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# Innovation behaviour at micro level - selection and identification

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# INNOVATION BEHAVIOUR AT MICRO LEVEL – SELECTION AND IDENTIFICATION

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## Abstract

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## 1. Introduction

The adoption of new technologies in primary agricultural production has been at the centre of traditional agricultural economic analysis for the last 50 years: One stream of studies empirically investigates technology adoption and diffusion taking into account farmers' perceptions with respect to the risk of future yields (e.g. Yaron et al 1992, Kim and Chavas 2003, Koundouri et al 2006). Others point to the importance of information gathering, learning by doing and resources' accumulation for the adoption decision (e.g. Sunding and Zilberman 2001, Baerenklau 2005). An increasing number of studies model the adoption decision as a sample selection problem where the farms have to pass a first threshold to be selected into the sample of potential adopters. Depending on the technology to be adopted, the selection threshold refers either to size, network access or a certain level of human capital (e.g. McBride et al. 2004, Moser and Barrett 2006 or Abdulai et al. 2008). Building on these findings our study aims to make a step forward by simultaneously modelling the effects of risk, social interaction, past innovation experiences and the sequential structure of adoption decisions. Different econometric models are applied to incorporate these potential factors and structural characteristics. A unique dataset on dairy producers in Northern Europe is used to empirically investigate the adoption of automatic milking systems (AMS).

## 2. Automatic Milking

Rising labor costs in the mid seventies were one of the main reasons for an increasing automation in the milking sector. Crucial steps were the development of a reliable cow identification system which could then be used for automatic concentrate feeders, the development of automatic cluster removers, sensors to detect udder health problems, and finally the development of automatic teat cup attachment systems (Meijering et al., 2002; Kochan, 2004). An entirely automated milking system (AMS) - also called robotic milking system (RMS) - was firstly developed in the Netherlands in the 1980s and the first commercial RMS was placed into production there in 1992. Until the mid of the 1990s about 250 farms worldwide used AM systems whereas the breakthrough of the AMS technology occurred at the end of the 1990s. Today AMS is in use on about 5,500 milk farms worldwide (Svennersten-Sjaunja and Pettersson, 2008). More than 90% of all dairy farms using AMS are located in northwestern Europe where investments are driven by high labor costs, a continuous increase in the average herd-size and a dominance of the family farm structure (Meijering et al., 2002). Originally, AMS were targeted for small family farms with up to 150 cows, however, with continuous

technological progress and increased management skills, AMS is now also installed on larger farms with more than 500 cows per herd.

In general there are two basic designs of automatic milking systems. The first is the single-stall system, in which one milking robot serves only one milking stall with approximately 60 cows. The second design is a multi-stall system, in which the robot travels along a rail between different stalls where each stall can service fewer than 60 cows (Hyde et al., 2007). Automatic milking relies on the cow's motivation to enter the system voluntarily where the main motive is the supply of concentrate.

Previous studies on the economics of different milking systems revealed that a minimum herd size of about 60 cows is needed for an automatic milking system to work more profitable than traditional milking systems (see Rotz et al. 2003; Hyde and Engle, 2002; Hyde et al. 2007, DeKoning et al. 2002). On farm sizes well above this threshold multi-stall AMS (one robot shared across two to four stalls) show greater potential net return than the use of two or more single-stall units (one robot per stall). The herd milk production level was found to have only a small effect on the economic difference between traditional and automatic milking systems with a greater difference at a higher level of production (Rotz et al. 2003). The potential benefit of AMS is improved if a substantial increase in production is maintained through a greater milking frequency. Studies showed that a large increase in the cost of labor can improve the net return of an automatic milking system over all herd sizes. Finally, farm net return with an AMS is significantly reduced if the economic life of the automatic system is reduced to represent a more rapid depreciation than normally occurs with traditional milking systems (Rotz et al. 2003). Two great advantages with AMS include reducing the workload of milking and milking more often than twice daily without incurring extra labor costs (Dijkhuizen et al. 1997). On average, a 10% reduction in total labor demand is reported compared with conventional milking systems with twice milkings per day (Sonck 1995, Schick et al. 2000, DeKoning et al. 2003). Furthermore, milking frequencies of more than twice daily can be reached under automatic milking which is desired for high-yielding cows as 3 milkings a day are expected to enhance lactation milk yield by 10 to 15% on average (Veysset et al 2001, Billon 2002, Svennersten-Sjaunja et al. 2000, Speroni et al. 2002; Oesterman and Bertilsson 2003, Wagner-Storch and Palmer 2003).

Others stress the consistency of the milking process with automatic milking technology: In a working AM system, the animals are treated in the same way at each milking and the routines are predictable for the cows which increases milk production (Rasmussen et al. 1990, Samuelson et al. 1993). Different research projects have been conducted to understand the effect of AMS on milk quality including both compositional and hygienic aspects. A comparison of conventional and automatic milking showed no differences between the milking systems for fat

and protein contents (Svennersten-Sjaunja et al. 2000). However, others revealed an increased level of free-fatty acid concentration (FFA) in milk collected from farms that had introduced AMS (Justesen and Rasmussen 2000) or when compared with levels of milk FFA before automatic milking was introduced (DeKoning et al. 2003). With respect to milk hygiene, reports from the Netherlands and Denmark indicated that the total bacterial count (TBC) increased in the bulk milk after introduction of automatic milking (Klungel et al. 2000, Rasmussen et al. 2002). Other studies, however, revealed that after 6 months the TBC stabilized and after 1 year the level of TBC was almost the same as on farms with conventional milking (Van der Vorst et al. 2002). Initial studies concluding in an increased somatic cell count (SCC) after introduction of AMS (see e.g. Klungel et al. 2000 or Kruip et al. 2002) were followed by studies showing that automatic milking does not increase the incidence of udder infections and SCC (e.g. Berglund et al. 2002, Zecconi et al. 2003 or Bennedsgaard et al. 2006, Svennersten-Sjaunja and Pettersson 2008). Finally, with respect to animal welfare, Hagen et al. (2005) note, that the cows kept in an AMS displayed an increased chronic stress (measured as heart rate variability) compared with cows kept in a loose housing system. On the other side, such stress was not observed during milking (Hagen et al. 2005) corresponding to the findings by Gygax et al. (2006) who could not confirm differences in milk cortisol between cows milked in an automatic vs such milked in a conventional system. It is clear from these previous studies that AMS is not only a new milking system, but rather a completely new management system. Mathijs (2004) as well as Hyde et al. (2007) stress that noneconomic factors such as lifestyle choices including avoiding labor management are at least as important as economic factors for the decision to adopt an automatic milking system. Meijering et al (2002) name the following key factors for a successful implementation of automatic milking systems: realistic expectations, consultancy support before, during and after implementation, effective system control and computer skills, an appropriate barn layout and functioning cow traffic, technical functioning and regular maintenance.

## 3. Adoption Literature Review

The economic literature on technology adoption started with the seminal work by Griliches (1957) who viewed adoption as a process of imitation. An alternative approach, the threshold model of adoption, was introduced by David (1975). This approach is based on the assumptions of explicit micro level behaviour, heterogeneity among individual units and a dynamic process of individual learning leading to a gradual diffusion of technology adoption over time. Feder et al (1985) emphasized that the introduction of discrete choice modelling allows the identification

of sources of such heterogeneity affecting the timing and extent of adoption. Another strang of early contributions to the literature (xxx) make use of expected utility modelling focusing on the identification of size effects, risk preferences and variations in human capital as potential factors for technology adoption choices. Later studies (see the surveys by Feder and Umali, 1993 as well as Sunding and Zilberman, 2001) emphasized the importance of considering the timing of adoption, investment irreversibility and input quality improvements with respect to adoption choices.

Putler and Zilberman (1988) examine computer and application ownership patterns in Californian agriculture. Their analysis indicates that the size of the farming operation, education level, age level, and the ownership of a farm-related nonfarming business significantly influence the probability of computer ownership. Foltz and Chang (2002) study the adoption and profitability of Recombinant bovine somatotropin (rbST) on dairy farms in Connecticut. Their research shows that larger farms with more productive technologies and with younger, more educated farmers are more likely to adopt rbST. Barham et al. (2004) investigate the dynamics of rbST adoption on dairy farms and examine the characteristics that distinguish among nonadopters, disadopters, as well as early and late adopters. Their results confirm previous findings showing that larger farms with complementary feeding technologies are more likely to adopt rbST whereas nonadopters appear quite unlikely to become adopters. Abdulai and Huffman (2005) try to explain diffusion of crossbred-cow technology for a sample of Tanzanian farmers and conclude that the adoption of such technology positively depends on the proximity of the farm to other users, on his schooling, and on his access to credit as well as extension services. So far, no empirical research has been undertaken which investigates the adoption of automatic milking technology in favor of conventional milking systems.

