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The influence of weather conditions on dairy production

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Abstract

Relatively little attention has been paid in the economics literature to the effects of meteorological conditions on milk production. Meteorological variables can be expected to affect milk production through their impact on the productivity of cows and the production of foodstuff. Rather than including meteorological variables as inputs in the milk production process, we propose a production function where these variables affect the productivity of cows and the production of forage, thereby indirectly affecting milk production. Using production and meteorological data from the Spanish region of Asturias corresponding to 382 dairy farms observed during a 6-year period from 2006 to 2011, the results from our estimated production function show that meteorological variables have a significant impact on milk production. We find that milk production is higher under warm weather conditions due to improvements in forage production.

Key words
Weather conditions, milk production, production function, separability, panel data, nonlinear least squares.

JEL: D24, Q12, Q54

1. Introduction

Agriculture is perhaps the economic activity most dependent on weather conditions, and the climate change that the planet has been undergoing in recent years (IPCC, 2013; Carraro, 2016) has led to a growing interest among researchers in the evaluation of the impact of weather conditions on agriculture. The economic evaluation of the influence of weather conditions has been analyzed from various perspectives. Some studies have evaluated the influence of weather conditions on land values (Mendelsohn *et al.*, 1994; Schlenker *et al.,* 2006) and agricultural profits (Deschênes and Greenstone, 2007). The effect of weather on production from an aggregate perspective has been analyzed using several methodologies (Demir and Mahmud, 2002; Barrios *et al.,* 2008; Nelson *et al.,* 2014; D'Agostino and Schlenker, 2016). Several other studies have considered the impact of weather on farms' productivity for specific crops. For example, Sherlund *et al.* (2002) and Tanaka *et al.* (2011) evaluate the impact of weather on rice production; Isik and Devadoss (2006) analyze its effect on the production of wheat, barley, potato and sugar; and Chen *et al.* (2013) estimate the influence of weather on grain productivity.

Animal scientists have closely studied the effects of weather conditions on animal performance (St-Pierre *et al*., 2003; Bohmanova *et al*., 2007; Mader *et al*., 2010). In particular, it has been well-documented that dairy cow performance is heavily affected by heat stress, and several variables have been used to evaluate this influence. While some studies use temperature to evaluate the incidence of heat stress on dairy cows (Barash *et al.,* 2001; Andre *et al.,* 2011), the thermal comfort of animals is influenced by variables other than temperature such as relative humidity, wind speed and solar radiation. Consequently, most studies use some thermal comfort index which encompasses several meteorological variables to obtain an apparent (or 'feel-like') temperature. The most commonly-used thermal comfort index in dairy studies is the THI (Temperature and Humidity Index), which is constructed with data on temperature and relative humidity. This index has been used to evaluate the impact of cows' thermal comfort on dairy cow performance in several studies using data from different countries with very different climatic conditions including Sudan (Ageeb and Hayes, 2000), Slovakia (Broucek *et al.*, 2007), New Zealand (Bryant *et al.*, 2007) Hungary (Solymosi *et al.*, 2010) and the U.S. (St-Pierre *et al.*, 2003).

However, few economic studies so far have analyzed the effect of weather variables on milk production. Kompas and Che (2006) use a dummy variable to control for a drought period and Moreira *et al*. (2006) use dummy variables to control for differences in climatic conditions in different geographical zones. To the best of our knowledge, only three published studies, all relatively recent and using data from the U.S., analyze the impact of meteorological variables on dairy farm productive performance (Mukherjee *et al.,* 2013; Key and Sneeringer, 2014; and Qi et al., 2015).

Mukherjee *et al.* (2013) analyze the productivity of dairy farms in Florida and Georgia, two of the warmest states in the United States, by estimating a production frontier that includes a THI that can shift the frontier up or down. Their results show that cows suffer from so-called *heat stress* which negatively affects their productivity, and they evaluate the positive impact on income corresponding to the use of fans and sprinklers to ameliorate this heat stress. Key and Sneeringer (2014) use U.S. data from the 24 states with the highest dairy production, covering a large range of climatic conditions. They estimate a production frontier where a measure of heat stress based on the THI is included as an efficiency determinant. A negative impact of heat stress on farms' technical efficiency is found. Finally, Qi et al. (2015) analyze the effect of weather conditions on the production frontier of dairy farms located in Wisconsin. The authors include measures of temperature and precipitation as technology shifters in a production frontier analysis. Their analysis shows that warmer summers and autumns diminish milk production whereas warmer winters and springs increase it. On the other hand, more precipitation in spring and winter reduces milk production but its effect in summer and autumn is not significant.

The aforementioned studies have in common that they include temperature and rainfall or humidity measures, either separately or in the form of a THI, as variables that shift milk production functions up or down or that act as determinants of technical inefficiency. In this study, we follow Topp and Doyle (1996) by explicitly considering that meteorology can affect both cows' thermal comfort as well as foodstuff (forage) production on the farm. As the impact of weather conditions can be positive for cow comfort and negative for forage production, and vice versa, their effects on milk production may cancel each other out and be difficult to identify. For example, Berman (2005) identifies a thermo-neutral zone for dairy cows that ranges from -5ºC to 24ºC, while Schlenker and Roberts (2006; 2009) find that the corn yield, corn being one of the main forage crops, increases with temperatures up to 29ºC. These results imply that there is a range of temperatures within which cows suffer from heat stress while corn yields improve. To resolve this identification issue, we propose a model in which weather variables influence cows' productivity and forage production in a separable manner.

Our work therefore makes two main contributions. Firstly, we have seen that there are very few studies to date that have taken a production economics approach to analyzing the effects of weather conditions on milk production. Moreover, all of these have used U.S. data. It can be argued that further contributions are needed, and from other geographical regions, in order to provide a more robust body of empirical findings with which to provide guidance for management and policy and that can serve as points of reference for future academic studies. Our work contributes to this effort. Secondly, and on a more methodological note, our empirical specification of the production technology explicitly models the channels through which weather variables can affect milk production. In particular, the model is simple yet sufficiently flexible to permit weather variables to have *direct effects* on cow performance and forage production and *indirect effects* on the remaining inputs to the production process. In this way, we can separate the effects of weather variables into their effect on cow performance and forage production.

