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ORIGINAL ARTICLE

Measuring farm productivity under production uncertainty

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Abstract
This research introduces a novel empirical application to the assessment of farm productivity growth. While the existing research on productivity change has primarily focussed on ex post output observations, it has been shown that ignoring production uncertainty can lead to unreliable results. Using a state-contingent framework to represent the stochastic production environment, we extend the recent line of research that merged the state-contingent approach and efficiency measurement to productivity change using the Malmquist and Luenberger productivity indices. Using a balanced panel of 117 arable crop farms surveyed in 2011 and 2015, we show through the study results that productivity decreased, with technological regress being the major source of productivity change. Differences in productivity change between non-stochastic and stochastic modelling show the relevance to consider the state-contingent framework when assessing farms' productivity.

KEYWORDS
agricultural productivity, data envelopment analysis, state-contingent framework, uncertainty modelling

JEL CLASSIFICATION
D22, D24, D81, Q12

1 | INTRODUCTION

Beginning with Farrell's (1957) work, there is a broad literature on measuring efficiency and productivity. The productive efficiency concept has received increasing attention and plays an important role in the business community as firms pay more attention to the efficient utilisation of resources. The agricultural sector is no exception and is, perhaps, even more concerned given its dependence on natural resources. Any change in land use and water quality management, for example, can affect annual and cumulative productivity growth and the sustainability of the sector. Measurement of the efficiency and productivity of agricultural producers is critically important for at least two reasons: first, since farmers usually own and work on their farms, the common expectation that market competition would mean that only the most productive (efficient) farmers are likely to survive and remain competitive in their industry is unlikely to hold true, and the process of adjustment will have both social and economic consequences (Nauges et al., 2011); second, efficiency and productivity estimates are important for policy purposes, since interventions taken to enhance efficiency and productivity performance require an accurate understanding of the relationships between observed characteristics and performance estimates (Fried et al., 2008).

Furthermore, production risk and uncertainty[1] are well-known problems that affect the efficiency and productivity estimates of farms (Chavas, 2008; Just & Pope, 1979). In agriculture, most of the uncertainty arises from unpredictable weather conditions, pest infestation and market instability. A central challenge to measuring the performance of producers operating under uncertainty is identifying an adequate conceptualisation of the stochastic environment in which production activities take place. Since most of the benchmarking techniques in the efficiency and productivity analysis area assume a nonstochastic decision environment, applying these traditional techniques to production activities such as agriculture, where uncertainty is the rule rather than the exception, uncertainty effects could be associated with either inefficiency or productivity deterioration.

Stochastic Frontier Analysis (SFA) is one of the most commonly used methods when dealing with production uncertainty in efficiency and productivity measurement (Kumbhakar & Lovell, 2000). Under the standard SFA procedure, conventional maximum likelihood is used to simultaneously estimate the parameters of the production function and to partition the error term into two components: a noise component capturing exogenous stochastic shocks and a producer-specific component representing technical inefficiency. Stochastic Frontier Analysis is a parametric procedure, which requires an assumption about a specific functional form of the production frontier. Various options have been proposed in the literature: the Cobb–Douglas and the translog are the most commonly used. The main advantage of the parametric SFA is its ability to measure productivity and efficiency scores while accounting for random statistical noise. However, since SFA estimates are sensitive to functional forms, biases and inconsistencies are likely to arise. The nonparametric Data Envelopment Analysis (DEA) is another method[2] that takes a different approach to estimating production frontiers. Unlike SFA, the nonparametric DEA does not require any underlying functional forms; its main limitations are that it does not consider the presence of a random error, and since it provides a relative measure of performance, it is highly sensitive to outliers.

Another approach that is particularly relevant for modelling production uncertainty relies on the general equilibrium theory and the modern finance theory in terms of a state-contingent approach. The latter is based on the groundbreaking works of Debreu (1952) and Arrow (1953) and differentiates outputs according to the state of nature in which they are realised. In this context, Chambers and Quiggin (2000) explained that the state-contingent approach can use all of the tools available in the contemporary production theory, including cost and distance functions.

[1]The distinction between risk and uncertainty was drawn more than 90 years ago by Frank Knight (Knight, 1921). He argued that risk can be appropriately measured by objective probabilities while uncertainty cannot.

[2]There has been a lively debate in the literature over which frontier method is better. The parametric SFA includes a statistical noise, but it is sensitive to functional forms. The nonparametric DEA, on the contrary, is more flexible in the sense that it does not require any predefined functional form, but because of its deterministic nature, it does not distinguish between noise and inefficiency. In this study, the state-contingent approach is adopted as it helps to overcome the main limitation of DEA by representing the stochastic production process in terms of state-contingent outputs.

