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Estimating the link between farm productivity and innovation in the Netherlands

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ESTIMATING THE LINK BETWEEN FARM PRODUCTIVITY AND INNOVATION IN THE NETHERLANDS

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This report investigates the link between farm innovation and economic performance. The study uses a unique survey dataset maintained by Wageningen Economic Research in the Netherlands. A structural multi-stage model of firm-level innovation is applied. The model contains four steps: first, the decision of the farmer to innovate at all; second the innovation intensity, measured by expenditures on innovation activities; third the output of the innovation process, which is measured by realized product, process, organisational or marketing-related innovation; fourth, productivity changes as a result of innovation. The analysis is performed for two types of farms – dairy and crop farms – and covers the period from 2004 to 2014. A number of factors are found to be decisive for the magnitude and success of farm innovations in the Netherlands. Among them regulations and standards, the level of co-operation with knowledge producing institutions, own product and process-related development activities, farm size, the age of the farm operator as well as confidence in business and sector developments. Based on these and other results, the report derives implications for policies aimed at promoting farm innovation and productivity and sustainability in the agricultural sector.

Keywords: Innovation, productivity, agriculture, Dutch farms

JEL codes: O31, Q12, Q16

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EXECUTIVE SUMMARY

This report sheds empirical light on the link between innovation and economic performance at the level of the individual farm. The study takes a broad view on innovation and considers all agronomic, technological, organisational and commercial activities that lead to, or are intended to lead to, technologically new or improved products or services.

The study uses a unique survey dataset among dairy and crop farms maintained by Wageningen Economic Research (2004 to 2014) in the Netherlands. This dataset allows a structural multi-stage model to be estimated with a view to ascertaining the effects of investment in innovation on the generation of product, process and organisational or marketing innovations. It also enables innovations to be linked to farm level productivity. The model contains four steps: first, the decision of the farmer to innovate at all; second the innovation intensity, measured by expenditures on innovation activities; third the output of the innovation process, which is measured_by realised product, process or organisational or marketing-related innovation; fourth, productivity changes as a result of innovation.

The results point to a number of factors that can enhance innovation at the farm level:

- regulations and standards can create a demand-pull for innovation
- the level of co-operation with knowledge producing institutions improves the likelihood of success
- own product and process-related development activities, farm size, the age of the farm operator as well as confidence in business and sector developments are all farm-specific characteristics that impact the size and success of innovations.

Furthermore, the study confirms that larger innovation investment leads to a higher probability of producing at least one successful product, process, organisational or marketing innovation. Innovations related to improving processes, farm organisation and marketing result in significant productivity gains.

Several recommendations for a more effective and efficient innovation policy can be made on the basis of the findings:

- Supply side: support of knowledge dissemination by knowledge producing institutions, and facilitating co-operation of individual farms with such institutions enhances the quality of innovations and the likelihood of success. Access to finance is of crucial importance for investing in innovations.
- Demand side: building up and communication of a ‘demand pull’ based on environmental, safety and health concerns leads to strong incentives to engage in innovation at farm level. Effective communication of market opportunities can contribute to a demand-driven innovation environment.
- Monitoring: periodic innovation surveys, such as the one used in this study, are needed to shed more light on the relationships between policies, innovation and productivity in a dynamic and cross-country comparative perspective.

1. Context and scope

Following the widely accepted OECD-Eurostat (2005) definition, innovation refers to all scientific, technological, organisational and commercial activities that lead to, or are intended to lead to, the implementation of technologically new or improved products or services. Innovation and economic performance at firm level are causally linked according to economic theory. To maintain a certain level of productivity and growth firms need to engage and invest in innovative activities. Modelling and analysing the link between firms' economic performance and their innovation activities, including models of technology adoption and diffusion, have been at the forefront of academic research over the last 50 years.

In agricultural economics, academic studies at micro-level have been mainly focused on disentangling the factors for adopting specific technologies and practices and predicting patterns of technology diffusion given a certain sectoral and policy context. Most farm and sector level performance studies conclude in a significant effect on productivity from investments in innovative technologies resulting in positive technological change over time. Others point to the crucial role of economic performance for the probability of investing in innovation and adopting innovative technologies at firm level. These linkages between firm performance, innovation and knowledge accumulation have been also receiving continued attention from researchers working in the area of the agri-food industry following and absorbing some of the work done outside the agri-food sectors. Here the relationship between firm performance, innovation behaviour and R&D remains a major research theme for economists and related disciplines (see Hashi and Stojcic, 2013, for a comprehensive overview).

Studies that empirically investigate the links between farm level engagement and investment in innovative activities, the actual production of innovation and the development of economic performance are barely available due to the lack of appropriate data. This document contains a farm level analysis using comprehensive panel data on two different farm types for the Netherlands and applying sound microeconometric modelling. A structural multi-stage modelling framework is developed to measure the dynamic link between innovation behaviour and economic performance at farm level. The first step aims to explain the decision of the farmer to innovate (the innovation decision function), the second step relates to the innovation input used by the farm (the innovation investment function), and the third step focuses on the output side of the innovation production process (the knowledge production function). Finally, the fourth modelling step consists of the production stage with knowledge as an input (the output production function). The basic model is based on the well-known CDM approach (introduced by Crepon, Duguet and Mairesse, see Crepon et al., 1998; Griffith et al., 2006; and Hashi and Stojcic, 2013) and captures the main features of farm behaviour, is parsimonious in parameters to be estimated and empirically tractable given the data at hand.

This report is structured as follows: Section 2 presents a comprehensive literature review on the link between firm and farm level performance and its innovation behaviour including technology adoption and diffusion. A multi-stage modelling approach and analytical structures are proposed in Section 3. Section 4 outlines the actual empirical application; Section 5 presents and discusses the estimation findings; and Section 6 concludes.

2. Literature review of micro-level approaches and conceptual considerations

The **link between farms' economic performance and their innovation (or technology adoption) behaviour** has been at the centre of academic and policy interest for decades (Sunding and Zilberman, 2001; Zilberman et al., 2012; Alston and Pardey, 2016). The seminal work by Griliches (1957) views the adoption of innovative technology as a process of imitation between different individual farmers. An alternative approach, the threshold model of adoption, was introduced by Davis (1979). This approach is based on the assumptions of explicit micro level behaviour, heterogeneity among individual units and a dynamic process of individual learning and resource accumulation leading to a gradual diffusion of technology adoption over time (Feder et al., 1985). Another strand of early contributions to the literature (Feder and Umali, 1993) makes 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. One stream of studies empirically investigates technology adoption and diffusion taking into account farmers' perceptions with respect to the risk of future yield (Yaron, Dinar and Voet, 1992; Kim and Chavas, 2003). These studies conclude that technological progress and investments in innovation significantly contribute to reducing the exposure to risk and downside risk over time. Sauer and Zilberman (2012) simultaneously model the effects of risk, social interaction, past innovation experiences by considering also the sequential implementation structure of the adoption decision. Their findings confirm previous studies according to which education-based peer-group behaviour, technology density and a positive impact of previous innovation experiences have a significant positive effect on the innovation process at farm level. Hence, a dynamic linkage between farm performance and innovation has been found (Alston and Pardey, 2016).

