversion parameters estimated at the farm level [1996-2006]

Each line represents a farmer risk aversion over time periods. We use a data visualization technique , namely "bushing", to treat the overlap of lines. So lines have been *brushed* so that streams of lines becomes darker and darker with overlap, leading to an emergence of a pattern. The emerging pattern is that, at the farm level, the risk aversion parameter do no fluctuate from one year to another, with the notable exception of the year 2003 - the year with a heat wave and droughts- where the majority of AR parameters increase. Then, in 2004, most of these parameters decrease again.

We observe the same pattern, with a stability over time, except in 2003, for the 4 main regions of interest in Figure 4, with some outliers, and some high variability in region 4 between 1998 and 2000, that can be due also to a heat wave in 1999 (see temperatures graph in Figure 1).

These preliminary results asses the fact that there is a global stability of farmer's risk aversion

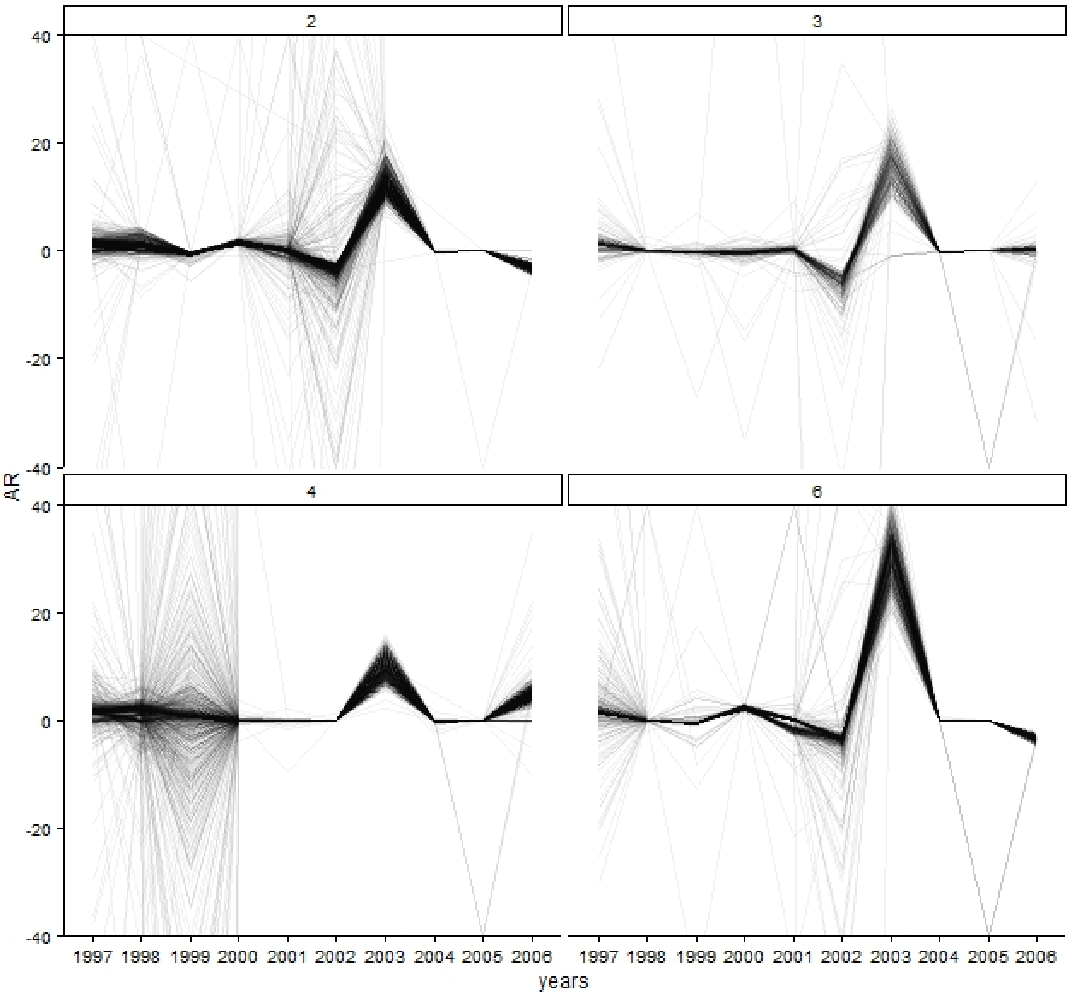

Figure 4: Risk aversion per region estimated at the farm level [1996-2006].

parameters over time for periods with no major climatic event. In case of a climatic shock, such as the 2003 heat wave, our results show that the individual risk aversion parameters change.

We provide new elements to the debate on the stability of risk preferences over time and on the impact of a shock on risk preferences. There is no consensus in the literature on whether risk preferences are stable over time or may change after a shock. In some previous studies, risk preferences are stable (Andersen et al., 2008; Chiappori and Paiella, 2011) while in others they are unstable (Guiso, Sapienza, and Zingales, 2011). Many studies (Eckel, El-Gamal, and Wilson, 2009; Andrabi and Das, 2010; Li, Li, and Liu, 2011; Cameron and Shah, 2012; Cassar, Healy, and von Kessler, 2011; Callen, 2011; Bchir and Willinger, 2013) suggest that exposed individuals have changing their preferences after a shock.

5 Conclusion

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