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Identifying heterogeneous flexibility of dairy farms using a panel smooth transition regression approach

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Abstract

Our objective is to identify the individual flexibility of dairy farms, which may be the result of heterogeneous input adjustment costs, based on their observed short-run responses to price variations. For this purpose, we propose an analytical framework based on the panel smooth transition regression model with farm-specific threshold parameters. Our model is estimated using data from a sample of French dairy farms over the period 2007–2018. Our empirical results reveal heterogeneous levels of flexibility for these farms, with the most flexible farms appearing to be more autonomous both financially and in terms of animal feed.

Keywords: dairy farms, short-run flexibility, random parameters, panel smooth transition regression, individual threshold level, input adjustment cost

JEL Classification: Q12, C34, C15, C33

1. Introduction

The ability of farmers to adjust their production choices in response to external events (e.g. changes in market conditions, climatic events and policy reforms) enables them to benefit from or mitigate the profit losses induced by these events. The closely related concepts of resilience, adaptive capacity and flexibility are proposed as key elements of farms' economic sustainability in the face of increasing climate variability and volatility in agricultural markets (Reidsma *et al.*, 2010; Robert, Thomas and Bergez, 2016).

In the economic literature, the concept of firm flexibility has been extensively discussed and applied to numerous industrial sectors (e.g. Hirsch *et al.*,

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2020; [Koppenberg et al., 2023](#)). The short-run flexibility of firms has been analysed primarily to determine their capacity to adjust production in response to fluctuations in product demand and, consequently, prices. This ‘output flexibility’ of firms is generally measured based on the notions developed by [Stigler \(1939\)](#), who defined firm flexibility as the firms’ ability to maintain their average production costs in the face of a variation in demand. This concept is formalised by [Mills \(1984\)](#) and [Mills and Schumann \(1985\)](#), who defined a measure of the flexibility of firms based on the curvature of their average cost function. Several enhancements to this analytical framework have been suggested and empirically implemented in the literature (e.g. [Von Ungern-Sternberg, 1990](#); [Crémieux et al., 2005](#); [Renner, Glauben and Hockmann, 2014](#)).

The flexibility of firms can also be reflected in their capacity to adjust their production factors in response to fluctuations in market prices. Indeed, the greater a firm’s ability to substitute its (substitutable) production factors in response to a variation in the price of one of the factors, the more flexible the firm. The firms’ ‘input flexibility’ has received less attention in the economic literature. Its measurement can be approximated by input price elasticities and input substitution elasticities derived from the parameters of a cost function and the production technology underlying it ([Magnani and Prentice 2006](#)). In economic models of firm production decisions, the parameters representing firms’ responses to price variations are generally assumed to be constant, such that firms are assumed to adjust their input demand similarly for any variation in input prices. [Önel \(2015, 2018a, 2018b\)](#) extended this analytical framework by considering that, due to input adjustment costs inherent in its production technology, a firm can respond differently depending on the magnitude of the input price variation it faces. Thus, these adjustment costs may lead to nonlinearities in production cost functions and associated input demand equations.

Some articles have relied on [Stigler’s \(1939\)](#) definition of firm flexibility to assess farm flexibility. These papers focus on output flexibility, that is, the capacity of farms to adjust their output level (tactical flexibility) and/or diversify their production (operational flexibility) in response to changes in output demand ([Weiss, 2001](#); [Renner, Glauben and Hockmann, 2014](#); [Hirsch et al., 2020](#)). These articles essentially rely on primary approaches and build on production frontier analysis to assess farm flexibility. All of them show that small farms, which do not benefit from economies of scale, can compete with large farms by employing more flexible production technologies, allowing them to adjust production quantities to fluctuating market conditions. To focus solely on the capacity of farms to diversify their production, these works do not explicitly consider the possibility of input substitutions, which are typically aggregated into a single input in their empirical applications ([Weiss, 2001](#); [Renner, Glauben and Hockmann, 2014](#)). By doing so, they focus on only one aspect of the flexibility and neglect their flexibility in terms of input uses. However, agricultural input prices, particularly in the dairy sector, are highly variable, implying that dairy farms must cope with significant fluctuations in

both output and input prices, and the ability to substitute inputs is an important lever that must be exploited in the face of such strong price variability. According to the technical livestock production literature (Peyraud *et al.*, 2010), dairy farms do have some flexibility to adjust their feeding strategy in the short term to be more resilient to price and climate shocks by adopting mixed feeding systems, diversifying their pastures and using concentrates when necessary.

This paper's objective is to determine the flexibility of dairy farms based on their observed short-run responses to input and output prices. We focus our analysis on the ability of dairy farms to adjust their feeding strategy, which is their primary production decision in the short run and represents an important lever for adapting to changes in their environment, particularly in economic context changes. For this purpose, we propose an original approach based on the works of Önel (2018a, 2018b). This approach recognises that adjusting input quantities in response to input or output price variations may be costly due to the existence of adjustment costs, which limits the flexibility of firms. Our empirical model is a threshold regression model of farm production decisions. It allows the representation of farm behaviours in two regimes of input adjustment: one corresponding to their behaviour in the face of small price variations and the other to their behaviour in the face of large variations. There is thus a switch between the two regimes of input adjustment, depending on whether the price variations are above or below a certain threshold. In the face of a price shock, farmers' ability to adapt their production decisions and to switch from one regime to another reflects the level of adjustment costs they face and their degree of flexibility.

In our view, our paper makes two important contributions to the literature.

First, we propose an analytical framework for assessing the flexibility of farms that differs from the standard framework in two important ways. On the one hand, we model the production decisions of farms using a dual approach, thereby avoiding the endogeneity issues inherent to the econometric estimation of farm production choice models based on primal approaches. On the other hand, our framework allows us to investigate farms' output and input adjustment behaviours. In fact, our application focuses on evaluating the flexibility of dairy farms in terms of input adjustment; however, output adjustments are implicitly taken into account in our empirical model, which consists of a system of input demand equations.¹ The possible combinations of inputs and their substitutability condition firms' flexibility in the broad sense (Stigler, 1939), and output and input flexibility ultimately depend on the same choice of firms regarding their production technology.

Second, the threshold regression model used by Önel (2018a, 2018b) accounts for the fact that the flexibility of firms is contingent on the adjustment cost structure of the industrial sector to which they belong, but it does

¹ For those interested in quantifying the output flexibility of farms, our empirical model could be adapted relatively easily by introducing a set of output supply equations. This, however, would necessitate a complication of the estimation procedure due to the addition of multiple parameters to the model, which is outside the scope of this paper.

not allow assessing the flexibility of each firm within each sector. Our principal methodological contribution is considering individual parameters within our threshold regression model. This allows us to account for the heterogeneity of farms in how they switch from one input adjustment regime to another and thus the heterogeneity of dairy farm flexibility. From an empirical viewpoint, we rely on the panel smooth transition regression (PSTR) model proposed and developed by [González, Teräsvirta and Van Dijk \(2005\)](#) as an extension of [Hansen's \(2000\)](#) threshold regression model, which allows for a smooth transition between the two extreme regimes. The heterogeneity of farmers in their adaptation to price variations is captured in our model by considering farm-specific random parameters in the transition function representing the way farmers switch from one regime to the other. Although panel threshold regression models are widely used empirically, to our knowledge, they have never been estimated with individual threshold levels. We propose here an approach, based on a stochastic version of the expectation maximisation (EM) algorithms ([Dempster, Laird and Rubin, 1977](#)), which allows one to estimate the threshold regression model with individual threshold parameters on panel data that exhibit a large individual dimension and a limited time dimension.