Developed and generalised by Chambers and Quiggin (2000), the state-contingent approach is based on the idea that producers can only manage uncertainty by changing input use. Higher flexibility is obtained to reflect producers' choices under a risky production environment by considering particular uncertain events. (e.g. bad, normal and good crop growing conditions). By allowing the change in input use between the different states of nature, the state-contingent method allows the producers to substitute state-contingent outputs against one another. Standard stochastic production functions fail to account for the possibility of substitutability between state-contingent outputs, where inputs have the same function regardless of which state is realised. Furthermore, it has been shown that the state-contingent approach yields more accurate estimates than other procedures that impose the substitutability restriction (Chambers et al., 2015; O'Donnell et al., 2010).

This work intends to add to our understanding of the state-contingent production theory by focussing on the productivity growth of arable crop farms, which is an important step towards understanding farmers' responses to changes in the production environment independently of their risk preferences. Specifically, we examine the total factor productivity (TFP) change and its components for a sample of arable crop farms in the Spanish region of Catalonia. Likewise, given the risks associated with agricultural production, which may be affected by high temperatures during the crop growth, rainfall volume and distribution, pest infestations and extreme weather events among many other factors, we are particularly interested in determining how the productivity of these agricultural holdings has changed over time under conditions of uncertainty; thus, we also evaluate the efficiency and technological change of these farms throughout the sample period (2011–2015).

There is a considerable body of literature dedicated to examining the performance of the agricultural sector under uncertainty.[3] Day (1965) and Fuller (1965) were the first to analyse field data on the impact of nitrogen application on maize yield. Just and Pope (1978) approached the problem differently, using stochastic production functions, they estimated the marginal effect of input levels on the mean and variance of output. In subsequent work, this approach was expanded by Antle (1983) to account for the effects of inputs on higher order moments (e.g. skewness and kurtosis) of production uncertainty. Kumbhakar (2002), among others, proposed to combine efficiency measurement with the consideration of risk preferences. Subsequently, this method was used by Orea and Wall (2012) to demonstrate that under uncertainty, productivity and welfare changes do not necessarily go hand in hand. In other studies, production uncertainty is evaluated by investigating the effect of some contextual variables on efficiency measures (Skevas et al., 2012; Wang, 2002). A common feature of the above-mentioned studies is the use of conventional stochastic frontier models, which are too simplistic to properly reflect the stochastic environment in which production decisions are made. In this context, O'Donnell et al. (2010) have shown that applying traditional efficiency and productivity analysis techniques to data resulting from production under uncertainty may lead to erroneous results.

There is a growing empirical literature on the use of the state-contingent approach in the agricultural sector. O'Donnell and Griffiths (2006), Chavas (2008), O'Donnell et al. (2010), Nauges et al. (2011), Chambers et al. (2011), Serra et al. (2014), Guesmi and Serra (2015), Skevas and Serra (2016) and Ait Sidhoum et al. (2020) are some of the most notable applications. However, all these papers focus exclusively on efficiency measurement and do not consider issues of productivity growth. This paper, therefore, offers a new and relevant step in the construction of productivity growth indicators under production uncertainty.

In this empirical study, we rely on the traditional Malmquist productivity index introduced by Caves et al. (1982) and the Luenberger productivity indicator (Chambers et al., 1996). Given the large number of empirical studies using both indices, the popularity

[3]See Chavas et al. (2010) for a good overview.

of both methods is indisputable. In particular, the Malmquist index is the most widely used index for measuring productivity change in agriculture (Bureau et al., 1995; Coelli & Rao, 2005; Kapelko et al., 2017; Latruffe et al., 2008; Zhengfei & Lansink, 2006). Its popularity is mainly due to its computational simplicity, as it does not require price information or underlying functional forms. Furthermore, the Malmquist index satisfies four of the most desirable properties of a TFP index: monotonicity, separability, identity and proportionality,[4] with the exception of circularity.[5] However, the latter one is only relevant when more than two periods are considered (Fried et al., 2008). This makes it especially suitable for our study given our focus on a balanced panel of farms observed in 2 years, 2011 and 2015.

