Farmers' heterogeneous responses to price variations: Identification of dairy farms flexibility based on a panel smooth transition regression approach

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Abstract

Our objective in this paper is to identify the heterogeneity in dairy farms' flexibility based on their observed short run responses to input and output prices. To this aim, we rely on an approach which recognizes that, following a variation in input or output prices, firms have to adjust their quantity of variable inputs, which may be costly, and that, in the presence of adjustment costs, the adjustment of input quantities will differ depending on the magnitude of the price variation. Our model of dairy farms' production decisions is based on a threshold regression model, which allows switching between two regimes of farm responses to prices depending on the magnitude of the price variations. We also rely on a random parameter approach to account for the unobserved heterogeneity of farms in our model. This approach is applied to a panel of dairy farms located in the west of France over the period 2007-2017. Our empirical results reveal heterogeneous levels of flexibility for these farms regarding their adjustment of feed concentrates and acreages (of silage maize, grass and crops) in response to significant variations in the price of milk and feed concentrates. An ex post analysis of our estimation results shows that farms endowed with more capital but less indebted, farm using a grass-based production system, farms producing their own feed and organic farms tend to be more flexible in their short run responses to changes in market conditions.

Introduction

Farmers' capability to adjust their production choices in response to external events (e.g. changes in market conditions, climatic events, policy reforms), allow them to benefit from, or to limit the loss of profit induced by, these events. The closely related concepts of resilience, adaptive capacity and flexibility, are indeed put forward as key elements of farms' economic sustainability in the face of increasing climate variability and volatility on agricultural markets (Reidsma et al., 2010; Robert et al., 2016). Although several economic studies have focused on long term adaptation of farmers to global changes, few studies have considered farms' adaptive capacity in the short run. Yet, as pointed out by Darnhofer (2014), farmers' capability to temporarily reallocate their resources when a disruption occurs, such as a sudden price decrease or a short drought, is also an important issue.

Farm short run adaptive capacity, which we refer to here as "farm flexibility", is of particular interest in the case of dairy farming for several reasons. First, milk and feed concentrate prices tend to vary a lot from year to the other, implying that dairy farm have to cope with significant variations in both output and input prices. Second, although dairy production can be impacted by various external events, the impact of these events depends on the management strategy, and particularly on the feeding strategy, of the farms. Maize silage-based production systems are more dependant on imported (concentrate) feed used to supplement maize, while grass-based production systems are more dependant on climatic hazards which have significant impacts on grass yields. Yet, as shown in the technical livestock production literature (Peyraud et al., 2010), dairy farms do in fact have some degree of flexibility to adjust their feeding strategy in the short run in order to be more resilient to price and climate shocks, by adopting mixed feeding systems, diversifying their pasture, and using concentrates when necessary.

While flexibility appears as a key aspect of the economic performance of farms, economic studies of farm production decisions generally find low elasticities of input uses and acreage choices in the short run. Most of these studies actually focus on crop production decisions. Böcker and Finger (2017) for instance conduct a meta-analysis on the estimated elasticities of demand for pesticides and conclude to the inelasticity of this demand with elasticity values significantly higher than -1. Crop acreages are also found to be inelastic to crop price changes by Carpentier and Letort (2012) with elasticities ranging from 0.1 to 0.3. Only few economic studies have been conducted on the price responses of input and acreage choices in livestock farms. One exception is Suh and Moss (2017) who also find input use to be price inelastic in dairy farms with an elasticity of demand for silage maize equal to -0.23.

This apparent rigidity of farm production decisions in the short run, should however be considered in the light of the heterogeneity of farm behaviours. Price responses revealed in the above mentioned studies indeed correspond to average behaviours, common to all farms for a given specialization in a given region. Yet these behaviours can differ from one farm to the other due to several (often unobserved) factors. Recent empirical works dealing with farm heterogeneity have essentially focused on the heterogeneity in production technologies among farms, like Alvarez and Corral (2010) who use a latent class model to differentiate dairy farms' production technologies according to their degree of intensification. Very few works have in fact focused on the heterogeneity of farmers' responses to market prices. Koutchadé et al. (2018) is one exception. These authors use a random parameter approach to account for the unobserved heterogeneity of farmers' behaviours and show that price elasticities of farmers' yield, input use and acreage choices do in fact display a significant heterogeneity among farms, even in a sample of relatively homogeneous farm specialized in crop production in a small geographical region.

Our objective in this paper is to identify this heterogeneity in dairy farms' flexibility based on their observed short run responses to input and output prices. Our approach differs from that of Koutchadé et al. (2018), who address the heterogeneity in farms' behaviour from a statistical view point, in that we aim at providing an economic explanation to the relative rigidity or flexibility of farms. A lack of flexibility in the responses of farm production decisions to market prices can in fact be due to the existence of adjustment costs related to the rigidity of quasi-fixed inputs or to additional administrative or transaction costs incurred by the farm when adjusting its variable input levels.

Different methodological frameworks, which are compared in the first section, have actually been developed in the economic literature to account for the impacts of adjustment costs on farm production decisions. Our approach relies on Önel (2018a; 2018b)'s works, who proposes a factor demand model in order to implicitly account for adjustment costs of the industrial sector in the United-States. This approach recognises that, following a variation in input price, firms have to adjust their quantity of variable inputs, which may be costly, and that, in the presence of adjustment costs, the adjustment of input quantities will differ depending on the magnitude of the price variation. His model, based on Hansen' s threshold regression model, allows for switching between two regimes that represent large and small input price changes based on a threshold level. The estimated threshold level corresponds to the level of price change, which leads to a different behavior in terms of inputs adjustment. An industrial sector able to rapidly adapt their production decisions face to an input price shock is assumed to have less adjustment costs.

