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

Christophe Bontemps and Stéphane Couture

Toulouse School of Economics-INRA & INRA-MIAT-Toulouse
(Christophe.Bontemps@toulouse.inra.fr)


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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 Sheeringer 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 adaptable/answerable to these questions?

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:

\[ y = f(x, \pi) + \varepsilon \]

where \( y \) is the observed output quantity, \( x \) is the vector of quasi-fixed input quantities \((x_1, \ldots , x_L)\), \( \pi \) is a vector of quasi-fixed inputs \((\pi_1, \ldots , \pi_{J-L})\), \( f(\cdot) \) is the mean production function, \( g(\cdot) \) is the production risk function. The random term \( \varepsilon \) 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:

\[ \text{Max}_x \quad E[U(y)] = E \left[ U(f(x, \pi) + \varepsilon) \right] \]

where \( p(y) \) denotes the milk production price, \( c \) the vector of variable input prices. We get the first-order conditions (FOC):

\[ \frac{\partial U(y)}{\partial y} \frac{\partial f(x, \pi)}{\partial x} = 0 \quad \forall j = 1, \ldots , J \]

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 \( \theta(\cdot) \). The effects of extreme climatic events on dairy farmers’ risk preferences:

\[ y = f(x, \pi) + g(x, z)\varepsilon \]

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

\[ \hat{f}(w) = \frac{\sum_{i=1}^n Y_i K_h(w - x_i)}{\sum_{i=1}^n K_h(w - x_i)} \]

where \( K(\cdot) \) is a univariate 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 \( f(\cdot) \), 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 \( \hat{e}_i = y_i - \hat{f}(w_i) \) of the first stage regression model.

We use a local linear nonparametric estimator of \( \varepsilon \) (resp. \( \hat{\varepsilon}_i \) on \( w_i \) to compute the estimator of the mean production function \( \hat{f}(w) \) and its derivatives \( \hat{f}_j(w) \) for \( j = 1, \ldots , J \) (resp. the variance \( \hat{\sigma}_i^2(w) \)).

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

\[ \theta(\cdot) = - \frac{1}{\hat{\sigma}_i^2(w)} \left[ \frac{\hat{f}_j(w)}{\hat{E}[\hat{f}(w)]} - \hat{e}_i \right] \]

Where \( \hat{\sigma}_i^2(w) \) is the estimated function of variance.\[ (4) \]

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. This total number of observations is 28458. The farm-level data were complemented with weather data for each region from the French Meteorological Institute.

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milk Prod. (1000 L)</td>
<td>251.78</td>
<td>123.34</td>
<td>17.01</td>
<td>1407.11</td>
</tr>
<tr>
<td>Irrigated Land</td>
<td>4.30</td>
<td>7.53</td>
<td>0.00</td>
<td>80.00</td>
</tr>
<tr>
<td>Forage crop (ha)</td>
<td>42.62</td>
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<td>0.00</td>
<td>300.10</td>
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<td>Purchased feed (kg/cow)</td>
<td>1420.60</td>
<td>424.65</td>
<td>0.00</td>
<td>8294.00</td>
</tr>
<tr>
<td>Irrigated Land (ha)</td>
<td>4.30</td>
<td>7.53</td>
<td>0.00</td>
<td>80.00</td>
</tr>
<tr>
<td>Milk Quota (1000 L)</td>
<td>214.65</td>
<td>121.69</td>
<td>0.00</td>
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<tr>
<td>Evapotranspiration</td>
<td>13.23</td>
<td>0.85</td>
<td>10.26</td>
<td>14.76</td>
</tr>
<tr>
<td>Hydric Stress</td>
<td>-0.32</td>
<td>0.65</td>
<td>-1.70</td>
<td>0.91</td>
</tr>
</tbody>
</table>

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 \( f(\cdot) \). As in any nonparametric estimation the choice of the bandwidth \( h \) is a crucial element in the practical implementation. For both the computation of \( f(\cdot) \) and \( \sigma_i^2(\cdot) \), we opted for the computation of cross-validated (CV) bandwidths for each year so that the local linear estimators are automatically balanced between bias and variance. We choose the 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 (1-test).

Finally, we also check ex-post whether the risk production function estimated where satisfying classical production function features (\( f^\prime > 0 \) and \( f'' < 0 \)).

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

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