For the sake of comparison, we also consider the Luenberger productivity indicator along with the Malmquist index. Introduced by Chambers et al. (1996), the Luenberger productivity indicator is a difference-based measure of productivity, and it can be viewed as a generalisation of the Malmquist index. The main normalisation property of the Luenberger productivity indicator is that it is translation invariant in the sense that if we decide to increase the size of the direction vector by a factor of 2, everything else constant, then the distance to the frontier will be reduced by 2. This property is crucial for the construction of difference (not ratio) in productivity. It should be noted that the Luenberger and Malmquist productivity indices were compared theoretically and empirically by Boussemart et al. (2003), and their findings suggest that the Malmquist index overestimates productivity change when compared to the Luenberger productivity indicator and that the latter should be favoured. However, under constant return to scale, and when comparing two periods of time, the Malmquist index remains the preferred tool for nonparametric analysis. While both indices can accommodate any orientation (Jiménez-Sáez et al., 2013; Wang, 2016), in this paper, we use an output-oriented approach as farmers have enough control over their inputs, but little control over their outputs due to unpredictable factors. The output-oriented assumption shows how much more outputs they could have achieved with the same level of inputs.

The remainder of this paper is structured as follows: in Section 2, the methodological basis for the Malmquist and Luenberger productivity indices is briefly presented. Next, in Section 3, we describe the panel and data, along with key descriptive statistics. In Section 4, we report and discuss the main results. Section 5 is dedicated to the concluding remarks.

2 | METHODOLOGY

A number of studies have been undertaken to investigate productivity growth, with many utilising deterministic approaches to compute productivity change. Applying these models to data sets generated by stochastic processes such as agricultural production may result in erroneous and biased estimates of efficiency and productivity measurement. Unpredictable rainfall trends, pest damages, volatile commodity prices and other uncertainty factors have all been a source of risk for agricultural producers. Following Chambers and Quiggin (2000), we represent a stochastic production technology in terms of state-contingent outputs.

Within the state-contingent sitting, consider a firm that makes production decisions under uncertainty over T periods of time. The uncertainty is represented by a set of states of nature

[4]The proportionality property is satisfied only if the Malmquist productivity index (MPI) is used under the assumption of constant returns to scale. It is worth mentioning that proportionality applies only to ratio-based indexes rather than difference-based measures (Fried et al., 2008).

[5]As pointed out by one reviewer, circularity also matters when dealing with multilateral comparisons between many units.

Ω, which contains a number of states ($e = 1, \dots, \Omega$) randomly chosen by nature. We assume that the producer chooses a technically feasible combination of inputs and random outputs before 'Nature' makes a draw. Random variable space is represented by the real vector space $\mathbb{R}^{\Omega}$. The stochastic production technology is defined as follows:

$$\mathrm{P}_t = \left\{ \left(x_t, \tilde{y}_t\right) : x_t \text{ can produce } \tilde{y}_t \right\} \tag{1}$$

where each firm uses the $x_t^n = \left(x_t^1, \dots, x_t^N\right)$ vector of nonstochastic input quantities (with $x \in \mathbb{R}_+^N$) to produce the state-contingent outputs $\tilde{y}_t = \left(y_t^e : e \in \Omega\right)$, being y_t^e the ex post value if nature chooses state e (with $\tilde{y} \in \mathbb{R}_+^{\Omega}$), in a specific period $t = 1, \dots, T$.

2.1 | The Malmquist productivity index

The Malmquist productivity index measures the productivity change of decision-making units between two data points by computing ratios of distance functions (Caves et al., 1982). It is based on the Shephard's (1970) distance functions, which provide a quantitative measure of the distance between the firm and the efficient frontier:

$$D^O\left(x, \tilde{y}\right) = \min_{\theta} \left\{ \theta > 0 : \left(x, \frac{\tilde{y}}{\theta}\right) \right\} \in \mathrm{P}_t \tag{2}$$

where $D^O\left(x, \tilde{y}\right)$ is an output distance function that measures the maximum amount by which a firm's output vector can be radially expanded, while keeping the input vector constant. $D^O\left(x, \tilde{y}\right)$ can be used to model multi-input multi-output utility and satisfies the well-known properties of distance functions, including positive linear homogeneity and the nondecreasing nature in $\tilde{y}$ (Coelli & Perelman, 2000).

As mentioned above, the Malmquist productivity index can be calculated as the ratio of two distance functions, using period t as the reference base. To avoid the selection of an arbitrary reference frontier, between t and $t+1$, Färe et al. (1994) suggested using the geometric mean of the two periods. Based on an output-oriented distance function and under constant return to scale, the Malmquist productivity index between t and $t+1$ can be defined as:

$$M\left(x_t, \tilde{y}_t, x_{t+1}, \tilde{y}_{t+1}\right) = \left[\frac{D_t^O\left(x_{t+1}, \tilde{y}_{t+1}\right)}{D_t^O\left(x_t, \tilde{y}_t\right)} \, \frac{D_{t+1}^O\left(x_{t+1}, \tilde{y}_{t+1}\right)}{D_{t+1}^O\left(x_t, \tilde{y}_t\right)} \right]^{1/2} \tag{3}$$

