The effects of extreme climatic events on dairy farmers' risk preferences : A nonparametric approach

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Motivation

Climate change is likely to increase average daily temperatures and the frequency of heat waves, which can reduce meat and milk production (Key and Sneeringer 2014)

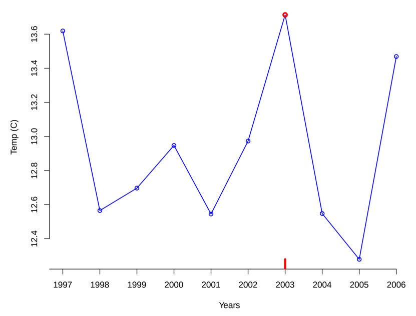


Figure 1: Average temperature (C) between 1996 and 2006 in France South-West region

Managing the risk of such intense events may influence dairy farmers' production decisions, and their risk preferences. The idea is to study precisely how a realized extreme event affects farmers' risk preferences.

Research questions:

1. Is there a change observed in dairy farmers' risk preferences over time?
2. Do extreme climatic events modify dairy farmers' risk aversion?
3. Is a nonparametric approach adapted/tractable to answer these question ?

Analytical framework

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

$$y = f(x, z) + g(x, z)\epsilon \qquad (1)$$

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.

The dairy farmer's optimisation programme is written as follows:

$$Max_x \;\; EU(\pi) = EU\Big(pf(x, z) + pg(x, z)\epsilon - cx\Big)$$

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

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

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

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. Rewritten in the following way:

$$pf_j(x, z) - c_j - \theta(.)pg_j(x, z) = 0 \quad \forall j = 1, ..., J \qquad (2)$$

where $\theta(x, z, p, c) = \frac{E[U'(\pi)\epsilon]}{E[U'(\pi)]}$ is the *risk preference function*.

Using a first-order polynomial approximation (see Kumbhakar and Tsionas (2010)) the risk preference function $\theta(.)$ takes the following form:

$$\theta(.) = -AR(\pi)\sigma_\pi \qquad (3)$$

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

Nonparametric estimation

We follow the multi-step procedure proposed by Kumbhakar and Tsionas (2010) for estimating the mean production function $f(\cdot)$, and the production risk function $g(\cdot)$ leading to the risk preference function $\theta(\cdot)$.

- In a first stage, we estimate mean production function $f(\cdot)$:

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

where w denotes the vector of all variable inputs (including variable inputs and quasi-fixed inputs), and ν is the error term. The function $f()$ can then be estimated by $\widehat{f()}$ using classical nonparametric regression methods.

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

Where $K()$ is a multivariate kernel function and h is a vector of bandwidths associated to the set of explanatory variables w. Since we are interested mainly by the derivatives of $f()$, we use the *local linear nonparametric estimation* procedure proposed by Li and Racine (2004) allowing simultaneous estimation of both the function and its derivatives $f_j(w)$ for $j = 1, \ldots, J$.

- In the second stage, we compute the sample residuals $\widehat{e_i} = Y_i - \widehat{f}(W_i)$ of the first stage regression model.
  Then we use a local linear nonparametric estimator of e_i (resp. e_i^2) on w to compute the estimator of the mean risk production function $\widehat{g}(w)$ and its derivatives $\widehat{g_j}(w)$ for $j = 1, \ldots, J$ (resp. the variance $\widehat{\sigma^2}(w)$).
- 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 2.

$$\hat{\theta}(\cdot) = \frac{1}{J}\sum_{j=1}^{J}\Big[\frac{\hat{f}_j(X) - c_j/p}{-\hat{g}_j(X)}\Big] \qquad (4)$$

Empirical application

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. The farm-level data were complemented with weather data for each region from the French Meteorological Institute.

