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DYNAMIC MICROECONOMETRIC APPROACHES TO ANALYSING AGRICULTURAL POLICY

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Abstract

Micro-econometric models have become a standard and powerful tool in analysing agricultural policies. In this paper we assess the contributions that have been made in the agricultural economics literature to dynamic microeconomic models of firms and households that are estimated using microdata. After discussing developments in dynamic investment models, dynamic household models, dynamic discrete choice models and dynamic efficiency models we give promising directions for future research and discuss implications for future data collection.

Key words: Dynamics, microeconomic models, agricultural policy analysis

1. Introduction

Micro-econometric models have become a standard and powerful tool in analysing agricultural policies. Demand for these models has been spurred by the strong policy involvement in agriculture. Research on microeconomic models in our field strongly benefited from the wide availability of data in agriculture. And with more and more data being available nowadays via national farm accountancy data networks (FADN), household panels, internet sources or specific repeated surveys the future opportunities for micro-econometric models are increasing.

One of the standard divisions in micro-econometric models has been between static and dynamic models. Static models assume the absence of intertemporal dependence of decisions over time and consequently the firms or households investigated find themselves in a situation of stochastic equilibrium (Cameron and Trivedi, 2005:10). Static models have dominated the agricultural economics literature and classic examples can be found among primal and dual models of cost minimization and profit maximization, agricultural household models, technology adoption models, efficiency analyses etc. A static model describes the equilibrium situation of a particular economic process. Although it can be investigated how the equilibrium situation changes if certain variables change exogenously (*comparative statics*), static models do not explain the transition path of variables over time.

A model is dynamic if it describes the evolution of variables over time (Stewart, 2005:23). In other words, in dynamic models it is explicitly recognized that actions taken now affect future states. E.g. current investment raises the capital stock now (if there is no long delay in building) but also in the future. Moreover, it changes the financial situation (solvability). Related examples can be found in household modelling: saving, labour supply, or decisions to go to college all have impact on current and future situations.

But why is it so important to know how variables change over time? In other words, why should we spend effort in specifying dynamic models and collect longitudinal datasets on various firms or households (panel data) to quantify the parameters of such models? A straightforward answer is of course that we want to know how behavior of economic agents evolves over time due to changes in the economic environment or due to changes in policies because that is just what dynamic models do. Static models can be used to predict how much we would invest, save or work if certain variables are

different but they do not explain how these changes occur. More importantly, static models may even lead to wrong predictions since the dynamics of the economic system are not considered. E.g. although we could assess the (static) effects on output of an increased capital stock due to investment using comparative statics, the capital stock considered in the analysis would probably be wrong since effects of depreciation, discounting and increased output in periods in between are ignored. Especially, the last effect is crucial. Static models simply ignore what happened in between the periods considered. Since static models are not able to describe this evolution they can also not be attained via performing a sequence of comparative static predictions over multiple time periods.

The ongoing need for dynamic microeconomic models was recently stressed again by Wolpin (2007) for a different reason. Microeconomists have recently spent much research on assessing treatment effects of policy interventions (see e.g. Lee, 2005). The methods developed in this literature allow for assessing causal policy effects *ex post*, i.e. after policies have already been introduced. Wolpin argues that there remains a need for sound *ex ante* policy evaluation that is best performed using dynamic structural microeconomic models.

In this paper we assess the developments that were made in dynamic microeconomic models in the agricultural economics literature. Given the width of this class of models we restrict the discussion to dynamic microeconomic models of firms and households that are estimated using microdata. Therefore, we do not consider dynamic CGE models or simulated microeconomic models.

The next section proceeds with an overview of four research areas in agricultural economics where microeconomic dynamic models have been prominent and are expected to remain prominent. This is followed by a discussion of promising future methodological challenges and a critical discussion of the usefulness of current microeconomic dynamic models for analyzing agricultural policies.

2. Overview of different microeconomic dynamic models

In this section we give an overview of four major groups of dynamic microeconomic models that have received considerable attention in the agricultural economics literature. In four subsections we discuss dynamic investment models, dynamic household models, dynamic discrete choice models and dynamic efficiency models, respectively. Each subsection starts by indicating why it is important to take a dynamic approach in that particular class of models and is followed by a review of major contributions in that area and some comments on the research that has been done.