The study by Feder et al. (1985) suggested that technology adoption choices are part of packages of different changes including also the introduction of new inputs as well as the expansion of the scale of operations. However, not much empirical documentation is available which explicitly relates the technology adoption decision to an increase in farm size in order to be able to take advantage of economies of scale. These are main contributions of this paper.

### *3.1 Risk*

One stream of studies empirically investigate technology adoption and diffusion taking into account farmers' perceptions with respect to the risk of future yield. Yaron et al. (1992) attempt to analyze the effect of price uncertainty on the degree of innovation exhibited by family farms in Israel. Kim and Chavas (2003) investigate the dynamic effects of technological progress on risk exposure by using the conditional moments of the estimated yield and profit for corn

farmers in Wisconsin. They conclude that technological progress significantly contributes to reducing the exposure to risk and downside risk over time. Koundouri et al. (2006) built on the framework suggested by Antle (1983, 1987) and followed by Kim and Chavas (2003) and develop a theoretical model to describe irrigation technology adoption by farmers facing production risk and incomplete information about new technology. The adoption decision is derived under the assumptions of farmers' risk aversion and uncertainty because of random climatic conditions and future profit development. The estimated first four moments of the farmers' profit distribution are incorporated in the technology adoption model as explaining factors. They found risk to play an essential role in farmers' decision to adopt the new technology.

*3.2 Learning, Network Externalities and Peer-Group Effects*

Sunding and Zilberman (2001) point out that a complete analytical framework for investigating adoption decisions should include information gathering, learning by doing and resources' accumulation. Rosenberg (1982) distinguishes between three different forms of learning: 'learning by doing', 'learning by using', and 'traditional learning'. Learning by doing relates to the supply of the technology, hence does not provide an explanation for why a firm would be an early or late adopter (McWilliams and Zilberman, 1996). Learning by using describes the effect of the users of a given technology (i.e. the demand side) increasing their productivity over time as they learn how to better use this new technology. Finally, traditional learning as the most commonly discussed form of learning which involves potential adopters gathering information about the performance of a new technology (i.e. its expected profit and variance). Firms or farms are uncertain about the value of the new technology and are thus hesitant to invest in the technology without having sufficient information on its performance. Such information may be obtained by observing and interacting with others adopting and using the technology (i.e. peer-group spillover effects, informational cascades), by talking to technology suppliers, or by experimenting with the new technology themselves. McWilliams and Zilberman (1996) point out, that potential adopters use the gained information to update their posterior expectations and beliefs about the new technology over time in a Bayesian manner (see also Lindner et al. 1979, Stoneman 1981, Jensen 1982). In the context of this paper learning by using as well as traditional learning will be of interest. Baerenklau (2005) points out, that traditional learning in the sense of 'learning from others' is more complicated as it may become rational for a forward-looking agent to postpone adoption (at least partially) until better information becomes available regarding the expected benefit of adoption. Such agents would tend to 'wait and see' what happens to their neighbors (i.e. free-riding on others' technology experiences) before they

assume the expected private costs of experimenting with a new technology themselves (i.e. an information or network externality). Foster and Rosenzweig (1995) as well as Besley and Case (1997) found that dynamic information externalities have only small observable effects on the less costly and reversible adoption of new seed varieties. For adoption decisions with respect to large, capital-intensive and irreversible decisions as examined in this study, a non-dynamic type of behavioural spillover – referred to as neighborhood effect or peer-group effect (Banerjee 1992, Baerenklau 2005) – may have greater relevance. Social scientists have examined such effects in several theoretical contributions (e.g. Coleman et al. 1966, Schelling 1971, for a more recent overview see also Brock and Durlauf 2001). However, with respect to empirical modelling confounding identification problems have to be considered (Manski 1993): i) endogenous (peer-group or neighbourhood) effects refer to the phenomenon that the propensity of an agent to behave varies with the behaviour of his peer-group; ii) exogenous (contextual: time and space related, i.e. fixed) effects describe the covariance between the propensity of an agent to behave and exogenous characteristics of the peer-group; and iii) correlated (unobservable influences, i.e. random) effects refer to the observation that agents in the same group tend to behave similarly because of similar individual characteristics or institutional constraints. Nevertheless, previous research on technology adoption behaviour has acknowledged the effect of such peer-group effects by noting the importance of network externalities as a function of the total number of technology users or by formulating the concepts of an informational cascade, first-movers based on signalling, and pure conformity preference. Brock and Durlauf (2001) found that nonlinear modelling can be used to identify these individual effects (see also An and Kiefer 1995 and Durlauf 2003), however, as Baerenklau (2005) notes, there remains a lack of empirical research that incorporates social interactions into behavioural models to explain technology adoption.

*3.3 Selectivity, Sequential Decisions and Path-Dependent Behaviour*

An increasing number of studies model the adoption decision as a sample selection problem where the adopting farms or firms have to pass a first threshold to be selected into the sample of potential adopters. Depending on the technology to be adopted, the selection threshold refers either to size, network access or a certain level of human capital. The modelling structure has then to correct for such sample selection bias. Asterbro (2003) uses a Heckman two-stage selection model to study how sunk costs and size affects the probability and depth of adoption (see also Smale et al. 1994, McBride et al. 2004, Dridi and Khanna 2005, Moser and Barrett 2006, or Abdulai et al. 2008). Smith et al. (2004) investigate the computer and internet use by Great Plains farmers by modelling the exposure to the technology as adoption threshold. Foltz

and Chang (2002) note that the decision of a farmer to adopt rbST is based on each farmer's self-selection instead of random assignment. Hence, their modelling approach consists of an index function model (i.e.probit) to endogenize the adoption decision with respect to yield and profit estimations. Different other contributions aim to tackle the phenomen that the adoption decision is not only subject to prior threshold criteria, moreover is part of a joint or sequential decision structure. Moreno and Sunding (2005) estimate a nested logit model of joint technology and crop choices aiming to acccount for unobserved correlation among these decisions. The results support their modelling choice of a nested structure alternative to a standard multinomial logit approach. Khanna (2001) applies a double selectivity model based on bivariate sequential probits to study the sequential decision to adopt two site-specific technologies, soil testing and variable rate technology and the impact on nitrogen productivity. The results indicate that the factors for the two sequential adoption decisions differ significantly and that nitrogen productivity gains from adoption depend on the soil quality given. Finally, a number of more business related studies investigate the effect of learning and path-dependent behaviour on the diffusion of innovations: Mazzoleni (1997) studies different path-dependencies of innovation behaviour related to different markets and found that different perceptions of the technology influenced the strategies of firms in the industry, the adoption behaviour of the individual users, and thus the market outcome of the diffusion processes (see also Coombs and Hull 1998, Canepa and Stoneman 2004).

The experiences with the implementation of automatic milking systems reported in the previous section suggest that a relevant empirical adoption model should incorporate the following aspects: (i) individual risk preferences to account for the tendency of farmers to care about profit developments in the first years after AMS adoption, (ii) sample selection due to a minimum herd size threshold, (iii) sequential decisions with respect to an increase in herd size and the adoption of automatic milking, (iv) learning by using, peer-group effects and network externalities based on the social interaction of the farmers with others who have already adopted the technology as well as the dissemination of individual experiences with AMS, and (v) the potential relevance of earlier experiences with the successful adoption of other technologies (e.g. organic dairy farming practices).

## 4. Conceptual Framework

We assume that risk averse dairy farmers utilize a vector of inputs **x** to produce an output q through a technology described by a well-behaved - continuous and twice differentiable - production function $f(\cdot)$. The individual farmer is assumed to incur production risk as milk yield

and quality might be affected not only by herd health but also by technology underperformance or failure. Such risk can be considered by a random variable $\varepsilon$ with its distribution $G(\cdot)$ which is exogenously determined. Dairy farmers in our sample are assumed to be price-takers in both the input and output markets as our study area consists of a relatively small and homogenous geographic area and hence factor price variability is low (Huffmann and Mercier 1991). Dairy farmers in Europe further face a minimum guaranteed milk price regulated by the dairy regime of the Common Agricultural Policy of the EU.