In a comprehensive review of recent empirical literature on the drivers for dairy farms' performance Sauer (2014) found that most studies conclude in a significant positive ***productivity effect by investments in innovative technologies*** resulting in positive technological change over time (see also Appendix Table A1). Technical change is regarded as the main driving force for changes in productivity and efficiency over time (countries Denmark, Finland, Germany, Iceland, the Netherlands, Poland, Ireland, Spain, the United States) followed by policy related factors (Germany, Denmark, the United States, the Netherlands, Finland, Norway, and Australia). Intensification of dairy farming operations (Australia), the realisation of economies of scale (Denmark, Ireland, Turkey) and innovative practices (Australia) are found to be also of high relevance regarding the explanation of change in productivity. However, it has to be noted that technical change and innovative practices are not always clearly defined or differentiated. Further, improvements in input quality, for example, genetic improvements (Iceland) are reported as effective productivity catalysts. Climate change related environmental changes (United States) can also be regarded as effective drivers for an increase in productivity as well as the improvement of human capital by education and extension services (Germany, Turkey). An increase in debt has been found to lower productivity change (Denmark), off-farm income on the other hand has been found to enhance productivity at dairy farm level (Denmark). Finally, allocative components are named as a significantly positive productivity driver (Netherlands) whereas the differentiation from policy related factors is not clear-cut.

Mayen, Balagtas and Alexander (2010) investigated the productivity and efficiency of organic and conventional dairy farms in the United States. Based on propensity score matching and stochastic frontier techniques and using a cross-section for 2005 the authors reject the homogeneous technology hypothesis and find that the organic dairy technology is approximately 13% less productive. Technical change was concluded as the main productivity driver. However, little difference in technical efficiency between organic and conventional farms was found. Cuesta (2000) analyses the technical efficiency of dairy farming in Spain by means of a stochastic frontier analysis using a balanced panel of farms for the years 1987-1991. The author finds a negative trend in technical efficiency over the period investigated but a positive trend in technical change, hence a net improvement in productivity of about 1% per year. Bruemmer et al. (2002) estimate and decompose productivity growth of dairy farms in Germany, the Netherlands and Poland for the period 1991-94. Applying a distance function approach they found that the growth in productivity in Germany and Poland (−5%) has been mainly dictated by the technical change component. In contrast, the productivity growth in the Netherlands has been mainly influenced by allocative efficiency components. Based on a stochastic frontier approach and a subsequent analysis of dominant effects Sipilaeinen and Heshmati (2004) found an average productivity growth of about 1% per year over the period 1989-2000 for Finnish dairy farms. Technical change is identified to be the most important source of productivity growth, whereas technical efficiency does not vary systematically over time. Nossal and Sheng (2010) investigate trends and drivers of productivity growth in Australia for 1977-2008. They emphasise that the temporary slowdown in dairy productivity was likely an outcome of poor seasonal conditions and limited resources as well as a resulting decline in input quality. The adoption of new technologies and management systems are found as the major driver for a growth in milk yields. Productivity development over time has been found to mainly increase labour related productivity.

Sipilaeinen (2008) investigates components for productivity growth in Finnish agriculture over the period 1990-2000. His analysis results in an average annual growth rate of about 0.9% to 1.2% depending on the modelling approach applied. The report concludes that technical change has been the main contributor to productivity growth on dairy farms, noting a significant negative productivity effect by the scale of operations. Policy changes as well as technical changes have been found to boost the efficiency and finally productivity of dairy farms in Germany and the Netherlands (Emvalomatis et al., 2011). The authors use a stochastic distance function modelling approach to measure a dynamic variant of dairy farms' efficiency. Using a panel of farms for the years 1995-2005 the persistence of inefficiency is measured and the study concludes that in the presence of adjustment costs the optimal strategy for a dairy producer could be to remain partly inefficient at a given point in time. Sauer and Latacz-Lohmann (2014) investigate the link between innovative investments and productivity by means of a stochastic distance frontier approach and Luenberger index formula. Using a large scale panel dataset for German dairy farms (1996-2010) they find that investments in innovative technology increase the productivity of dairy production by shifting out the production frontier. The findings further imply that investments in innovative dairy technologies require a sufficient level of complementary education to trigger also an increase in efficiency at farm level. The quality of human capital in terms of educational training seems finally crucial for a lasting increase in efficiency as a result of innovation. Finally, Slade and Hailu (2016) study the cost efficiency of dairy farms under two different regulatory regimes and conclude that differences in cost efficiency are primarily explained by allocative decisions: farms in the more regulated environment are overcapitalised and overly reliant on home-grown feed due to lacking incentives for further process optimisations.

On the other hand, there are numerous empirical studies that emphasise the crucial **role of farm performance for the probability of adopting** new innovative practices and technologies in dairy production. Zepeda (1994) estimates a system of equations for the adoption of several technologies and a sample of Californian dairy farmers. The results illustrate the joint dependence of the endogenous variables productivity and adoption. By applying Granger-causality testing procedures, Weersink and Tauer (1991) found that for US farms there is a causality between herd size and more productive technology with the latter caused by the former. The authors conclude that economic factors and other factors leading to structural changes may lead to larger dairy farms which are then in a position to adopt new technologies. Foltz and Chang (2002) investigate the adoption of rbST (recombinant bovine somatotropine) in Connecticut milk production and conclude that the scale effect is significant with respect to the adoption probability. Younger and more educated farmers owning larger dairy herds are more likely to use rbST. McBride et al. (2004) revealed that larger farms in the US adopted the highest percentage of automatic milking units and were the most likely to employ a nutritionist and to use rbST. Barham et al. (2004) further explore the dynamics of rbST adoption for Wisconsin farms and confirm that larger and more productive farms with complementary feeding technologies are more likely to adopt rbST. Applying a hazard function approach, Abdullai and Huffman (2005) find that in addition to herd size, positive externalities between neighbouring farms as well as superior market access also play a significant role in determining the adoption of crossbred-cow-technology among Tanzanian farmers. Rahelizatovo and Gillespie (2004) examine the adoption of best-management practices on Louisiana farms using a count data modelling approach. Their empirical results support the notion that larger, more productive dairy operations are more intensive adopters of technology. Kumbhakar et al. (2009) jointly estimate the choice of technology and the level of technical efficiency for dairy farms in Finland. Their findings suggest that technology choice is endogenous and that production efficiency affects technology choice decisions as such efficiency affects output as well as innovation behaviour. Khanal et al. (2010) find that empirically sorting out the link between farm performance and technology adoption has to account for the effect of other technologies using proper corrections for selection bias. Finally Khanal and Gillespie (2013) confirm previous findings for the US by concluding that higher net returns over total costs are significantly associated with the adoption of artificial insemination (AI) techniques and that adopters are run by relatively younger and more educated farmers that also produce more milk per cow than non-adopters.