2.1. Dynamic investment models

Undoubtedly, dynamic microeconomic models are most prominent in research on investment, or more broadly adjustment of quasi-fixed factors labour, capital and sometimes land. The vast literature on this subject that appeared in the last two decades is characterized by two major elements: adjustment costs and uncertainty.

Adjustment costs were introduced in the economics literature by the end of the 1960's (Gould, 1968; Treadway, 1969) and started to appear in the agricultural economics literature in the 1980's. The

adjustment costs hypothesis states that firms incur additional costs in adjusting their stocks of quasi-fixed factors, inhibiting immediate adjustment. Examples of adjustment costs are foregone production due to implementation of new machinery, administrative fees or search costs. Originally, most studies assumed symmetric convex adjustment costs, providing a theoretical explanation for sluggish adjustment, but later studies also considered more flexible adjustment costs specifications that were able to explain asymmetries in adjustment and periods of zero investment often observed at the micro-economic level (Oude Lansink and Stefanou, 1997; Gardebroek, 2004; Gardebroek and Oude Lansink, 2004).

Just like with static micro-econometric models of production, primal and dual approaches can be discerned in dynamic investment models. In the primal approach, first-order conditions are derived from the multi-period objective function. By combining these conditions for different periods, the unobserved dynamic shadow price can be substituted out, yielding a condition that equates marginal costs and benefits of investment in period t to marginal costs and benefits in period $t+1$, the so-called Euler equation. Assuming rational expectations, i.e. farmers know the underlying process that determines future values of crucial variables, expected values of period $t+1$ variables can be replaced by their observed counterparts. The resulting equation is usually estimated using panel data and a Generalised Method of Moments (GMM) estimator. Although this approach is very common in general economics, in agricultural economics it became less popular than the dual approach. Notable exceptions are Lopez (1985), Thijssen (1994), Gardebroek (2004) and Gardebroek and Oude Lansink, (2004). An advantage of the primal approach is that the production and adjustment costs functions are explicitly specified so that alternative specifications can be tested and compared.

The dual approach to specifying dynamic investment models, as developed by McLaren and Cooper (1980) and Epstein (1981) has gained substantial popularity in the agricultural economics literature. Crucial in this approach is the assumption of static expectations on prices and technology, i.e. each period producers assume that current values of these variables remain indefinitely. Under a set of regularity conditions, the continuous long-run objective function can be approximated by a convenient differentiable functional form (e.g. quadratic). Differentiating this value function with respect to the rental rate of capital and rewriting the obtained expression yields an expression for optimal investment. Vasavada and Chambers (1986), Leblanc and Hrubovcak (1986) and Vasavada and Ball (1988) applied the dual dynamic model to annual data on U.S. agricultural production. Howard and Shumway (1988) used annual data on U.S. dairy production to investigate dynamic adjustments in the dairy industry. Luh and Stefanou (1991, 1993) extend measures of growth and learning to the dynamic case using annual data of U.S. agricultural production. Applications of the dual dynamic model using panel data include Fernandez et al. (1992) focusing on long term measures of economies of scope and scale and Stefanou et al. (1992) who focus on the production structure of the German dairy industry before and after the introduction of the milk quota. Chang and Stefanou (1988) and Oude Lansink and Stefanou (1997) analyse asymmetric adjustment costs using panel data of dairy and cash crop farms that display a typical pattern of disinvestments, zero investments and investments in farm assets. Two important contributions that focused explicitly on expectations formation are Luh and Stefanou (1996) who allowed for non-static expectations in the dual framework and Thijssen (1996) who compared a dynamic investment model based on rational expectations with a model based on static expectations and rejected the rational expectations model. Richards and Jeffrey (1997) investigated the impact of

dairy quotas on investment using a dual dynamic approach. A final study worth mentioning is Pietola and Myers (2000) who explicitly considered uncertainty in a dual adjustment cost model.