Moreover, the Malmquist productivity index can be decomposed into efficiency change (*MECH*) and technological change (*MTCH*) (Färe et al., 1994):

$$M\left(x_t, \tilde{y}_t, x_{t+1}, \tilde{y}_{t+1}\right) = \frac{D_{t+1}^O\left(x_{t+1}, \tilde{y}_{t+1}\right)}{D_t^O\left(x_t, \tilde{y}_t\right)} \times \left[\frac{D_t^O\left(x_{t+1}, \tilde{y}_{t+1}\right)}{D_{t+1}^O\left(x_{t+1}, \tilde{y}_{t+1}\right)} \, \frac{D_t^O\left(x_t, \tilde{y}_t\right)}{D_{t+1}^O\left(x_t, \tilde{y}_t\right)} \right]^{1/2} \tag{4}$$

$$M\left(x_t, \tilde{y}_t, x_{t+1}, \tilde{y}_{t+1}\right) = MECH \times MTCH \tag{5}$$

Regarding the interpretation of the Malmquist productivity index and its components, any growth in TFP, efficiency and technological change is associated with values above one. Values below one, on the contrary, reflect deterioration.

2.2 | The Luenberger productivity indicator

Alternative to the Malmquist productivity index, Chambers (1996) suggested the use of a non-parametric technique to measure productivity change using directional distance functions (DDF). The Luenberger productivity indicator is a difference-based measure of productivity change based on Luenberger's (1992) shortage function, which is closely related to the DDF. The DDF allows to simultaneously contract inputs and expand desirable outputs of a given firm using a pre-assigned direction vector (Chambers et al., 1996). Given $\vec{g} = g_{\widetilde{y}} \in \mathbb{R}_+$ which is the directional vector[6] that measures the potential adjustments of the state-contingent outputs to the efficient frontier, the state-contingent directional output distance function can be represented as:

$$\begin{gathered} \vec{D}_h^O\left(x_s, \widetilde{y}_s, g_{\widetilde{y}}\right) = \max \beta \\ \text{s. t.} \\ \sum_{i=1}^{I} \lambda^i \widetilde{y}_h^{im} \geq \widetilde{y}_s^m + \beta g_{\widetilde{y}}, m = 1, \ldots, M \\ \sum_{i=1}^{I} \lambda^i x_h^{in} \leq x_s^n, n = 1, \ldots, N \\ \lambda^i \geq 0, i = 1, \ldots, I \end{gathered} \tag{6}$$

where h and s have two possible values, t and $t+1$. We can write four models in one using h and s, as seen in Model (6): $\vec{D}_h^O(x_s, \widetilde{y}_s) = \vec{D}_t^O(x_t, \widetilde{y}_t)$, $\vec{D}_h^O(x_s, \widetilde{y}_s) = \vec{D}_t^O(x_{t+1}, \widetilde{y}_{t+1})$, $\vec{D}_h^O(x_s, \widetilde{y}_s) = \vec{D}_{t+1}^O(x_t, \widetilde{y}_t)$ and $\vec{D}_h^O(x_s, \widetilde{y}_s) = \vec{D}_{t+1}^O(x_{t+1}, \widetilde{y}_{t+1})$. For example, $\vec{D}_h^O(x_s, \widetilde{y}_s) = \vec{D}_t^O(x_{t+1}, \widetilde{y}_{t+1})$ means that Model (6) evaluates the data corresponding to farms observed in period $t+1$ with respect to the technology estimated in period t.

We now turn to the definition of the Luenberger productivity indicator by Chambers (1996) and its components. The Luenberger productivity indicator is constructed as the arithmetic mean of the DDFs between the two periods:

$$\begin{aligned} L\left(x_t, \widetilde{y}_t, x_{t+1}, \widetilde{y}_{t+1}\right) = \frac{1}{2} & \left[\left(D_t\left(x_t, \widetilde{y}_t; g_{\widetilde{y}}\right)\right) - D_t\left(x_{t+1}, \widetilde{y}_{t+1}; g_{\widetilde{y}}\right)\right. \\ & \left. + \left(D_{t+1}\left(x_t, \widetilde{y}_t; g_{\widetilde{y}}\right)\right) - \left(D_{t+1}\left(x_{t+1}, \widetilde{y}_{t+1}; g_{\widetilde{y}}\right)\right]\right) \end{aligned} \tag{7}$$

Unlike the ratio-based Malmquist productivity index, the Luenberger productivity indicator is additively decomposed into measures of efficiency change and technological change. The ratio- and difference-based productivity measures vary in a number of ways, one of which is the overestimated values of the Malmquist productivity index compared with the Luenberger productivity indicator (Boussemart et al., 2003). Another problem that may arise by using ratio-based indices is when the denominator is equal to zero (Epure et al., 2011).