2. Model specification

In our empirical model we will include the THI as a variable conditioning the productivity of cows. Other weather variables capturing exposure to wind, rainfall and sun are also relevant to milk production as both the quantity of forage produced as well as its nutritional quality depend on weather conditions. This is especially true of rainfall, temperature and the amount of sunlight, and the effects of these factors on forage production will also be taken into account in our empirical model.[1]

We consider that milk production (y) is carried out using cows (x_1), expenditures on forage production inside the farm (x_2), labor (x_3), concentrates (x_4), forage purchases (x_5) and animal expenses (x_6). The Spanish State Meteorological Agency (AEMET) provides daily data on a series of weather variables including temperature (MV_1), humidity (MV_2), rainfall (MV_3), wind (MV_4) and sun exposure (MV_5). We incorporate the weather variables into our analysis by assuming that, instead of being direct inputs in milk production, these variables can influence the productivity of the production factors used by farmers. As cow performance is considered to be affected by temperature (MV_1) and humidity (MV_2), we include the THI as a determinant of cow productivity. We use the formula proposed by Yousef (1985) for THI calculation, which has been used by Ageeb and Hayes (2000), Mukherjee *et al.* (2013) and Key and Sneeringer (2014), among others.[2]

On the other hand, we consider that the complete set of meteorological variables can influence the production of forage inside the farm. Hence, we define the milk production technology as:

$$y = F(f_1(x_1, THI), f_2(x_2, MV_1, \dots, MV_5), x_3, \dots, x_6) \qquad (1)$$

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[1] See, for example, the following Penn State Cooperative Extension website devoted to forage quality: http://www.forages.psu.edu/topics/forage_qa/index.html. See also: https://swap.stanford.edu/20130413002000/http://www.epa.gov/climatechange/impacts-adaptation/agriculture.html.

[2] This THI is calculated on a daily basis using the formula $THI = 41.2 + MV_1 + 0.36T_{dp}(MV_1, MV_2)$. MV_1 is the average daily temperature and T_{dp} is the dew point temperature (i.e., the temperature at which the water vapor content in the atmosphere starts to condense into liquid water), which in turn is a function of the air temperature (MV_1) and the relative humidity (MV_2).

where $F(\cdot)$ is the production function that characterizes the technology and $f_1(\cdot)$ and $f_2(\cdot)$ are functions that captures the influence of meteorological variables on the productivity of cows and the production of forage inside the farm respectively.

The interpretation of the function $f_1(\cdot)$ is straightforward in that it captures the fact that milk production not only depends on the number of cows (x_1) but also on the effect of temperature and humidity conditions on the productivity of these cows. As for $f_2(\cdot)$, it is common in the literature for milk production functions to include a series of inputs such as land, machinery, fertilizers and so on whose role is fundamentally to produce forage, the intermediate input used in the production of milk. What matters for milk production is the quantity and quality of forage produced. Unfortunately, these variables are rarely observed, as in our case where we only have information on expenditures on forage production (x_2) on the farm. While these expenditures will obviously influence the quantity and quality of forage produced, they are not the only determinants as weather conditions will also play a role (Schlenker and Roberts, 2006). As such, the function $f_2(\cdot)$ can be considered as a production function for forage, where expenditure on forage production and weather conditions both contribute to the quantity and quality of forage produced.

The model specification in (1) assumes that weather variables do not have any *direct* impact on milk production. Instead, this impact comes through their influence on the productivity of cows and the production of forage. Additionally, the model specification assumes that $f_1(\cdot)$ and $f_2(\cdot)$ are separable from the inputs other than cows and forage production, implying that weather variables do not have a direct effect on the productivity of these other inputs.[3] As cows are generally inside the cowshed in our sample, the model captures the idea that only temperature and humidity (*THI*) directly affect cow productivity whereas the complete set of weather variables is allowed to affect forage production. *Indirect* effects of weather variables on the productivities of the remaining inputs will be allowed in the model through second-order terms. Thus, the productivity of, say, concentrates will depend on the values of $f_1(\cdot)$ and $f_2(\cdot)$, which in turn depend on weather conditions.

When specifying the functions $f_1(\cdot)$ and $f_2(\cdot)$, we need to account for the fact that farm data are provided on a yearly basis while weather data are provided on a daily basis. We aggregate the weather variables by splitting each year into two periods: the cold period which includes January, February, March, October, November and December, and the warm period that comprises the central part of the year from April to September. For each period we use the average values of the weather conditions in our empirical specification, so that the function $f_1(\cdot)$ is defined as follows:

$$f_1(x_1, THI; \gamma) = \ln x_1 + \sum_{p=1}^{2} \gamma_p THI_p \quad (2)$$

where subscript *p* refers to the cold (*p* = 1) and warm (*p* = 2) periods within the year.

We also need to take into account the fact that not all of the forage produced in a period *t* will be used to feed cattle in period *t*, as some of it will be stored and used for feed in

[3] In particular, Chambers (1988) pp. 41-45 shows that weak separability is necessary to allow the separation of some subsets of variables into what he labels *micro-production functions*, which in this case correspond to $f_1(\cdot)$ and $f_2(\cdot)$.

the following period, *t+1*. The function $f_2(\cdot)$ in (1) should therefore capture forage actually used in the present period, part of which will correspond to forage produced in the previous period. To model this, we begin by specifying the production function for forage in a given period as follows:

$$g_2(x_2, MV_w; \delta) = \ln x_2 + \sum_{w=1}^{5} \sum_{p=1}^{2} \delta_{wp} MV_{wp} \tag{3}$$

where the subscript w ($w = 1, \dots, 5$) stands for the five different weather variables provided by AEMET. For each weather variable we also consider two periods within the year. To express the forage actually used as feed in a given period t, we take the antilog (exponential) of the function $g_2(\cdot)$ in (3) to capture forage actually produced in period t. Then we form a linear combination in levels of actual production in period t and $t-1$ to express the forage actually used as feed in period t, with the function $f_2(\cdot)$ expressed as the logarithm of this linear combination, i.e.:

$$f_2(x_2^t, x_2^{t-1}, MV^t, MV^{t-1}; \alpha, \delta) =$$
$$\ln\left[\alpha x_{2t} e^{\left(\sum_{w=1}^{5} \sum_{p=1}^{2} \delta_{wp} MV_{wp}^t\right)} + (1-\alpha) x_{2t-1} e^{\left(\sum_{w=1}^{5} \sum_{p=1}^{2} \delta_{wp} MV_{wp}^{t-1}\right)}\right] \tag{4}$$

where vector MV^t is defined as $MV^t = (MV_{11}^t, \dots, MV_{51}^t, \dots, MV_{12}^t, \dots, MV_{52}^t)$, and α is a parameter to be estimated. From (4) it is clear that the function capturing forage used for feed in period t, $f_2(\cdot)$, depends on weather conditions in both the present and previous periods.[4]

[4] The linear combination of the forage variables is carried out to ensure that past and present forage are not considered to be different inputs, as would be the case if past forage were included as a separate variable. This ensures that we are imposing the desirable property that the productivity of a unit of forage consumed in a given period should be independent of the period in which it is produced.