Given all these contributions to the scientific literature, how should we judge the impact of this adjustment costs literature, which has been around for a number of decades, on policy analysis? It is striking that the number of scientific articles where it is an explicit aim to analyse a particular policy or development in the agricultural sector using an adjustment cost framework is limited. Most papers combine methodological contributions with an empirical description of an agricultural sector based on the estimated dynamic model. Authors compare static with dynamic elasticities, provide dynamic measures of economies of scale and scope etc. The studies with the strongest policy implications are a number of studies (e.g. Fernandez et al., 1992; Richards and Jeffrey, 1997) that analyse the effects of production quotas using a dynamic adjustment costs framework, but also these studies only give general implications. It seems that these models are hardly being used to analyse dynamic policy effects or to predict long-term changes in farming sectors. Maybe (researchers think) there is less potential for such articles to be published, or maybe researchers are more interested in contributing to the modelling library instead of using models to answer policy questions. Nevertheless, the impact of this literature on the policy debate has been very modest.

Another critical remark should be made on the concept of adjustment costs itself. Despite all the theoretical work done, adjustment costs remain a rather theoretical concept. We can estimate functions that approximate them, but they never directly show up in our datasets. In that respect the concept of adjustment costs has similarities with the concept of transaction costs. Theoretically these concepts make sense but they are hard to get grip on. And even if they are present, are they really big enough to prevent or slow down adjustment? Moreover, given that most data available used is yearly data the question arises whether we can really assess adjustment costs in this time span. Although for buildings that might take more than one year to be finished this may be plausible, for machinery which is usually bought at once within a given year this is harder to believe. Overlooking the literature, one can question whether convex adjustment cost functions were included in our optimization problems because we were convinced on the existence and importance of adjustment costs or primarily because of the nice implication that the first-order condition of an optimization problem with convex adjustment cost can be rewritten into an equation where current investment is a linear function of one period lagged investment. In other words, theoretical models with convex adjustment costs directly result in a dynamic equation that can be estimated. Whatever the answer to this question, it is striking that with the dawn of option models to explain investment the concept of adjustment costs seems to have disappeared.

Whereas adjustment costs models stress the presence of adjustment costs as a reason for sluggish adjustment of quasi-fixed factors, investment models based on real options theory (Dixit and Pindyck, 2004) focus on the role of uncertainty in combination with irreversibility of investments. In those circumstances firms have an option to wait to invest until new information on uncertain events arrive, and the uncertainty is therefore responsible for investment thresholds. This flexibility in combination with the stochastic process of the uncertain variables (e.g. prices or policies) provide the dynamics of these models.

Most studies based on real options theory use simulation techniques to calculate investment thresholds and option values of waiting. However, there are also a number of studies that used microdata to estimate these models. Richards (1996) estimates a friction model of asymmetric investment for the Alberta dairy industry and uses option theory as an explanation for the obtained thresholds in cattle investment. Richards and Patterson (1998) use option theory to explain reluctance of workers to take agricultural jobs. In their empirical analysis they use wage rates and a parity bounds model to calculate option values. Using a similar empirical approach and panel data for Dutch specialised pig farms Wossink and Gardebroek (2006) estimated an option model to show how policy uncertainty on a system of environmental market permits led to reluctance of farmers to investment and hence failure of the system. In a dynamic dual framework Pietola and Myers (2000) estimated the stochastic transition equations for output and rental prices as a Geometric Brownian motion and showed that this framework allows for deriving a consistent system of variable input and dynamic factor demand equations under stochastic transition equations. Based on their framework Pietola and Myers derive implications for structural adjustment in the Finish hog industry. Pietola and Wang (2000) derived thresholds for investment in piglet contracts using time-series data on piglet prices.

What is striking at these applications is that the models estimated can hardly be called structural models of firm behaviour. Some studies estimate a system of switching regressions explaining different regimes of adjustment and yielding investment thresholds and use the option theory as a theoretical motivation. Other studies just use time-series econometrics to assess the time-series properties of the available data and then simulate thresholds and option values. Major steps need to be taken to connect option theory to a structural system of equations that fully describe firm behaviour. However, it is interesting to observe that the limited number of studies reported here mostly have a clear policy interest.

2.2. Dynamic household models

The connection between the farming business and the farmer's household that is characteristic for family farms has led to research on agricultural household models. In household models consumption, production and labour supply decisions are integrated in one model. Many of these decisions have long term consequences, e.g. dissaving to consume durable goods, investing or taking a permanent off-farm job. In principle, these long-run effects can be analyzed with static long run models. However, decisions taken now usually also have direct effects on future circumstances. For example, borrowing for investment implies repayment in subsequent years. Investing in a milking robot may lead to a weakened financial position blocking other big investments in the near future, but on the other hand also leads to a reduced labour need. Therefore, it is natural to focus on the dynamics of household decisions. Dynamic household models are more commonly known as intertemporal household models. See Deaton (1992) for an introduction to dynamic household models. In terms of structure and empirical strategies used they have much in common with primal investment models. From the dynamic utility maximization problem, first-order conditions are derived and solved yielding a set of Euler equations that are estimated using dynamic panel data methods.