Outside of dairy production not many empirical studies exist that aim to measure the links between technology adoption, innovation and farm performance. No study that investigates the dynamic linkages between innovation behaviour and performance has been found. The majority of empirical studies that investigate sources of productivity growth decompose a growth index into efficiency changes, technical progress, and scale components without explicitly including innovation activities. Here, technical change is identified as the main contributor to productivity growth (Hadley et al., 2006; Karafillis and Papanagiotou, 2011; O'Donnell, 2012; Läpple et al., 2015; Xayavong et al., 2015). Karafillis and Papanagiotou (2011) construct an innovation index based on farmers' uptake of different innovative technologies and farm practices. Olive farms in Greece reaching higher innovation scores also tend to show higher scores in total factor productivity. Diversification with respect to innovations has been found to positively contribute to farm performance in Xayavong et al. (2015). Läpple et al. (2015) develop an index that goes beyond measuring innovation through adopted technologies, adding indicators for knowledge acquisition and renewal of machinery.

The linkages between firm performance, innovation and knowledge accumulation have been, however, receiving continued attention by researchers working in the area of the ***agri-food industry***. For example, Knudson et al. (2004) note that an appropriate theory of innovation and entrepreneurship still needs to be developed for the agri-food industry. This holds especially with respect to a conceptual framework that enables to understand, identify, and develop entrepreneurs. Traill and Meulenberg (2002) study twelve food-manufacturing companies in six European countries and conclude that firms have a dominant product, process or market orientation, that determines also the types of innovation accorded most importance as well as the way in which innovations are organised and realised. Henson and Traill (2000) find seven clusters of firms distinguished not only by their emphasis on product and process innovation but also by their international focus, distribution channels, and size of market. They conclude that innovation promotion by public policy should therefore offer different packages of incentives depending on type of company and innovation. Furtan and Sauer (2008) investigate empirically the determinants of firms' performance in the Danish agri-food industry with a particular emphasis on innovation. However, the authors find no significant relationship between the innovative activity of a firm as measured by the number of products introduced, and the size of the firm. Further, no significant influence of new product introductions on value addition has been found in this study. Capitanio et al. (2009 and 2010) find that for the Italian agri-food sector innovation behaviour follows different patterns whereas the probability of introducing product innovation is influenced by the quality of human capital, the geographical context and also the age of the firm. Process innovation showed to be related more to the financial structure and the size of the firm whereas for product innovation the capacity to build relationships on the relevant markets seems key for success. Finally, Karantininis, Sauer and Furtan (2010) deal with the link between innovation behaviour, vertical market integration and firm networks. Their empirical results for Denmark indicate that organisation, integration as well as contractual arrangements, are key determinants for a firm's innovation behaviour. Economies of scale play an important role as does the firm's orientation on export whereas the sector the firm is operating in shows not to be of crucial relevance for its innovation behaviour (Ghazalian and Fakih, 2016). Much of the standard literature, hence, focuses on R&D investment as opposed to more detailed empirical analyses of the innovation process within firms or farms. This might be due to the long-term nature of the process and the requirement of rather long time series of fairly consistent data at the firm or farm level. Further, the development of public agricultural research systems to overcome the suboptimal investment in agricultural innovation at the micro level contributed to this bias in the innovation related literature for the agricultural sector.

Beyond the agri-food sector, the **relationship between firm performance, innovation behaviour and R&D** remains a major research theme for economists and related disciplines (e.g. Hashi and Stojcic, 2013 for a comprehensive overview). Early studies predominantly reported a positive relationship between innovation and measures of firm performance (in most cases R&D expenditure, see e.g. Griliches, 1986 and Lichtenberg and Siegel, 1991, for the United States, Goto and Suzuki, 1989, for Japan, Wakelin, 1998, for the United Kingdom). Other studies, however, stress the inadequacy of R&D expenditure as an input-oriented measure for innovation activity as the latter also encompasses learning-by-doing, embodied knowledge or human capital enhancement and also ignores the actual process of innovation, co-operation, firm size or timing (OECD-Eurostat, 2005; Kemp et al., 2003; Hall and Mairesse, 2006; Bessler and Bittelmeyer, 2008). Empirical modelling progress subsequently led to a new generation of models aiming to capture the complexities of the innovation process (Crepon et al., 1998; Hall and Kramarz, 1998; Loof and Heshmati, 2002 and 2006).

According to these efforts the innovation process consists of four stages: (i) the decision to innovate, (ii) the decision on the level of innovation activities, (iii) the conversion from innovation expenditure/input to innovation output, and (iv) the relation between innovation output and actual firm performance. Assuming a one-directional causality from the decision to innovate to firm's performance these stages can be sequentially estimated by incorporating various firm, industry or institutional characteristics depending on the dataset at hand.

The *first two stages*, however, are jointly estimated in systemic approach as in many cases the same explanatories are used in both stages (i.e. the decision to innovate and the decision on how much to invest in innovation). As innovation input, R&D investment is mainly applied in absolute or relative (intensity as the ratio to total sales turnover) terms. Previous R&D are considered as potentially explaining factors, predominantly firm size, export intensity, human capital, forms of co-operation, and public support. The effect of firm size (most commonly measured by number of employees) has been found to be ambiguous which might simply reflect industry-specific characteristics (Cohen and Klepper, 1996; Klomp and Leeuwen, 2001; Loof and Heshmati, 2002 and 2006; Kemp et al., 2003). Export intensity has been found to positively influence the decision to innovate, however, it has to be noted that the characteristics of the foreign market is essential. Furthermore, the socio-economic environment that the firm operates in is likely to be significant in terms of access to finance, institutional support, cultural values, cooperation with research entities etc. (Klomp and Leeuwen ,2001; Loof and Heshmati, 2002 and 2006; Kemp et al., 2003). It is relevant to note that the decision to innovate (stage i) also might be influenced or triggered by more psychological and/or sociological processes, factors or effects. Hence, this points to the need for more behaviour-oriented surveys and empirical studies on individual decision making and planning in the area of innovation at the micro level.