Our approach is applied to a panel of dairy farms located in the West of France from 2007 to 2018. Our empirical results show that these farms' feeding strategies vary based on the magnitude of price fluctuations they experience. In actuality, they tend to substitute three sources of animal feed (feed concentrate, fodder maize and grassland) in response to relatively small variations in market prices but become less flexible in adjusting their acreage, and thus their feed concentrate quantities, in response to larger price variations. Our estimation results also reveal a significant heterogeneity among farms regarding the level of price variation up to which they continue to adjust flexibly their feeding strategy. An *ex post* analysis of our results allows us to highlight some specific features of the most flexible farms, which appear to be more autonomous financially and more self-sufficient in terms of animal feed.

The remainder of the paper is organised as follows. [Section 2](#) presents the literature review on the determinants of the flexibility of firms, in general, and dairy farms, in particular. [Section 3](#) presents our empirical model of dairy farm input use decisions that identifies their individual levels of flexibility. [Section 4](#) describes the estimation strategy used to estimate this model. [Section 5](#) presents and discusses our empirical results. Finally, [Section 6](#) concludes the paper.

2. On the flexibility of dairy farms

2.1. Firms' flexibility and short-run input adjustments

The capacity of a firm to adjust its production choices in response to changes in the economic context determines its flexibility in the short run. As described in the seminal work of [Stigler \(1939\)](#), firms must choose between technological and organisational alternatives that can only be modified over the long term. This choice, determined by a trade-off between flexibility and efficiency,

binds firms to a particular cost structure, which determines their ability to make short-term adjustments to price fluctuations (Zeller and Robison, 1992). In fact, according to Stigler (1939), the flexibility of firms mainly depends on the characteristics of the fixed production factors that determine their production technology. As one departs from the technically optimal production level, that is, the level of production that minimises the firm's average production cost, partial inadaptability or indivisibility of these fixed factors notably causes sharp increases in the marginal costs of variable inputs. Firms can therefore increase their flexibility by relying on more divisible and adaptable fixed factors, which allow, at lower costs, greater variation of variable inputs when they have to adjust their production in response to short-term changes in market conditions. However, this higher flexibility comes at the expense of incurring higher costs at the technically optimal production level. This conceptual framework suggests two important points. First, flexibility is not a free good, and the minimum average cost of production for a given technology rises as its level of flexibility increases. Second, a context with high variability in the firms' economic environment will favour greater flexibility. In contrast, a context with low variability will favour greater efficiency (Mills, 1984).

2.2. Flexibility of dairy farms in their feeding strategy

Although our analytical framework could be applied to different types of farms or firms, we focus on the flexibility of dairy farms' livestock feeding decisions, which is their primary production decision in the short run and thus represents an important lever for them to use in dealing with market price variations. The feed ration of dairy cows is essentially composed of feed concentrates, which are purchased on the market, and grass and fodder, which are generally produced on the farm.

In the very short term, dairy farmers can adjust the amount of feed concentrates provided to each cow to adjust their milk yield, and thus the production of milk at the farm level, in response to price variations. Therefore, feed concentrates constitute an easily adjustable component of the cow feed ration, even though their market prices exhibit significant fluctuations, making the use of an additional unit of concentrate costly. In practice, all dairy farms use a mixture of feed concentrates and forages and thus rely on an additional production factor to feed their cows: land. However, if we refer to Stigler's (1939) terminology, this fixed production factor is only moderately divisible (due to the fragmentation of plots) and is adaptable only from one cropping season to the next. In reality, the allocation of the farm's total area to different uses (grassland, forage and cereals) is determined at the beginning of the cropping season and is based on the farmers' expectations of future production conditions, since they cannot observe them at that time. Farmers' acreage options are also constrained by a set of constraints unique to each farm (agronomic constraints, plot fragmentation, etc.). Therefore, although feed concentrates are variable inputs that can be easily adjusted by all farmers on a very short-term basis, adjusting crop acreage appears to be a more restrictive and potentially

more discriminatory process factor determining the dairy farmers' flexibility in adjusting their feeding strategy.

2.3. Short-run input adjustment costs that underpin dairy farm flexibility

As discussed earlier, due to the rigidity of their fixed or quasi-fixed production factors, such as capital equipment, labour or land, adjusting input quantities in response to a change in input or output price can be costly for farmers. Particularly in the case of dairy farms, an important decrease in the use of concentrates to feed animals (due, for instance, to a sharp increase in feed concentrate price) necessitates the production of more fodder crops or the encouragement of grazing pasture. This can involve a reorganisation of the farm and a reallocation of land allocation to convert cropland to pasture and/or fodder crops. In that case, dairy farmers may also need new machinery and more workers to produce on-farm animal feed.

Some microeconomic models of short-term crop production decisions (Carpentier and Letort, 2012, 2014; Koutchadé, Carpentier and Femenia, 2018, 2021) introduce implicit acreage adjustment costs in the objective function of farmers' profit maximisation to account for the fact that farmers are restricted in their acreage choices by agronomic and technical constraints, such as crop rotation, work peaks or machinery, which prevent them from specialising in single-crop farming. Koutchadé, Carpentier and Femenia (2018) significantly improved this modelling framework by considering farm-specific parameters, especially in the model's implicit acreage adjustment cost function. They could account for the heterogeneous responses of crop producers to economic drivers by specifying random parameters. Moreover, empirical application confirms the heterogeneity of farmers' acreage adjustment costs in cereal farming and shows that ignoring the variability in the considered farmers' responses to economic incentives can result in inaccurate estimations of production decisions.

Thus, differences in their short-term responsiveness to price fluctuations can result from differences in the adjustment costs dairy farms incur when adjusting their feeding sources, particularly their acreage. In fact, although adjustment costs are typically mentioned in the economic literature dealing with long-run adjustments of quasi-fixed inputs, most notably capital stocks, this concept also seems applicable in the case of short-run adjustments of production factors. According to Stigler (1939), there is no clear distinction between the short and long run; rather, firms adjust their inputs over a continuum of time spans. Some variable inputs, such as concentrates, can be easily adjusted in the very short term, suggesting low adjustment costs. Meanwhile, some inputs, also considered variable, can be adjusted over a longer period (short/medium term), such as acreage choices, and are subject to a set of constraints (land availability, etc.) limiting their possibility of instantaneous adjustment. Therefore, these inputs are probably characterised by higher adjustment costs. Each variable input can in fact be characterised

by adjustment costs that are either convex, if these costs increase with the level of input adjustment, or nonconvex, if they are nonincreasing in the level of input adjustment required to adjust the production level (Önel, 2018a, 2018b). Therefore, the farms with the lowest adjustment costs are expected to adjust their production choices across the broadest range of price fluctuations, making them the most flexible farms. As adjustment costs are not directly observable in economic farm data, our approach, based on the framework of Önel (2018a, 2018b) and presented in the next section, aims to reveal them from observed farms' responses to price variations to characterise these farms' flexibility.

3. Modelling framework

Our theoretical framework, presented in the first subsection, builds upon Chambers and Just's (1989) maximisation of a dual farm profit function in the presence of fixed allocable inputs. It provides a reference point for developing the empirical threshold regression model described in the second subsection.

3.1. Model of livestock farms' production decisions

This study focuses on the short-term production decisions of dairy farmers, who allocate one fixed input, land, among three on-farm feeding sources (fodder maize, grassland and cereals), supplemented by feed concentrate to produce milk. Because we are dealing with short-term production decisions, we assume that their herd size will be fixed. Most works have focused on heterogeneity in farm production behaviours (Alvarez and Del Corral, 2010; Sauer and Paul, 2013; Koutchadé, Carpentier and Femenia, 2018; Renner, Sauer and El Benni, 2021), so we assume that farmers are risk neutral.