[6]In our empirical application, we chose an identical directional vector (the output mean value). Then, the output-oriented DDF can be defined as $D^o(x, \widetilde{y}) = \max\left\{1 + \beta \overline{\widetilde{y}}\right\}$, where $\overline{\widetilde{y}}$ is the sample average value and it is well known that $\beta = 0$ identifies the efficient firms

As mentioned, the Luenberger productivity indicator in Model (7) can be decomposed into efficiency change (LECH) and the technological change (LTCH) components:

$$LECH\left(x_t, \widetilde{y}_t, x_{t+1}, \widetilde{y}_{t+1}\right) = \left[\left(D_t\left(x_t, \widetilde{y}_t; g_{\widetilde{y}}\right)\right) - D_{t+1}\left(x_{t+1}, \widetilde{y}_{t+1}; g_{\widetilde{y}}\right)\right], \tag{8}$$

and

$$\begin{aligned} LTCH\left(x_t, \widetilde{y}_t, x_{t+1}, \widetilde{y}_{t+1}\right) = \frac{1}{2}\ &\left[\left(D_{t+1}\left(x_{t+1}, \widetilde{y}_{t+1}; g_{\widetilde{y}}\right)\right) - D_t\left(x_{t+1}, \widetilde{y}_{t+1}; g_{\widetilde{y}}\right)\right. \\ &\left. + D_{t+1}\left(x_t, \widetilde{y}_t; g_{\widetilde{y}}\right) - D_t\left(x_t, \widetilde{y}_t; g_{\widetilde{y}}\right)\right] \end{aligned} \tag{9}$$

where

$$L\left(x_t, \widetilde{y}_t, x_{t+1}, \widetilde{y}_{t+1}\right) = LECH + LTCH \tag{10}$$

Regarding the interpretation of the Luenberger productivity indicator and its components, any growth in TFP, efficiency and technological change is related to positive values. In contrast, negative scores are associated with performance deterioration, while values equal to zero indicate stagnation.

3 | SAMPLE AND DATA DESCRIPTION

The empirical application was based on a balanced panel data of arable crop farms. These data have been collected through a survey aimed at analysing the performance of crop farms in the Spanish region of Catalonia.[7] The arable crops consist of cereals, protein and oilseeds crops (COP). A farm is considered specialised if more than 80% of overall farm revenues were obtained from COP crops. A total of 117 farms were surveyed between September and November in 2011 and during the same period in 2015 (234 observations in total).

The data set contains detailed physical, structural and economic information on irrigated and nonirrigated COP farms across two provinces of the region of Catalonia (Barcelona and Lleida). In particular, the data set contains information on the area allocated to COP crops; expenditure and quantities on crop-specific inputs, including fertilisers, pesticides and seeds; capital equipment; the number of hours worked by paid and unpaid workers; and other inputs (water, energy, fuels, lubricants, insurance, contract work and other farming overheads). Furthermore, the surveys were specifically designed to implement an empirical representation of state-contingent technologies. To this end, the first part of the questionnaire[8] was conducted before the starting of the growing season in September 2011 and 2015 to gather predicted yields for three different states of nature. Specifically, we have requested farmers to provide expected yields under bad, normal and ideal states of nature. Eliciting accurate ex ante information is challenging, as it is difficult to obtain objective responses from farmers on what represents a bad, normal or ideal state of nature. Experts from the largest Catalan farmers' association—Unió de Pagesos (UdP)—that was responsible for carrying out the survey,[9] recommended collecting output data for bad, normal and ideal states of nature as the most appropriate and pragmatic method for gathering ex ante information. According to UdP, yields

[7]These data have been already used in previous works. The first period (collected in 2011) has been explored by Chambers et al. (2014); Chambers et al. (2015); Guesmi and Serra (2015); Serra et al. (2014) while the second period of this panel has been analysed by Ait Sidhoum (2018) and Ait Sidhoum et al. (2020). These papers, however, focus exclusively on efficiency analysis and do not consider issues of productivity change.

[8]The second part of the questionnaire was conducted at the end of the season to gather ex post production data.

[9]The interviews were conducted by technicians from UdP who know the farmers well, which may have minimised farmers' incentives to give biased responses.

TABLE 1 Summary statistics (average and standard deviation) for the main variables used in the analysis.