Our main contribution compared to the works of Önel is to consider individual threshold levels of price variation in order to account for the heterogeneity of adjustment costs among farm. We consider that, face to a price shock, the capacity of a farmer to adapt his production decision, that is represented by the farm-specific parameters of the transition between the two regimes, provides us information on her level of adjustment costs, and her level of flexibility. To do so, we rely on a smooth transition regression (PTSR) (Gonzales et al., 2005) model in which we introduce individual random parameters. This approach is applied to a panel of dairy farms located in the west of France over the period 2007-2017. Our empirical results reveal heterogeneous levels of flexibility for these farms regarding their adjustment of feed concentrates and acreages (of silage maize, grass and crops) in response to significant variations in the price of milk and feed concentrates. An *ex post* analysis allows us to highlight the specific features of flexible farms.

The rest of the paper is organised as follows. A first section is devoted to a literature review on farm adjustment costs. In a second section, we present our theoretical framework and the empirical model used to identify farms' flexibility at individual levels. Our estimation strategy is presented in a third section and our empirical results in a fourth section. Finally we conclude.

1. Literature review on adjustment costs' structure

Different methodological frameworks have actually been developed in the economic literature to account for the impacts of adjustment costs on firm production decisions.

The first category of approach focus on investment decisions using dynamic models. In the agricultural economics' literature, the existence of adjustment costs prevent farms from immediately adjusting their capital or labor stock, hence their output level and variable input quantities (e.g. Gardebroek and Oude Lansink, 2004; Pietola and Myers, 2000). The rigidity of investment decisions is confirmed in livestock farming, especially in pig sector (Pietola and

Myers, 2000; Gardebroek and Oude Lansink, 2004; Boetel et al. , 2007). Dairy farmings are much less studied, maybe because they require less important investment to extend. The growing literature on the investment decisions results in the improvement of theoretical and empirical models. As a result, the structure of adjustment costs is increasingly discussed. For example, Lansink and Gardebroek (2004) relax the assumption usually made that all farms have the same cost adjustment structures. Their empirical application confirms the heterogeneity of adjustment costs, which allows them to identify groups of farms with a similar adjustment cost structure. These models are however designed to analyze long term behaviours of farms, which is not our purpose here. Our concern is to obtain insight in short term behaviours of farms that does not require investment nor technological change.

Some micro-econometric models of crop production decisions (Carpentier and Letort, 2012 and 2014; Koutchadé et al., 2018) rely on a concept borrowed from the Positive Mathematical Programming (PMP) literature (Howitt, 1995) and introduce implicit adjustment costs of acreage in their objective function in order to account for crop diversification motives in acreage choices. This approach implicitly consider that farmers are restricted in their acreage choices by agronomic and technical constraints. For example, an expected work peak, a lack of machines and/or a greater risk of pests prevent farmers to specialize in a single-crop farming. Despite of clear benefits of this approach based on an implicit cost function, it can be seen as a black box approach, in which it may be difficult to interpret the estimated effects. Nevertheless, Koutchade et al. (2018) make a distinct improvement in estimating farm-specific parameters of this cost function. A random parameters model allow them to account for the heterogeneous responses of crop producers to economic drivers. From their empirical application, they confirm the heterogeneity of cost adjustments in cereal farming, and conclude that ignoring the variability in the considered farmers' responses to the economic incentives results in significant misestimation of production decisions. However, adjustement costs only concern acreage choices, and they do not allow to account for adjustment costs in input use decisions. Although all their parameters are farm-specific, they implicitly consider that the differences of behaviour in terms of input decisions between farmers are explained by heterogeneity of the production function, and not by heterogeneity of the structure of adjustment cost.

A third modelling framework, recently proposed by Önel (2018a; 2018b), is of particular interest for our purpose. This approach recognises that, following a variation in input price, firms have to adjust their quantity of inputs, which may be costly, and that, in the presence of adjustment costs, the adjustment of input quantities will differ depending on the magnitude of the price variation. Two cases are in fact possible, depending on the structure of adjustment costs faced by the firm. On the one hand, if adjustment costs are convex, these costs increase with the adjustment of input quantities, implying larger price elasticities of input for smaller price variations. On the other hand, if adjustment costs are non-convex, they are non-increasing with the adjustment of input quantities, implying larger price elasticities of input for higher price variations: in that case, a small adjustment of input quantities, following a small variation in input price, is costly compared to the profit gained from this small adjustment. Firms will thus adjust more their inputs for large price variations. Önel (2018a) uses a threshold regression model (Hansen, 2000) of input demand to implicitly account for these adjustment costs. In this model, the price elasticities of input are allowed to vary depending on observed input price variations. More precisely, the price parameters of the model take one value below a certain threshold level of price variation and another value above this threshold. For our purpose, the advantage of this approach is that adjustment costs concern the quasi-fixed inputs, but also variable input uses, making this approach adapted to analysis of the short-term behaviour. Önel propose this framework first to show that parameters of the cost function are nonlinear, while the linearity in the parameters is generally assumed in the empirical literature. At the same time, his empirical application allows him to compare adjustment costs structure between industrial sectors of the United States. Note that he assumes that the structure of adjustment costs are identical for all firms within each industrial sector. Our use of this framework is different. If the non-linearity of farmers' behaviour is confirmed in our sample (this is not the goal of this paper, even if this result would lead important implications that need to be discussed), our main objective is, starting from this framework, to relax the assumption of homogeneous structure of adjustments costs, and to use the responsiveness of farmers face to price change in order to identify the level of flexibility.

2. Modelling framework

Our theoretical framework, presented in the first sub-section, builds upon Chambers and Just (1989)'s farm profit maximization problem in the presence of fixed allocable inputs. It provides a reference point for the development of the threshold model described in the second sub-section.

2.1. Model of livestock farms' production decisions

We rely on the framework originally proposed by Chambers and Just (1989) and generalized by Fezzi and Bateman to model livestock farms' production decisions. In this framework, farmers are assumed to allocate their total land quantity by maximizing an indirect restricted multi-output profit function. From this framework, one can derive the profit maximizing input demand and output supply given a fixed land allocation via Hotelling's lemma (see further details in Fezzi and Bateman, 2011).