The first dynamic household models, often denoted as life-cycle models mainly focused on optimal intertemporal consumption (consumption smoothing) in relation to borrowing, lending and insurance. Langemeier and Patrick (1993) estimated a life-cycle model using time-series and cross-section data to

investigate whether farm family consumption is liquidity constrained. Phimister (1995) investigated the effect of borrowing restrictions on farm family consumption using 2 years of panel data of Dutch dairy farmers. Despite the use of panel data, panel data estimation techniques are not used in this paper.

Benjamin and Phimister (1997; 2002) used dynamic household models to analyze farm investment decisions. Their models allow taking the financial situation of the farm household into account. It is obvious that these models are closely related to dynamic investment studies, e.g. by including an adjustment cost function. Both studies use panel data and the Arrelano-Bond dynamic panel data estimator. A related study is Chavas and Thomas (1999) who analysed the dynamics of land prices assuming dynamic utility maximization with a budget constraints that includes consumption and costs and benefits of different farm assets.

Analysing dynamic effects of labour allocation decisions is another motivation for the use of dynamic households models. Phimister, Vera-Toscano and Weersink (2002) use a dynamic theoretical household model developed by Hyslop (1999) to analyze differences in female labour participation in rural and urban areas in Canada. Their empirical analysis consists of a static and dynamic random effects probit model with included covariates based on the theoretical household model.

Looking at the number of studies based on dynamic household models, it can be concluded that this type of model is not frequently applied in agricultural economics focusing on developed countries. More applications can be found on households in developing countries (see De Janvry et al. 2002 for a review), which is natural given the relatively greater connection between farm business and household in these countries. Some recent interesting studies are Bellemare and Barrett (2006) who investigated the simultaneity of market participation and production decisions, Park (2006) who analysed households' joint production, storage and trade decisions taking transaction costs and price and yield risks into account, and Holden et al. (2004) who integrated bio-economic elements (soil degradation and agronomic factors in crop growth) in a dynamic household model in order to analyse the effects of increased non-farm income on welfare, production and soil degradation.

However, the greater emphasis on rural development issues in Western countries could lead to an increased interest in dynamic household models. Issues like rural incomes and labour supply are naturally analyzed from a household perspective. The limited number of studies can also be explained from the strong data requirements for estimating these models. Not only does one need panel data on the farming business, but also on the household situation, information that may be more difficult to obtain. Another explanation for the limited use of dynamic household models lies in the solution of the optimization problem. Just like is the case with static household models, closed form solutions can only be obtained under the assumption of separability, i.e. absence of market failures. Since this assumption is too strong in most applications only reduced form equations can be estimated.

2.3. Dynamic discrete choice

Dynamic discrete choice models typically elaborate on a framework in which a firm operator decides among K possible alternatives in N (finite) discrete periods of time. Alternatives are indicated by a set

of dummy variables $d_k(t)$, with $d_k(t) = 1$ if alternative k is chosen at time t and $d_k(t) = 0$ otherwise. The condition $\sum_{k=1}^K d_k(t) = 1$ indicates that alternatives are mutually exclusive. Also, each alternative option is associated with a one period reward function $R_k(t)$ that is known to the firm operator at time t , but that is random from the perspective of periods prior to t , i.e. the firm operator does not know the outcome with certainty prior to t . It is assumed that reward represents short-term profit, which is defined as revenue minus variable costs.