To estimate the production function (1) empirically, we specify a translog production function for $F(\cdot)$ where the functions $f_1(\cdot)$ and $f_2(\cdot)$ are included as arguments substituting cows (x_1) and expenditures on forage production (x_2):

$$\ln y = \sum_{h=1}^{n} \beta_h D_h + \beta_1 f_1(x_1, THI; \gamma) + \beta_2 f_2\big(x_2, MV_{wp}; \alpha, \delta\big) + \sum_{i=3}^{6} \beta_i \ln x_i$$
$$+ \frac{1}{2}\beta_{11} f_1(x_1, THI; \gamma)^2 + \beta_{12} f_1(x_1, THI; \gamma) f_2\big(x_2, MV_{wp}; \alpha, \delta\big)$$
$$+ \sum_{j=3}^{6} \beta_{1j} \ln x_j \, f_1(x_1, THI; \gamma) + \frac{1}{2}\beta_{22} f_2\big(x_2, MV_{wp}; \alpha, \delta\big)^2$$
$$+ \sum_{j=3}^{6} \beta_{2j} \ln x_j \, f_2\big(x_2, MV_{wp}; \alpha, \delta\big) + \frac{1}{2}\sum_{i=3}^{6}\sum_{j=3}^{6} \beta_{ij} \ln x_i \ln x_j + \sum_{t=2008}^{2011} \beta_t D_t$$
$$+ \epsilon \qquad (5)$$

where $\beta's$, $\delta's$, $\gamma's$ and α are parameters to be estimated, D_t is a vector of time dummy variables, and D_h are individual (farm) dummy variables.[5] Symmetry restrictions are imposed so that $\beta_{ij} = \beta_{ji}$. Given the specification in (5), the output elasticities of the inputs other than cows and forage production, say x_3, take the following form:

$$\frac{\partial \ln y}{\partial \ln x_3} = \beta_3 + \beta_{13} f_1(x_1, THI; \gamma) + \beta_{23} f_2(x_2, MV_1, \dots, MV_5; \alpha, \delta) + \sum_{j=3}^{6} \beta_{3j} \ln x_j \qquad (6)$$

where it is clear that the THI and the meteorological variables affect the output elasticity of input x_3 indirectly through their impact on cow productivity and forage production.

[5] The final equation estimated by non-linear least squares is found by substituting equations (2) and (4) into equation (5). The full expression for the equation actually estimated can be found in the online Appendix A (equation A.1).

A simpler alternative to incorporating the effect of weather variables on milk production by interacting with cows and forage production expenses while maintaining separability would be to add these weather variables to the translog function imposing *weak separability* restrictions.[6,7] In a translog setting, Berndt and Christensen (1973a, 1973b) demonstrate that two inputs x_i and x_j are weakly separable from another input x_k if and only if $\frac{\partial y}{\partial x_i}\beta_{jk} - \frac{\partial y}{\partial x_j}\beta_{ik} = 0$. Thus, if $\beta_{ik} = 0$, weak separability requires β_{jk} to be null. This implies that if the interaction effects between weather conditions and, say, concentrates are null, the interaction between forage production expenses and concentrates must also be null in order for weather conditions and forage production expenses to be weakly separable from the rest of the inputs. The model specification we propose in (5) is the simplest way of maintaining separability if we do not wish to restrict the interactions of cows and forage expenses with the remaining inputs to be null. Given this lack of restrictions on the interactions, we will label the specification in (5) as the *general model specification*.

For comparative purposes, we will also estimate the model where the weather variables are added as technology shifters to the translog production function. As before, part of the forage produced in the current year is consumed this year and the rest is consumed in the following year. Forage used in the present year, x_2^u, is defined as:

[6] In principle, the separability assumptions could be tested rather than imposed. However, in that case the larger model involves estimating a non-linear model including a function with 191 parameters (plus 316 individual and 4 time effects), which is unfeasible with our dataset.

[7] Weak separability of a subset of variables from the other variables will require the marginal rate of substitution between any two variables in the subset to be independent of any other variable outside the subset (Chambers, 1988; p. 42).

$$x_2^u = \alpha x_{2t}^p + (1-\alpha) x_{2t-1}^p \qquad (7)$$

where α is a parameter to be estimated and x_{2t}^p and $x_{2t-1}^p$are expenditures on forage production in periods t and $t-1$. The model to be estimated in this case is:

$$\begin{aligned}\ln y = {} & \sum_{h=1}^{n} \beta_h D_h + \beta_1 \ln x_1 + \beta_2 \ln x_2^u + \sum_{i=3}^{6} \beta_i \ln x_i + \frac{1}{2}\beta_{11}(\ln x_1)^2 + \beta_{12} \ln x_1 \ln x_2^u \\ & + \ln x_1 \sum_{j=3}^{6} \beta_{1j} \ln x_j + \frac{1}{2}\beta_{22}(\ln x_2^u)^2 + \ln x_2^u \sum_{j=3}^{6} \beta_{2j} \ln x_j \\ & + \frac{1}{2}\sum_{i=3}^{6}\sum_{j=3}^{6} \beta_{ij} \ln x_i \ln x_j + \sum_{t=2008}^{2011} \beta_t D_t + \sum_{p=1}^{2} \gamma_p THI_p \\ & + \sum_{w=1}^{5}\sum_{p=1}^{2} \delta_{wp} \left[\alpha MV_{wp}^{t} + (1-\alpha) MV_{wp}^{t-1}\right] + \epsilon \qquad (8)\end{aligned}$$

This is similar to the general model (5), with the difference being that in (5) weather is assumed to act through cows' productivity and forage production whereas in (8) weather variables are considered technology shifters and their effect comes through homothetic shifts of the technology according to the weather conditions. Note that symmetry restrictions are again imposed so that $\beta_{ij} = \beta_{ji}$.

As the farm uses forage produced in the previous year, we include the weather variables of the previous year in the model, assuming that they influence milk production in the same proportion (α) as that which forage produced in the previous year is consumed in the present year.[8] Given that the model in (8) imposes restrictions on the interactions

[8] The lagged values of the THI are not included as this affects cow performance, not forage. The final equation estimated by non-linear least squares is found by substituting equation (7) into equation (8). The full expression for the equation estimated can be found in the online Appendix A (equation A.2).

of weather variables with remaining inputs, we label it the *restricted interactions model specification*.