By specifying the profit function as a normalized quadratic function, solving the farmer's optimization program leads to an econometric model of acreage and input use decisions that can be synthetized by this equation:

$$y_{it}^{j} = \alpha_{0i}^{j} + \mathbf{x}_{it}'\boldsymbol{\alpha}_{\mathbf{1}}^{j} + \mathbf{z}_{it}'\boldsymbol{\alpha}_{\mathbf{2}}^{j} + \varepsilon_{it}^{j} \tag{1}$$

Subscripts *i* and *t* respectively denote the cross-sectional and time dimensions of our panel data and superscript j belongs to $\mathcal{J}$, the set of livestock farmers' acreages and input uses choices we consider. The vector of dependent variable $\mathbf{y}_{it} \equiv \left(y_{it}^{j}, j\epsilon\mathcal{J}\right)$ contains acreage shares and input quantities. $\mathbf{x}_{it} \equiv \left(\mathbf{p}_{it}/\mathrm{w}_{nit}, \mathbf{w}_{it}/\mathrm{w}_{n,it}\right)$ contains a set of output and input prices normalized by the price of input *n.* Other observable factors that can potentially have an impact on farmers' production decisions, such as market prices not included in $\mathbf{x}_{it}$ or weather conditions, are included in $\mathbf{z}_{it}$. The parameters included in vector $\boldsymbol{\alpha}_{\mathbf{1}}^{j}$, respectively vector $\boldsymbol{\alpha}_{\mathbf{2}}^{j}$, capture the effects of $\mathbf{x}_{it}$, respectively $\mathbf{z}_{it}$, on y_{it}^{j}. In model (3), these effects are assumed to be common to all farms and farmers. Additive term α_{0i}^{j} is a random farm-specific parameter aimed at capturing the effects of unobserved factors, such as farmers' skills or farms natural endowments, on y_{it}^{j}. Finally, ε_{it}^{j} is a stochastic error term.

2.2. Threshold model of livestock farms' production decisions

The linear model of agricultural production decisions presented above does not account for potential costs incurred by farmers when adjusting their inputs in response to price variations. In fact, it assumes homogenous reactions of farmers to any level of price change. Yet, a change in input quantities following a change in input or output price might be costly for farmers. There may exist direct adjustment costs such as transport costs, costs of training, costs arising from changes in contracts, etc… Adjustment costs may also be caused by the rigidity of quasi-fixed factors, since variable input use is tied to the amounts of capital equipment, the structure of labour and the allocation of land. For instance, important decrease in the use of concentrates to feed animals requires producing more fodder crops or encouraging grazing pasture. It involves a reorganization of the farm and a new land allocation in order to convert cropland to pasture and/or fodder crops. Farmers may also need new machinery and more workers to produce on-farm animal feed. Farmers might thus significantly adjust their animal feeding strategy for large price shocks only (non-convex adjustment costs), or, on the contrary, be more responsive to smaller price shocks that imply smaller adjustments of animal feeding (convex adjustment costs).

We modify our empirical model in order to implicitly account for such adjustments costs (as Önel, 2018). More precisely, we introduce a non-linearity in the response of farmers to input and output prices. Our model relies on the fact that, if a farmer reacts differently according the level of price change, then we consider he faces to adjustment costs that affect his production decisions. We propose a modelling approach based on a threshold regression model in order to investigate the existence of adjustment costs in the response of farm inputs to price variations. The parameters associated to the price variables can vary according to a regime-switching mechanism that depends on a threshold variable. We use the change in the ratio of input price to output price compared to the previous period as transition variable. The prices ratio allows us to accurately represent the price signal as perceived by farmers, who take their production decisions comparing the evolution of input and output prices. Finally, while Önel's model relies on Hansen's threshold regression approach (2000), we propose a model based on the works of Gonzales et al. (2005) and Fok et al. (2005) to allow for individual threshold parameters.

The threshold version of our model can be written as:

$$y_{it}^{j} = \alpha_{0i}^{j} + \mathbf{x}_{it}'\boldsymbol{\beta}_{\mathbf{1}}^{j} + \mathbf{xG}_{it}{}'\boldsymbol{\beta}_{\mathbf{2}}^{j} + \mathbf{z}_{it}'\boldsymbol{\alpha}_{\mathbf{2}}^{j} + \varepsilon_{it}^{j} \tag{2a}$$

where $\mathbf{xG}_{it}$ is a vector containing the product of each component of $\mathbf{x}_{it}$ with G_{it}, the value taken by function G for farmer *i* in year *t*. G is a transition function, normalized to be bounded between 0 and 1. As proposed by Gonzales et al. (2005), introducing this transition function in the model allows representing a smooth transition between two regimes of responses to price variations, contrary to Hansen's threshold regression approach (2000) that only allows for an abrupt transition between the two regimes. G is a continuous function of an observable transition variable q_{it} and depends on farm-specific random parameters, γ_i and c_i, that respectively reflect the speed and the threshold of transition.

This transition function has a logistic form:

$$G(q_{it}; \gamma_i, c_i) = \frac{1}{(1 + \exp(-\,\gamma_i\,(q_{it} - c_i))} \tag{2b}$$

With $\gamma_i > 0$. This smooth transition regression approach may be interpreted in two distinct ways. First, we can consider that there are two extremes regimes associated with the two extremes values of the transition function: $G_{it} = 0$ and $G_{it} = 1$, and that farmers progressively move from one regime into another. The response of y^j to changes in prices contained in **x is** represented by $\boldsymbol{\beta}_{\mathbf{1}}^{j}$ in the first extreme regime and by $\boldsymbol{\beta}_{\mathbf{1}}^{j} + \boldsymbol{\beta}_{\mathbf{2}}^{j}$ in the second extreme regime. Second, this might be regarded as an infinity of regimes and possible values for the price response parameter are $\boldsymbol{\beta}_{\mathbf{1}}^{j} + \boldsymbol{\beta}_{\mathbf{2}}^{j}G_{it}$, depending on the value of q_{it}.