The objective of the firm operator at any time $t = 0, \dots, N$ is to maximise the discounted present value of the short-term profits, $R_k(t)$. The optimal value function $V(\cdot)$ for the problem then solves:

$$V(S(t), t) = \max_{\{d_k(t)\}_{k \in K}} E \left[\sum_{\tau=t}^N \rho^{\tau-t} \sum_{k \in K} R_k(\tau) d_k(\tau) \middle| S(t) \right] \quad (1)$$

where $\rho > 0$ is the discount factor, $E(\cdot)$ is the mathematical expectations operator, and $S(t)$ is the predetermined state space at time t . The state space consists of all factors, known to the firm operator that affect the current period short-term profit (e.g. input and output prices, fixed inputs and firm-specific factors affecting the production technology). Maximisation of (1) involves choosing the optimal sequence of control variables ($d_k(t)$) over the finite horizon of $t = 0, \dots, N$. The optimal value function can also be rewritten as (Keane and Wolpin, 1994):

$$V(S(t), t) = \max_{k \in K} \{V_k(S(t), t)\} \quad (2)$$

where $V_k(S(t), t)$ is the choice k specific value function that satisfies the Bellman equation and after augmenting V_{kt} by an error term v_{kt} , equation (2) can be written in a reduced form where discrete choice k is chosen if

$$V_{kt} + v_{kt} > V_{jt} + v_{jt}, \quad \forall j \neq k \quad (3)$$

The dynamic theoretical model given in (1) usually simplifies into a reduced form expression such as (3) and is frequently estimated using standard univariate or multivariate probit models. However, such models typically ignore the interdependence of production decisions that may be caused by adjustment costs in changing between discrete choices. Dynamic discrete choice estimation methods are capable of accounting for such time-interdependencies in discrete choices. This is accomplished by employing a Geweke-Hajivassiliou-Keane (GHK) simulated maximum likelihood method or any other estimation method that accounts for correlation of errors over time. The GHK method estimates the parameters of the reduced form equation along with a variance-covariance matrix of error terms. The method requires panel data, but becomes computationally burdensome in case the time period is large.

Dynamic discrete choice models have been applied to a wide variety of problems in agriculture. A number of authors have applied these models to *technology choices*. Pietola and Oude Lansink (2001) modelled farmers choices between organic and conventional farming technologies using an

endogenous Probit-type switching model estimated with Maximum Likelihood Estimation (MLE). Their estimation accounted for the possibility of serial correlation of the period-by-period choices since the farmers' choices may be expected to have persistency over time (e.g. due to adjustment costs). In their model, serial correlation may also arise if next period choices are affected by past revenue shocks. Furthermore, Pietola and Oude Lansink (2005) employed the GHK simulated Maximum Likelihood method to estimate energy saving technology choices of Dutch glasshouse firms. Their model allowed for time-constant, firm-specific effects and serial correlation of errors and it is estimated on panel data. The unobserved error sequences are simulated in the model such that they are consistent with the observed technology choices. The authors found evidence for persistence of technology choices over time through error terms that are correlated over time.

Dynamic discrete choice models have also been used to estimate farmers' occupational choices. Pietola et al. (2003) analyse farmers' choices between three discrete occupational options: (1) exit and close down the farming operation; (2) exit and transfer the farm to a new entrant; (3) continue farming and retain the option to exit later. The optimisation problem is formulated as a recursive optimal stopping problem. The unknown parameters are first estimated by a switching-type multivariate probit model and then by the simulated maximum likelihood (SML) method, controlling for serial correlation of the errors.

Miranda and Schnitkey (1995) estimate a dynamic discrete choice model of dairy cow replacement by solving Bellman's equation every time that model parameters are perturbed. Their model results suggest an unobserved premium on replacement which provides an explanation for the higher than recommended replacement rate of livestock. The unobserved replacement premium is likely caused by genetic improvements causing higher expected yields for new livestock and by imperfections in the market for heifers.

Another group of studies analysed the dynamics of consumers choice behaviour. Keane (1997) used data on ketchup purchases and estimated a dynamic discrete choice model using simulated maximum likelihood. His estimation method accounts for heterogeneity in preferences and persistence of consumer choices. He found evidence for true state dependence in the choice process, after controlling for heterogeneity. Simulating his model, he found that the long-term effect of a promotion-induced purchase on future purchase probabilities is positive but small. Gould and Dong (2003) used a household panel over such a short time period to analyse the interdependence of cheese purchases over time resulting from e.g. habit formation. Their model specified an autocorrelated error structure. The authors found empirical evidence for serial interdependence in cheese purchases.