3. Data

The empirical application is carried out using data from dairy farms located in the region of Asturias in northwest Spain. Asturias is one of main milk-producing regions in Spain, and milk production accounted for 52% of total agricultural production in the region in 2011.

The economic data used in the empirical analysis consists of an unbalanced panel of 1,325 observations corresponding to 383 specialized dairy farms (milk accounting for over 90% of sales revenues) observed during a 6-year period from 2006 to 2011. These farms were enrolled in a voluntary record-keeping program conducted by the regional government which gathers information on nine Dairy Farmer Management Associations located in Asturias.

The dependent variable in the model is the *production of milk* (y) and is measured in liters. As mentioned above, six inputs are considered: *cows* (x_1), defined as the number of adult cows in the herd (all the farms in the sample use Holstein-Frisian cows); *forage production expenditure* (x_2), defined as the cost of seeds, fertilizer, fuel, land, other raw materials, and machinery hire and amortization; *labor* (x_3), which includes family labor and hired labor and which is measured using Social Security contributions; *concentrate feeds* (x_4) is the amount of concentrates used by the farm measured in kilograms; *forage purchases* (x_5), defined as expenditure on the acquisition of forage; and *animal expenses* (x_6), which includes expenditure on veterinary services, milking, electricity, water and the amortization of buildings and technical installations.[9] All the monetary variables were deflated using specific price indexes available from the Spanish Ministry of Agriculture (2018). As lagged variables are included in our model, the final sample used for estimation purposes comprises 939 observations corresponding to 316 farms over the period 2007-2011.

The data on weather variables are provided by AEMET. The data come from 10 meteorological stations spread across Asturias, which has an area of 10,604 km^2, and includes daily values of temperature (maximum and minimum) measured in degrees Celsius, relative humidity (maximum and minimum) measured as the actual vapor content in the atmosphere as a percentage of the maximum vapor content, rainfall measured in liters per square meter, maximum wind speed measured in kilometers per hour, and hours of sun exposure.

Each farm is assigned the weather information corresponding to its nearest meteorological station following two criteria. First, farms and meteorological stations are classified into two groups, coastal and interior. This is a relevant classification because in Asturias the mountains are near to the coast and the meteorology can be quite different among relatively nearby areas depending on whether there are mountains between a given area and the coast. Thus, each farm is assigned to the closest meteorological station within its group: coastal farms are assigned to their closest coastal meteorological station and interior farms are assigned to their closest interior

[9] The use of the categories *forage production expenses* and *animal expenses* as inputs can also be found in Roibas and Alvarez (2012), Orea et al. (2015) or Alvarez and Arias (2015), among others.

meteorological station. The data assigned are the mean daily weather variables in each one of the two periods within the year.

[INSERT TABLE 1 AROUND HERE]

Descriptive statistics of the economic and weather data are shown in Table 1. Differences among farms are quite large as the standard deviation of milk production is 73% of the mean production. The average farm size in the sample is larger than the average Spanish farm (31 cows in 2010; Eurostat, 2015) but quite similar to the average farm size in some of the main milk-producing countries in Europe such as France or Germany (46 cows; Eurostat, 2015).

Climate conditions are quite temperate in Asturias. Average temperatures are not very different between the cold and the warm periods and humidity is always high as it is a coastal region and the differences in humidity between the cold and warm periods are small. When comparing the values corresponding to maximum and minimum temperatures, it occurs that in the cold period the minimum temperatures are more disperse than the maximum temperatures, whereas in the warm period the opposite occurs. Hence, in the empirical application we use the minimum temperature for the cold period and the maximum temperature for the warm one. The opposite occurs with relative humidity and therefore maximum humidity is used in characterizing the cold period while minimum humidity is used for the warm period. These are the values for temperature and humidity which appear in Table 1. Rainfall and wind are relatively high and there are moderate differences between the cold and warm periods, especially for rainfall. Finally, sun exposure is not too high and is moderately higher in the warm period, as would be expected given the differences in the durations of day and night along the year which correspond to the latitude of the region of Asturias (43º N).

4. Results

We estimate several versions of the general and restricted specifications of the model in equations (5) and (8) which differ according to the assumptions made regarding the effects of THI and weather variables on production. The models are nonlinear in nature so we estimate them using nonlinear least squares.[10] As specified in equations (5) and (8), we estimate the models accounting for fixed effects by including dummy variables for each farm. The estimation procedure was carried out using the econometrics package TSP.

We first present the results from the *general model specification* (5). We estimate four variants of this model. In *Model 1* we estimate the complete model where weather affects both cow productivity and forage so that the weather variables and the THI indexes are all included. In *Model 2* we assume that the weather variables only affect the production of forage, so we include the weather variables but not the THI indexes. In *Model 3* we assume that the weather variables only affect the productivity of cows, so that only the THI indexes are included. Finally, in *Model 4* we assume that the weather variables do not affect milk production. Thus, Models 2-4 are restricted (nested) versions of Model 1.

[10] See Greene (2018, Chapter 7) for an overview of the nonlinear least squares (NLLS) estimator, which is the nonlinear counterpart of the OLS estimator when the model to be estimated is nonlinear in parameters.

[INSERT TABLE 2 AROUND HERE]

The parameter estimates are shown in Table 2. The logarithms of the inputs were transformed by subtracting their sample mean, which means that the first-order coefficients of the inputs can be interpreted as the output elasticities for a representative farm characterized by an input endowment equal to the sample geometric mean.

The results of some specification tests are reported at the bottom of Table 2. The first set of *F*-tests (i) compare Models 2, 3 and 4 with Model 1. Model 2 cannot be rejected against Model 1 but Models 3 and 4 are rejected against Model 1. Models 2 and 3 are non-nested and the *F-test* cannot be used to compare these models. However, under the assumption that residuals are normally distributed, it is possible to compare these models using the Vuong test. The Vuong-test (ii) rejects Model 3 in favor of Model 2. The next *F*-test (iii) compares Models 2 and 4, and Model 4 is rejected. A final *F*-test (iv) comparing Model 3 and Model 4 shows that Model 4 cannot be rejected. Therefore, the preferred model is Model 2.

The estimates from the *restricted interactions model specification* where weather variables are included as technology shifters (8) are presented in Table 3. In this specification the weather variables enter the production function without interaction terms with the inputs. Again, we estimate four variants of the model, analogous to those in Table 2 for the general model: *Model 1* is the complete model, including the whole set of weather variables; *Model 2* includes the whole set of weather variables except the THI; *Model 3* includes the THI and excludes the rest of weather variables; and *Model 4* assumes that the weather variables do not affect milk production. Hence, *Model 1* nests the other three models.