Our model differs from the model originally proposed by Gonzales et al (2005) in that we consider individual-specific parameters in the transition function. To our knowledge, Fok et al.

(2005) is the only paper that considers individual threshold parameters. These authors examine the existence of common nonlinear business cycle features in 19 US manufacturing sectors based on a multi-level smooth transition model. However, their approach is best suited to time series panels (i.e., data with a large temporal dimension and a small cross-sectional dimension), whereas our data contain observations for a large number of farms over a relatively short period of time, as is typically the case for samples of farm accounting data used to estimate farmers' behaviour.

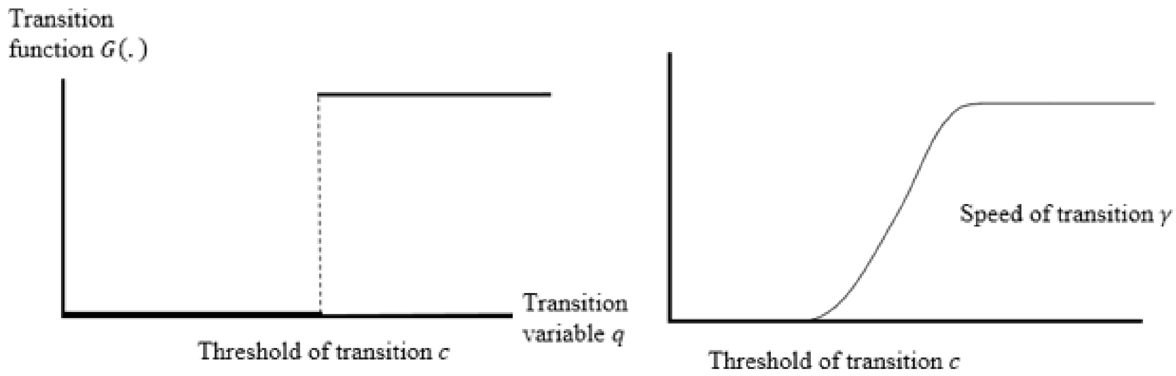


Figure 1. Approaches of Hansen and Gonzales: standard and smooth threshold regression model

Figures 1 and 2 graphically illustrate the differences between our approach and those of Hansen and Gonzales et al. These graphs report the value of the transition function G according to the value of the transition variable q. For each approach, farmers are in the first regime when the transition function is equal to 0 and in the second regime when the transition function is equal to 1. The differences between the three approaches lie in the way farmers switch from the first to the second regime.

In Hansen's model illustrated by the right-hand graph in Figure 1, the transition between the two regimes consists in a jump at a threshold level, c, which is the same for all farmers. Gonzales et al's model, illustrated by the left-hand side graph in Figure 1, allows for a smooth transition between the two regimes, the speed of this transition being characterized by a parameter γ also common to all farmers. Our approach, illustrated by the last graphs in Figure 2, simultaneously allows for individual threshold and speed of transition levels.

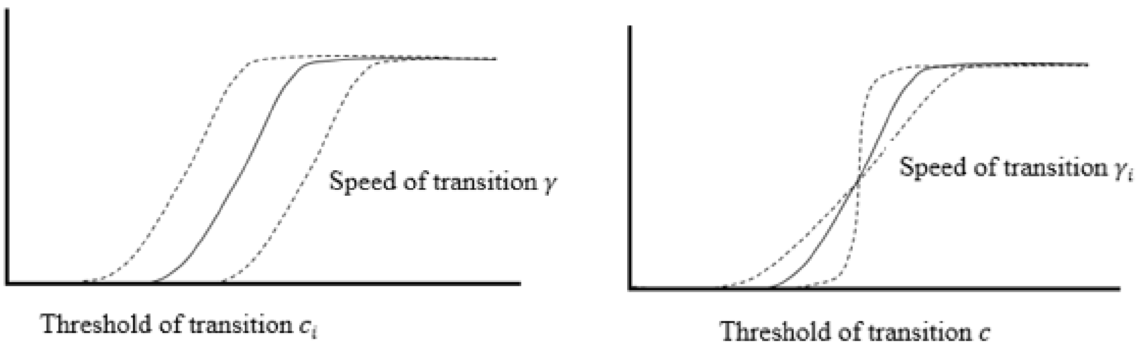


Figure 2. Our approach: individual smooth threshold regression model

Our model has the advantage to contain all others models. If the threshold of transition is not significantly different between farmers and the speed of transition tends toward infinite, our model reduces to the threshold model of Hansen. If the threshold and the speed of transition are not significantly different between farmers, we obtain the smooth threshold model of Gonzales et al. Finally, if the speed of transition tends towards zero, our model reduces to a linear random parameters model.

2.3. Economic interpretations and contributions to the literature

Our proposed modelling framework can contribute to the empirical literature in agricultural production economics by allowing the representation of nonlinearities in farmers' behaviours and by accounting for the existence of heterogeneous adjustment costs.

Nonlinearities in farmers' behaviour

Considering that farmers respond differently depending on the magnitude of the price variation they face implies the existence of nonlinearities in farmers' behaviour. These nonlinearities can have important implications in terms of policy recommendation as the impacts of economic incentives on farmers' production choices depend on the economic context. Yet, despite its relevance, few works in agricultural production economics have focused on this issue and allowed the representation of nonlinearities in inputs demand or output supply.