Our modelling framework relies on the farm profit maximisation problem in the presence of fixed allocable inputs proposed by Chambers and Just (1989) and generalised by Fezzi and Bateman (2011) to fit the case of dairy farms by permitting the number of potential land allocations to differ from the number of possible farm outputs. As demonstrated by Fezzi and Bateman (2011), by specifying the farm profit per area as a normalised quadratic function, optimal acreage shares and input use decisions can be expressed as a system of reduced form equations:

$$y_{it}^j = \alpha_{0i}^j + \mathbf{z}'_{it} \boldsymbol{\alpha}_1^j + \mathbf{x}'_{it} \boldsymbol{\alpha}_2^j + \varepsilon_{it}^j \quad (1)$$

The subscripts i and t , respectively, denote the cross-sectional and time dimensions of our panel data and the superscript j belongs to \mathcal{J} , the set of livestock farmers' acreages and input uses choices we consider, namely cereals, grassland and fodder maize acreages and feed concentrate purchases. The vector of dependent variable $\mathbf{y}_{it} \equiv (y_{it}^j, j \in \mathcal{J})$ contains acreage shares² and feed concentrate quantities. $\mathbf{x}_{it} \equiv (\mathbf{p}_{it}/w_{nit}, \mathbf{w}_{it}/w_{n,it})$ contains a set of output and

2 In the model, only fodder maize and grassland acreage shares are included, as the cereal acreage share is redundant and can be calculated by subtraction.

input prices normalised by the price of one input n (pesticides in our case). The prices incorporated into the acreage share equation are those observed when farmers make land allocation decisions, whereas the prices incorporated into the feed concentrate equation are those observed at the time feed concentrates are purchased. Farmers may actually adjust their use of concentrates after observing the yields of fodder maize and grass produced at the farm. Other observable factors that may influence the production decisions of farmers, such as market prices not included in \mathbf{x}_{it} or weather conditions, are included in \mathbf{z}_{it} . The parameters included in vector α_1^j , respectively vector α_2^j , capture the effects of \mathbf{z}_{it} , respectively \mathbf{x}_{it} , on y_{it}^j . In model (1), these effects are assumed to be common to all farms and farmers. The α_{0i}^j additive term 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.

3.2. Accounting for input adjustment costs in the model

The linear model of dairy farmers' production decisions presented earlier assumes homogenous responses of farmers to any price variation level. Thus, this model does not account for potential input adjustment costs, which, as explained in Section 2, may lead dairy farmers to significantly adjust their animal feeding strategy only for large price variations (in the case of nonconvex adjustment costs that are nonincreasing in the level of input adjustment) or be more responsive to smaller price shocks that entail smaller adjustments of animal feeding (in the case of convex adjustment costs that are increasing in the level of input adjustment).

Different methodological frameworks have been developed in the economic literature to account for the impacts of adjustment costs on farm production decisions (e.g. Gardebroek and Oude Lansink, 2004; Pietola and Myers, 2000). However, these approaches essentially aim at analysing farm behaviours in the medium or long term by focusing on capital adjustment costs. Meanwhile, our main objective here is to analyse short-term agricultural production choices that do not require investment or technological change. Recently proposed by Önel (2018a, 2018b), a second modelling framework is of particular interest for our purposes. This approach acknowledges that firms must adjust their quantity of inputs in response to a change in input price, which can be costly. Moreover, in the presence of adjustment costs, the adjustment of input quantities will vary depending on the magnitude of the price variation. In fact, Önel (2015, 2018a, 2018b) points to two possible cases, 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 nonconvex, they are nonincreasing with the adjustment of input quantities, implying greater price elasticities of input for larger price variations: in this case, a small adjustment

of input quantities following a small variation in market price is costly relative to the profit gained from this small adjustment. Thus, firms will adjust their inputs to account for greater price fluctuations. Önel (2018a, 2018b) employed a threshold regression model (Hansen, 2000) to implicitly account for these adjustment costs. In this model, input price elasticities can vary depending on observed input price variations. Specifically, the model's price parameters take one value below a threshold level of price variation and another value above this threshold. Adjustment costs thus can apply to quasi-fixed inputs and variable input uses, making this approach adapted to the analysis of short-term behaviours. Önel (2018a, 2018b) proposed this framework to highlight input adjustment costs' nonlinearity and potential nonconvexity. Moreover, her empirical application enabled her to compare the structure of adjustment costs between industrial sectors in the United States. Note that she assumed that the structure of adjustment costs within each industrial sector is the same for all firms. Here, we propose a method that is based on Önel's framework and present our model's unique features to better represent the heterogeneity of the farm's flexibility in terms of input uses. Specifically, we do not consider only two possible input adjustment regimes in response to price fluctuations common to all farms, but rather a continuum of regimes unique to each farm. As explained in the next subsection, this is achieved by relying on a PSTR model in which we introduce random parameters to represent farm-specific transition functions.

3.3. Our threshold model of livestock farms' production decisions

As in Önel (2018a, 2018b), we modify our empirical model to implicitly account for the existence of adjustment costs, which cause farmers' responses to changes in input and output prices to vary in proportion to the magnitude of those variations. We thus propose a modelling approach based on a threshold regression model in which the parameters associated with price variables can vary according to a regime-switching mechanism that depends on a transition variable. We use the absolute variation in an input-price-to-output-price ratio compared to the previous year as a transition variable. This transition variable permits us to represent the price signal perceived by farmers, who make production decisions based on the evolution of input and output prices. This variable assumes small values if input and output prices do not fluctuate significantly from 1 year to the next or if they vary in the same direction, resulting in a stable price ratio.³ Finally, Önel's model relies on Hansen's threshold regression approach, whereas we use a PSTR model based on the works of González, Teräsvirta and Van Dijk (2005) and Fok, Van Dijk and Franses (2005) to allow for individual threshold parameters.

3 The use of the absolute change in the price ratio as a transition variable implies that both increases and decreases in the price ratio induce changes in the responses of farmers to prices that are of the same magnitude, even those of opposite sign. The relatively small time dimension of our panel data motivates this admittedly restrictive assumption of a 'symmetric threshold' model.

The threshold version of our model can be written as follows:

$$y_{it}^j = \alpha_{0i}^j + \mathbf{z}'_{it} \alpha_1^j + \mathbf{x}'_{it} \beta_1^j + \mathbf{x} \mathbf{G}'_{it} \beta_2^j + \varepsilon_{it}^j \quad (2a)$$

where $\mathbf{x} \mathbf{G}'_{it}$ 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 normalised to be bounded between 0 and 1. As proposed by [González, Teräsvirta and Van Dijk \(2005\)](#), incorporating this transition function into the model enables the representation of a smooth transition between two regimes of responses to price variations, as opposed to [Hansen's \(2000\)](#) threshold regression approach, which only permits a sudden 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:

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

where $\gamma_i > 0$. From an empirical point of view, compared with [Hansen's \(2000\)](#) threshold model, this model requires more degrees of freedom to estimate the additional parameter, γ_i , and tends to be computationally more demanding given the nonlinear form of the G function. However, it allows for the representation of a continuum of regimes. This smooth transition regression approach may be interpreted in two distinct ways. First, we can consider that there are two extreme regimes associated with the two extreme values of the transition function: $G_{it} = 0$ and $G_{it} = 1$. We also consider that farmers progressively move from one regime to another. The response of y^j to changes in prices contained in \mathbf{x} is represented by β_1^j in the first extreme regime and by $\beta_1^j + \beta_2^j$ in the second extreme regime. Second, this could be regarded as an infinity of regimes and possible values for the price response parameter, $\beta_1^j + \beta_2^j G_{it}$, depending on the value of q_{it} .

In contrast to the model originally proposed by [González, Teräsvirta and Van Dijk \(2005\)](#), our model takes individual-specific parameters in the transition function into account. The work of [Fok, Van Dijk and Franses \(2005\)](#) is the only paper we are aware of that considers individual threshold parameters. On the basis of a multi-level smooth transition model, these authors investigated the existence of common nonlinear business cycle characteristics in 19 US manufacturing sectors. Nevertheless, their approach is best suited to time-series panels of data (i.e. data with a large temporal dimension and a small cross-sectional dimension). In contrast, our data contain observations for a large number of farms over a relatively short period, as is typical for the samples of farm accounting data used to estimate farmers' behaviour.