[INSERT TABLE 3 AROUND HERE]

The important implication of this specification is that we did not find a statistically significant influence of weather variables on milk production. In particular, we carried out *F*-tests and a Vuong test to compare the performance of Models 1, 2, 3 and 4, and the values of these statistics are shown at the end of Table 3. The validity of Model 4, where weather variables are not included, cannot be rejected.

Finally, it is of interest to compare Model 2 in the *general model specification* (Table 2) with Model 2 from the specification with weather variables as technology shifters (Table 3) using the Vuong test. The results of this test are reported at the bottom of Table 3 (Specification test (v)), and show that Model 2 in the *general model specification* is preferred at the 5% level of significance. Our discussion of results from here on will therefore focus on Model 2 of the general specification. We carried out a Ramsey RESET test including the squared of the fitted values of the dependent variables to check the model specification. The test statistic takes a value of 1.57, so the hypothesis that the model was well-specified could not be rejected (the test is distributed as an *F-test* with degrees of freedom 1 and 581, giving a *p*-value 0.211).

As the preferred model is Model 2, we find that there is no evidence that the THI affects the productivity of cows but that there is strong evidence of weather variables affecting the productivity of forage production expenses. Some words on the parameter estimates of this model are in order. As stated above, the model was estimated by nonlinear least squares. To account for fixed effects, dummy variables for each farm were included. We carried out an *F*-test to compare the model with individual dummy variables to a version of the model with a common intercept for all farms. The latter was conclusively rejected, thereby justifying the fixed effects specification.[11]

The logarithms of the inputs were transformed by subtracting their sample mean and the same transformation was applied to the weather variables. With this, the first-order parameters can be interpreted as output elasticities for a representative farm characterized by an input endowment equal to the sample geometric mean and which operates under the weather conditions corresponding to the sample average value of the meteorological variables.[12]

As we would hope, all first-order coefficients (output elasticities for the representative farm with sample average input endowment and operating under sample average weather conditions) are positive, and they are all highly significant with the exception of the labor input.[13] Regarding the extent to which the results conform to microeconomic theory, 696 of the 939 observations complied with the monotonicity conditions, representing 74.12% of the total. The scale elasticity (0.864) shows

[11] The test value was 6.713 yielding a *p*-value of 0, clearly rejecting the common intercept ('pooled') specification.
[12] Recall that these sample averages refer to the averages over the period of the variables used, which in some instances are themselves minima or maxima. Thus, for *temperature*, the sample averages refer to the average of the minimum temperature for the cold period and the average of the maximum temperature for the warm period. Similarly, the sample averages for *relative humidity* are the averages of the maximum humidity for the cold period and of the minimum humidity for the warm period.
[13] Other studies have found a non-significant labor elasticity (Ahmad and Bravo-Ureta, 1995; Cuesta, 2000). Note that the relative variation of the labor input is considerably smaller than that of the remaining inputs, with the standard deviation being 53% of the mean value. The next smallest relative variation is for cows, and is 61%, and for the other inputs it is over 75%.

decreasing returns to scale at the sample mean and on the basis of a Wald test is statistically lower than 1 at any conventional level of significance.[14] It should be noted that 87% of forage produced is estimated to be consumed in the present period, with the remaining 13% consumed in the following period ($\hat{\alpha} = 0.868$). Comparing the estimates from the different models in Tables 2 and 3, we find that when the effects of weather variables on forage production are taken into account the estimates of α rise from values in the range (0.54-0.58) in the models in Table 3 and the first two models in Table 2 to a value of 0.86 in Models 1 and 2 of Table 2. When the weather variables are modelled as technology shifters and this specification is inappropriate, the estimate of α is biased (in our case, underestimated).

Comparing Models 2 and 4, one of the most important differences between the estimates with and without the weather variables concerns the dummy variables capturing time effects.[15] When the weather variables are included, none of the time dummy variables is significant, whereas one of these – corresponding to 2009 – was highly significant in the model without weather variables. This implies that differences in productive performance due to shifts in the production function can be explained by differences in weather conditions over this period. It should be noted, however, that a test of whether the set of estimated coefficients of the time dummy variables in the model with weather variables was statistically different from the set of estimated

[14] The Wald test follows a chi-squared distribution: the test statistic took a value of 14.4 which is significant at any usual level of significance.

[15] The remaining parameters, and hence quantities such as the scale elasticity, are quite similar between Models 2 and 4. This absence of dramatic changes in the remaining model parameters indicates that Model 2 works well.

coefficients of the time dummy variables in the model without weather variables could not reject that they were equal.

Looking more closely at the effects of individual weather variables on forage production we find that high temperatures and humidity favor this production during the warm period, which may be expected. The variables capturing rainfall are not significant. High average wind speed increases forage production in the warm period. Sun exposure was found not to be significant in the warm period, which could be due to the relative stability of sun exposure over the warm period in the different years and locations. However, sun exposure shows a positive and significant effect in forage production in the cold period.

In an attempt to quantify the effects of the weather variables on farm performance, we exploit the estimated production function parameters by simulating some weather scenarios and calculating their impact on production and profits. In the first exercise, we simulate the volume of production, revenue (using the average price of milk for each year) and profits (defined as milk revenue minus expenditure on forage production, social security, concentrates, forage purchases and animals) for a representative farm with an input endowment corresponding to the (arithmetic) mean of the sample under two scenarios: (i) weather conditions equal to the sample mean, and (ii) the actual average weather conditions each year. The results are reported in Table 4, where it should be kept in mind that milk production under average weather conditions in the sample changes due to the time dummy variables.

The results of this simulation show that there are small differences between production, revenue and profits under each scenario for the first four years analyzed. However, for the last year, 2011, the effect of weather is quite important. Operating under actual weather conditions in 2011 leads to a difference in revenue compared to what would have been achieved under average conditions of approximately €4,500, representing an increase in profits of 10%.

Comparing the production predicted by the model under actual weather conditions for each individual observation with its predicted production if weather conditions corresponded to those of the sample mean, we find that the standard deviation of production was 16,927 liters.[16] This represents 4.4% of average production predicted by the model under actual weather conditions, highlighting the significant swings in output that can be caused by changes in the meteorological conditions.