One exception is Hennessy (2018) who argues that antibiotic demand in livestock farms may be discontinuous at individual level, in the sense that own-price responses of antibiotic demand are inelastic for low prices but elastic at higher prices. To take into account for this potential non-linearity in price responses, he uses a Lambert production technology, which is a special class of the extreme value distribution density function. Two specificities of this production function allow the representation of discontinuous price responses. First, it supports strictly positive output when no input is applied (this can be the case for antibiotics, which are not essential inputs). Second, its marginal productivity is increasing over low input levels and over high input levels. In these conditions, the producer input demand is discontinuous, and collapse to zero at the technology's inflection point. Hennessy's framework thus allows accounting for nonlinearities in the demand of "nonessential" inputs; it is however not well suited when essential inputs (such as animal feed in livestock production systems) are considered. The usual production technologies, of quadratic form for example (Carpentier and Letort, 2012, 2014; Koutchade et al. 2018) are flexible, but do not allow for non-linearity in input demand. Indeed, own price elasticities increase with an increase in input prices but in a linear way.

Heterogeneity of farm adjustment costs and flexibility

We explain here how our proposed modelling framework can be used to characterize adjustments costs and determine the level of flexibility of each farm.

The starting point of our analysis is the characterization of the two extreme regimes in our model. In fact, the analysis of farmers' behaviour depends on the values of parameters that characterize each regime. As a reminder, the two extreme regimes are similar for all farmers. The first regime corresponds to a context of small price variations and the transition function is equal to 0. The second extreme regime corresponds to a context of large price variations and the transition function is equal to 1. Of course, the parameters characterizing farmers' behaviours in these regimes are obtained from the estimation of the model. Two cases are possible. In a first case, farmers are more responsive to small than to large price variations. That case can arise when adjustment costs are convex and increase with the adjustment of input quantities that is required in response to a price variation. In a second case, farmers are more responsive to large than to small price variations. That case can arise if adjustment costs are non-convex and a small adjustment of input quantities, following a small price variation, is costly compared to the benefits generated be the input adjustment. In the first case input price elasticities are higher in the first than in the second extreme regime, and conversely, in the second case input elasticities are higher in the second regime.

We can then analyse how each farmer switches from one regime to the other by comparing the two farm-specific parameters of the transition function in our model, namely the threshold c_i

and speed of transition level γ_i. Our interpretation is that a farmer tends to switch smoothly and slowly from one regime to the other (small γ_i) when this switch requires an investment in capital or labour, or a change in production technology. In fact, as in dynamic models of investment decisions, this lack of flexibility may be explained by the rigidity of quasi-fixed inputs. Our interpretation of the threshold level c_i is slightly different. We use this parameter to characterize the capacity of farmers to adapt their short-term production decisions. Consider for instance a case where the transition from one regime to the other is quite abrupt and quick (high γ_i) for all farmers. In that case, a farmer characterised by a low threshold level probably faces less adjustments costs than the others since she/he is able to adjust more quickly her/his short-term production decision. In this case, several factors can explain the flexibility/rigidity of farmers, depending on the farming system (share of grassland, farm-produced feed, etc…), the structural features of the farm (total area, fragmented plots, etc…) or the managerial ability of the farmer.

3. Estimation strategy

This section presents the distributional assumptions and the approach used to estimate the panel smooth transition regression model defined by equations (2a) and (2b).

3.1. Distributional assumptions

Each equation of our model livestock farmers' production choices comprises fixed parameters $\boldsymbol{\beta}_1^j$, $\boldsymbol{\beta}_2^j$ and $\boldsymbol{\alpha}_2^j$, and two types of random components : (*i*) random parameters that includes the additive farmer-specific effects α_{0i}^j and the parameters of the transition function, γ_i and c_i and (*ii*) the error term of the model, ε_{it}^j. Let vector $\boldsymbol{\delta}_i \equiv (\boldsymbol{\alpha}_{0i}, \gamma_i, c_i)$, with $\boldsymbol{\alpha}_{0i} \equiv (\alpha_{0i}^j, j\epsilon\mathcal{J})$, collect the model's random parameter and vector $\boldsymbol{\varepsilon}_{it} \equiv (\varepsilon_{it}^j, j\epsilon\mathcal{J})$ collect the error terms. We assume that the random parameters follow a normal distribution with $\boldsymbol{\delta}_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Omega})$. This probability distribution describes the distribution of the random parameters across the farmers' population represented in the considered sample. We do not impose any restriction on the structure of $\mathbf{\Omega}$ and hence allow all farmer-specific effects (including the parameters of the transition function) to be correlated between them and across equation. This notably allows capturing the potential correlation between the production decisions of each farmer, which could for instance be attributed specific skills of farmers or to natural endowments of farms, The error term vector is assumed to be normally distributed with $\boldsymbol{\varepsilon}_{it} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Psi})$. We assume the covariance matrix $\mathbf{\Psi}$ to be diagonal, which notably implies that the error terms of the model are independently distributed across time. This assumption is not too restrictive here since price and climatic shocks, which are the main elements that could potentially simultaneously impact all farmers production decisions in the short run, are captured by the effects of exogenous variables in $\mathbf{x}_{it}$ and $\mathbf{z}_{it}$ Finally, we assume that random parameter vector $\boldsymbol{\delta}_i$, error term vector $\boldsymbol{\varepsilon}_{it}$, price variables included in $\mathbf{x}_{it}$ and control variables included in $\mathbf{z}_{it}$ are mutually independent and that $\mathbf{x}_{it}$ and $\mathbf{z}_{it}$ are strictly exogenous with respect to these error terms. These are standard assumptions in short panel data econometric models of farmers' production choices (see e.g., Koutchadé et al, 2018).

3.2. Estimation approach

The parameters we seek to estimate comprise the price effects, $\boldsymbol{\beta}_1^j$ and $\boldsymbol{\beta}_2^j$, and control variables effects, $\boldsymbol{\alpha}_2^j$, in each equation. These fixed parameters are collected in vector $\boldsymbol{\theta} \equiv (\boldsymbol{\beta}_1^j, \boldsymbol{\beta}_2^j, \boldsymbol{\alpha}_2^j, j \epsilon \mathcal{J})$. We also seek to estimate the parameters characterizing the distribution of random parameters, $\boldsymbol{\mu}$ and $\mathbf{\Omega}$, and the covariance matrix of random terms, $\mathbf{\Psi}$.