2.4. Dynamic efficiency models

The economics profession has by now developed a vast literature on analysing technical and economic efficiency with parametric and nonparametric approaches. Prominent in the category of nonparametric methods is Data Envelopment Analysis, which is essentially a Linear Programming technique that builds on early work of Banker, Charnes and Cooper (1984). Parametric methods mainly centre around stochastic frontier analysis which finds its origin in the work of Meeusen and van den Broeck (1977) and Aigner Lovell and Schmidt (1977). Theoretical and empirical studies on analysing

efficiency have typically ignored the presence of adjustment costs and the consequential interdependence of production decisions over time. This may lead to incorrect measures of efficiency, i.e. measures of efficiency which suggest unattainable efficiency gains. This is illustrated in Figure 1 below.

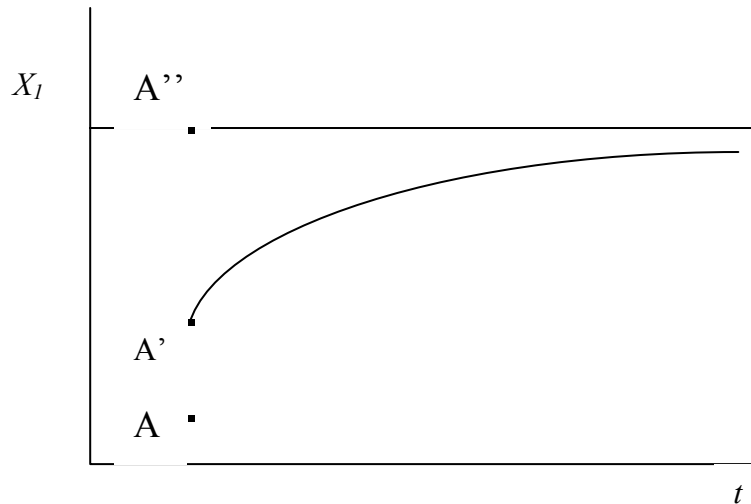


Figure 1. Efficiency and dynamic adjustment

In Figure 1, A represents an observation of input x_1 on a farm in a particular time period. The curve starting at A' represents the optimal adjustment of this input over time and A'' represents the long term optimal value. Static approaches typically assume that firms adjust to long term optimal values instantaneously and would measure efficiency as the ratio of A and A'' . Dynamic approaches on the other hand account for the optimal adjustment path and would measure efficiency as the ratio of A and A' .

Only few authors have by now modelled dynamic aspects in the analysis of production efficiency. Sengupta (1995) introduces the first order conditions of dynamic optimisation in Data Envelopment Analysis. Nemoto and Goto (1999, 2003) include the stock of capital at the end of the period in the DEA framework in a similar way as outputs. Silva and Stefanou (2007) develop nonparametric measures of technical, allocative and economic efficiency using an inter-temporal cost minimisation framework with technology that accounts for costs of adjustment. Their efficiency measures are explicitly inter-temporal as they describe the efficiency at a particular point in time along its adjustment path. Silva and Oude Lansink (2007) also develop technical, allocative and economic efficiency measures within a similar framework as Silva and Stefanou (2007). However, their paper introduces the concept of a directional distance function. Econometric approaches to measuring dynamic efficiency that explicitly account for the interdependence of production decisions over time are rare to date. A few studies have implicitly accounted for interdependence of production decisions over time by modelling the dynamics of efficiency. Lee and Schmidt (1993) use a nonlinear model that allows for any arbitrary pattern of temporal change in technical inefficiency but with the restriction that the pattern is identical for all firms. Battese and Coelli (1992) model technical inefficiency as an exponential function of time. Cornwell, Schmidt and Sickles (1990) allow firm

effects to vary over time but in quadratic form. Kumbhakar (1990) allows for an alternative specification, where technical inefficiency is an exponential function of quadratic time. Finally, Ahn and Sickles (2000) estimated a model in which technical inefficiency levels are permitted to be serially correlated with potentially different patterns across firms. Tsionas (2006) extended this model to allow for a simultaneous estimation of the inefficiency effects.

However, there are several promising paths for further development of econometrically estimated dynamic efficiency measures. One promising path for future research is the application of parametrically estimated dynamic directional distance functions. This concept allows for a computationally more simple estimation method and more easily allows for the use of a self-dual flexible functional form such as the quadratic, than the radial distance functions that are predominantly applied in the literature. Using self-dual functional forms allow for a more straightforward decomposition of economic efficiency into technical, scale and allocative efficiency. Moreover, the efficiency measures developed within the directional distance function context satisfy the condition of additivity in its decomposition (of economic efficiency into scale, allocative and technical efficiency).