These farms can be assumed to maximize expected discounted net benefits from the technology applied based on their individual expectations about future price increases. The farmer decides on a potential expansion of the farm's operations and decides on a potential adoption of the new technology. Following Dixit and Pyndick (1994) and McWilliams and Zilberman (1996) the decision criteria in each period is based on the assumption that the expansion of the scale of operations exceeds a certain threshold (i.e. a hurdle), following

(1) $\mathrm{E}[\mathrm{U}\varpi^{1}] - \mathrm{E}[\mathrm{U}\varpi^{0}] - \mathrm{K} > 0$

where $\mathrm{E}[\mathrm{U}\varpi^{1}]$ is the expected utility with adoption, $\mathrm{E}[\mathrm{U}\varpi^{0}]$ is the expected utility without adoption, and K refers to the scale threshold. Each farmers faces two choices: the choice of expanding the scale of production ($D_1$) and the choice of adopting the technology ($D_2$). Hence, the dairy farmer maximises the expected utility of profit $\varpi$ described by (2)

(2) $\max_{\mathrm{D1,D2}}\{\mathrm{E}[\mathrm{U}\varpi(\mathrm{D1},\mathrm{D2})] - \mathrm{H}[\mathrm{r},]\}$

x

**?????**

***David, your help please ! Could you write me a proper model exposition here leading to what I have written before. I got somehow lost following up what you have proposed.....***

As outlined in the previous section labor input ($x_l$) is essential in the dairy farm production process. The efficiency of labor use critically depends on the utilized milking technology and can be captured by incorporating a function $h(\alpha)$ in the milk production function $q = f[h(\alpha)x_l, \mathbf{x}]$ where $\alpha$ is a vector of heterogeneous farm and farmer characteristics. The risk averse dairy farmer maximises the expected utility of profit $\varpi$ described by (1)

$$(1)\ \max_{\mathbf{x},x_l} E[U(\varpi)] = \max_{\mathbf{x},x_l} \int \{U[\, pf(\mathbf{x}, h(\alpha)x_l, \varepsilon) - \mathbf{r}'\mathbf{x} - r_l x_l\,]\} dG(\varepsilon)$$

where $U(\cdot)$ is the von Neumann-Morgenstern utility function, and $p$ and $r$ as the non-random output and input prices respectively. The first-order condition for labor input choice is given by

$$(2)\ E[r_i U'] = E\left\{p \frac{\partial f(\varepsilon, h(\alpha)x_l, \mathbf{x})}{\partial x_l} U'\right\} \Leftrightarrow \frac{r_l}{p} = E\left\{\frac{\partial f(\varepsilon, h(\alpha)x_l, \mathbf{x})}{\partial x_l}\right\} + \frac{\mathrm{cov}[U'; \partial f(\varepsilon, h(\alpha)x_l, \mathbf{x})/\partial \mathrm{x_l}]}{E[U']}$$

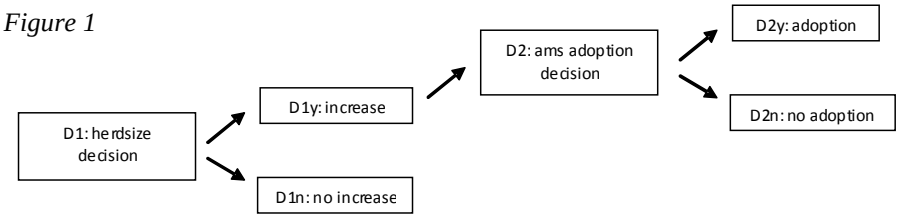
with $U' = \partial U(\varpi)/\partial \varpi$ and with the first term on the right-hand side denoting the expected marginal product of the labor input, and the second term measuring deviations from risk-neutral behaviour in the case of assumed risk-aversion (Koundouri et al. 2006).

The decision whether or not to adopt a more labor efficient milking technology can be modeled as a binary choice, where the farmer chooses to adopt (=1) or not (=0). In the case of adoption, labor use efficiency is increased: $h^1(\alpha) > h^0(\alpha)$ for $0<\alpha<1$. The dairy farmer will adopt the new and more efficient milking technology if the expected utility with adoption ($E[U\varpi^1]$) is greater than the expected utility without adoption ($E[U\varpi^0]$): $E[U\varpi^1] - E[U\varpi^0] > 0$. Future profit flows after adopting the new milking technology are not known with certainty due either to ignorance of the exact technology performance or to the higher probability of technology failure as a consequence of errors in the use and maintenance of this technology. Furthermore, investing in the new milking technology entails sunk costs because of a fixed cost portion and the risk linked to a potential resale of the equipment. As Dixit and Pindyck (1994) point out, additional information on the performance and risks of the new technology might possess a positive value for the individual farmer. Linked to such information is the case that some dairy farmers may prefer to delay the adoption until more information becomes available and consequently, an extra premium may enter the technology adoption decision: $(E[U\varpi^0])$: $E[U\varpi^1] - E[U\varpi^0] > InfV$ where $InfV \geq 0$ represents the value of new information for the individual dairy farmer. *InfV* can be described as a function of the initial fixed costs of technology investment, the level of uncertainty related to the new technology (e.g. access to peer-group experiences, extension services), and the farmer's own characteristics and experiences (e.g. age, farming experience, successful technology innovations in the past).

*4.1 Sequential Selection*

A second layer of the model is related to the reported threshold for adopting automatic milking technology in terms of a required minimum herd size of about 60 cows. This threshold can be conceptualized along the lines of a double selectivity sequential adoption problem: The decision to increase the scale of milk production by an increase in herdsize or not (*D1*) is followed by the decision to invest in the automatic milking technology or not (*D2*). If the farmer decides not to increase the herdsize (*D1n*) then the AMS adoption decision (*D2*) is not relevant (see figure 1).

*Figure 1*




A rational farmer would increase the herdsize if the expected benefits $U_{D1}^{*}$are greater than zero where

(5) $U_{D1}^{*} = U(D1y) - U(D1n) > 0$

and correspondingly would adopt the new milking technology if the expected benefits $U_{D2}^{*}$ are greater than zero with

(6) $U_{D2}^{*} = U(D2y) - U(D2n) > 0.$

The net benefts $U_{D1}^{*}$ and $U_{D2}^{*}$ are latent variables, assumed to be random functions of vectors of observed exogenous variables $Z_1$ and $Z_2$

(7) $U_{D1}^{*} = Z_1\gamma_1 + \varepsilon_1$ and $U_{D2}^{*} = Z_2\gamma_2 + \varepsilon_2$

where $\varepsilon_1$ and $\varepsilon_2$ are random error terms and $\gamma_1$ and $\gamma_2$ are vectors of unknown coefficients. The observable choices of the dairy farmer are

(8) $D_1 = D_{1y}\ \ if\ \ U_{D1}^{*} > 0;\ D_1 = D_{1n}$ otherwise and

(9) $D_2 = D_{2y}\ \ if\ \ U_{D2}^{*} > 0\ \ and\ D_1 = D_{1y};\ D_2 = D_{2n}\ \ otherwise.$

However, the selection equation (9) is defined only over the subsample where $D_1 = D_{1y}$ (since $D_1 = D_{1n}\ and\ D_2 = D_{2y}$ is not observed). This three-way grouping leads to a bivariate sequential model with the probabilities of the three outcomes

(10) $Pr_{D1y,D2y} = \Pr(D_1 = D_{1y}; D_2 = D_{2y}) = \Phi_2(Z_1\gamma_1, Z_2\gamma_2, \rho)$

(11) $Pr_{D1y,D2n} = \Pr(D_1 = D_{1y}; D_2 = D_{2n}) = \Phi(Z_1\gamma_1, \rho) - Pr_{D1y,D2y}$

(12) $Pr_{D1n,D2n} = \Pr(D_1 = D_{1n}) = 1 - \Phi(Z_1\gamma_1)$

where $\Phi$ and $\Phi_2$ are the cumulative distribution functions of the standard normal distribution and the standard bivariate normal distribution with correlation coefficient $\rho$, respectively.