Our model being fully parametric, we rely on a maximum likelihood (SML) approach for its estimation. The sample log-likelihood is equal to a sum of log-likelihoods associated to each individual farm: $\ln \mathcal{L} = \sum_i \ln \ell_i$. The individual likelihoods, can be expressed as:

$$\ell_i(\boldsymbol{\theta}, \boldsymbol{\Psi}, \boldsymbol{\mu}, \boldsymbol{\Omega}) = \int_{\boldsymbol{\delta}} f(\mathbf{y}_i|\mathbf{x}_i, \mathbf{z}_i; \boldsymbol{\delta}, \boldsymbol{\theta}, \boldsymbol{\Psi}) g(\boldsymbol{\delta}; \boldsymbol{\mu}, \boldsymbol{\Omega})\, d\boldsymbol{\delta} \tag{5}$$

$f(\mathbf{y}_i|\mathbf{x}_i, \mathbf{z}_i; \boldsymbol{\delta}, \boldsymbol{\theta}, \boldsymbol{\Psi})$ denotes the probability density function of the observed sequence of production choices of farmer i, $\mathbf{y}_i$, conditional on exogenous variables, $\mathbf{x}_i$ and $\mathbf{z}_i$, and on individual random parameters, $\boldsymbol{\delta}_\mathbf{i}$. $g(\boldsymbol{\delta}; \boldsymbol{\mu}, \boldsymbol{\Omega})$ denotes the probability density function of the random parameter vector, $\boldsymbol{\delta}_\mathbf{i}$.

Maximizing the sample likelihood would involve the computation of as many two-dimensional integrals as the number of farms in our sample. Econometricians generally rely on Simulated Maximum Likelihood (SML) approaches to solve such optimization problems. This is the choice made by Fok et al. (2005) for the estimation of their model, which is comparable to ours from that point of view. The maximization of the simulated likelihood is however further complicated by the nonlinear form of the transition function $\mathbf{G}_{it}$ which depends on random parameters $\boldsymbol{\delta}_\mathbf{i}$ and enters the explanatory variables of the model. To overcome this issue, Fok et al. (2005) use a two-step iterative procedure involving, in a first step, the maximization of the sample simulated likelihood for given values of the transition function parameters, and, in a second step, the solve of a numerical optimization program to find transition function parameters. This two-step procedure is however quite involving and its convergence not guaranteed. We do not use it here but instead rely on a Stochastic Approximate expectation-maximization (SAEM) algorithm which is a specific type of Monte Carlo expectation-maximization (MCEM) algorithms (Lavielle, 2014). MCEM algorithms are frequently used by statisticians when faced to complex likelihood maximization and allow the computation of estimators that are asymptotically equivalent to ML estimators.

5. Results

5.1. Data

Our model is estimated on an unbalanced panel data sample of 444 dairy farms located in the West of France and observed between 2007 and 2017. This sample contains 3,300 observations and notably provide information on acreages, milk produced, animal density and feed inputs used at the farm level. Table 1 bellow reports some descriptive statistics of these variables. Our sample appears to be relatively homogenous in terms of production system, since all farms produce fodder maize, grassland and cereals and make use of concentrates to feed their animals. If heterogeneity of farms is confirmed by our empirical application, this one is potentially unobserved in our data.

Table 1. Descriptive statistics of the sample

	Sample Average	Standard Deviation
Total available land (ha)	68	22
Quantity of milk produced (liter/cow)	7,093	1,256
Quantity of feed concentrate used (kg/cow)	1,177	537
Fodder maize acreage share	28	8
Grassland acreage share	46	13
Animal density (cow/ha)	0.83	0.18

Concerning the transition variable, we do not consider the changes in input prices in the previous period (in absolute value) as Önel, but we use the changes in a price ratio (in absolute value) calculated as the animal feed price on the milk price. The evolution of this transition variable is represented in the figure 3 (not in absolute value in order to appreciate its real variations). The main advantage of this transition variable is to better characterize the economic context. According the evolution of animal feed and milk prices, farmers face to four different economic situations. The price ratio will be stable in two cases, (i) if the milk and concentrates prices does not change much from year to year, and (ii) if these prices evolve in the same direction (an increase in all prices, or a decrease in all prices). These contexts correspond to the first regime. The price ratio will be particularly high: (i) if the milk price increases and/or the concentrate price drops sharply, creating an economic situation particularly favourable for farmers (this was the case in 2014), (ii) if the milk price decreases and/or the concentrate price increases sharply, leading this time to a bad economic situation (this was the case in 2009, 2013 and 2016). These contexts correspond to the second regime.

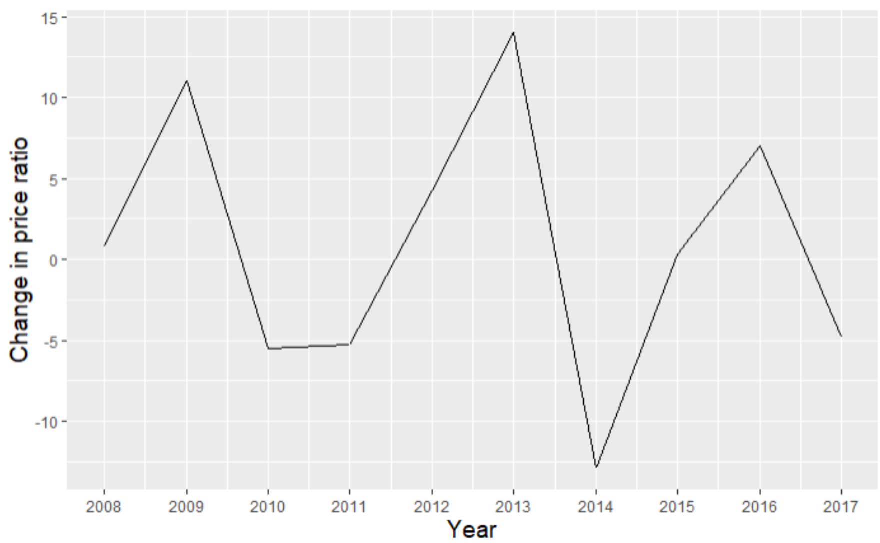


Figure 3. Evolution of the transition variable

5.2. Estimation results

We simultaneously estimate a system of production decisions, composed of use of feed concentrates, choices of grassland and fodder maize. In this model, which thus seeks to estimate the responses of feed concentrate uses to the prices of concentrate, milk and cereals, we use the change in price ratio with respect to the previous period as the threshold variable. The main parameter estimates of the model are reported in Table 2. Due to space limitation, the estimates of the coefficients associated to other explanatory variables as weather conditions (Eq. 6) are not reported here.