	Symbol	Units	2011 Average	2011 Std. dev	2015 Average	2015 Std. dev	Full period 2011–2015 Average	Full period 2011–2015 Std. dev
Land	x_1	Hectares	76.76	58.34	76.01	59.40	76.38	58.72
Labour	x_2	Hours	605.22	631.42	857.62	779.13	727.22	718.29
Capital	x_3	Euros	139,650.02	103,351.21	152,702.06	131,802.90	146,702.29	118,116.06
Fertilisers	x_4	Kilograms	4230.95	3045.88	5990.10	4741.62	5110.53	4071.78
Pesticides	x_5	Litres	87.96	103.02	100.70	114.21	94.33	108.68
Other[a]	x_6	Euros	9260.84	7155.59	9028.43	6864.96	9144.63	6995.46
Ex post output	y	Euros	57,156.44	42,478.43	54,998.62	44,491.74	56,077.53	43,402.95
Output under bad state	y_1	Euros	31,833.73	27,963.95	33,001.29	28,336.69	32,417.51	28,087.61
Output under normal state	y_2	Euros	52,880.95	42,637.73	51,987.96	39,794.42	52,434.46	41,141.31
Output under ideal state	y_3	Euros	72,579.91	62,345.23	70,883.29	55,419.32	71,731.60	58,844.70

Note: Monetary variables are expressed in 2015 EUR.

[a]Other includes energy and seeds costs.

TABLE 2 Descriptive statistics for both the Malmquist and Luenberger productivity indices and their components (2011–2015).

	Ex post		Bad		Normal		Ideal	
	Luenberger	**Malmquist**	**Luenberger**	**Malmquist**	**Luenberger**	**Malmquist**	**Luenberger**	**Malmquist**
TFP change								
Average	−0.049	0.781	0.028	1.028	0.027	0.998	0.022	0.978
Std. dev	0.136	0.253	0.173	0.350	0.159	0.278	0.141	0.241
Correlation	0.564		0.820		0.840		0.720	
Efficiency change								
Average	0.149	1.857	0.074	1.263	0.110	1.240	0.099	1.209
Std. dev	0.217	0.604	0.220	0.643	0.189	0.458	0.182	0.375
Correlation	0.724		0.771		0.711		0.786	
Technological change								
Average	−0.199	0.451	−0.047	0.854	−0.083	0.824	−0.077	0.829
Std. dev	0.188	0.190	0.087	0.158	0.097	0.148	0.098	0.149
Correlation	0.707		0.611		0.456		0.468	

under normal conditions can be used as a reference for farmers (i.e. the average yield over a 10-year period); then, identification of yield data for the bad and the ideal state of nature should be relatively easy.

Measuring productivity change requires the computation of efficiency and technological change within the nonparametric framework of data envelopment analysis. For our estimation procedure, we rely on previous empirical studies and select the following inputs: arable land (x_1 in hectares), labour use (x_2 in hours), capital (x_3 in euros), fertilisers (x_4 in kilograms), pesticides (x_5 in litres of active ingredient), and energy expenses and seed expenses (x_6 in euros). Regarding the outputs, in additional to the realised ex post COP crop output value (y in euros), three alternative COP crop output values representing each state of nature: bad (y_1 in euros), normal (y_2 in euros) and ideal (y_3 in euros) growing conditions, have been used to account for production uncertainty. Descriptive statistics are provided in Table 1.

4 | RESULTS

The Malmquist and Luenberger productivity indices were computed for each of the farms in the sample and for each state of nature. Since it has been shown that the presence of outliers may affect the DEA results, we have used the superefficiency method proposed by Banker and Chang (2006) to detect and remove potential outliers in the data set. Thus, observations with extreme superefficiency ratings were eliminated from the sample for both periods.[10] Table 2 summarises the results for both indices (Malmquist and Luenberger) and their components for both ex ante and ex post production. Although the calculated values of both indexes vary from each other because of differences in their computation, the Spearman rank correlation coefficients indicate that both indexes are significantly correlated and follow a similar pattern.

Column 1 in Table 2 reports the summary statistics of the Luenberger productivity indicator and its components for the ex post state. These findings indicate that, on average, farms experienced a TFP decrease of 4.9% from 2011 to 2015. This regression is mostly due to the negative evolution of technical change (−19.9%), while efficiency change increased by 14.9%. Column 3 of Table 2 lists the results of the Malmquist productivity index and its components for the ex post state. The average Malmquist TFP change shows a similar trend, with a regression of −21.9%, but with a significantly larger efficiency change (+85.7%) and strong technological regress (−54.9%). While the results from both indices are relatively similar and the same patterns[11] have been found in earlier studies, the differences between both indices are however more pronounced than one would expect. Together, both indices seem to indicate a considerable technological regress, as well as an increased efficiency change. In other words, this means that the distance between our sample farms and the efficient frontier decreased and resulted in an increase in technical efficiency. One might speculate that the sharp technological decline may have resulted from the presence of adverse shocks such as droughts.[12] For example, for our sample farms, we observe a significant decrease in precipitation rates across the regions where the farms are located between 2011 and 2015 (SMC, 2020). However, we must remain cautious with the interpretation of these results because our decomposition is sensitive to the underlying technologies and farms whose performance is being evaluated, an inaccurate estimate of one component inevitably leads to an inaccurate estimate of the other component.