The *third stage* **-** the transformation of innovation inputs to innovation output – is commonly modelled by testing factors, for example, co-operation, previous innovation experience, financial constraints, organisational characteristics, etc. (Klomp and Leeuwen, 2001; Kleinknecht and Oostendorp, 2002), although the empirical findings show a significant variation in the magnitude and direction of the effect. Innovation output can be measured by product and/or process related innovations whereas in most studies product related innovation is exclusively considered based on the share of turnover from new products, number of patents and new product announcements (Klomp et al., 2002; Loof and Heshmati, 2002) with sales of new products regarded as the most robust measure most adequately capturing the entire innovation process. Empirical evidence, however, on the influence of innovation input on the actual production of innovation output is mixed which holds also with respect to the impact of process-related factors.

To finally approximate the relation between innovation output and actual firm performance in the *fourth modelling stage*, most common measures for performance are productivity, sales, export revenues and profits (Bessler and Bittelmeyer, 2008). Here, most empirical studies reveal a positive and significant relationship between innovation and firm performance: e.g. Loof (2000) using sales of new products per employee and either employment growth, value added per employee, sales per employee, operating profit per employee or return on assets; Loof et al (2001) with respect to productivity; Bessler and Bittelmeyer (2008) found that innovation only leads to a temporary advantage for firms with a diminishing effect in the long run. As other significant controlling factors firm size and age as well export intensity, foreign ownership and co-operation are reported (Griffith et al., 2004; Chudnovsky et al., 2006; Raffo et al., 2008; Crespi and Zuniga, 2011; Hall et al., 2013).

According to this stream of thought **innovation** refers to all scientific, technological, organisational and commercial activities that lead to, or are intended to lead to, the implementation of technologically new or improved products or services (OECD-Eurostat, 2005). Innovations in the form of technology, organisation and human capital influence the behaviour of economic agents in a new way to enhance the firm's economic performance by an increase in productivity, efficiency, or profitability. Innovations in the form of new products lead to the expansion of the firm's operations into new market segments (Hashi and Stojcic, 2013). Whereas the traditional view has been that innovative firms only experience a transitory performance effect as knowledge quickly diffuses and is imitated by rivals (Knight, 1921), more current evidence suggests that innovative firms are able to reap economic benefits over a considerable period of time (Loof and Heshmati, 2006). Schumpeter's (1942) original thesis of creative destruction suggests that the entrepreneur's search for change is the main driver for innovation. However, later Schumpeter also recognised the role of human and financial capital accumulation in large firms as a prerequisite for innovation. The evolutionary model (Nelson and Winter, 1982) further suggests that firms have to upgrade existing routines by innovation to maintain a superior market position. The endogenous growth literature considers the simultaneity between innovation and performance (Aghion and Howitt, 1998) where incentives to innovate are closely linked to the performance of the institutional framework. Klette and Griliches (2000) finally suggest a multi-stage model of firm behaviour arguing that innovation essentially enhances product quality independent of firm size but crucially linked to the positioning in the market, demand structure and institutional setting. The empirically testable multi-stage model of innovation behaviour (Crepon et al., 1998) captures this theoretical evidence tracing the innovation process from a firm's decision to innovate to its performance.

3. Empirical and econometric framework

Based on the most current literature, a structural **multi-stage modelling framework** is formulated to measure the dynamic link between innovation behaviour and economic performance at farm level. The first step aims to explain the decision of the farmer to innovate. A farm is considered as having done an innovation decision if the farm showed any innovation activities (the innovation decision function) related, for example, to in-house R&D, outsourced research and advice, training courses, certification, market introduction, patents, trademark registered, plant variety rights, etc. The second step relates to the innovation input (or intensity) used by the farm which is approximated by the actual expenditures on the above mentioned innovation activities (the innovation investment function). The third step focuses on the output side of the innovation production process (the knowledge production function) whereas innovation output is measured either by realised product, process or organisational/marketing (OM) related innovation. Finally, the fourth modelling step consists of the production stage with knowledge as an input (the output production function) and output approximated by several different measures, for example, total factor productivity or relevant partial input productivity measures. The model is based on Crepon et al. (1998), Griffith et al. (2006) and Hashi and Stojcic (2013) and captures the main features of farm behaviour, is parsimonious in parameters to be estimated, and empirically tractable given the data at hand.

The **econometric implementation** of this structural model is hampered by potential bias related to selectivity and simultaneity. Selectivity bias may arise due to the fact that not all farms report or actually engage in reportable innovation activities. Simultaneity bias may arise due to the fact that many potential factors may (endogenously or exogenously) influence a farm's decision to innovate, its level of expenditure on innovation, and its final production performance. The proposed multi-stage model addresses these issues by considering a selection corrected form of estimation for stages one and two, and also by linking stages three and four (i.e. innovation input and output, production output and innovation output).

Following Griffith et al. (2006) the model is estimated for all farms in the sample of Dutch farms meaning that predicted values are used for all farms to proxy innovation effort in the knowledge production function. This reflects the well-known fact that all farms exert some innovative effort but not all farms report this effort and assumes that the process of innovation investment and knowledge production is the same for all (reporting and non-reporting) farms. For example, farmers may well spend a fraction of their working time per day to consider how the processes they are working on could be further optimised in terms of resource efficiency etc. (innovative effort). However, below a certain threshold a farm will not bother to report this effort as actual innovation related activity. Nevertheless this effort leads to the production of knowledge. Knowledge output is allowed to take several forms including product, process and marketing innovations based on the assumption that such innovative effort can be considered as a public good within the farm used to produce several outputs without depletion.

The first stage — the innovation decision — is based on the concept of innovative effort. Formally – abstracting from variation over time - we can write this equation as follows where i = 1, N index farms, d_i^* as an unobserved latent variable approximating innovative effort, and z_i of determinants of innovation effort, β as a vector of parameters to be estimated, and e_i as a stochastic error term:

$$d_i^* = z_i'\beta + e_i \qquad [1]$$

If we estimate equation [1] based on the actually observed innovative effort in terms of reported expenditures we create potential selection bias. To adequately address this issue we instead assume the following selection equation describing whether a farm is pursuing (or reporting) innovation related activities or not (see Griffith et al., 2006):

$$da_i = \begin{cases} 1 \; if \; da_i^* = w_i'\alpha + \varepsilon_i > tl \\ 0 \; if da_i^* = w_i'\alpha + \varepsilon_i \leq tl \end{cases} \qquad [2]$$

with da_i as the observed binary endogenous variable equal to zero for non-innovation activities and one for innovation activities pursuing or reporting) farms, da_i^* as the corresponding latent variable indicating that farms decide to pursue (or report) innovation activities if the variable is above a certain threshold level *tl*, *w* as a vector of variables explaining the innovation decision, α as a vector of parameters of interest and ε_i as error term.