Table 2. Parameters estimates

	Demand of concentrates	**Share of fodder maize acreage**	**Share of grassland acreage**
Transition function $\boldsymbol{G}(.)$			
Average threshold parameter c_i		11.03**	
Average speed of transition parameter γ_i		0.42**	
Parameters estimated in the linear part (extreme regime 1): $\boldsymbol{\beta}_1'$			
Feed price	-1.41**	0.088**	0.028
Milk price	5.14**	-0.72**	0.22**
Fertilizer price	-0.43*	0.15**	0.043
Cereal price	4.14**	-0.14**	-0.21**
Parameters estimated in the non-linear part: $\boldsymbol{\beta}_2'$			
Feed price	-0.52**	-0.099**	-0.016
Milk price	0.37**	0.063**	0.032

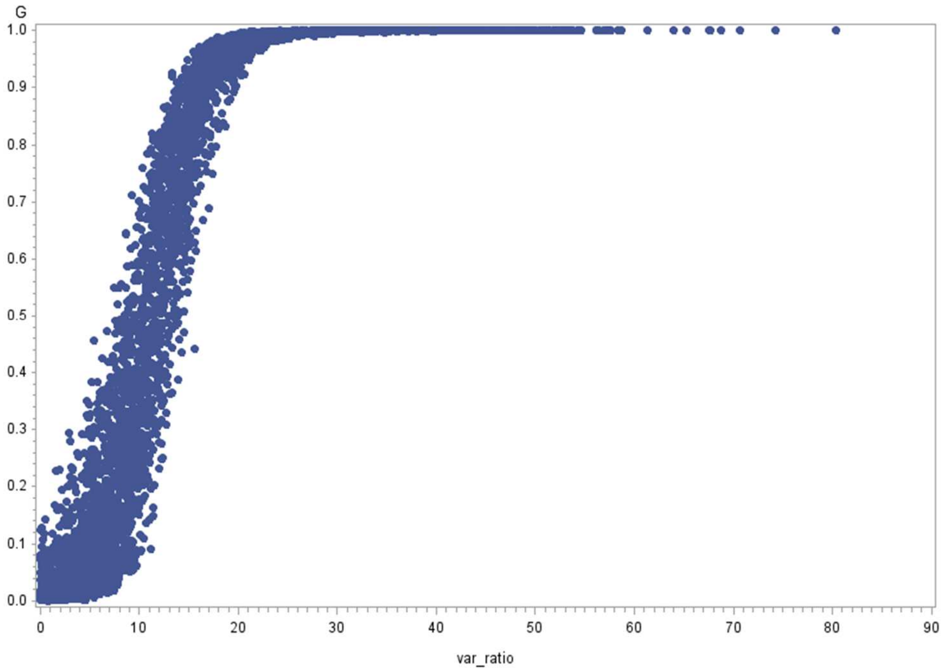
Note: *** parameters estimates are significantly different from zero at the 1% level of significance.

All parameters of the production choice model are significantly estimated and lie in their expected ranges. The price of feed concentrate has a negative impact on the quantities of concentrates purchased by farmers, and a positive impact on acreage share of fodder maize, which is a substitute for concentrates. The effect of milk price on concentrates is positive, suggesting that an increase of milk price encourages farmers to stimulate their milk production by favouring concentrates as animal feed. The cereal price positively affects their uses of concentrates and negatively affects the acreage share allocated to fodder maize. This may have two explanations depending on their use of crop production. If farmers produce cash crops for the market, an increase in crop price will modify the land allocation between forage and crop. In that case, an increase in concentrates uses will allow them to compensate the loss of forage area. If famers use their crops production to animal feed, then an increase in crop price will modify the price ratio between the different alternatives of animal feed, in favour of concentrates.

Given the significance of parameter estimates in the non-linear part of the model ($\boldsymbol{\beta}_2$), our results highlight the non-linear responses of French dairy farmers input use decisions to variations in input prices. Farmers' behaviour change when the variation of price ratio compared to the previous year is around 11% on average (c_i parameters). Our results show that when farmers face larger change in price ratio, the impacts of prices on quantities of concentrates purchased are strengthened. In fact, the second extreme regimes is characterized by more pronounced responses in terms of use of concentrates to change in prices, indicating a non-convex structure of adjustment costs. On the contrary, the impacts of prices on the allocation of land are lessened, indicating a convex structure of adjustment costs This result is comparable to that found by Antle and Capalbo (2000). In an economic context characterized by small variations in the price ratio, farmers respond to price changes by changing the amount of concentrates fed and the allocation of their land between grassland and corn. Larger changes in concentrate prices would require larger adjustments in land allocations. However, the adjustment costs of making larger changes in land allocation are too high, since farmers are constrained by the availability of equipment and labor. The only possible response to a price change is then to intensify practices and increase the use of concentrates.