*4.2 Peer-Group/Neighboring Effetcs*

A third component refers to the formalisation of effects based on the social interaction of the farmer with other members of the relevant peer-group (i.e. a non-dynamic type of behavioural spillover effect). Such network externalities and the dissemination of experiences based on learning by using the automatic milking technology in the ”neighbourhood” can be approximated by a spatial diffusion measure for the new technology (see Brock and Durlauf 2001, Baerenklau 2005). Taking a certain time lag into account with respect to the manifestation of such social interaction or peer-group effects *pg* is defined as a weighted proxy for the diffusion of the AMS technology in the neighboring region(s):

(13) $pg_{it}^{c} = \left(\frac{N_c^{ams}}{N_c}\right)_{t-1}$

where *i*, *t* and *c* denote farm *i*, time *t*, and region/county *c*, respectively. $N_c^{ams}$ as the number of farms in the county/region having adopted the AMS technology and $N_c$ as the total number of farms in the respective county/region.

*4.3 Identification Problem*

As outlined above, serious identification problems have to be considered with respect to the empirical modelling of factors for innovation behaviour based on social interaction. Endogenous effects, as e.g. peer-group or neighbourhood based influences have to be distinguished from exogenous effects, as e.g. time and space related influences affecting the individual farmer and his peer-group in the same way. Finally, unobservable (i.e. random) effects refer to the notion that farmers belonging to the same ”group” tend to show similar behavioural patterns as a function of similar individual characteristics and/or structural and/or institutional constraints (e.g. similar past experiences with respect to core farming practices and innovation, similar structural farming conditions, similar exposure to policy/social events at the same point in time etc.) By applying a modelling approach that allows for the consideration of both fixed and random effects with respect to the AMS adoption decision an effort to empirically capture and probably identify these effects can be made. Exogenous and endogenous fixed effects are distinguished from random effects based on the grouping structure of the observations.

*4.4 Previous Innovation Experiences*

Previous innovation behaviour and experiences with the adoption of new technologies and farming practices as e.g. the adoption of organic farming can have a potential effect on the current adoption decision. If the concept of path dependency at the micro-level is broadly defined the effects of such historical innovation patterns and experiences have to be taken into account with respect to the explanation of current innovation behaviour. We follow Penrose (1959) and others who analysed how the growth of a firm's both organically and through acquisition is strongly influenced by the experience of its managers and the history of the firm's development at any point in time. Hence, by incorporating proxies for the succesful adoption of organic farming practices as the major technology innovation for dairy farmers in preceeding years, and for potential cross-fertilization with other individual characteristics as e.g. experience, peer-group effects, risk behaviour we aim to account for such path dependency in terms of individual innovation behaviour (see also Foltz and Chang 2002, Baerenklau 2005).

## 5. Data and Econometric Modelling

More than 90% of all dairy farms using AMS are located in northwestern Europe where investments are driven by high labor costs, a continuous increase in the average herd-size and a dominance of the family farm structure (Meijering et al., 2002). This study uses a unique dataset based on a pooled cross-section for 241 dairy farms in Denmark for the years 2002 to 2006. It includes information on farms which had just adopted the new milking technology, i.e. information on the production situation at the time the decision to adopt/not to adopt was made. The farms were selected by a stratified random sampling procedure based on the farm accounts data base collected by the Danish Agricultural Advisory Services, Skejby, Denmark. The farms in the sample are located all over Denmark and the relevant “neighboring/peer-group region” were defined based on the Danish communal structure as in place before the communal reform in 2006. The average dairy farm in the sample produced with a herdsize of about 123 cows and the average farmer had about 15 years of dairy farming experience. Up to 40% of all “neighboring or peer-group” dairy farms had experience with the adoption of AMS at the time the average farm adopted the new milking technology (see table 1). The different econometric modelling steps are based on the conceptual framework outlined above.

*[Table 1]*

### *5.1 Risk Proxies*

The use of a moment-based approach for the estimation of production risk is based on a flexible representation (see Antle 1983). This avoids the problem of potential model misspecification with respect to the probability function of farmers' profit $\varpi(\cdot)$, the distribution of risk $G(\cdot)$, and farmers' risk preferences as described by the utility function $U(\cdot)$ in (1). Hence, the sample moments of the profit distribution are estimated and subsequently used as explanatory variables for the farmers' adoption decision. As our dataset contains information on the situation at the time the adoption decision was made, the estimated profit function has not yet been affected by the adoption decision. The estimated moments of the profit distribution can be assumed to be exogenous to farmers' decision at the time of adoption. Hence, the first estimation step consists of estimating the profit function and then computing the moments of the profit distribution for each observation (i.e. farm *i* time *t*). Following the procedure outlined by Kim and Chavas (2003) based on Antle (1983) we first regress farm profit $\varpi$ (profit per cow) on a vector of variable input prices $\boldsymbol{r}$ (labor price, fodder price, concentrates price, veterinary price, cow price), milk output price $p$, a vector of fixed inputs $\boldsymbol{z}$ (land, capital), and a vector of extra profit shifters $\boldsymbol{c}$ (farmer's age, farmer's experience, type of breed, yield per cow, off-farm income, geographical location, climatic and soil conditions, and time) as well as an iid error term $u$:

(14) $\omega_{it} = \varphi(\mathbf{r}_{it}, p_{\mathrm{it}}, \mathbf{z}_{it}, \mathbf{c}_{it}; \beta) + u_{it}.$

Assuming profit maximisation and applying a flexible translog functional form (14) is estimated by OLS providing consistent and efficient parameter estimates. The $j$th central moment of profit conditional on input use is defined as

(15) $\mu_j(\cdot) = E\{[\omega(\cdot) - \mu_1]^j\}$

where $\mu_1$ denotes the mean of profit. Thus, the estimated errors from the mean effect regression ($\hat{u} = \omega - \varphi(\cdot)$) are estimates of the first moment of the profit distribution. These are squared and regressed on the set of explanatory variables from (14), which gives

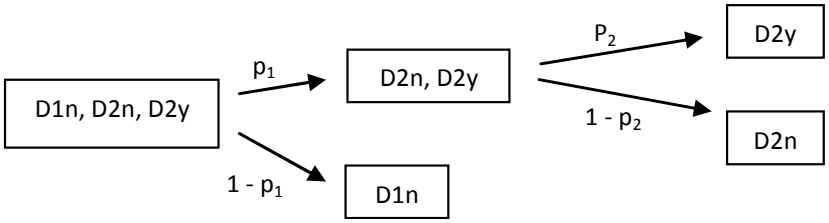
(16) $\hat{u}_i^2 = \vartheta(\mathbf{r}_{it}, p_{\mathrm{it}}, \mathbf{z}_{it}, \mathbf{c}_{it}; \delta) + \varepsilon_{it}.$

By using OLS on (16) we obtain consistent and efficient estimates of the variance (2nd moment). This procedure is followed to estimate also the third (i.e. skewness) and fourth (i.e. kurtosis) central moments based on the estimated errors raised to the power of three and four, respectively, used as dependent variables. The estimates obtained for the four moments are used as proxies for the individual farmer's milk production risk by incorporating them into the subsequent models of AMS technology adoption along with a vector of other explanatory variables.

*5.2 Adoption Model I: Robust Sequential Logit*

If the adoption of the AMS technology is conceptualized as a sequential selectivity problem it can be estimated as a sequential logit model based on separate logistic regressions for each step, decision or transition (see Khanna 2001, Fu et al 2006, Buis 2007 and 2009). Such a model is known in the literature as a sequential response model (Maddala 1983) or a sequential logit model (Tutz 1991).[1] Figure 2 shows the hypothetical process which is to be quantitatively described by using a sequential logit model:

*Figure 2*




Corresponding to the three levels $D_{1n}$, $D_{2n}$, $D_{2y}$ the process consists of two transitions. The first transition refers to a choice between no increase in herd size, i.e. $D_{1n}$, on the one hand and $D_{2n}$ and $D_{2y}$ on the other. The second transition consists of a choice between an adoption of AMS, i.e. $D_{2y}$, and no adoption of AMS, i.e. $D_{2n}$, but only for those that have chosen $D_{2y}$ and $D_{2n}$ in first transition. The sequential model aims to model the probabilities of passing these transitions by estimating a logistic regression for each transition on the sub-sample that is at risk. Corresponding to equation (10) above, the probabilities $p_1$ and $p_2$ in figure 2 can be approximated for farm i at time t as

$$(17)\ p_{1it} = \Pr(y_{it} \epsilon \{\mathrm{D_{2nit}}, \mathrm{D_{2yit}}\} | \mathbf{x_{it}}) = \frac{\exp(\varepsilon_{1it})}{1+\exp(\varepsilon_{1it})}(\boldsymbol{\beta}\mathbf{x}_{it})$$

$$(18)\ p_{2it} = \Pr(y_{it} \epsilon \{\mathrm{D_{2yit}}\} | \mathbf{x_{it}}, y_{it} \epsilon \{\mathrm{D_{2nit}}, \mathrm{D_{2yit}}\}) = \frac{\exp(\varepsilon_{2it})}{1+\exp(\varepsilon_{2it})}(\boldsymbol{\gamma}\mathbf{z}_{it})$$

where $\mathbf{x_{it}}$ and $\mathbf{z_{it}}$ are vectors of regressors for farm *i* at time *t* (i.e. [i] farm size proxied by the amount of milkquota; [ii] farmer characteristics as age and experience; [iii] farm characteristics: organic or conventional, debt of the farm, off-farm income, private consumption, subsidies received, hired labor; [iv] herd and production characteristics: type of breed, yield per cow, fodder expenses, veterinary expenses, labor per cow; [v] neighboring/ peer-group effects; [vi] yearly effects; [vii] risk proxies: the estimated moments based on (14), cross effects between

[1] Others refer to it as continuation ratio logit (Agresti 2002), nested dichotomies (Fox 1997) or Mare model (Mare 1980, Shavit and Blossfeld 1993). See Cameron and Heckman (1998) for a critique.

moments and farmers experience as well as moments and neighboring/peer-group proxy)[2]. The term $\frac{\exp(\varepsilon_{it})}{1+\exp(\varepsilon_{it})}$ ensures that the predicted probability remains between 0 and 1 by modelling the effects of $\mathbf{x_{it}}$ and $\mathbf{z_{it}}$ as S-shaped curves. The coefficients can be interpreted as log odds ratios and the likelihood function is given in Maddala (1983) or Buis (2009). The maximum likelihood estimates are obtained by maximizing the likelihood function with respect to the parameters by numerially approximating the integrals based on maximum simulated likelihood (Train 2003, Buis 2009). The simulations involved need to be repeated for each observation and by using a drawing procedure based on a Halton sequence a more regular sequence of numbers can be generated (Drukker and Gates 2006).[3] To address the likely problem of heteroscedasticity because of pooled cross-sectional data we first test for such heteroscedasticity and secondly estimate the robust covariance matrix using the Huber-White sandwich estimator (see Huber, 1967 and White, 1980). The latter provides consistent estimates of the covariance matrix for parameter estimates even when the fitted parametric model fails to hold because of misspecification or violation of the error related assumptions. Despite several cross variable terms are used in the model, the auxiliary regressions performed showed no severe collinearity in the explanatory variables. To examine the validity of the final model specification we test for a group wise insignificance of the parameters in (17) and/or (18) by a generalized likelihood ratio testing procedure. A Runs test to test for possible serial correlation is applied (see Greene, 2000). Finally, several alternative pseudo-$R^2$ measures have been computed to judge on the overall model quality. The outlined sequential logit model is finally also estimated in a slightly modified specification by considering previous innovation experiences as outlined in the previous section. Hence, $\mathbf{x_{it}}$ and $\mathbf{z_{it}}$ are modified by incorporating additional explanatory variables (i.e. [viii] organic farming practices adopted before or not, cross effects between organic technology and farming experience, between organic technology and peer-group effects, and between organic technology and the individual risk proxies).

*5.3 Adoption Model II: Robust Probit and Mixed-Effects Logistic Regression*

The preceeding model is designed to empirically capture the selectivity problem. However, these models are not able to capture the influences by random effects based on different groupings of dairy farms in the sample. To empirically identify such random effects beside obvious fixed effects we apply a two-stage estimation procedure: First, we estimate a binary probit model (i.e. selection model) and use the estimates to form the inverse Mills ratio to

[2] Possible endogeneity of the monetary variables 'debt of the farm', 'off-farm income', 'subsidies received', and 'private consumption' is addressed by using the estimates for those variables based on a instrumental variables regression procedure (IV) as explanatory variables in the adoption model as outlined by (17) and (18).

[3] This procedure is implemented in the *seqlogit* package in Stata which is used here (Buis 2007).

address the sample selection problem. Secondly, we estimate a mixed-effects logistic regression incorporating the estimates for the inverse Mills ratio as an additional regressor to control for selection bias. Following Maddala (1983) the probit model assumes that

(19) $P(L = 1|Z = z) = \Phi(z'\gamma)$

where $L$ is a binary response variable, $Z$ is a vector of regressors and $\Phi$ as the cumulative distribution function of the standard normal distribution. By using the concept of a latent variable model, the decision to increase the herdsize is generated as

(20) $L^*_{2it} = \boldsymbol{\gamma}\mathbf{z}_{it} + \varepsilon_{2it}$

with $L^*_{2it}$ denotes the latent variable, $\mathbf{z_{it}}$ is a vector of regressors for farm $i$ at time $t$ as outlined above, and $\varepsilon_2 \backsim N(0,1)$. $L$ as an indicator for whether the latent variable meets the herdsize threshold $H_{it}$, following

(21) $L_{it} = \begin{cases} 1 \; if \; L^*_{2it} > H_{it} \\ 0 \; otherwise \end{cases}$

and taking the value 1 as the herdsize of the respective farm $i$ is more than 60 cows, and the value 0 if it is below or equal to 60 cows at time $t$. The log-likelihood function to be maximised is given in Maddala (1983). Subsequently, the estimates obtained by (20) are used to generate the inverse Mill's ratio as the ratio of the probability density function over the cumulative distribution function. This ratio is needed to account for possible sample selection bias in the second stage of the model (Heckman 1979, Greene 2000). This stage (i.e. outcome model) consists of a mixed-effects logistic regression to estimate the technology adoption decision (see e.g. Agresti et al 2000, Hartzel et al 2001, Hedecker 2003) by accounting for fixed and random effects. Hence, we are able to predict the discrete outcome variable even if observations might be correlated. If $L_{1ijt}$ descibes again the binary dependent variable based on the AMS adoption decision, realized for farmer $i$ at time $t$ and part of a group of farms $j$ as $l_{1ij}$, which takes the value of either 0 or 1, for $i = 1,..., M$; $j = 1,..., n_{ij}$. Abstracting from time the stochastic component is described by a Bernoulli distribution with mean vector $n_{ij}$

(22) $L_{1ij} \sim \text{Bernoulli}\left(\mathrm{l}_{1\mathrm{ij}} \middle| \pi_{\mathrm{ij}}\right) = \pi_{\mathrm{ij}}^{\mathrm{l}_{1\mathrm{ij}}}(1 - \pi_{\mathrm{ij}})^{1-\mathrm{l}_{1\mathrm{ij}}}$

where $\pi_{ij} = \Pr(L_{1ij} = 1)$. The vector of random effects, $\mathbf{b_i}$, is restricted to be mean zero with a symmentric positive semi-definite variance covariance matrix (see Hedecker 2003). The systematic component is

(23) $\pi_{ij} = \frac{1}{1+\exp\left(-\left(\mathbf{x_{ij}\beta + r_{ij}b_j}\right)\right)}$

where $\mathbf{x_{ij}}$ is the vector of known fixed effects explanatory variables for farm *i* in group *j* as outlined above, $\boldsymbol{\beta}$ as the vector of fixed effects coefficients to be estimated, $\mathbf{r_{ij}}$ is the vector of known random effects explanatory variables and $\mathbf{b_i}$ as the vector of random effects for farm *i* based on group *j* (along the following factors as a consequence of [i] neighboring/peer-group effects, [ii] farm group effects, [iii] time, and [iv] soil/climatic conditions). The likelihood function must marginalize over the random effects and is given in Hedeker (2003) or Bates (2007). It can not be evaluated exactly and thus the maximum-likelihood solution must be approximated, e.g. based on Laplacian approximation.[4] The outlined two-stage probit and mixed-effects logistic regression model is also estimated in a slightly modified specification by considering previous innovation experiences as outlined in the previous section. Finally different diagnosis tests and robust estimation procedures are applied as outlined for adoption model I.

## 6. Results and Discussion

The overall quality of the four models estimated is largely satisfactory: The likelihood ratio and other diagnosis tests indicate no severe misspecification and the different alternative R-square measures show a high predictive power (see table 2 and table 3). The models estimated show a high consistency with respect to the individual parameter coefficients and their significance which suggests robust empirical results.