[10]Only 13% of the farms were found to be dominating observations (outliers) according to the Banker and Chang (2006) method. Although such a sample size might appear to be small, it does not compromise the main contribution of this study, which is the extension of conventional productivity measures to allow for a state-contingent approach.

[11]Previous studies showed that the Malmquist index overestimates the Luenberger indicator.

[12]Decreased precipitation rates are likely to affect crop yield and this may result in negative effects on technological change and TFP growth (Umetsu et al., 2003).

Table 2 presents information on the average TFP change of both indices and their components for each of the three states of nature. The overall Luenberger TFP change displays only a minor variation across the three states of nature, from an average increase of 2.8% in the bad state of nature to an increase of 2.7% and 2.2% under the normal and ideal conditions, respectively. The state-contingent technological change deteriorated on average between 2011 and 2015, irrespective of whether bad (−4.7%), normal (−8.3%) or good (−7.7%) crop-growing conditions. In contrast to the technological change, the average efficiency change of our sample farms increased from 7.4% in the bad state to more than 10% in the normal and good states of nature. Turning now to the ex ante values of the Malmquist productivity index, similar trends but with different magnitudes are observed. The Malmquist TFP index values show no significant differences across the different states of nature. The average values are close to unity, indicating stagnation. In terms of the efficiency change component, our sample farms experienced a significant change over the period of study with a gain ranging from 26.3% in the bad state of nature to about 20.9% in the ideal states of nature.[13] While these efficiency change values seem to be dependent on the state of nature, the results of the nonparametric Kolmogorov–Smirnov test reject the hypothesis that these values come from different distributions. A similar conclusion can be made for the technological change component.

Our findings are especially notable for the significant differences between ex post and ex ante values. Variation in productivity change between nonstochastic and stochastic technology shows the relevance to consider the state-contingent production technology when assessing farms' productivity. Our results confirm relevant earlier studies on the development of state-contingent performance measures in agricultural production. O'Donnell et al. (2010) showed that nonstochastic information does not adequately represent the stochastic decision environment in which production takes place, resulting in productivity and efficiency measures that are downwardly biased. Similar conclusions are reported by Serra et al. (2014) and Chambers et al. (2015). More specifically, when comparing the average values of technical efficiency change between nonstochastic and stochastic technology, our results point to an overestimation of the technical efficiency change, which contrasts with the technological change estimates that exhibit a considerable downward bias as a result of ignoring the stochastic production conditions.

We have also explored the potential determinants of productivity change for both indices and their components. Detailed information on the estimation procedure, variables used, relevant results and discussion is given in Appendix S1.

5 | DISCUSSION

The results from our analysis suggest that there is a large difference between the ex post and ex ante[14] productivity values, especially with respect to the Malmquist productivity index. If accurate, these findings are important because this is the first empirical application comparing productivity indices of nonstochastic and state-contingent technologies. Previous studies have shown that ignoring the stochastic nature of agricultural production can lead to unreliable results, where poor performances arising from the unpredictable nature of agricultural activities may be associated with an inefficient use of resource inputs (O'Donnell et al., 2010; Serra et al., 2014). These papers, however, focus exclusively on estimates of efficiency performance, while in our study, we retain a specification that allows agricultural performance to be decomposed into efficiency and

[13]One possible explanation of these results is that farmers are risk-averse, which would mean that they prepare for the worst conditions, implying that inputs are not combined in optimal proportions under ideal conditions.

[14]The overall ex ante value corresponds to the average of the three states of nature.

technological change. As noted above, we found that ignoring the stochastic conditions leads to an overestimation of efficiency change and an underestimation of technological change. However, one must acknowledge that the ex post productivity values for both indices appear implausible; therefore, great care and caution are needed when interpreting these results.