[Figures 1 and 2](#) depict the distinctions between our methodology and those of [Hansen \(2000\)](#) and [González, Teräsvirta and Van Dijk \(2005\)](#). These graphs

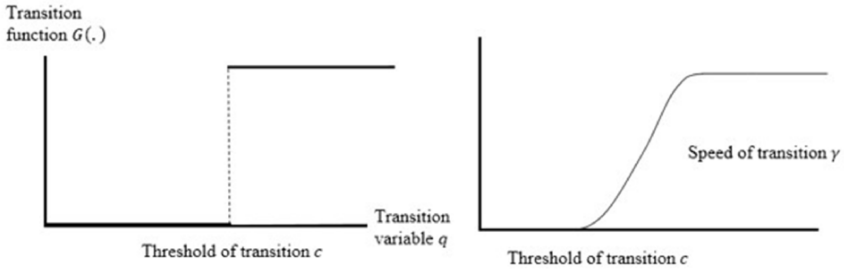


Fig. 1. Approaches of Hansen (2000) and González, Teräsvirta and Van Dijk (2005): standard and smooth threshold regression model.

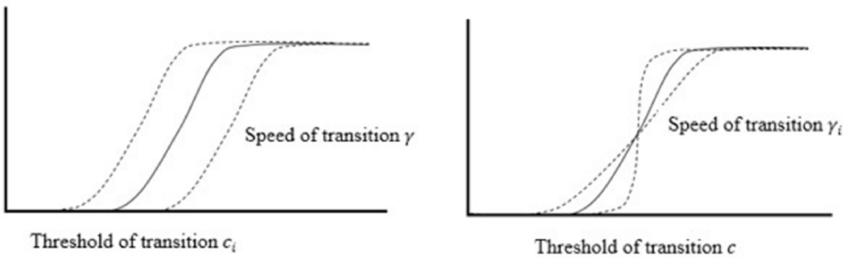


Fig. 2. Our approach: individual smooth threshold regression model.

display the value of the transition function G according to the value of the transition variable q . For each strategy, farmers are in the first regime when the transition function equals 0 and the second regime when it equals 1. The distinction between the two methods lies in how farmers switch from the first to the second regime.

In Hansen’s (2000) model illustrated by the left-hand graph on Figure 1, the transition between the two regimes consists of a jump at a threshold level, c , which is the same for all farmers. Meanwhile, the model of González, Teräsvirta and Van Dijk (2005), illustrated by the right-hand side of Figure 1, allows for a smooth transition between the two regimes; the speed of this transition being characterised by a parameter γ is also common to all farmers. Our approach, illustrated by Figure 2, simultaneously allows for individual threshold and speed of transition levels.

Our model has the advantage of containing all the other models. If the transition threshold does not significantly vary among farmers and the transition speed tends towards infinite, our model reduces to the threshold model of Hansen (2000). If the threshold and the speed of transition do not vary significantly among farmers, the smooth threshold model of González, Teräsvirta and Van Dijk (2005) is obtained. Finally, if the transition speed tends towards zero, our model reduces to a linear random parameter model.

3.4. Heterogeneity of farm adjustment costs and flexibility

We explain here how our proposed modelling framework can be used to characterise adjustments costs and determine each farm's flexibility level.

Our analysis begins with the characterisation of the two extreme regimes in our model. In fact, the analysis of farmer behaviour is contingent on the values of the parameters that characterise each regime. As a reminder, the similarities between the two extreme regimes apply to all farmers. The first regime corresponds to a context of small price variations (or, at the very least, a context in which input and output prices vary in the same way), and the transition function is equal to 0. The second extreme regime corresponds to a situation with large output or input price variations (or where input and output prices vary, even moderately, in opposite directions), and a transition function is equal to 1. Of course, the parameters that characterise the farmers' behaviours in these regimes are obtained from the estimation of the model. As underlined by [Önel \(2018a, 2018b\)](#), two cases are possible. In the first case, farmers are more sensitive to small than to large price variations. This situation can occur when adjustment costs are convex and increase with the required adjustment of input quantities in response to a price variation. In the second scenario, farmers are more responsive to large price fluctuations than to small ones. This situation can occur if adjustment costs are nonconvex and a small adjustment of input quantities in response to a small price change is costly relative to the benefits generated by the input adjustment. In the first case, input price elasticity is greater in the first extreme regime than in the second, and conversely, in the second case, it is greater 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 the transition level γ_i . Our interpretation is that farmers tend to transition smoothly and gradually from one regime to another (small γ_i) when this transition necessitates an adjustment of capital or labour, which are quasi-fixed-inputs, or a change in the production technology of the farm. 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 characterise the ability of farmers to adapt their short-term production decisions. Consider, for example, the case of a quite abrupt transition from one regime to the other (high γ_i) for all farmers. If the input adjustment costs are convex (input use elasticities are higher in the first regime), a farmer characterised by a high threshold level c_i faces less adjustment costs than the others. He/she can adjust her/his short-term production decision for a wider range of price variations, and he/she would only switch to the second regime when price variations are too large and induce too substantial adjustment costs. 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.

4. Estimation strategy

This section presents the distributional assumptions and our approach to estimate the PSTR model defined by [Equations \(2a\)](#) and [\(2b\)](#).

4.1. Distributional assumptions

Each equation in our model of dairy farmers' production choices comprises fixed parameters, β_1^j , β_2^j and α_1^j , and two types of random components: (i) random parameters that include additive farmer-specific effects, α_{0i}^j , and the parameters of the transition function, γ_i and c_i , and (ii) error terms of the model, ε_{it}^j . Let vector $\delta_i \equiv (\alpha_{0i}, \gamma_i, c_i)$, with $\alpha_{0i} \equiv (\alpha_{0i}^j, j \in \mathcal{J})$, collect the model random parameters and vector $\varepsilon_{it} \equiv (\varepsilon_{it}^j, j \in \mathcal{J})$ collect the error terms. We assume that the random parameters follow a normal distribution with $\delta_i \sim \mathcal{N}(\mu, \Omega)$. This probability distribution describes the distribution of the random parameters across the farmers' population represented in our sample considered. The diagonal elements of Ω correspond to the variances of the random parameters δ_i . The unobserved factors that affect the dairy farmers' production choices are represented by additive terms α_{0i} , or in the form of the transition function representing their switch from one regime to another. A significant heterogeneity among dairy farmers in these unobserved factors, characterised by parameters γ_i and c_i , will thus be reflected by high values of the corresponding variance parameters in the matrix Ω . We do not restrict the structure of Ω and hence allow all farmer-specific parameters (including the transition function parameters) to be correlated between them and across equations. This notably allows the capture of the potential correlation between the production decisions of each farmer, which could be attributed, for example, to the farmers' skills or the natural endowments of the farms. The error term vector is assumed to be normally distributed with $\varepsilon_{it} \sim \mathcal{N}(0, \Psi)$. We assume that the covariance matrix Ψ is diagonal, which indicates that the model's error terms are independently distributed across time and uncorrelated across equations. By imposing these constraints, we can considerably reduce the estimation burden of the model. The resulting limitations are certainly strong, but they need to be qualified for two main reasons. First, since no restrictions are imposed on the variance-covariance matrix of random parameters, Ω , correlations are allowed between the individual, time-invariant, random elements of each equation. Second, the effects of climatic variables and the effects of prices, which vary more across time (than across farms) in our sample, account for the majority of the temporal shocks that are likely to simultaneously impact dairy farms' feed concentrate use and acreage choices. In fact, [Koutchadé, Carpentier and Femenia \(2018\)](#), who also worked on a random parameter microeconomic production choice model (applied to cereal acreage choices), found no significant correlation between errors when relaxing the constraints on the independence of error terms at the expense of increased computational complexity in running the

stochastic approximate EM (SAEM) algorithm. Finally, we assume that the random parameter vector δ_i , error term vector ε_{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 exogeneity assumptions are standard in short panel data econometric models of farm production choices (e.g. Lacroix and Thomas, 2011; Platoni, Sckokai and Moro, 2012; Bayramoglu and Chakir, 2016; Koutchadé, Carpentier and Femenia, 2018). In particular, the climatic and price variables, \mathbf{x}_{it} and \mathbf{z}_{it} , included in our case are determined by factors external to individual farms and can thus reasonably be considered exogenous with respect to the models' random elements. Furthermore, as already mentioned, these vary mostly across time in our sample and can therefore be considered uncorrelated with the time-invariant random parameters contained in δ_i .