*[Table 2]*
*[Table 3]*

With respect to the decision to adopt the AMS technology all models show a positive and significant influence of the scale of milk production, a negative and significant effect of the farmer's age but a positive significant effect of farming experience. With respect to farm characteristics the overall debt of the farm and the amount of off-farm income have a negative effect on the probablity of adopting the new milking technology. On the other hand, the amount of private consumption showed to have a significantly positive effect on the adoption probability. With respect to herd characteristics, we found a negative and significant effect of the amount of fodder used but a positive and significant effect of veterinary expenses per cow. These results confirm earlier findings with respect to the scale of the production: larger dairy farms are more likely to adopt new technology. Further our findings confirm earlier studies

[4] This procedure is implemented by the *xtmelogit* command contained in Stata which is used here.

concluding in the importance of the farmer's age and education: younger and better educated dairy farmers are more likely to adopt new technology (see Putler and Zilberman 1988, Foltz and Chang 2002, Barham et al. 2004). However, the finding that farming experience influences the probability of AMS adoption is somehow contradictory but could be explained by measurement of the variable as the number of years operating the current farm. Hence, farmers tend to aquire a certain level of learning-by-doing with respect to the current milking technology before they decide to switch to a new milking technology. A soft budget constraint could explain the negative effect of the dairy farm's off-farm income on the probability of adopting the AMS technology: the farm is able to operate with a less productive technology for a longer time span. Putler and Zilberman (1988) on the other hand stress the importance of nonfarming business for the adoption of new technology. Due to our findings farms at the negative as well as positive edge of financial risk management (i.e. high debt or high off-farm income) are less likely to adopt new technology. Dairy farms experiencing high veterinary costs per cow might consider a technology investment as a way to avoid sources of costly diseases by minimising the effects of human labor. In a working AM system, the animals are treated in the same way at each milking and the routines are predictable for the cows which increases milk production (Rasmussen et al. 1990, Samuelson et al. 1993). This is consistent with findings that automatic milking does not increase the incidence of udder infections and SCC (Bennedsgaard et al. 2006, Svennersten-Sjaunja and Pettersson 2008), findings that cow stress was not observed during automatic milking (Hagen et al. 2005), and findings that the milk cortisol level was not increased in an automatic compared to a conventional system (Gygax et al. 2006). Contrary to prior reasoning by more technical studies on automatic milking (see e.g. DeKoning et al. 2003), the level of labor used per cow showed not to be of significance for the adoption decision. This could possibly be explained by the fact that farmers and other labor already operating on a relatively high level of labor productivity are those most interested in a further increase of their labor productivity by adopting such labor saving technology.

With respect to the farmers' risk perceptions our analysis revelead the following: The first moment – expected profit – effects the technology adoption decision significantly positive, i.e. the higher the expected profit the higher the probability of AMS adoption. The second moment – profit variablility – showed to have a significant negative influence on the adoption probability, i.e. the higher the probability of facing extreme profit gains or losses the lower the probability of AMS adoption. For the third moment – skewness of profit – again a significantly negative effect on the adoption decision has been found, i.e. the higher the downside profit risk the lower the probability of adopting the new milking technology. The fourth moment – kurtosis of profit – finally effects the probability of technology adoption also negative and this effect has

been found to be significant. A higher kurtosis of the profit distribution means more of the variance is due to infrequent extreme deviations from the mean profit, as opposed to frequent modestly-sized milk profit deviations. These findings are generally in line with theoretical reasoning and previous empirical studies: Given the farmers' general risk aversion and the uncertainty related to the profit developmeent after adoption Kim and Chavas (2003) and Koundori et al (2006) both conclude that the farmers' decision to adopt a new technology is significantly effected by risk considerations. In addition to these results we found that the cross-effect of these risk proxies with farmers' experience showed to significantly influence the farmers' AMS adoption decision. We found that the experience of the farmer with the operation of the current business helped to adjust extreme profit expectations (first moment). This confirms findings by Meijering et al. (2002) on the importance of realistic expectations with respet to AMS adoption. On the other hand, the farmer's experience are found to decrease the farmer's response to changes in the second to forth moment. These findings indicate that the more experienced the farmer is in terms of running the current milk business the less responsive he/she is to milk profit variance and infrequent milk profit deviations. Hence, the farmer's probability of adopting a new milking technology to hedge against profit outlier activity increases (see also Koundori et al. 2006).

Time showed to have mixed but rather positive effects on the milking technology adoption decision for the farms in the sample. This could reflect the role of information accumulation and positive learning-by-doing effects in the relevant dairy farming community over time. The proxy for neighboring/peer-group effects showed to be positive and significant with respect to the AMS adoption decision. In addition the cross effects with the risk proxis (second to fourth moment) were found to be also significantly positive, i.e. a decreasing negative effect of on farmer's response to changes in milk profit variance, skewness and kurtosis. Hence, our results reveal that such social interaction effects decrease the individual farmer's responsiveness to risk exposure and consequently increase the probability of new technology adoption. In our second modelling approach random effects were used to model unobservable factors related to such peer-group influences, but also to control for individual farm, time, or soil/climatic related effects. The estimates show a significant positive effect on the probability of adopting automatic milking technology by the neighboring/peer-group based farm grouping and a significant positive effect by the time based farm grouping. Hence, we are able to empirically approximate such neighboring/peer-group effects based on social interaction and learning-by-doing in the wider peer-group. These findings are in line with, and even enforce, the findings by Baerenklau (2005) and others: Peer-group based spillover effects as well as "bandwagon" effects generated by early adopters have an impact on the individual adoption decision. Studies on AMS

concluded that automatic milking is not only a new milking system, but rather a completely new management system, noneconomic factors such as lifestyle choices are at least as important as economic factors for the decision to adopt an automatic milking system (Hyde et al. 2007). Neighbourhood/Peer-group effects play an important role with respect to the social diffusion of such lifestyle changes which can be considered as "social network externalities" and as a function of the total number of technology users. Such effects can be also due to pure "conformity preferences" by the dairy farmers producing ancillary benefits from social acceptance (Baerenklau 2005). Our findings correspond to these conclusions by adding current empirical evidence on the importance of such "soft" factors for the adoption decision.
Finally, previous innovation experiences proxied by the adoption of organic farming practices in previous years showed to have a significant positive influence on the probability of adopting AMS technology. Further the cross-effects of such previous adoption experiences with overall milk farming experience as well as with neighboring/peer-group externalities showed to have a positive impact on the adoption probability in the sample. Such cross fertilization significantly increases the probability of adopting the new milking technology. Such a significant positive effect on the probability of adopting AMS has been finally also found for the cross-terms of previous innovation experiences and the different risk proxies in the form of profit moments: Previous experiences with a successful technology adoption lead to an additional adjustment of extreme profit expectations (first moment) and, on the other hand, to an additional decrease in responsiveness to milk profit variance and infrequent profit deviations (second to fourth moment). Hence, the farmer's probability of adopting a new milking technology to hedge against profit outlier activity increases as he/she has previous experiences with a successful technology adoption. These results somehow confirm previous studies on other livestock and dairy related technologies concluding in a higher adoption probability for farms having adopted complementary technologies before (Barham et al. 2004). Such experiences likely contribute to realistic expectations with respect to the adoption of AMS named by Meijering et al. (2002) as a key factor for a successful implementation of this new milking technology.

## 7. Conclusions

Using different quality response models this empirical study investigates factors for the adoption of a new milking technology at the farm level accounting for problems of sequential selection and behaviour identification. The results suggest the importance of the farmer's risk perception, significant effects of peer-group behaviour, and a positive impact of previous innovation experiences. These findings are relevant for policy or technology suppliers aiming to efficiently

set incentives for an effective technology adoption. Neglecting to account for these effects can change the estimated subjective beliefs of possible adopters and thus the incentive to adopt the technology, as well. On the other hand, using relevant peer-groups to spread adoption-related information can induce a faster technology diffusion. In addition, policy makers should consider the importance of the farmer's risk perception when designing economic instruments to foster technology adoption in order to adequately reflect risk reducing benefits by adopting the technology. Future research should focus on disentangling such unobservable effects based on social interaction by using large balanced panels to track individual farm behaviour before and after technology adoption.