A second promising avenue for future research is the application of the GHK simulated maximum likelihood method which allows for measuring correlation into error terms over time. Proceeding on this avenue requires estimation of a composite error term, with both one-sided and two-sided errors. Successful application of the GHK simulated maximum likelihood method would provide insight into the interdependence of inefficiency over time, in addition to interdependence of the error term over time.

3. Challenges in future work on dynamic microeconomic models

3.1. Incorporation of behavioural economics and bounded rationality

The behavioural economic literature that recently caught lot of attention has shown that economic agents often act in ways that conflict with the rationality hypothesis (Camerer et al., 2004). E.g. many studies have found that economic agents value losses differently from similar-sized gains and this valuation also depends on the reference point, e.g. a high or low income. Other studies showed that economic agents are often overconfident (Dittrich, et al., 2005) and impatient with respect to immediate gains that are discounted differently than gains in the more distant future ('hyperbolic discounting' see e.g. Laibson, 1997). Behavioural economics tries to improve the realism of the psychological foundations of economic theory. Many of its results were obtained from experimental studies that tested particular behavioural aspects. Therefore, there is a challenge to incorporate these findings in dynamic micro-econometric models. Moreover, many behavioural economic studies focus on consumer choices and it is therefore interesting to investigate how these findings relate to decision making by firms, e.g. in investment decisions. Are key findings of behavioural economics like loss aversion or hyperbolic discounting also relevant to firm decision making or are there other psychological processes that are important? De Bondt and Thaler (1994) indicate how general findings from the behavioural economic literature relate to financial decision making by firms. Another important lesson from the behavioural economic literature is that economic agents are heterogeneous

in their behaviour. They discount the future at different rates, use different reference points etc. This heterogeneity may also be expected in firm investment decision making.

Whereas the behavioural economic literature links economic choices with psychology, the related work on bounded rationality focuses more on formal modelling of limited cognitive capacity (Conlisk, 1996). An interesting line of work in this area focuses on the use of rules of thumb in economic decision making. Examples of rules of thumb in decision making are ‘spend all accumulated profits if output prices rise again after a period of decline’ or ‘invest in exceptionally good years’ or ‘invest if my colleagues or competitors invest’ (herd behaviour (Scharfstein and Stein, 1990)). Characteristic for rules of thumb is that they represent simple decision rules and differ from the mathematically optimal rule that characterizes the mainstream literature discussed above. The behavioural economic literature often denotes rules of thumb as heuristics (see Gilovich and Griffin, 2002 or Kahneman, Slovic and Tversky, 1982). Although the literature on this topic is scarce and hardly taken up the earliest applications go back several decades. Baumol and Quandt (1967) already recognized that information gathering for rational optimizers may be costly and that it may be more optimal for firms to take pricing decisions using rules of thumb. Day et al. (1974) presented a static model for firms’ decisions on production and investment and compared their approach in qualitative terms to the neoclassical investment model. Following this early work a small number of other studies have appeared that focused on rules of thumb in economic decision making, mostly with respect to consumer choice. Lettau and Uhlig (1999) give an overview of the limited work that has been done in this field. They contributed to the literature by integrating a simple ‘spend-all-in-good-times’ rule of thumb in an explicit dynamic framework and allowing for agent learning on the success of rules of thumb for consumption. Their approach might be extended to dynamic household models or even to dynamic models of firm behaviour.

3.2. Bayesian econometrics

In recent years Bayesian econometric methods have become more and more popular. Although Bayesian econometric theory already has been around for decades, it is the combination with sampling techniques (MCMC methods) that has spurred the empirical implementation of Bayesian methods. See Koop (2003), Lancaster (2004) or Koop et al. (2007) for accessible texts on this subject. Bayesian methods have a lot to offer for dynamic microeconomic models. First, of course the well-known feature of Bayesian techniques that prior information can be used in the estimation procedure. Although some researchers may consider this to be subjective, we think that for many variables in dynamic models this makes sense. There exist natural bounds on discount factors, depreciation rates, risk parameters or production elasticities that can be specified as prior information. A second advantage of Bayesian methods is that they are very well suited to deal with heterogeneity in behaviour. Bayesian random coefficient models are superior to classic random coefficient models (Gardebreek, 2006) and can be used to obtain firm specific slope parameters. This allows for modelling of individual slope parameters but also for differences in discounting, depreciation of capital goods and interest rates. Heterogeneity in behaviour can also be taken into account using so-called model averaging (Koop, 2003:265-282). E.g. different behavioural objectives or different expectation formation processes lead to different models and instead of choosing one particular model, Bayesian model averaging attaches probabilities to different models yielding an averaged model that can be used in subsequent policy analyses. So, where Bayesian random coefficient models allow for