The second stage — the innovation investment — is conditional on the first stage, i.e. on farm i pursuing (and/or reporting) innovation activities. We can observe the amount of resources invested in innovation related activities and state

$$d_i = \begin{cases} d_i^* = z_i'\beta + e_i \; if \; da_i > 0 \\ \quad 0 \; if \; da_i = 0 \end{cases} \qquad [3]$$

Equation [2] and [3] are estimated as a generalised Probit model based on a maximum-likelihood and Heckman procedure to account for potential selectivity bias assuming bivariate normal error terms with zero mean, constant variances and not correlated with *w* and *z* indicated by the correlation coefficient $\rho_{e\varepsilon}$.

The third stage — the knowledge or innovation production — can be described by

$$k_i = d_i^*\gamma + x_i'\delta + u_i \qquad [4]$$

with k_i as knowledge proxied by product, process, marketing or organisational innovation indicators, and the latent innovation effort d_i^* entering as explanatory variable, x_i as a vector of other determinants of knowledge production, γ and δ as parameters to be estimated, and finally u_i as an error term. Equation [4] can be estimated as separate probit equations based on product, process or marketing innovation indicators or as a system of equations simultaneously estimated by appropriate maximum-likelihood techniques. The farms' innovative effort is considered by including d_i^* as the predicted value from equations [2] and [3]. Hence, equation [4] is estimated for all farms, not only for the sub-sample of those farms reporting innovation activities. Incorporating the estimated value for d_i provides for an instrument of the innovation effort and therefore accounts for potential endogeneity with respect to the effect of unobservable farm characteristics in the knowledge production process.

The final stage — the output production — is approximating the farm's performance based on

$$y_i = k_i^* \theta + p_i' \pi + c_i' \tau + v_i \qquad [5]$$

where y_i is a performance indicator as e.g. a total factor productivity proxy based on non-parametric index calculations, k_i as the knowledge input proxied by the product, process or marketing innovation indicators based on equation [4], p_i' as a vector of determinants and c_i' as a vector of controls for the productivity level of farm i, and finally v as an error term. Potential endogeneity with respect to k_i is accounted for by using the predicted values from the knowledge production function. Such a specification could be estimated by a generalised Tobit or other suitable estimator.

The outlined structural model can be estimated by a three-step procedure (e.g. Griffith et al., 2006): equations [2] and [3] are estimated as a linked Heckman procedure considering potential selection issues, whereas equation [4] can be separately or simultaneously estimated for various innovation output(s) incorporating the predicted value for innovative effort obtained by equation [1], finally equation [5] is separately estimated incorporating the predicted values for innovation investment from equation [2]. Alternatively, equations [3] and [4] can be simultaneously estimated (see e.g. Loof and Heshmati, 2006 or Hashi and Stojcic, 2013) to account for potential endogeneity issues regarding innovation output as an input to production. Furthermore, if innovation effort is not predicted and incorporated for the full sample (and only for the reported innovators) then potential selection bias can be addressed by obtaining the Mill's ratio from equation [2] (the innovation investment stage) and include it as an explanatory in equation [3] (the innovation output stage).

Due to data limitations and software availability we finally estimate in stage I a random-effects Probit model with year and farm related fixed effects based on a Heckman procedure which provides us with estimates for innovation investment intensity per farm and year. The latter are then incorporated along other explanatory variables in stage II as part of the innovation/knowledge production functions separately estimated as random-effects Probit models. Finally, innovation related estimates produced by stage II estimations are incorporated in the various output production models estimated in stage III of our structural modelling procedure. Here different partial and total productivity measures are used and in addition a production theory based average production function, as well as a frontier production function, are estimated. We apply the Arellano-Bond type dynamic panel data estimator as well as a stochastic frontier type estimator. All estimation models are based on Jackknife clustered resampling techniques (either based on years, farm or region) to ensure the robustness of the results. We further use various other robustness checks, for example, Wald testing procedures for the joint significance of demand pull, confidence, development, innovation, technology, regional and year related variables, autocorrelation tests and pseudo R-square measures.

4. Empirical implementation: Data and variables

This study takes advantage of the data from the *LEI innovation survey* conducted by the Wageningen Economic Research (former Landbouw Economisch Instituut, LEI). The data sets span the period 2004 to 2014 and cover 455 dairy farms and 574 arable farms in the Netherlands. The innovation data is complemented by production and technology data based on the Farm Accountancy Data Network (FADN) also maintained by LEI. The latter is a stratified sample of about 1 500 farms operating in the Dutch agricultural and horticultural industries. It covers detailed information on costs, sales, technology and other socioeconomic characteristics of farms and farmers on a yearly basis. Farms monitored by the FADN were asked to complete the innovation survey related questionnaire consisting of different sections on realised innovations, innovation activities, organisation of marketing, business confidence and cooperation.

According to the analytical framework outlined above we consider the following *dependent variables* for our estimations (Table 1).

Table 1. Dependent variables used in the estimation

Model stage	Dependent variable	Measured
I - Innovation decision	Engagement in innovation activities	Binary 1 - yes, 0 - no activities observed
II - Innovation investment	Resources invested in innovation activities, innovation intensity	Continuous $[0;\infty]$ [in logs] observed
III - Knowledge / innovation production	Product, process, organisational or marketing innovation output	Binary 1 - yes, 0 - no output observed
IV - Output production	Performance indicator (e.g. partial labour or cow or land productivity, total factor productivity)	Continuous $[0;\infty]$ [in logs] Estimated or observed