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## Tables

*Table 1 The Average Sample Farm*

| *Variable (Total Sample n = 1000)* | *Mean* | *Min* | *Max* | *StDev* |
|---|---|---|---|---|
| Yield per Cow (kg milk per year) | 7,831.31 | 3,022.33 | 11,297.41 | 1,318.17 |
| Labor per Cow (hours per year) | 38.66 | 20.57 | 113.04 | 7.46 |
| Veterinary Expenses per Cow (DKK per year) | 693.62 | 37.61 | 1,927.88 | 273.45 |
| Fodder per Cow (DKK per year) | 2,613.47 | 9.37 | 17,122.56 | 2,652.17 |
| Concentrates per Cow (DKK per year) | 1,752.94 | 0 | 13,989.82 | 1,707.57 |
| Capital per Cow (total assests in DKK) | 165.49 | 5.56 | 1,018.70 | 69.59 |
| Land (Ha) | 129.13 | 0 | 366.6 | 55.09 |
| Cows (n) | 123 | 28 | 292 | 41 |
| Milkquota (kg milk) | 956,424 | 100,499 | 256,900 | 343,812.5 |
| Milk Price (DKK per kg) | 2.49 | 1.92 | 3.84 | 0.33 |
| Labor Price (DKK per hour) | 104.45 | 31.27 | 147.62 | 8.94 |
| Cow Price (DKK per 100kg) | 778.29 | 683 | 901.5 | 95.30 |
| Profit per Cow (DKK per year) | 3,354.97 | 0 | 29,286.73 | 2,832.06 |
| Age (years) | 42.29 | 23 | 73 | 8.02 |
| Experience (years of farming experience) | 15.44 | 2 | 37 | 7.99 |
| Organic (1-yes, 0-no) | 0.39 | 0 | 1 | 0.49 |
| Debt (DKK) | 1.26e+0.7 | 0 | 5.29e+07 | 6,741,843 |
| Off-Farm Income (DKK per year) | 117,210.9 | 0 | 507,663 | 115,038 |
| Private Consumption (DKK per year) | 223,321.7 | 0 | 603,090 | 92,441.25 |
| Subsidies (DKK per year) | 217,190.9 | 0 | 1,163,651 | 245,533.9 |
| Breed (1-Red Danish, 2-Danish Black&White, 3-Jersey, 4-Mixed) | 2.17 | 1 | 4 | 0.68 |
| Peer-Group Effects (#AMS Adopters/#Total Dairy Farms in Region) | 0.04 | 0 | 0.37 | 0.07 |
| Percentage of Hired Labor (%) | 0.37 | 0 | 0.86 | 0.21 |

1: base year 2002, 2: 1 DKK = 0.135 Euro (31.12.2002),
3: producer price index for agricultural materials p.a. 2003: 106.03, 2004: 109.64, 2005: 108.27, 2006: 107.92;
general inflation % p.a. 2003: 2.1, 2004: 1.2; 2005: 1.8, 2006: 1.9;
price index for milk and dairy products p.a. 2003: 104.95, 2004: 105.29, 2005: 105.47, 2006: 103.92;
price index for machinery p.a. 2003: 106.03, 2004: 109.37, 2005: 112.83, 2006: 114.93 (sources: OECD, Danmark Statistic).

*Table 2 Estimates*

| ***model I) sequential logit*** | | | ***model II) probit / mixed-effects logistic regression*** | | |
|---|---|---|---|---|---|
| (n = 1000) | coefficient[1] | robust se | (n = 1000) | coefficient[1] | robust se |
| ***decision to increase herdsize (logit 1)*** | | | ***decision to increase herdsize (probit)*** | | |
| **farm size** | | | **farm size** | | |
| milkquota | 0.099** | 0.026 | milkquota | 0.004*** | 7.09e-04 |
| milkquota x milkquota | -3.350e-05*** | 1.210e-05 | milkquota x milkquota | -9.64e-05*** | 9.43e-06 |
| **farmer characteristics** | | | **farmer characteristics** | | |
| age | -1.065*** | 0.187 | age | -0.162*** | 0.054 |
| experience | 1.854*** | 0.356 | experience | 0.104** | 0.041 |
| **farm characteristics** | | | **farm characteristics** | | |
| debt of farm (estimate)[2] | 2.505*** | 0.696 | debt of farm (estimate)[2] | -1.80e-07 | 1.56e-07 |
| off-farm income (estimate) | 0.029 | 0.016 | off-farm income (estimate) | -7.58e-06 | 6.86e-06 |
| private consumption (estimate) | -0.327 | 1.081 | private consumption (estimate) | 9.73e-06 | 5.03e-06 |
| subsidies received (estimate) | -0.025*** | 0.004 | hired labor/total labor | 3.589** | 1.411 |
| hired labor/total labor | 31.408*** | 8.635 | | | |
| **herd characteristics** | | | **yearly effects** | | |
| breed | 14.054*** | 2.912 | 2003 | -0.505 | 0.474 |
| fodder | 0.046*** | 0.016 | 2004 | -1.026* | -1.93 |
| veterinary expenses per cow | -0.008*** | 0.001 | 2005 | -0.438 | 0.571 |
| **neighborhood/peer-group effect** | | | 2006 | -0.192 | 0.649 |
| weighted neighborhood adoption proxy | -21.071 | 18.965 | | | |
| **yearly effects** | | | constant | -0.380 | 0.628 |
| 2003 | -8.756*** | 3.264 | | | |
| 2004 | -5.430*** | 1.669 | | | |
| 2005 | 2.522*** | 0.845 | | | |
| 2006 | -6.321** | 2.995 | | | |
| **risk effects** | | | | | |
| 1st profit moment (mean) | 0.749*** | 0.173 | | | |
| x experience | 0.022** | 0.011 | | | |
| x weighted neighborhood adoption proxy | 2.511 | 2.989 | | | |
| 2nd profit moment (variance) | -0.177*** | 0.024 | | | |
| x experience | 0.101*** | 0.014 | | | |
| x weighted neighborhood adoption proxy | -1.989* | 1.227 | | | |
| 3rd profit moment (skewness) | -0.222*** | 0.078 | | | |
| x experience | 0.043*** | 0.006 | | | |
| x weighted neighborhood adoption proxy | 3.382* | 1.758 | | | |
| 4th profit moment (kurtosis) | -0.031*** | 0.009 | | | |
| x experience | 0.008*** | 0.001 | | | |
| x weighted neighborhood adoption proxy | 0.558 | 2.687 | | | |
| **previous innovation experience/organic farming adoption** | | | | | |
| organic farming (1-yes, 0-no) | -2.636*** | 0.639 | | | |
| x experience | -0.520 | 0.056 | | | |
| x 1st profit moment | -0.295* | 0.148 | | | |
| x 2nd profit moment | 0.212 | 0.164 | | | |
| x 3rd profit moment | 0.147 | 0.142 | | | |
| x 4th profit moment | 0.006 | 0.025 | | | |
| constant | -2.829 | 5.290 | | | |

1: * - 10%-, ** - 5%-, *** - 1%-level of significance.

2: due to likley endogeneity the estimates for those variables based on a instrumental variables regression procedure (IV) are used.