parameter heterogeneity in one model, Bayesian model averaging takes into account the existence of different models. Model averaging also allows for comparing models based on bounded rationality assumptions with standard investment models based on the assumption of full rationality. Interesting in this respect is the recent work by Houser (2003) who uses an empirical Bayesian approach to estimate a labour supply life-cycle model that is flexible in the specification of expectations and can be used to infer one homogeneous agents' decision rule.

3.3. Data collection and revision of EU-FADN

The EU-FADN is expected to be revised in the near future and this leads to the natural question: what improvements can be made with respect to the current FADN to improve the contribution of dynamic models to policy analysis?

First, econometrically estimated dynamic models would benefit from increasing the time period that farms are observed in the panel. This is because longer time periods improve the information on unobserved heterogeneity within farms. Also, the analysis of an important policy issue like farm entry and exit would benefit from observing farms over a longer period.

Second, related to the first issue, the estimation of dynamic models would greatly benefit from including more household characteristics such as composition of the household, off-farm work employment, education of the operator and social network of the operator. These variables may make a very important contribution to explaining dynamic decisions and allow further development of dynamic household models.

Third, it is observed that the current FADN contains a limited list of capital goods used on the farm; more detailed information on investments in different capital goods would therefore be desirable. Also information about investments in intangible assets such as production rights, intellectual property rights and emission rights are currently missing and will surely be an important element in dynamic decision making now and in the future. Finally, investments in certificates or shares of the agribusiness would allow for a better analysis of the chain organisation.

4. The usefulness and use of dynamic microeconomic models for policy analysis

The overview of the literature on dynamic micro-econometric models in section two demonstrates a wide domain of applicability, with many potential implications for policy analysis. Dynamic micro econometric models have the potential to provide better insights into the long-term impacts of policy measures than static models. This is because dynamic models can explicitly account for changes in factors which are believed to be fixed in the short-term such as capital, production rights, land and (family) labour. Nevertheless, the literature on analyzing policy changes is still dominated by static models (e.g. Boots et al., 1997), also for the analysis of policy impacts in the long run. Clear examples of static models that dominate the analysis of policy measures are GTAP and CAPRI (see Arfini, 2005).

An explanation for the limited policy relevance of the current literature on micro-econometric models may be threefold. First, micro-econometric dynamic models often do not perform very well in terms of their explanatory power; hence researchers are reluctant to use dynamic rather than static models for policy analysis. The worse performance of dynamic micro-econometric models is largely explained by the fact that decisions on quasi-fixed factors such as land and labour are driven by other objectives (e.g. household-specific objectives) than decisions on short-term variable factors of production.

Second, developments in the long-term are determined by a wide range of conditions (on e.g. prices, state of technology, policy parameters) that are not under the control of the operator at the moment the decisions are made. Therefore, the operator has to base its decisions on its own expectations on such future conditions. Worse, such future conditions have to be specified in dynamic models and may become an important source of error and hence cause worse predictive power and lower reliability of policy simulations. Third, the domain of microeconomic dynamic models is less well developed than that of static models and researchers may be biased to making methodological contributions rather than providing insights into important policy issues. And important policy issues are abound. The ongoing reform of the Common European Policy, the impact of biofuels crops combined with rising demand for food crops on agricultural world markets, demands for food safety etc. all require in depth long-run analyses that specifically account for dynamic processes.

Clearly, there is a scope for a much more prominent role for dynamic models in the analysis of policy measures than their role to date. For this to achieve, it is necessary to let policy issues determine more prominently the specification and use of dynamic models. Researchers should become more aware of the potential to let model innovation go hand in hand with sound analyses of cutting-edge policy issues.

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