4.2. Estimation approach

The parameters we seek to estimate comprise the price effects, β_1^j and β_2^j , and control variables effects, α_1^j , in each equation. These fixed parameters are collected in vector $\theta \equiv (\beta_1^j, \beta_2^j, \alpha_1^j, j \in \mathcal{J})$. We also aim at estimating parameters μ and Ω , characterising the distribution of the random parameters, and the covariance matrix of random terms, Ψ .

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

$$\ell_i(\theta, \Psi, \mu, \Omega) = \int f(\mathbf{y}_i | \mathbf{x}_i, \mathbf{z}_i; \delta, \theta, \Psi) g(\delta; \mu, \Omega) d\delta \quad (3)$$

$f(\mathbf{y}_i | \mathbf{x}_i, \mathbf{z}_i; \delta, \theta, \Psi)$ 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, δ_i . $g(\delta; \mu, \Omega)$ denotes the probability density function of the random parameter vector, δ_i .

Maximising 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 ML approaches to solve such optimisation problems. This is the estimation method chosen by Fok, Van Dijk and Franses (2005) for their model, which is comparable to ours in this regard. The maximisation of the simulated likelihood is however further complicated by the nonlinear form of the transition function \mathbf{G}_{it} , which is determined by random parameters δ_i and enters the model's explanatory variables. To overcome this issue, Fok, Van Dijk and Franses (2005) used a two-step iterative procedure involving, in the first step, the maximisation of the sample-simulated likelihood for the given values of the transition function parameters, and, in the second step, the solution of a numerical optimisation programme to find the transition function parameters. However, this two-step procedure is quite

involving, and its convergence is not guaranteed, especially in our case where the individual dimension of our panel dataset is much larger than its time dimension (i.e. our sample contains a large number of individual farms for which we obtained few observations over time). We do not use this two-step procedure here, but instead rely on an SAEM algorithm, a specific type of the Monte Carlo EM (MCEM) algorithm (Lavielle, 2014). When faced with complex likelihood maximisation, statisticians frequently employ MCEM algorithms, which permit the computation of estimators that are asymptotically equivalent to ML estimators. Technical details on these algorithms, particularly the SAEM algorithm, and their use for the estimation of microeconomic random parameters of agricultural production choices can be found in Koutchadé, Carpentier and Femenia (2018, 2021). Here, the R programming language was utilised to implement the SAEM algorithm and to estimate our model. The authors will provide the codes upon request.

5. Results

5.1. Data

Our model is estimated using data provided by a French farm accounting agency, *Cerfrance*. This unbalanced panel dataset contains 5,172 observations of 714 dairy farms in the West of France observed between 2007 and 2018, with 2–12 years of data for each farm and an average of 7 years of observation per farm. The three dependent variables of our model, namely, the quantities of concentrates, the share of fodder maize acreages and the share of grassland acreages, as well as the milk and feed concentrate prices observed by farm and by year, are observed in this database. Other input and output prices used as explanatory variables in the model (fertiliser, pesticide and cereal prices) are price indices provided by the French Department of Agriculture. We also use the data provided by the French National Meteorological Service (*Météo France*) to build climate indicators used as control variables in the model. Although our sample covers a relatively small area, climate conditions are likely to impact dairy farmers' production decisions, especially for maize, which is very sensitive to water and heat stress during the spring and summer periods.⁴ We constructed two cumulative rainfall indicators: one for June and July and other for August and September. A third indicator is constructed by summing the days during which the temperature exceeded 29°C, corresponding to the maximum temperature beyond which maize development is slowed and its growth reduced (Girardin, 1998).

Table 1 reports some descriptive statistics of these variables. Our sample appears to be relatively homogeneous in terms of the production system, since all farms produce fodder maize, grassland and cereals and use concentrates to feed their animals. The farms in our sample are located in the French territorial division *Ille-et-Vilaine* in the Brittany region, the first French dairy

⁴ Climatic conditions (precipitation and temperature) may have important impacts on the yield and energy content of grass and maize fodder. Farmers will adjust the amount of concentrates to maintain a balanced feed ration in the face of these climatic events.

Table 1. Descriptive statistics of the sample

	Sample average	s.d.	Min.	Max.
Number of observations per farm	7.20	2.03	2.00	12.00
Quantity of feed concentrate used (ton/cow)	1.20	0.56	0.01	5.40
Fodder maize acreage share	0.28	0.08	0.03	0.60
Grassland acreage share	0.45	0.12	0.06	0.92
Milk price (euros/l)	0.32	0.22	0.17	0.44
Feed concentrate price (euros/kg)	0.27	0.06	0.10	0.74
Cereal price index (1 in 2015)	1.03	0.21	0.65	1.34
Fertiliser price index (1 in 2015)	1.00	0.19	0.76	1.91
Total available land (ha)	67.18	23.68	15.75	222.61
Milk yield (1,000 l/cow)	7.14	1.24	2.65	10.60
Animal density (cow/ha)	1.12	0.24	0.52	4.25
Rainfall at flowering (in mm)	111.77	41.03	37.31	256.16
Rainfall at maturation (in mm)	106.49	37.48	33.40	209.29
Heat (number of days)	1.69	0.99	0.00	4.00

region, producing 20 per cent of the national production. Dairy farms in this area mostly rely on intensive forage systems, characterised by fairly high milk yields, moderate use of pasture and rather important use of concentrate-based supplementary feeding, although there is still some heterogeneity in this regard in our sample, as shown by the standard deviations and extreme values reported in [Table 1](#).

As mentioned previously, with respect to the threshold variable used in the transition function of the model, we do not exactly follow [Önel \(2018a, 2018b\)](#), who used the variation, in absolute terms, of the input prices compared with the previous period. Instead, we use the variation in the input (feed concentrate)-to-output (milk) price ratio. We select the price of concentrate as an input for two reasons: (i) it is the only input involved in the animal feed decision that is purchased on the market and not produced on the farm and (ii) feed concentrates are subject to significant price variations. The evolution of this threshold transition variable is represented in [Figure 3](#). The main advantage of this transition variable is that it better characterises the economic context faced by dairy farms. Farmers can face four primary economic contexts based on the evolution of animal feed and milk prices, two of these contexts lead to a stable price ratio: if milk and feed concentrate prices do not fluctuate significantly or if these prices evolve in the same direction (an increase in both prices or a decrease in both prices). In these circumstances, farmer behaviour resembles that of the first extreme regime. Meanwhile, the price ratio will be especially high in absolute terms if only one of the two prices increases or decreases significantly, whereas the other remains stable, or if the two prices evolve in opposite directions. A sharp increase in milk price and/or decrease in concentrate price creates an economic situation particularly favourable for dairy farmers (this was the case in 2014). A sharp decrease in milk price and/or