*Table 2 Estimates (continued)*

| ***decision to adopt automatic milking technology (logit 2)*** | | | ***decision to adopt automatic milking technology (me logistic regression)*** | | |
|---|---|---|---|---|---|
| (n = 1000) | coefficient[1] | robust se | (n = 1000) | coefficient[1] | robust se |
| **farm size** | | | **farm size** | | |
| milkquota | 0.012*** | 0.002 | milkquota | 4.21e-04** | 1.87e-04 |
| milkquota x milkquota | -2.53e-06 | 6.03e-07 | milkquota x milkquota | -4.44e-08*** | 1.58e-08 |
| **farmer characteristics** | | | **farmer characteristics** | | |
| age | -0.129** | 0.058 | age | -0.004*** | 8.84e--4 |
| experience | 0.132*** | 0.045 | experience | 0.004** | 0.002 |
| **farm characteristics** | | | **farm characteristics** | | |
| debt of farm (estimate)[2] | -0.851*** | 0.231 | debt of farm (estimate)[2] | -0.024** | 0.011 |
| off-farm income (estimate) | -0.011** | 0.005 | off-farm income (estimate) | -4.67e-04** | 2.10e-04 |
| private consumption (estimate) | 0.611*** | 0.242 | private consumption (estimate) | 0.042* | 0.016 |
| subsidies received (estimate) | 1.89e-04 | 0.005 | subsidies received (estimate) | 9.75e-05 | 9.41e-05 |
| hired labor/total labor | -1.121 | 1.292 | | | |
| **herd characteristics** | | | **herd characteristics** | | |
| breed | -0.493** | 0.217 | breed | -0.019** | 0.008 |
| fodder | -0.002*** | 8.33e-04 | fodder | -7.53e-05*** | 3.01e-05 |
| veterinary expenses per cow | 0.002** | 7.81e-04 | veterinary expenses per cow | 6.77e-05** | 3.11e-05 |
| | | | yield per cow | -1.41e-05 | 1.01e-05 |
| | | | labor per cow | -3.38e-04 | 0.001 |
| **neighborhood/peer-group effect** | | | **neighborhood/peer-group effect** | | |
| weighted neighborhood adoption proxy | 7.142*** | 1.394 | weighted neighborhood adoption proxy | 0.413*** | 0.167 |
| **yearly effects** | | | **yearly effects** | | |
| 2003 | -17.709*** | 1.841 | 2003 | -0.001 | 0.184 |
| 2004 | 0.148 | 1.212 | 2004 | 0.126*** | 0.028 |
| 2005 | -1.091* | 0.624 | 2005 | 0.031 | 0.032 |
| 2006 | 18.289*** | 1.401 | 2006 | 0.091* | 0.037 |
| **risk effects** | | | **risk effects** | | |
| 1st profit moment (mean) | 2.447*** | 0.702 | 1st profit moment (mean) | 0.034*** | 0.003 |
| x experience | -0.173*** | 0.044 | x experience | -0.008*** | 0.001 |
| x weighted neighborhood adoption proxy | -3.181 | 2.485 | x weighted neighborhood adoption proxy | -0.012 | 0.041 |
| 2nd profit moment (variance) | -2.403*** | 0.691 | 2nd profit moment (variance) | -0.021*** | 0.006 |
| x experience | 0.123*** | 0.042 | x experience | 0.090*** | 0.003 |
| x weighted neighborhood adoption proxy | 17.329*** | 2.938 | x weighted neighborhood adoption proxy | 0.009*** | 0.004 |
| 3rd profit moment (skewness) | -1.136*** | 0.301 | 3rd profit moment (skewness) | -0.003** | 0.001 |
| x experience | 0.053*** | 0.013 | x experience | 1.12e-05*** | 7.95e-05 |
| x weighted neighborhood adoption proxy | 4.043*** | 1.534 | x weighted neighborhood adoption proxy | 0.059*** | 0.023 |
| 4th profit moment (kurtosis) | -0.147*** | 0.444 | 4th profit moment (kurtosis) | -5.90e-05*** | 3.10e-06 |
| x experience | 0.003*** | 8.52e-04 | x experience | 3.72e-06** | 1.62e-06 |
| x weighted neighborhood adoption proxy | 1.399*** | 0.326 | x weighted neighborhood adoption proxy | 0.009*** | 0.003 |
| **previous innovation experience/organic farming adoption** | | | **previous innovation experience/organic farming adoption** | | |
| organic farming (1-yes, 0-no) | 3.569*** | 0.896 | organic farming (1-yes, 0-no) | 0.064** | 0.031 |
| x experience | 1.804*** | 0.427 | x experience | 0.003*** | 0.001 |
| x 1st profit moment | -4.622*** | 1.364 | x 1st profit moment | -0.103*** | 0.016 |
| x 2nd profit moment | 4.016*** | 1.198 | x 2nd profit moment | 0.004*** | 0.001 |
| x 3rd profit moment | 0.429*** | 0.141 | x 3rd profit moment | 0.009*** | 0.001 |
| x 4th profit moment | 0.059** | 0.027 | x 4th profit moment | 0.002*** | 2.66e-04 |
| | | | x weighted neighborhood adoption proxy | 0.134*** | 0.024 |
| | | | **soil/climatic cluster effects** | | |
| | | | cluster 2 | -3.34e-04 | 0.052 |
| | | | cluster 3 | 0.049 | 0.046 |
| | | | cluster 4 | 0.031 | 0.034 |
| | | | cluster 5 | 0.006 | 0.034 |
| | | | cluster 6 | 0.030 | 0.042 |
| | | | cluster 7 | 0.011 | 0.034 |
| | | | **random effects** | | |
| | | | weighted neighborhood adoption proxy (28 groups) | 1.501*** | 0.466 |
| | | | farms (241 groups) | 1.38e-05 | 0.566 |
| | | | time (5 groups) | 1.835** | 0.950 |
| | | | soil/climatic clusters (8 groups) | 0.194 | 0.307 |
| | | | | | |
| | | | inverse Mill's ratio (sample selection) | 0.034*** | 0.002 |
| constant | -68.349*** | 19.397 | constant | 0.088 | 0.092 |

1: * - 10%-, ** - 5%-, *** - 1%-level of significance.

2: due to likley endogeneity the estimates for those variables based on a instrumental variables regression procedure (IV) are used.

*Table 3 Diagnosis and Model Specification Tests*

| ***diagnosis tests*** | | | |
|---|---|---|---|
| ***model I) sequential logit*** | | ***model II) probit / mixed-effects logistic regression*** | |
| Log-Likelihood | -98.843 | Log-Pseudolikelihood [probit]<br>Log-Likelihood [me logistic] | -34.405<br>-125.887 |
| LR chi2(66) [overall specification] | 343.97*** | Wald chi2(12) [probit]<br>LR chi2(1) [me logistic] | 113.19***<br>31.49*** |
| successes completely determined<br>[1st sequence / 2nd sequence] | 835 / 743 | Pseudo R2 [probit] | 0.731 |
| McKelvey and Zavoina's R2 | 0.997 / 0.661 | McKelvey and Zavoina's R2 [probit / me logistic] | 0.987 / 0.974 |
| McFadden's Adj. R2 | 0.910 / 0.831 | McFadden's Adj. R2 [probit / me logistic] | 0.629 / 0.548 |
| Count R2 | 0.998 / 0.952 | Count R2 [probit / me logistic] | 0.986 / 0.970 |
| serial correlation / Runstest<br>$H_0$ = residuals follow random order | -5.32 (not rejected) | serial correlation / Runstest [probit / me logistic]<br>$H_0$ = residuals follow random order | -17.40 / -15.88 (not rejected in both cases) |
| heteroscedasticity / White's test<br>$H_0$ = homoscedastic error | 861.097***<br>(rejected, Huber-White-Sandwich robust estimator applied) | heteroscedasticity / White's test [probit / me logistic]<br>$H_0$ = homoscedastic error | 471.24*** / 214.49***<br>(rejected in both cases, Huber-White-Sandwich robust estimator applied) |

| ***specification tests*** | | |
|---|---|---|
| ***model I) sequential logit*** | | ***model II stage 2) mixed-effects logistic regression*** |
| sLR-tests on groupwise insignificance | | |
| $H_0$ = first sequence variables have no significant effect (chi2(30)) | 623.02*** (rejected at 1%-level) | --- |
| $H_0$ = second sequence variables have no significant effect (chi2(28)) | 48.02** (rejected at 5%-level) | --- |
| $H_0$ = farm size related variables have no significant effect (chi2(2)) | 549.29*** (rejected at 1%-level) | 51.40*** (rejected at 1%-level) |
| $H_0$ = farmer related variables have no significant effect (chi2(2)) | 180.75*** (rejected at 1%-level) | 6.14** (rejected at 5%-level) |
| $H_0$ = time related variables have no significant effect (chi2(4)) | 61.08*** (rejected at 1%-level) | 29.57*** (rejected at 1%-level) |
| $H_0$ = farm characteristics related variables have no significant effect (chi2(5)) | 27.08*** (rejected at 1%-level) | 15.64*** (rejected at 1%-level) |
| $H_0$ = risk related variables have no significant effect (chi2(12)) | 55.10*** (rejected at 1%-level) | 118.50*** (rejected at 1%-level) |
| $H_0$ = previous innovation related variables have no significant effect (chi2(6)) | 53.07*** (rejected at 1%-level) | 75.60*** (rejected at 1%-level) |
| $H_0$ = climate/soil related variables have no significant effect (chi2(6)) | --- | 49.90*** (rejected at 1%-level) |

1: * - 10%-, ** - 5%-, *** - 1%-level of significance.