These implausible findings are most likely the result of the data collection procedure and our empirical representation. First, collecting accurate state-contingent data is not straightforward, and objective responses from farmers on what constitutes a state space are difficult to obtain. As noted, technicians from Udp recommended collecting output data for three states of nature (bad, normal and good). However, these are obviously subjective beliefs that will presumably vary between farmers. As a result, there is a risk of identification bias. Second, another important concern is about the accuracy and consistency of the data collection process over the sample period. Indeed, data consistency requires that common definitions and methodological standards are applied, and a certain level of steadiness is maintained over the sample period. Another problem is linked to the fact that the surveys have been conducted in two phases: before and at the end of the growing season. During Phase 1 (autumn 2011 and 2015), ex ante production data and planned input use were collected. In Phase 2 (spring/summer 2012 and 2016), we collected the ex post data. While such discrepancies may result in measurement bias, attention still needs to be given to refine the elicitation process used in our work. Finally, our measures do not account for statistical noise; thus, any noise in the data can bias the productivity level and its components.

6 | CONCLUSIONS

The goal of this study was to measure productivity growth in the Catalan COP sector during 2011–2015, while accounting for the stochastic conditions under which production takes place through the state-contingent framework. This paper offers a new and relevant step in the construction of productivity change indicators under production uncertainty. More precisely, we analysed TFP change and its components (efficiency change and technological change) for the realised ex post and ex ante (state-contingent) data. For this, we have used the conventional Malmquist productivity index and the difference-based Luenberger productivity indicator. Our empirical analysis constitutes the first attempt to assess the productivity growth of sample farms under production uncertainty using both the Malmquist and Luenberger approaches.

The comparison of the results derived from both indices shows that the Malmquist productivity index overestimated the efficiency and technological change compared with the values of the Luenberger productivity indicator. While these results are compatible with Boussemart et al.'s (2003) findings that ratio-based productivity approaches overestimate productivity change when compared to difference-based indicators, one needs to be very cautious when interpreting them.

The main findings of the study were the following. First, for the ex post state, the productivity of arable crop farms decreased from 2011 to 2015. Second, an analysis at the farm level allowed us to identify that the main driver of the TFP decline was the negative shift in the production frontier, while our sample farms recorded a strong efficiency change. The third finding is that when considering production uncertainty through ex ante information, the overall TFP displays only a minor variation across the three states of nature. Furthermore, these results are not compatible with the argument that farm performance improves with the improvement of conditions during the growing season, but seem to follow the opposite trajectory, suggesting that farmers may anticipate the worst-case scenario. Fourth, the state-contingent technological change declined on average between 2011 and 2015, irrespective of the state of nature. Fifth, strong differences in productivity values between nonstochastic (ex post) and stochastic (ex ante) production technology show the importance of considering production uncertainty when assessing farms' productivity. While these results need to be interpreted with care, these differences could be due to the possibility of substitution between state-contingent outputs (which contrasts with the ex post approach), where farmers can adjust their production scale in response to new conditions.

If accurate, the fact that most farms in the sample show a strong technological regress raises the question as to what policymakers can do in this respect. First, legislators could help those farmers who are behind in terms of adopting technological innovations. For example, policymakers could promote the adoption of precision farming practices such as remote sensing and global positioning systems, where production decisions can be matched with seasonal conditions (Gadanakis et al., 2015). These innovations, however, are costly, and farmers will need financial assistance and advisory support services. Second, while direct and decoupled payments (Pillar 1) have been shown to reduce farmers' productivity performance, additional funds should be allocated to those measures that aim to strengthen agricultural competitiveness while at the same time reducing environmental impacts (Rural Development Programme). Such measures have been shown to be able to improve farms' productivity (Mennig & Sauer, 2020). Finally, any policy measure should be reviewed periodically to ensure that it remains still relevant, which calls for periodic data collection to monitor the evolution of agricultural productivity under production uncertainty.

To conclude, it is worth mentioning that there are different avenues for further follow-up research. The analysis should not be limited to farm economic outputs, but should also include environmental issues. In this context, it would be interesting to extend the approaches for dealing with undesirable outputs along the lines of Murty et al. (2012) or Murty and Russell (2018) to productivity measurement. Another future avenue for research is to check in depth the robustness of our results. This includes the use of an event-specific production framework (Chambers et al., 2011; Skevas & Serra, 2016). Moreover, it would be interesting to compare our findings with those obtained using parametric approaches. Third, we also suggest comparing our results with recent methodologies introduced in the literature by Wang et al. (2016) and Arabi et al. (2015). Finally, much more attention will be needed in future on the determinants of state-contingent performance measures. Policymakers would benefit greatly from state-contingent productivity analyses based on the use of farm-level data containing information on farmers' perceptions and attitudes towards farming activities.

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DATA AVAILABILITY STATEMENT

The author chose not to share data because it is proprietary and confidential.

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