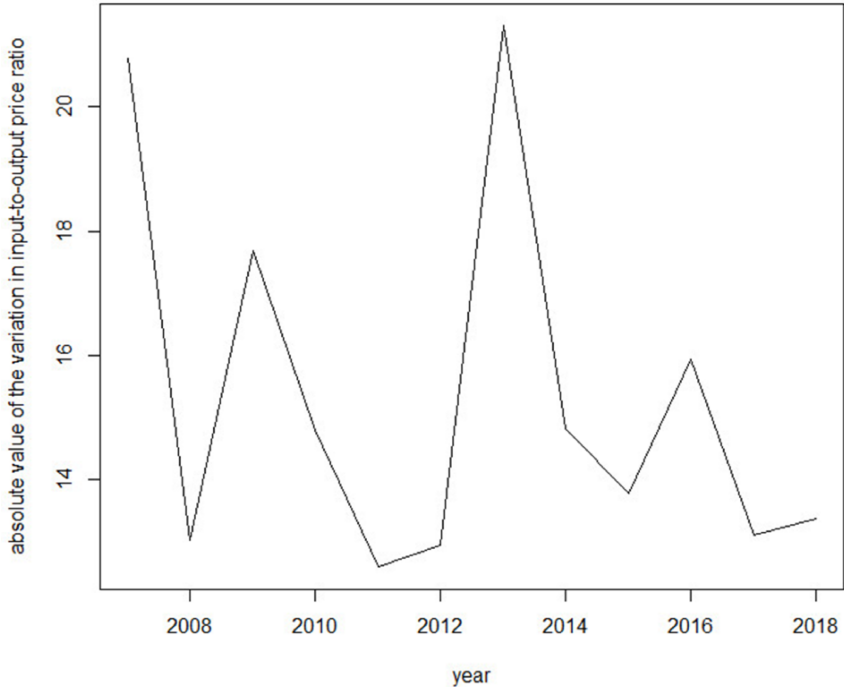


Fig. 3. Evolution of the threshold transition variable.

increase in concentrate price leads to a bad economic situation (this was the case in 2009, 2013 and 2016). In these types of economic contexts, farmer behaviours are close to those represented in the second extreme regime.

5.2. Estimation results

Parameter estimates of the dairy farm production decision model defined by equation system (2a) and transition function (2b) are reported in Table 2.

5.2.1. Overall estimation results and goodness of fit of the model

The values of the Sim- R^2 criterion reported at the bottom of Table 2 measure the quality of prediction of the input choices observed by dairy farmers. This criterion is analogous to the R^2 criterion of the conventional linear regression model: for a given choice variable, it is defined as the ratio of the empirical variance of the model's predictions for this variable to the empirical variance of the observed variable (Koutchadé, Carpentier and Femenia, 2018). This criterion, with values ranging from 0.71 to 0.83, shows a good fit between the model and the data for all production decisions.

The parameters characterising the distribution of the additively separable random farm effects, α_{0i} , are all significantly estimated. The significance and magnitude of their estimated standard deviations notably show an important

Table 2. Parameter estimates of the input use equation system and transition function

	Quantity of feed concentrates	Share of fodder maize acreages	Share of grassland acreages
Input use equation system			
Distribution of individual farm effects α_{0i}			
Mean ^a	-0.54**	0.53**	0.37**
s.d. ^b	0.40**	0.03**	0.10**
Effects of price and climate variables α_1			
Fertiliser price	-0.43*	0.15**	0.04
Cereal price	4.14**	-0.14**	-0.21**
Rainfall at flowering	0.37**	-0.15**	0.09**
Rainfall at maturation	0.28*	-0.04	0.08**
Heat	0.09*	-0.04**	0.01
Effects of Milk and concentrate prices in the first extreme regime β_1			
Feed price	-1.41**	0.08**	0.03
Milk price	5.14**	-0.72**	0.22**
Changes in the effects of milk and concentrate price in the second extreme regime β_2			
Feed price	-0.52**	-0.10**	-0.02
Milk price	0.37**	0.06**	0.03
Transition function G			
Distribution of threshold parameters c_i			
Mean ^a	0.11**		
s.d. ^b	0.02**		
Distribution of the speed of transition parameter γ_i			
Mean ^a	0.42**		
s.d. ^b	0.02**		
Sim- R^2 criterion	0.73	0.83	0.71

*This denotes estimated parameters significantly different from zero at the 10 per cent level.

**This denotes estimated parameters significantly different from zero at the 5 per cent level.

^aThe estimated means of random parameters are the estimated elements of vector μ , the expectation of the random parameter distribution.

^bThe estimated standard deviations of random parameters are the (square roots of) estimated diagonal elements of matrix Ω , the variance-covariance matrix of the random parameter distribution.

variability across farmers regarding their ‘average’ feeding strategy, in terms of feed concentrate and grass rations.⁵ This heterogeneity might be attributed to several unobserved farms and farmers’ characteristics, such as personal skills, time availability or environmental awareness.

Parameters α_1 , associated with the price and climatic control variables included in \mathbf{z}_{it} , are generally significant and are in expected ranges. Our results

⁵ The estimated covariances of random parameters, not reported here but available from the authors upon request, show a significant and negative correlation between the α_{0j} parameter in the feed concentrate and grassland acreage equations, suggesting that dairy farmers with feeding strategies based on the high use of feed concentrates have the least grassland in their acreage, and conversely.

show that the price of cereals has a negative impact on the use of feed concentrate. Depending on how farmers use their cereal production, two mechanisms can explain this effect. On the one hand, if cereals are cash crops intended to be sold on the market, an increase in cereal price will incentivise farmers to increase their cereal production and thus reduce their fodder maize and grassland acreages. In that case, increasing feed concentrates will allow farmers to compensate for the loss of the forage area. The same mechanism can explain the positive impact of fertiliser price on the forage acreage (and the negative impact on feed concentrate) through its negative impact on the cereal acreage. On the other hand, if farmers use the cereal production to feed animals on their farms, an increase in the price of cereals will change the comparative advantage of feed concentrate compared to cereals in favour of concentrates. We also find that climate conditions primarily affect the composition of the feed ration. Our results suggest that an increase in precipitation and high temperatures increase the use of concentrates. Under unfavourable conditions characterised by excessive water or high temperature, maize growth can be inhibited, prompting farmers to increase the amount of concentrates added to the feed ration. The impact of weather variables on crop acreage decisions is less straightforward. The favourable spring rainfall conditions for grass growth and quality appear to encourage farmers to produce more grass at the expense of maize forage.

5.2.2. Estimated dairy farms' flexibility in responses to milk and feed concentrate price variations

We now turn to our main parameters of interest, characterising the flexibility of dairy farmers in their responses to milk and feed concentrate price variations. Our estimated parameters in the first extreme regime, β_1 , representing farmers' behaviours in the case of minimal variations in the input-to-output price ratio, show a negative impact of the price of feed concentrate on the amounts of concentrates purchased by farmers, and a positive impact on the acreage share of fodder maize, which is a substitute for concentrates. In this case, milk price has positive effects on both feed concentrates and grassland acreages. This indicates that an increase in milk price may encourage farmers to stimulate their milk output by increasing their ration of feed concentrate and/or by maximising the benefits of grass. In fact, early grass silage, which is rich in energy and protein, stimulates the appetite and milk production of cows. Both of these choices (an increase in feed concentrate or grassland acreage) lead to a decrease in the use of fodder maize to feed animals; hence, the effect of milk price on the acreage of maize acreage is negative.

Estimated β_2 parameters represent the changes in the behaviours of dairy farmers when the market conditions they face change drastically. The significance of these estimates highlights the nonlinearity of the adjustment of dairy farmers' inputs in response to changes in input and output prices. Our results show that when farmers are confronted with a substantial change in the input-to-output price ratio, the impacts of prices on the purchased quantities of feed concentrates are intensified. In fact, the second extreme regime is characterised by feed concentrates with more pronounced responses to milk

and concentrate prices, indicating a nonconvex structure of adjustment costs. In contrast, the impacts of prices on land allocation appear smaller, indicating a convex structure of adjustment costs in the case of acreage adjustment. This result is comparable to that found by [Antle and Capalbo \(2001\)](#). In an economic context characterised by small variations in the price ratio, farmers respond to price changes by adjusting the amount of feed concentrates and allocating their land between grassland and maize. Larger price variations would require larger adjustments in land allocation, but such large adjustments become too costly for farmers who, as a result, primarily rely on adjustments in feed concentrates to adjust their production of milk. These results are consistent with the fact that, as explained in [Section 2](#), feed concentrates are an easily adjustable component of the cows' feed ration, whereas a set of specific technical and agronomic constraints specific to each farm limits farmers' acreage choices.