In a second simulation exercise, we analyzed the effects on production and profit for the representative farm in the year 2011 when the temperature rises by a maximum of 2º Celsius. We find that an increase of 1ºC would increase profits by €3,071 (or 7.5%), rising to €5,509 (13.5%) for a 1.5ºC increase and €8,590 (21%) for a 2ºC increase.[17]

5. Summary and conclusions

The process of climate change that the planet is undergoing has increased the interest and timeliness of economic studies evaluating the effect of weather conditions on agriculture. However, despite the attention devoted by animal scientists to the effect of

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[16] The formula used was $\sqrt{\frac{\sum_{i=1}^{N}\left(\hat{y}_{it}^{MV}-\hat{y}_{it}^{\overline{MV}}\right)^2}{N-1}}$, where $\hat{y}_{it}^{MV}$ is the predicted production under actual weather conditions and $\hat{y}_{it}^{\overline{MV}}$ is the predicted production under the sample average weather conditions.

[17] See Figures 1 and 2 in the on-line Appendix B.

weather on dairy production, very few studies in the economic literature have analyzed the effect of weather on milk production. We contribute to this literature by considering the effect of weather conditions on both cow productivity (through the effect of weather variables on cows' thermal comfort) and forage production inside the farm. To do so, we construct a production model in which the weather variables are included in a separable way in the production function in order to assess their expected impact on cow productivity and foodstuff production. In the specification of the production technology, the weather variables affect cow productivity and forage production *directly*, and affect the productivity of the remaining inputs *indirectly* through their effects on cows and forage.

Our results show that weather conditions can have an important impact on milk production. In simulation exercises, we found that differences in weather conditions from average conditions can lead to large deviations in production, and differences in profits of up to 10% for the representative farm. The impact of weather variables in our analysis comes through their effect on forage production, as the effect on cow performance of the THI was not found to be significant.

For a more complete assessment of the impact of weather conditions on milk production, more research is needed in several directions. Milk production is carried out in several geographical zones around the world and the effect of weather will depend on the climatic conditions in each zone. This will lead to the use of different forage crops that will be affected by weather in a different way to those harvested in Asturias.

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Table 1: Descriptive statistics of economic and weather variables

	Mean	Std. Dev.	Minimum	Maximum
Milk (liters)	401423	293404	22685	2672774
Cows (number)	49.70	30.52	6	249
Forage production expenditures (€)	20510	17665	851	172591
Labor (€ social security expenditure)	4859	2577	215	20400
Concentrates (Kg.)	189607	144374	11855	1220100
Forage purchases (€)	8909	12692	10	176843
Animal expenses (€)	17330	13577	577	129768
Weather data				
THI Period 1	54.51	1.34	51.67	57.02
THI Period 2	62.53	0.81	60.59	64.20
Temperature Period 1 (ºC)*	6.80	1.35	4.45	9.60
Temperature Period 2 (ºC)**	20.91	1.36	17.53	23.75
Humidity Period 1 (%)***	94.24	2.82	85.34	98.07
Humidity Period 2 (%)****	61.87	4.63	53.95	73.58
Rainfall Period 1 (mm/m^2)	3.40	0.87	1.58	5.72
Rainfall Period 2(mm/m^2)	1.90	0.58	0.82	3.09
Wind Period 1 (Km/h)	32.76	9.74	11.16	50.38
Wind Period 2 (Km/h)	27.93	6.01	9.46	40.70
Sun exposure Period 1 (Hours/day)	3.87	0.57	2.76	4.78
Sun exposure Period 2 (Hours/day)	5.58	0.48	4.82	6.50

* Minimum temperature for cold period. ** Maximum temperature for the warm period. *** Maximum humidity for the cold period. **** Minimum humidity for the warm period.

Table 2: Estimates of general model specification

		Model 1		Model 2		Model 3		Model 4	
Param.	**Variable**	*Value*	*t-st.*	*Value*	*t-st.*	*Value*	*t-st.*	*Value*	*t-st.*
$\boldsymbol{\beta_1}$	$f_1(x_1, THI)$	0.490	14.96	0.494	15.05	0.501	15.15	0.497	15.13
$\boldsymbol{\beta_2}$	$f_2(x_2, MV_{wp})$	0.024	2.08	0.023	2.10	0.080	3.94	0.080	3.97
$\boldsymbol{\beta_3}$	$\ln x_3$	0.023	1.19	0.017	1.18	0.018	1.19	0.019	1.25
$\boldsymbol{\beta_4}$	$\ln x_4$	0.255	13.40	0.256	13.35	0.261	13.62	0.260	13.65
$\boldsymbol{\beta_5}$	$\ln x_5$	0.026	4.24	0.025	4.09	0.027	4.50	0.028	4.56
$\boldsymbol{\beta_6}$	$\ln x_6$	0.046	2.00	0.051	2.23	0.056	2.53	0.056	2.54
$\boldsymbol{\beta_{11}}$	$\frac{1}{2}\left(f_1(x_1, THI)\right)^2$	0.282	2.43	0.280	2.44	0.295	2.50	0.275	2.33
$\boldsymbol{\beta_{12}}$	$f_1(x_1, THI) \times f_2(x_2, MV_{wp})$	-0.051	-1.59	-0.049	-1.52	-0.056	-1.03	-0.052	-0.95
$\boldsymbol{\beta_{13}}$	$f_1(x_1, THI) \times \ln x_3$	0.032	0.60	0.030	0.57	0.010	0.17	0.012	0.21
$\boldsymbol{\beta_{14}}$	$f_1(x_1, THI) \times \ln x_4$	-0.087	-1.33	-0.086	-1.32	-0.088	-1.32	-0.081	-1.22
$\boldsymbol{\beta_{15}}$	$f_1(x_1, THI) \times \ln x_5$	-0.010	-0.49	-0.009	-0.48	0.004	0.20	0.005	0.24
$\boldsymbol{\beta_{16}}$	$f_1(x_1, THI) \times \ln x_6$	0.017	0.24	0.017	0.23	-0.007	-0.09	-0.009	-0.13
$\boldsymbol{\beta_{22}}$	$\frac{1}{2}\left(f_2(x_2, MV_{wp})\right)^2$	0.029	1.69	0.028	1.65	0.092	1.86	0.091	1.84
$\boldsymbol{\beta_{23}}$	$f_2(x_2, MV_{wp}) \times \ln x_3$	0.023	1.40	0.023	1.41	0.029	1.13	0.027	1.07
$\boldsymbol{\beta_{24}}$	$f_2(x_2, MV_{wp}) \times \ln x_4$	-0.021	-1.04	-0.022	-1.08	-0.098	-2.74	-0.096	-2.70
$\boldsymbol{\beta_{25}}$	$f_2(x_2, MV_{wp}) \times \ln x_5$	0.016	2.35	0.016	2.36	0.019	1.85	0.019	1.93
$\boldsymbol{\beta_{26}}$	$f_2(x_2, MV_{wp}) \times \ln x_6$	-0.075	-3.12	-0.076	-3.14	-0.045	-1.27	-0.046	-1.31
$\boldsymbol{\beta_{33}}$	$\frac{1}{2}(\ln x_3)^2$	0.001	0.04	0.000	0.00	0.002	0.09	0.001	0.04
$\boldsymbol{\beta_{34}}$	$\ln x_3 \times \ln x_4$	0.008	0.23	0.008	0.24	0.017	0.49	0.016	0.45
$\boldsymbol{\beta_{35}}$	$\ln x_3 \times \ln x_5$	0.005	0.56	0.005	0.59	-0.005	-0.56	-0.005	-0.55
$\boldsymbol{\beta_{36}}$	$\ln x_3 \times \ln x_6$	-0.048	-1.55	-0.049	-1.56	-0.034	-1.02	-0.033	-0.99
$\boldsymbol{\beta_{44}}$	$\frac{1}{2}(\ln x_4)^2$	-0.115	-2.30	-0.115	-2.30	-0.082	-1.62	-0.085	-1.70
$\boldsymbol{\beta_{45}}$	$\ln x_4 \times \ln x_5$	-0.019	-1.46	-0.019	-1.48	-0.026	-1.95	-0.027	-2.03