To model the decision of the farm manager to engage in innovation a binary variable is used, carrying the value 1 if there had been some innovation activities and 0 if there were none in the respective year. To approximate the resources that are invested by a particular dairy or arable farm in (product, process and/or organisational/marketing related) innovation a continuous variable is used based on the amount invested in euros actually reported by the farm in the respective year. To model the production of knowledge/innovation in stage III a binary variable is applied carrying the value 1 if the farm reported a product, process and/or organisational/marketing related innovation in the respective year. Finally, to approximate the contribution of knowledge/innovation to the production of economic output (milk etc.) various continuously measured partial and total performance/productivity indicators are applied (observed indicators: output per labour, output per cow, output per land, non-parametrically estimated indicators: total factor productivity). The survey used in this study defines product innovations as "(…) products (for marketing) that are new or significantly improved with respect to the base features (a new product), technical specifications, features such as taste, colour, race, for example, packaging or the usability or durability. The innovation must be new for the company; the innovation does not necessarily need to be new for the market." Process innovations are defined as "(…) new or significantly improved technologies in clear, and new or improved methods for the manufacture and supply of products (and services). Consider, for example, new machines, installations, stables or greenhouses and accessories, or computer systems. The innovation must be new for your company, but does not necessarily need to be new to the market or the sector." Finally, the survey defines organisational and marketing innovations as related to "(…) business organisation and management, as offices opened in the Netherlands or abroad, new company was established, set up new partners in company, a manager of an undertaking or manager, change of legal form (for example, membership, general partnership, private company). Marketing, as a new form of packaging of products, clearly for the first time or new contracts/agreements with customers, or modified by sales channel, start home sales. New partnerships for example, establishment or membership of, a marketing organisation (such as producer organisation), study club or other entrepreneurial network; cooperation with educational institutions (such as internships and presentations). Quality Assurance, new certification or quality marks." (*LEI, 2012*).

Figure 1 shows the average annual gross and net investment per cow for all dairy farms in the sample, Figure 2 reports these figures per ha land for arable farms in the sample. Figure 3 compares the investments in innovation related activities by dairy and arable farms in the period investigated whereas Figure 4 shows the share of dairy and arable farms that report a product, process and/or organisational/marketing related innovation. Finally, Figure 5 reports the partial labour productivity for dairy and arable farms in the samples. As the descriptive statistics indicate (Table A2) the relatively low number of product innovations realised in the period considered suggest a careful interpretation of estimations related to this type of innovation.

It is evident that investment per dairy farm has been the highest in the years 2008 and 2009 and for arable farms in the years 2012 and 2013 partly due to price developments and prospects. Over the period investigated the (reported) investment in innovation related activities per farm and year has been increasing on average. This positive trend has been more consistent for dairy farms compared to arable farms. Considering the shares of farms that actually report product, process and/or organisational/marketing innovations, Figure 5 reveals that the largest share of dairy and arable farms pursues process related innovations (11.6% of all dairy farms and 16.7% of all arable farms). On average per year about 6% of all dairy farms and nearly 8% of all arable farms report organisational/marketing related innovations and about 1.2% (dairy) and 1.8% (arable), respectively, report finally product related innovations. Considering further the productivity development of the farms in the samples over the period investigated the simple partial labour productivity indicator suggests that arable farmers produce a higher total gross output (sales) per labour unit than their colleagues engaged in dairy production (on average EUR 77 per hour labour versus EUR 111 per hour labour). This means an increase in output per labour of about 110% (dairy) and about 140% (arable) over the period considered.