Our estimation results reveal a significant heterogeneity in the behaviours of our sample farmers. In fact, as discussed in [Section 5.2.1](#), the estimated standard deviations of farm-specific additive terms α_{0i} reflect a significant heterogeneity in the level of input used by dairy farmers, but, more importantly, our results also show a significant heterogeneity in how dairy farmers adjust their production decisions in response to price variations. This heterogeneity is reflected in the estimated distribution of random parameters, c_i and γ_i , characterising the transition function G . In actuality, as described previously, dairy farmers tend to substitute all their feeding sources by adjusting both feed concentrates and forage acreages in response to small changes in market conditions, but they become less flexible on acreages and primarily adjust feed concentrates in response to large market changes. The way in which they switch from a rather flexible feeding strategy to a more restricted one is determined by their farm-specific threshold level, c_i (with an estimated mean equal to 11 per cent variation in price ratio) and transition speed, γ_i (with an estimated mean equal to 0.42). Both of these parameters vary from one farmer to the other, as reflected in their significantly estimated standard deviations.

The estimation procedure used to estimate our model, based on the SAEM algorithm, allows a statistical calibration of the individual parameters of the model for each farmer in our sample. These parameters are computed as the mode of their simulated probability distribution given the observed data available for each farmer (details regarding this calibration procedure can be found in [Koutchadé, Carpentier and Femenia, 2018](#)). After calibration, the c_i and γ_i parameters can notably be used to define transition functions unique to each farm.

[Figure 4](#) depicts the estimated transition functions for each individual. Specifically, it is the value of the estimated transition function with respect to the absolute value of variation in the input-to-output price ratio for each farmer. The transition from one regime to another is quite rapid, and the slope of the transition function among farmers is relatively uniform. In fact, although significant, the estimated standard deviation of the transition speed parameter, λ_i ,

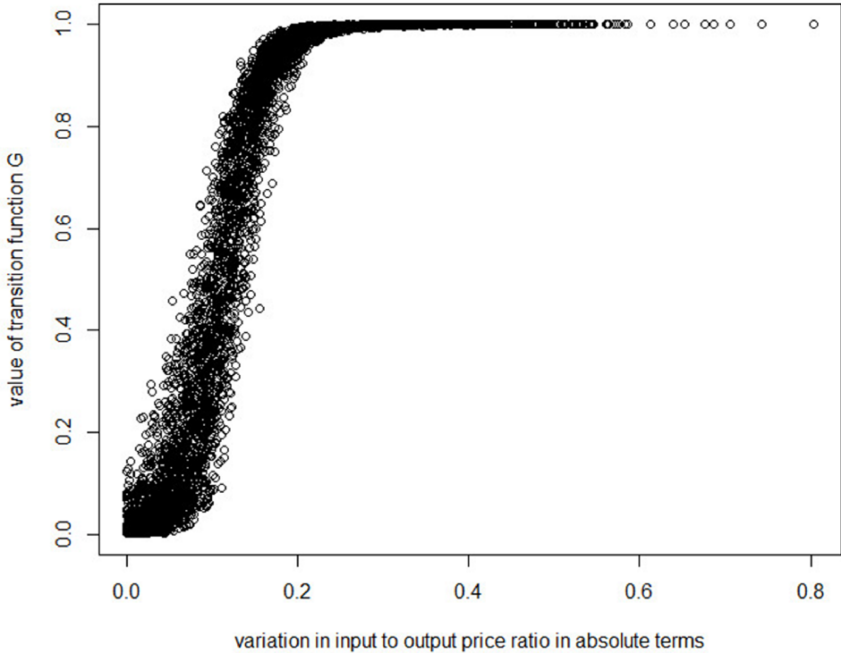


Fig. 4. Estimated transition functions.

is relatively small (0.02) compared to its estimated average (0.42). This might be due to the fact that the second regime is mainly characterised by an increased use of concentrates, so the decision to increase the proportion of concentrates in the feed can be made immediately and does not require special additional equipment. [Figure 4](#) illustrates that the estimated threshold levels, the c_i parameters, do, in fact, exhibit greater heterogeneity, which is consistent with our estimation results because the average estimated standard deviation of c_i is equal to 2 per cent for an estimated average value of 11 per cent. In our sample of dairy farmers, the individual estimated threshold levels range from 6 to 16 per cent. This suggests the existence of heterogeneity in the responses of farmers to price variations, with this heterogeneity being primarily characterised by the differences in the input-to-output price ratio that induce a switch between the two extreme regimes of input adjustments.

To better characterise the degree of flexibility of each farm, we illustrate the differences in farm behaviour between the two extreme regimes in our model by calculating the price elasticity of feed concentrates and acreage shares for various values of the transition function, G . In [Table 3](#), these elasticities are computed at the sample average for G values close to 0 (the first extreme regime), close to 1 (the second extreme regime) and equal 0.5 (the intermediate regime). In the first extreme regime, farmers decrease the quantity of concentrates (-0.32) and (slightly but significantly) increase the proportion of

Table 3. Elasticities according to the level of the transition function G

	Elasticity of concentrates		Elasticity of maize fodder		Elasticity of grassland	
	Concentrate price	Milk price	Concentrate price	Milk price	Concentrate price	Milk price
$G \rightarrow 0$	-0.32	1.38	0.08	-0.82	0.02	0.16
$G = 0.5$	-0.37	1.43	0.04	-0.79	0.01	0.17
$G \rightarrow 1$	-0.42	1.48	-0.01	-0.75	0.007	0.18

land devoted to fodder maize (0.08) in response to an increase in the price of concentrates. In the second extreme regime where G equals 1, an increase in the concentrates price will encourage farmers to decrease the quantity of concentrates even more (-0.42), without modifying their land allocation. When the price of milk varies, the mechanisms remain the same. The price elasticity of the concentrate increases between the two extreme regimes (1.38 to 1.48), whereas the elasticity of the maize fodder decreases in absolute values (-0.82 to -0.75).

These results illustrate that the first extreme regime is characterised by a substitution between different feeding sources (feed concentrates, grass and forage) in response to price changes. Meanwhile, in the second regime, farmers respond to price fluctuations by altering the amount of concentrates fed to their animals. The switch in the farm feeding strategy between the first and second regimes can be attributed to the existence of increasing acreage adjustment costs, which at some point limit potential land adjustments. This suggests that farmers who transition more rapidly from the first to the second extreme regime incur greater adjustment costs associated with acreage decisions and, consequently, have less flexibility to adjust their feeding strategy. Since no additional costs are associated with the adjustment of feed concentrates, confirmed by high-price elasticities, the least flexible farmers seem to use them to compensate for the lack of flexibility in their land allocation choices. This suggests that the least flexible farmers are also the most impacted by the highly variable price of feed concentrates.

5.2.3. Determinants of dairy farms' flexibility

To investigate the differences between flexible and less flexible farms, we classify the farms in our sample into three groups based on their level of flexibility and compare the descriptive statistics of key variables characterising the structure and production practice of farms belonging to the various groups. We thus build three groups of farmers according to the level of variation in the price ratio from which they move to the second extreme regime. Farmers in the first group move to the second extreme regime when the price ratio fluctuates between 26 and 31 per cent, farmers in the second group move to the second extreme regime when the price ratio fluctuates between 31 and 35 per cent and farmers in the third group move to the second extreme regime when

the price ratio fluctuates between 35 and 51 per cent. Meanwhile, farmers in the third group are regarded as the most flexible, as they exploit the possibility of substituting feed ration components, including land allocation, in the majority of economic contexts.⁶

Table 4 presents the characteristics of these three groups of farms. The first three columns of the table present the mean and standard deviation of different variables that describe farming practices and farm structure by the group. The next three columns present the difference in means between the groups for each variable. Student's *t*-tests are used to test the mean equality between the groups. Group 1 (the least flexible farm) and Group 3 (the most flexible farm) have statistically distinct means for all variables. The most flexible farms appear to have substantial financial independence and food self-sufficiency. These farmers also have less intensive farming practices: the animal density per hectare and the quantities of feed concentrates purchased are significantly lower for Group 1. In a similar manner, the proportion of grass in the animal feed ration is increased at the expense of feed concentrates. Lastly, this group contains a greater proportion of organic farms, indicating that organic farms are the most flexible type of farm.