$\boldsymbol{\beta_{46}}$	$\ln x_4 \times \ln x_6$	0.073	1.57	0.072	1.55	0.110	2.33	0.109	2.33
$\boldsymbol{\beta_{55}}$	$\frac{1}{2}(\ln x_5)^2$	0.008	1.88	0.008	1.89	0.009	2.03	0.009	2.10
$\boldsymbol{\beta_{56}}$	$\ln x_5 \times \ln x_6$	-0.012	-1.01	-0.012	-1.01	-0.015	-1.23	-0.015	-1.23
$\boldsymbol{\beta_{66}}$	$\frac{1}{2}(\ln x_6)^2$	0.036	0.70	0.037	0.72	0.013	0.25	0.015	0.30
$\boldsymbol{\beta_{2008}}$	D_{2008}	-0.003	-0.20	-0.004	-0.32	-0.017	-1.55	-0.017	-1.59
$\boldsymbol{\beta_{2009}}$	D_{2009}	-0.016	-1.13	-0.018	-1.43	-0.028	-2.24	-0.033	-3.03
$\boldsymbol{\beta_{2010}}$	D_{2010}	0.004	0.15	-0.002	-0.14	-0.009	-0.43	-0.019	-1.56
$\boldsymbol{\beta_{2011}}$	D_{2011}	0.014	0.66	0.011	0.74	-0.012	-0.76	-0.005	-0.47
$\boldsymbol{\alpha}$	----	0.868	17.30	0.867	17.77	0.562	4.80	0.572	4.88
$\boldsymbol{\delta_{11}}$	Temperature_1	0.256	0.92	0.264	0.95				
$\boldsymbol{\delta_{12}}$	Temperature_2	0.476	3.14	0.473	3.15				
$\boldsymbol{\delta_{21}}$	Humidity_1	0.013	0.16	0.014	0.17				
$\boldsymbol{\delta_{22}}$	Humidity_2	0.094	2.16	0.096	2.19				
$\boldsymbol{\delta_{31}}$	Rain_1	-0.150	-1.23	-0.146	-1.20				
$\boldsymbol{\delta_{32}}$	Rain_2	0.140	0.85	0.140	0.86				
$\boldsymbol{\delta_{41}}$	Wind_1	-0.042	-1.36	-0.043	-1.40				
$\boldsymbol{\delta_{42}}$	Wind_2	0.081	2.03	0.082	2.06				
$\boldsymbol{\delta_{51}}$	Sun Exposure_1	0.876	1.90	0.900	1.97				
$\boldsymbol{\delta_{52}}$	Sun Exposure_2	-0.852	-1.53	-0.848	-1.53				
$\boldsymbol{\gamma_1}$	THI_1	0.005	0.22			0.013	0.58		
$\boldsymbol{\gamma_2}$	THI_2	-0.006	-0.30			0.006	0.36		
$\boldsymbol{R^2}$		0.992		0.992		0.992		0.992	
Specification tests									
(i) ***F*-tests**: ***M2 v M1; M3 v M1; M4 v M1***				0.076 (p-0.93)		2.417 (p-0.01)		2.060 (p-0.02)	
(ii) **Vuong-test**: ***M3 v M2***						2.387 (p-0.02)			
(iii) ***F*-test**: ***M4 v M2***								2.465 (p-0.01)	
(iv) ***F*-test**: ***M4 v M3***								0.273 (p-0.76)	

Table 3: Estimates of model with weather variables included as technology shifters