Figure 1. Investment in dairy farms, 2004-14

EUR per cow

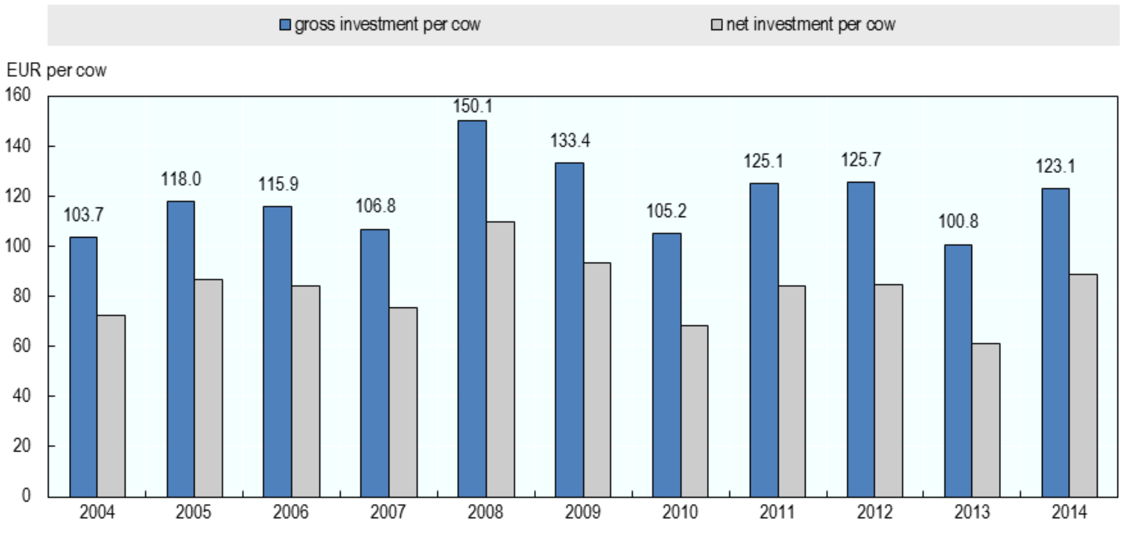

Figure 2. Investment in arable farms

EUR per hectare

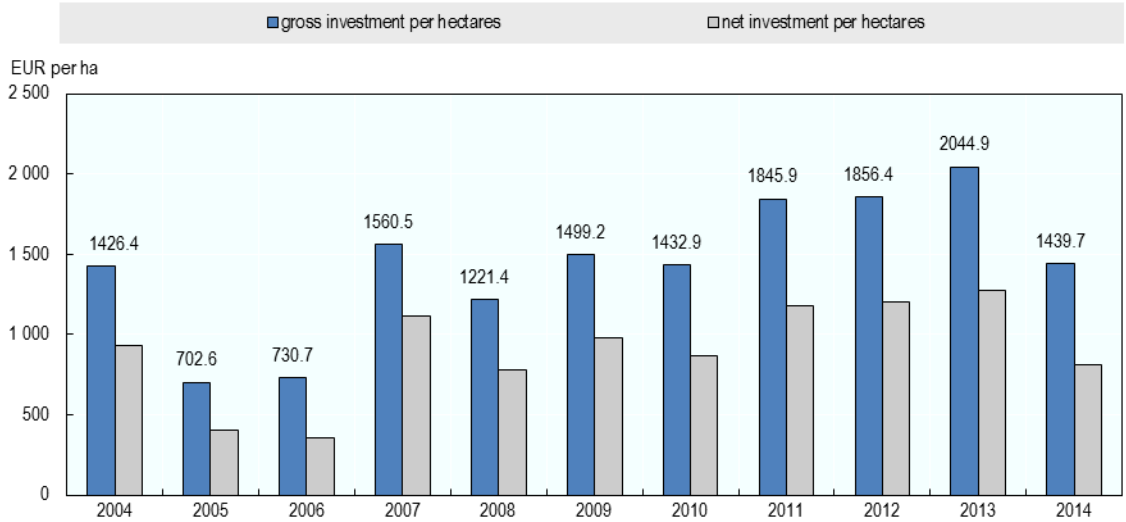

Figure 3. Reported investment in innovation

EUR per cow, EUR per hectare

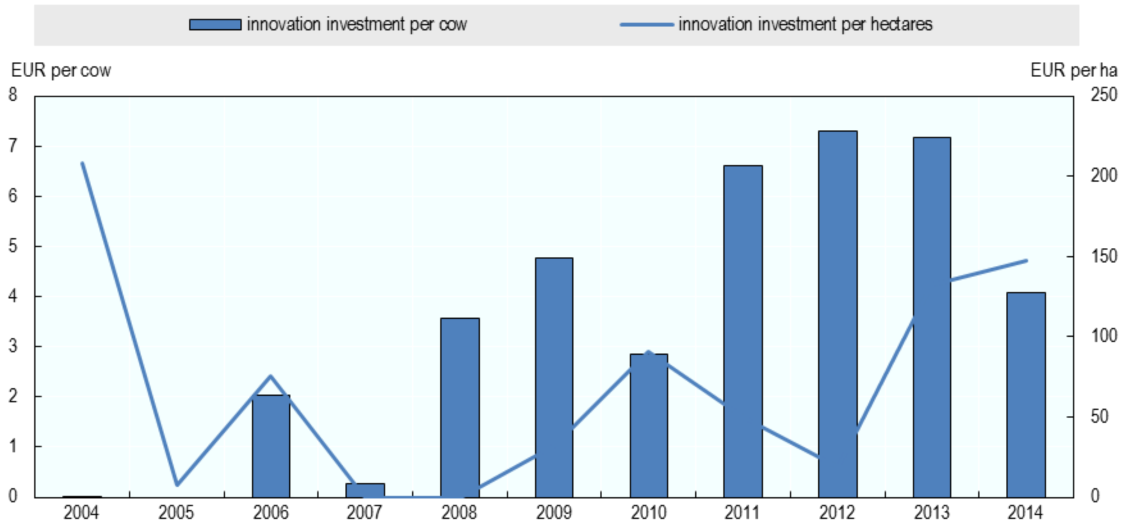

Figure 4. Share of farms with innovation, by type of innovation

% of farms

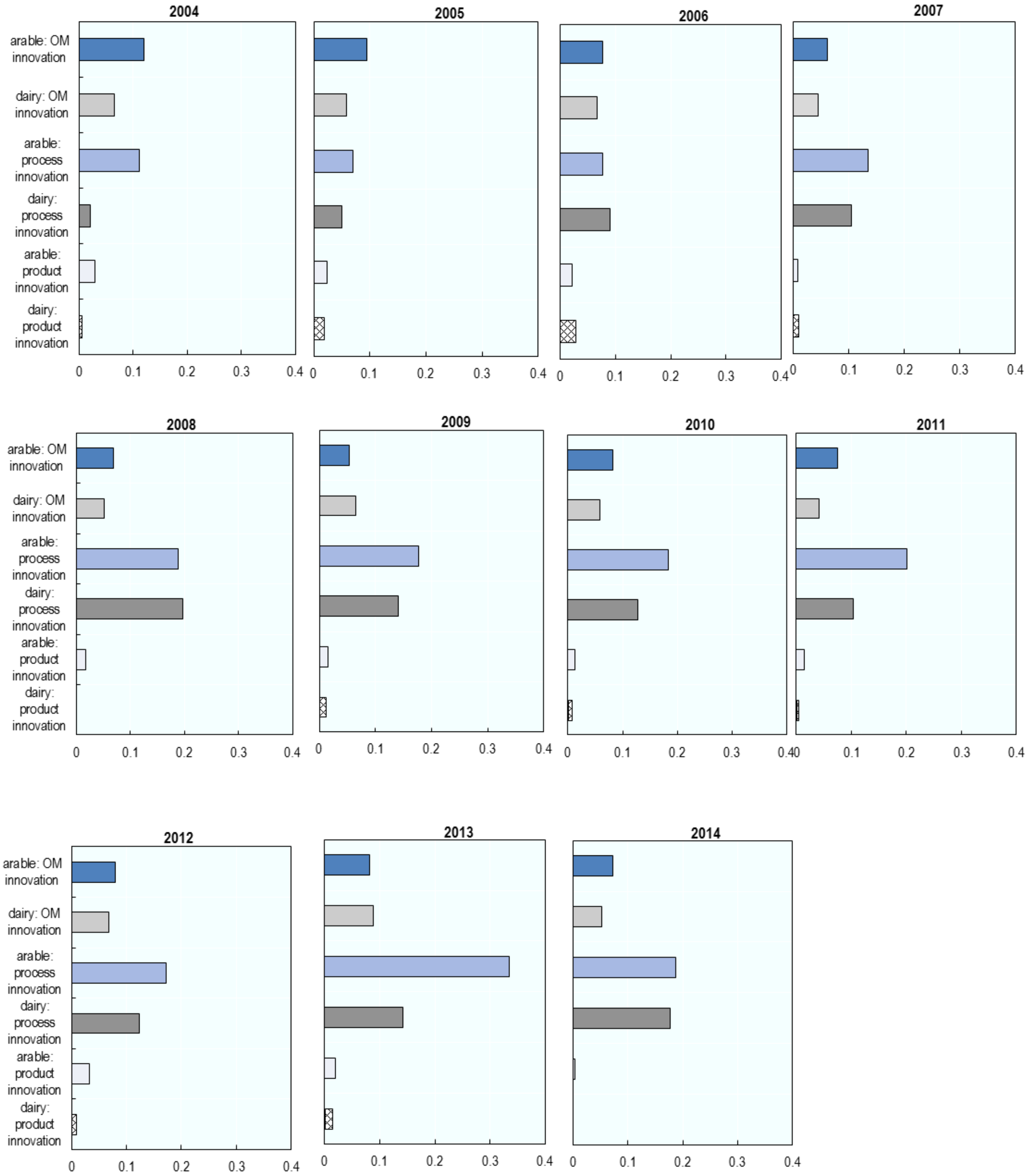

Figure 5. Partial labour productivity

EUR output per labour hour

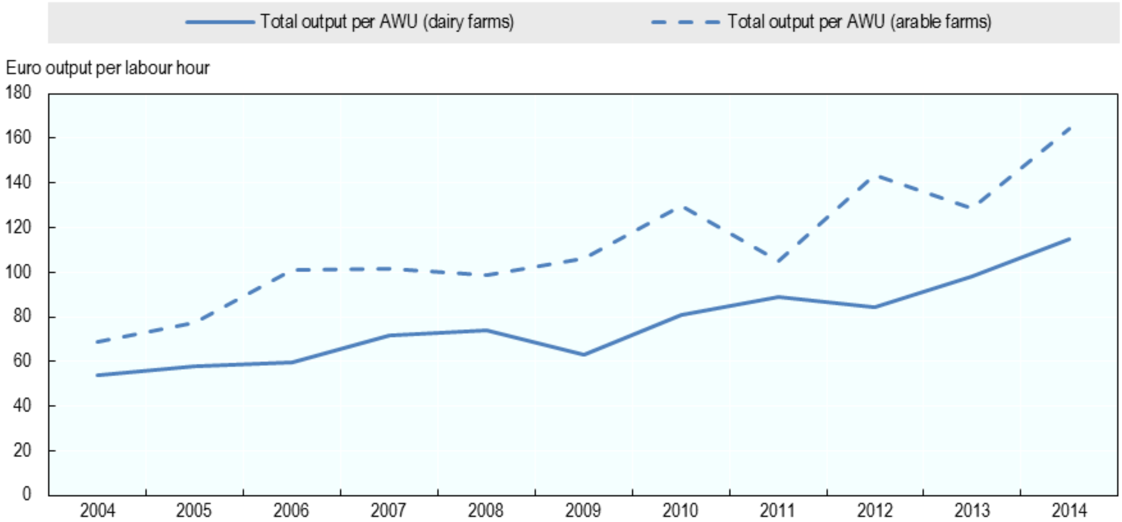

Table A2 gives summary statistics on all variables used in the different estimation stages. Those variables are grouped according to the underlying core hypotheses being tested. First, the potential effects of demand pull factors related to regulation and standards as well as aspects related to environmental, health and safety aspects with respect to products, processes and organisation or marketing of the dairy and arable operation. Further, the source of information related to the particular innovation is important for the intensity of innovation and also the production of knowledge. Given the survey data it is possible to distinguish several sources for product and process development (own, other, and co-operative). Co-operation with other businesses along the supply chain should impact innovation behaviour and performance. If a dairy or arable farm sells output via marketing contracts could also impact its engagement in innovation activities. If some form of innovation protection – such as certification, trademark, plant breeding labelling, or a patent – is applied should also incentivise more innovative activities at farm level. The effect of public support on the level and intensity of innovation at farm level is also investigated. Unfortunately, in the LEI innovation survey information is only provided as to how far the farmer has been aware of existing as well as relevant innovation related funding sources. Confidence in the development of the dairy or arable business and the wider sector should stimulate investments in innovative products, processes and marketing. According to the survey, it is possible to test for the effects of short-term versus long-term business confidence at the farm level. Furthermore, various economic and financial characteristics are controlled for and also technology aspects with respect to the individual farm operations, namely gross assets, off-farm income, size, production system, and production technique. Individual farmer characteristics – age and education – should also influence the level and productivity of farm level innovation. Finally, location and time related indicators are considered to control for largely unobservable effects by farm location, the timing of the survey conducted as well as other assumed policy and climate or animal health and crop pest related events.

5. Results discussion and implications

This section summarises the estimates for the different structural modelling steps: the innovation decision, the innovation investment, the knowledge or innovation production and the output production. Unbalanced panel data are used to consider issues of selectivity, simultaneity and endogeneity as well as dynamic aspects to a limited extent. However, great care has to be taken in interpreting the results, these do not necessarily suggest causal relationships.