Graph 1 represents the estimated individual transition functions. More precisely, it represents, for each farmer, the value of the estimated transition function according the level of change in concentrates price. The transition from one regime to another is quite fast and quite homogeneous between farmers. In fact, the estimated speed of transition (λ_i) is around 0.42 on average and does not vary much between farmers. This can be explained by the fact that, the second regime being mainly characterized by an increased use of concentrates, the decision to increase the proportion of concentrates in the feed can be made immediately and does not require special additional equipment. The estimated threshold of transition (c_i) ranges between …% and …% across farmers. This suggests that there is some heterogeneity in responses to prices that can be identify by the threshold of transition between the two extremes regimes.

Graph 1. Estimated Transition functions



We propose to distinguish farmers' behaviours according their level of adjustment costs in order to confirm that farmers with less adjustment costs are more reactive to price changes. Then, we construct four groups of farmers based on the level of price variation they need to reach the second regime. Farmers in the top quantile belong to the first group, while farmers in the last quantile belong to last group. Finally, in table 4, we compare elasticities of farmers of each group in two cases, when the price ratio varies by 5% and when it varies by 25%. Our results show that farmers who move more quickly from one regime to another have more adjustment costs and are less responsive to price changes. The first regime is characterized by a substitution between different feed sources (concentrates, grass, forage) to respond to price changes. In the second regime, farmers adapt to the change in price by mainly modifying the quantity of concentrates fed to their animals. In this case, the adjustment costs associated with changes in land allocation are too high. We can therefore assume that farmers who move quickly to the second regime are less flexible in terms of land allocation and their way of reacting to price changes is therefore mainly to adjust their amount of concentrates. Farmers who stay longer in the first regime exploit the different substitutions that exist between the different feed sources, and can thus control their expenditure on concentrates.

In a context of large change in price ratio (around 25%), the own-price elasticities of concentrates demand range from -0.32 to -1.06 and the milk price elasticities of maize fodder range from -0.67 to -1.14, depending on the level of farmers' adjustment costs. This confirms a significant heterogeneity in short term responses of farms to prices change.

Table 4. Elasticities per group of farms

	Own-price elasticity of concentrates		**Milk price elasticity of maize fodder**	
	5% price change	25% price change	5% price change	25% price change
Group 1	-0.24	-0.32	-0.73	-0.67
Group 2	-0.33	-0.44	-0.81	-0.74
Group 3	-0.42	-0.55	-0.87	-0.80
Group 4	-0.83	-1.06	-1.22	-1.14

By investigating the characteristics of farms in each group (Table 5), we find some interesting features for the most flexible farms: they have better financial autonomy and food self-sufficiency. These farmers seem to have less intensive farming practices: animal density per hectare and the quantities of concentrates purchased are significantly lower. Similarly, the proportion of grass in the animal feed is greater at the expense of concentrates.

Table 5. Characteristics of farms according their flexibility

	Group 1		Group 2		Group 3		Group 4	
	mean	e.t.	mean	e.t.	mean	e.t.	mean	e.t.
Total area	69	*25*	68	*23*	66	*21*	65	*24*
Livestock density (cow/forage area)	1.19	*0.23*	1.13	*0.23*	1.13	*0.23*	1.04	*0.21*
Share of grassland	0.37	*0.09*	0.41	*0.10*	0.45	*0.09*	0.56	*0.12*
Concentrates (€/cow)	503	*151*	380	*116*	332	*103*	246	*99*
Share of farm-produced food	0.21	*0.12*	0.27	*0.13*	0.34	*0.15*	0.46	*0.19*
Share of organic farm	0.03	*0.16*	0.03	*0.16*	0.02	*0.15*	0.16	*0.37*
Gross margin (€/litre)	218	*38*	231	*40*	237	*41*	261	*56*
Unit of agricultural workers	1.84	*0.65*	1.72	*0.60*	1.71	*0.61*	1.70	*0.80*
Capital (€/1 000 litre)	865	*235*	890	*245*	924	*266*	1007	*362*
Debts (€/1 000 litre)	377	*202*	356	*200*	354	*212*	343	*244*

The heterogeneity of production conditions and farm behavior is increasingly included in microeconomic models of agricultural production. Our approach propose an economic explanation for this heterogeneity in production behaviour. Our results highlight the strong heterogeneity of production behaviors among farmers, thus confirming the idea that farms face different levels of adjustment costs that constrain their ability to adapt to price variations observed on the markets. These adjustment costs are linked to their availability of quasi-fixed inputs quasi-fixed (especially capital), but also to their production system, which allows them to be more or less flexible. Systems based on a high use of corn fodder and concentrates offer farmers fewer possibilities for substitutions between the different sources of animal feed.

Conclusion

By relying on a panel smooth transition model, we have been able to identify non-linear responses of French dairy farmers input use decisions to variations in input and output prices. These non-linearities can be attributed to the existence of input adjustment costs, which incite farmers to react differently to small or large price variations. These adjustment costs may partially explain the apparent rigidity of farm production decisions in the short run. These costs have to be taken into account in the estimation of price elasticities used to simulate the impact of public policies on farm production decisions.

From a methodological viewpoint, we have proposed a new version of an estimation procedure aimed at estimating smooth transition models with individual parameters of transition function. Our approach allows dealing with the specificity of farm accountancy panel data that generally have large individual and short time dimensions.

We have also proposed an analytical framework in order to implicitly account for adjustment costs in production behaviour of farmers. Our simple model allows to distinguish farmers according to their speed of reaction in response to price changes, and to identify the most flexible farmers in the short run. Our results confirm the interest of our approach since we identify very heterogeneous production behaviors. As this capability to adjust their production choices appears as a key aspect of farms' economic sustainability, our approach can help identifying public actions levers in order to encourage farmers to be more reactive to price fluctuations.

We apply this approach to dairy farms, although we recognize that our theoretical model does not account the specificity of production decisions within livestock farms. In counterpart, our framework could be directly applied to other farm sector, to analyze crop farmers' decisions regarding pesticide uses, for instance.

Potential extensions of this framework are already being considered. One of these is to improve the identification of key parameters in estimating simultaneously the system of production decisions, composed of acreage and input decisions equations, with a threshold of transition common to all equations.

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