		Model 1		Model 2		Model 3		Model 4	
Param.	**Variable**	*Value*	*t-st.*	*Value*	*t-st.*	*Value*	*t-st.*	*Value*	*t-st.*
$\boldsymbol{\beta_1}$	$\ln x_1$	0.487	14.41	0.488	14.50	0.496	14.95	0.497	15.13
$\boldsymbol{\beta_2}$	$\ln x_2^u$	0.080	3.79	0.079	3.78	0.080	3.95	0.080	3.97
$\boldsymbol{\beta_3}$	$\ln x_3$	0.018	1.20	0.029	1.20	0.018	1.21	0.019	1.25
$\boldsymbol{\beta_4}$	$\ln x_4$	0.257	13.05	0.259	13.17	0.260	13.47	0.260	13.65
$\boldsymbol{\beta_5}$	$\ln x_5$	0.027	4.42	0.027	4.45	0.028	4.56	0.028	4.56
$\boldsymbol{\beta_6}$	$\ln x_6$	0.056	2.44	0.055	2.42	0.056	2.52	0.056	2.54
$\boldsymbol{\beta_{11}}$	$\frac{1}{2}(\ln x_1)^2$	0.256	2.12	0.256	2.13	0.272	2.29	0.275	2.33
$\boldsymbol{\beta_{12}}$	$\ln x_1 \times \ln x_2^u$	-0.060	-1.08	-0.057	-1.02	-0.050	-0.91	-0.052	-0.95
$\boldsymbol{\beta_{13}}$	$\ln x_1 \times \ln x_3$	0.017	0.31	0.015	0.26	0.011	0.20	0.012	0.21
$\boldsymbol{\beta_{14}}$	$\ln x_1 \times \ln x_4$	-0.079	-1.17	-0.080	-1.19	-0.081	-1.21	-0.081	-1.22
$\boldsymbol{\beta_{15}}$	$\ln x_1 \times \ln x_5$	-0.001	-0.04	0.000	0.02	0.005	0.24	0.005	0.24
$\boldsymbol{\beta_{16}}$	$\ln x_1 \times \ln x_6$	0.009	0.12	0.005	0.07	-0.010	-0.14	-0.009	-0.13
$\boldsymbol{\beta_{22}}$	$\frac{1}{2}(\ln x_2^u)^2$	0.098	1.95	0.101	2.00	0.091	1.83	0.091	1.84
$\boldsymbol{\beta_{23}}$	$\ln x_2^u \times \ln x_3$	0.027	1.05	0.026	1.02	0.027	1.06	0.027	1.07
$\boldsymbol{\beta_{24}}$	$\ln x_2^u \times \ln x_4$	-0.081	-2.23	-0.084	-2.32	-0.096	-2.68	-0.096	-2.70
$\boldsymbol{\beta_{25}}$	$\ln x_2^u \times \ln x_5$	0.020	1.97	0.020	1.97	0.020	1.94	0.019	1.93
$\boldsymbol{\beta_{26}}$	$\ln x_2^u \times \ln x_6$	-0.052	-1.43	-0.053	-1.47	-0.047	-1.31	-0.046	-1.31
$\boldsymbol{\beta_{33}}$	$\frac{1}{2}(\ln x_3)^2$	0.003	0.10	0.005	0.19	0.001	0.03	0.001	0.04
$\boldsymbol{\beta_{34}}$	$\ln x_3 \times \ln x_4$	0.019	0.52	0.017	0.48	0.016	0.45	0.016	0.45
$\boldsymbol{\beta_{35}}$	$\ln x_3 \times \ln x_5$	-0.004	-0.45	-0.004	-0.43	-0.005	-0.55	-0.005	-0.55
$\boldsymbol{\beta_{36}}$	$\ln x_3 \times \ln x_6$	-0.039	-1.17	-0.036	-1.07	-0.033	-0.98	-0.033	-0.99
$\boldsymbol{\beta_{44}}$	$\frac{1}{2}(\ln x_4)^2$	-0.094	-1.83	-0.094	-1.82	-0.087	-1.71	-0.085	-1.70
$\boldsymbol{\beta_{45}}$	$\ln x_4 \times \ln x_5$	-0.027	-2.07	-0.027	-2.06	-0.027	-2.04	-0.027	-2.03

$\boldsymbol{\beta_{46}}$	$\ln x_4 \times \ln x_6$	0.107	2.24	0.110	2.31	0.111	2.34	0.109	2.33
$\boldsymbol{\beta_{55}}$	$\frac{1}{2}(\ln x_5)^2$	0.009	2.08	0.009	2.14	0.009	2.11	0.009	2.10
$\boldsymbol{\beta_{56}}$	$\ln x_5 \times \ln x_6$	-0.013	-1.05	-0.013	-1.08	-0.015	-1.24	-0.015	-1.23
$\boldsymbol{\beta_{66}}$	$\frac{1}{2}(\ln x_6)^2$	0.011	0.22	0.012	0.22	0.015	0.30	0.015	0.30
$\boldsymbol{\beta_{2008}}$	D_{2008}	-0.004	-0.15	-0.001	-0.02	-0.017	-1.55	-0.017	-1.59
$\boldsymbol{\beta_{2009}}$	D_{2009}	-0.009	-0.23	-0.001	-0.03	-0.034	-2.60	-0.033	-3.03
$\boldsymbol{\beta_{2010}}$	D_{2010}	0.012	0.24	0.018	0.46	-0.022	-0.93	-0.019	-1.56
$\boldsymbol{\beta_{2011}}$	D_{2011}	0.011	0.34	0.025	0.93	-0.002	-0.11	-0.005	-0.47
$\boldsymbol{\alpha}$	------	0.542	4.94	0.579	5.24	0.572	4.84	0.572	4.88
$\boldsymbol{\delta_{11}}$	$Temperature_1$	-0.021	-0.60	-0.020	-0.55				
$\boldsymbol{\delta_{12}}$	$Temperature_2$	-0.011	-0.62	-0.004	-0.27				
$\boldsymbol{\delta_{21}}$	$Humidity_1$	-0.007	-0.83	-0.007	-0.79				
$\boldsymbol{\delta_{22}}$	$Humidity_2$	0.003	0.62	0.002	0.49				
$\boldsymbol{\delta_{31}}$	$Rain_1$	-0.026	-1.37	-0.027	-1.54				
$\boldsymbol{\delta_{32}}$	$Rain_2$	-0.010	-0.40	-0.013	-0.55				
$\boldsymbol{\delta_{41}}$	$Wind_1$	-0.002	-0.51	-0.002	-0.53				
$\boldsymbol{\delta_{42}}$	$Wind_2$	0.000	0.09	0.001	0.17				
$\boldsymbol{\delta_{51}}$	Sun $Exposure_1$	0.070	1.09	0.045	0.82				
$\boldsymbol{\delta_{52}}$	Sun $Exposure_2$	0.000	0.00	-0.003	-0.04				
$\boldsymbol{\gamma_1}$	THI_1	-0.005	-0.25			-0.002	-0.14		
$\boldsymbol{\gamma_2}$	THI_2	0.014	0.85			-0.002	-0.24		
$\boldsymbol{R^2}$		0.992		0.992		0.992		0.992	
Specification tests									
(i) *F*-tests: *M2 v M1; M3 v M1; M4 v M1*				0.407 (p-0.67)		0.746 (p-0.68)		0.629 (p-0.82)	
(ii) Vuong-test: *M3 v M2*						1.025 (p-0.31)			
(iii) *F*-test: *M4 v M2*								0.675 (p-0.75)	
(iv) *F*-test: *M4 v M3*								0.044 (p-0.96)	
(v) Vuong test: *M2 (restricted spec.) v M2 (gen. spec.)*				1.982 (p-0.05)					

Table 4: Impact on milk production, revenue and profits of different weather conditions

	2007	2008	2009	2010	2011
Milk production (*l*): average weather	382829	381307	376004	382100	386946
Milk production (*l*): actual weather	382227	380124	374153	382622	400193
Total Revenue (€): average weather	141750	150582	122389	123770	131666
Total Revenue (€): actual weather	141527	150115	121787	123939	136174
Profit (€): average weather	54171	63003	34810	36191	44087
Profit (€): actual weather	53948	62535	34207	36359	48594
Profit Variation (€)	-223	-467	-602	169	4507
Profit variation (%)	-0.41	-0.74	-1.73	0.47	10.22