The feeding strategy of the least flexible farms is based primarily on the high use of concentrates and fodder maize. Despite the fact that concentrates are an easily adjustable and adaptable input, the lack of flexibility of these farms is primarily due to their inability to adjust land use. This can be attributed to their production system, which affords them few opportunities to substitute feed sources. Their long-term investments in capital and equipment, reflected in high debt levels, may compel them to maintain an intensive production system based on intensive use of concentrates and high milk yields per dairy cow. These farms may also have a plot structure that prevents them from using land for cow grazing.

The values reported in Table 4 also suggest that the less flexible farms in our sample have lower gross margins per litre of milk average (222 euros/l) than the more flexible farms (258 euros/l). A closer look at our data reveals that these gross margin differences are all the more pronounced when price variations are significant. In fact, when the price of concentrate increases by more than 20 per cent (which occurs in one-third of our observations), the difference in the gross margin between flexible and less flexible farms increases: the least flexible farms maintain an average gross margin of 217 euros/l of milk, whereas the most flexible farms enjoy an average gross margin of 267 euros/l of milk. This result validates Stigler's (1939) assertion that firms have an incentive to be flexible when market prices are highly variable, as is the case in the current agricultural market.

Several studies have attempted to identify the heterogeneity of production technologies on dairy farms in various European countries. These studies usually use input use intensity, production specialisation or organic farming as

⁶ Note that the average variation of the price ratio in our sample is 15 per cent, and the average maximum variation of the price ratio observed for each individual, regardless of group, is 35 per cent. Farmers in each group therefore experience comparable price fluctuations on average.

Table 4. The characteristics of farms according to their flexibility

	Group 1: 26%–31%		Group 2: 31%–35%		Group 3: 35%–51%		Difference in means G1/G2	Difference in means G2/G3	Difference in means G1/G3
	Mean	s.d.	Mean	s.d.	Mean	s.d.			
Number of farmers	181		353		178				
Total area	78	25	65	21	60	22	13**	5**	18**
Livestock density	1.16	0.24	1.11	0.23	1.10	0.21	0.05	0.01	0.06**
Yield (l/cow)	8,034	936	7,185	1,067	6,175	1,120	849**	1,010**	1,859**
Share of grassland	0.35	0.08	0.44	0.10	0.56	0.10	-0.09**	-0.12**	-0.21**
Concentrates (euros/cow)	478	157	370	126	254	100	108**	116**	224**
Share of farm-produced food	0.25	0.13	0.31	0.16	0.41	0.19	-0.06**	-0.1**	-0.16**
Share of organic farm	0.05	0.23	0.03	0.18	0.12	0.32	0.02	-0.09**	-0.07**
Gross margin (euros/l)	222	38	234	44	258	52	-12**	-24**	-36**
Unit of agricultural workers	1.87	0.65	1.71	0.61	1.69	0.78	0.16**	0.02	0.18**
Capital (euros/1,000 l)	907	244	903	290	973	311	4	-70**	-66**
Debts (euros/1,000 l)	390	200	347	212	348	233	43**	-1	42*

*This denotes the difference in means between the groups significantly different from zero at the 10 per cent level.

**This denotes the difference in means between the groups significantly different from zero at the 5 per cent level.

direct criteria to distinguish different groups of farms according to their production technology (Kumbhakar, Tsionas and Sipiläinen, 2009; Alvarez and Del Corral, 2010; Sauer and Paul, 2013; Renner, Sauer and El Benni, 2021). These studies generally conclude that the most productive dairy farms are those with the largest, most capital-intensive operations and the highest animal density. These types of farms appear to be relatively similar to those entering our first group, which corresponds to the least flexible farms. This suggests that the analysis of farm productivity alone may not be sufficient to evaluate the sustainability of farms, particularly their adaptability to a highly variable economic and climatic context.

6. Conclusion

By relying on a panel smooth transition model of dairy farmer production choices, we have identified farmers' heterogeneous flexibility in their short-run responses to input and output price variations. Our proposed approach to identify nonlinear and heterogeneous farm behaviours contributes to the literature in several aspects. First, we propose a way to identify farm flexibility based on their observed short-run responses to input and output prices. Our approach differs from those commonly used to study farm flexibility in that it is based on a dual econometric model of farmers' input demand and thus focuses on their ability to adjust their inputs in response to price variations. In contrast, previous studies primarily considered farm flexibility in terms of output mix. Moreover, our econometric model estimated and calibrated for each farm in our sample could be used to conduct simulations of the public policies' effect (e.g. environmental or agricultural) on farmers' choices, which was not the case in previous research that relied primarily on production frontier analyses to characterise farm flexibility. Second, we propose an original framework to implicitly account for adjustment costs in farmers' production behaviour. Our straightforward model distinguishes farmers according to their responsiveness to price changes and identifies the most flexible farmers in the short term. Third, we propose a new estimation procedure for PSTR models with individual random parameters defining the transition function. This method reveals farm heterogeneity without requiring the specification of *ad hoc* criteria differentiating farms and is suited to the characteristics of farm accountancy panel data, which typically have large individual and short-time dimensions.

We identify significantly heterogeneous production behaviours on a sample of French dairy farms, thereby validating the utility of our methodology. Different levels of adjustment costs impede the ability of farms to adapt to observed price fluctuations in the market. Some farmers are considered more flexible in our approach, in the sense that they adjust their feeding strategy more easily to price variations. An *ex post* analysis confirms their specific characteristics: they use less intensive, more grass-based practices, making them more food self-sufficient. Organic farms are also overrepresented among the most flexible farms.

Despite the originality of our framework in describing the heterogeneity of dairy producers' responses to short-term price fluctuations, we acknowledge that it has certain limitations. First, it essentially takes into account the adjustment of the farms' feeding strategy but does not consider the potential adjustment of their herd size. This assumption actually allows us to improve the empirical tractability of our model and is, at least in our empirical application, not so strong because the herd size varies very little in the short run in the sample we consider. Moreover, this permits our analytic framework to be directly transposable to other types of farmers' decisions, such as the selection of fertiliser or pesticide use for crop producers. Second, we focus primarily on the farmers' adjustment to price shocks, although it would be interesting to also analyse their adjustment to climate shocks. This could be accomplished by considering a climate indicator as a transition variable in the model but would require a sufficiently synthetic index to represent the impact of climate variations on the input choices of all farmers. Third, we could expand our model by simultaneously estimating the input demand and output supply equations for milk and cereals to evaluate the capacity of farms to alter their production level. This would allow us to compare our results directly with those of the literature, specifically [Hirsch *et al.* \(2020\)](#), who measured the output flexibility of European dairy farms.

As the ability to adjust their production choices appears to be a key aspect of farms' economic sustainability, our approach can help identify levers of public actions to encourage farmers to be more reactive to price fluctuations. This is all the more important given the current state of high input costs: between June 2021 and June 2022, the price of cattle feed increased by nearly 30 per cent. In light of the findings of our paper, the impact of these price shocks on the input market will affect farmers differently depending on their ability to react and, in particular, their capacity to substitute feed sources. In the current highly volatile economic environment, our method can be utilised to predict the impact of external shocks on input markets and, consequently, the effects of potential policy measures that could be implemented to assist farmers ([Hamermesh and Pfann, 1996](#)).

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Conflict of interest

The authors declare that there is no conflict of interest.

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