	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
X_3	Farm Land (ha)	65.12	42.42	0.10	997.00
X_4	Forage crop (ha)	42.62	26.87	0.00	300.10
X_5	Livestock (Heads)	64.04	29.77	6.90	367.40
Z_1	Milk Quota (1000 L)	214.65	121.69	0.00	2102.74
Z_2	Temp (C)	13.23	0.85	10.26	14.76
Z_3	Evapotranspiration	2.56	0.27	2.09	3.32
Z_4	Hydric Stress	-0.32	0.65	-1.70	0.91

Table 1: Descriptive statistics, (1996-2006)

Nonparametric estimation implementation

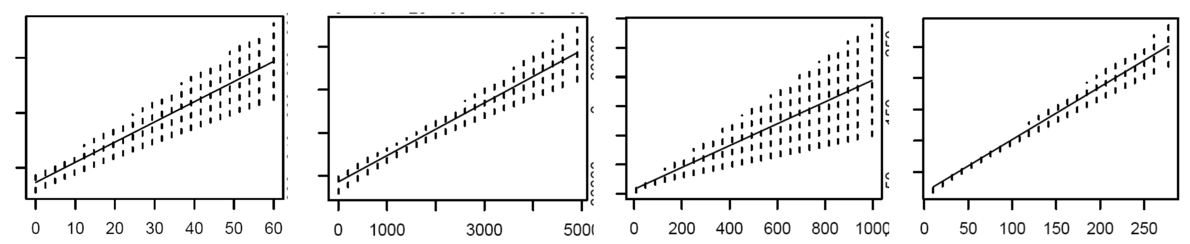
We use up-to-date nonparametric estimation techniques to compute the ingredients needed for estimating $\theta(\cdot)$ according to 4. As in any nonparametric estimation the choice of the bandwidth a is a crucial element in the practical implementation. For both the computation of $\widehat{f}(\cdot)$, $\widehat{g}(\cdot)$ 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 $f'' < 0$).

Results

As an illustration, we report the partial nonparametric regression plots and results of the significance test for the production function $\widehat{f}(\cdot)$ for the year 2003.



	for *Irrigated Land*	for *Feed*	for *Farm land*	for *Heads*
P-value :	< 2e-16 ***	< 2e-16 ***	<2e-16 ***	<2e-16 ***

We provide below very preliminary results of the distribution of the AR nonparametrically estimated for each dairy farm each year with a special emphasis on the extreme climatic event year 2003 (in red).

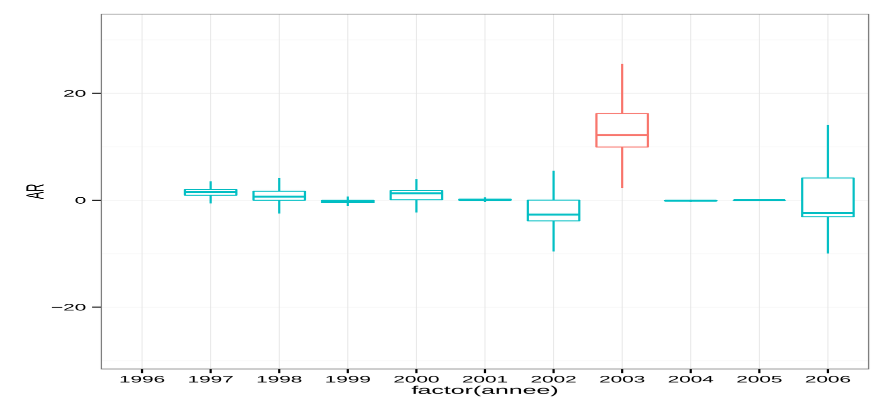


Figure 2: Distribution of estimated AR over time (1996-2006)

References

Hayfield, T. & Racine, J. S. (2008), 'Nonparametric econometrics: The np package', *Journal of Statistical Software* **27**(5).

Just, R. & Pope, R. (1978), 'Stochastic representation of production functions and econometric implications', *Journal of Econometrics* **7**, 67–86.

Just, R. & Pope, R. (1979), 'Production function estimation and related risk considerations', *American Journal of Agricultural Economics* **61**, 276–284.

Kumbhakar, S. & Tsionas, E. G. (2010), 'Estimation of production risk and risk preference function: a nonparametric approach', *Annals of Operations Research* **176**, 369– 378.

Li, Q. & Racine, J. (2004), 'Cross-validated local linear nonparametric regression', *Statistica Sinica* **14**(2), 485–512.

Racine, J., Hart, J. & Li, Q. (2006), 'Testing the significance of categorical predictor variables in nonparametric regression models,', *Econometric Reviews* **25**.