Table 2 summarises estimates for the determinants of whether a farm undertakes investments in innovation (generally referred to as R&D) and, if so, how much investment. The first and third columns of the table show estimates of such determinants of whether a dairy or arable farm engages in innovation investment in the period 2004-14. The second and fourth columns in Table 2 show the corresponding estimates of the determinants of how much farms invest in innovation conditional on doing innovation investment at all. The numbers reported are marginal effects at the sample means for the probability of investing in innovation and marginal effects for the expected value of the innovation intensity conditional on investing in innovation at all, respectively. Estimates for the knowledge or innovation production functions are reported in Table 3 for dairy and arable farms. The first and fourth columns show the results for product related innovation, the second and fifth for process related innovation, and finally the third and sixth columns show the results for organisational and marketing innovations. The numbers reported are marginal effects evaluated at the sample means (i.e. changing the value of binary dummy variables from 0 to 1). Finally, the estimates are reported for the productivity functions (Table 4). The coefficients summarised in Table 4 represent elasticities or semi-elasticities since the dependent variable is specified in log form (i.e. the log of output per labour, the log of output per cow, and the log of output per ha land).

The first stage of the structural model delivers estimates for the determinants of whether a farm undertakes investments in innovation and, if so, how much investment. The first and third columns in Table 2 (“engage in innovation”) show estimates of such *determinants of whether a farm engages in innovation investment* in the period 2004-14. The numbers reported are marginal effects on the probability to engage in innovation at all. Many of the explanatory variables are binary dummy variables taking the value 1 when the factor is important to the farmer’s decision or used in the farm’s production process (Table A2.) and the value zero if it is unimportant or not used. Therefore, the “marginal” effect relates to a change in the binary variable from 0 to 1.

Demand pull related factors show a strong positive effect on the probability to engage in innovation at farm level for both dairy and arable farms. The marginal effect by environmental, safety and/or health aspects related to the production showed to be significant (by about 7% and 6% compared to other dairy or arable farms for which such aspects are not relevant, conditional on the mean values of all other explanatory variables). The marginal effect of regulation and standards related to production and products showed to be significant only with respect to dairy production (by about 7% again conditional on the mean values of all other explanatory variables). This might be due to the fact that changes in crop regulations are more gradual and are therefore hard to capture empirically. Farms in the sample that co-operate with knowledge producing institutions (universities, research institutes etc.) are significantly more likely to engage in innovation (by about 21% compared to other arable farms in the sample and by about 6% compared to other dairy farms in the sample). Co-operation along the supply chain (vertical and/or horizontal) shows a mixed (but insignificant) effect on the probability of engaging in innovation activities for both dairy and arable farms. Arable farms that sell (parts or all of) their products via marketing contracts show a lower probability of engaging in innovation activities at farm level (compared to their colleagues not using such contracts). This might be related to the positive impact found for own product/process development activities with respect to innovation intensity (see below). Farms that use contractual arrangements might have a lower incentive to engage in own (non-co-operative) product/process development activities.

Table 2. Stage I innovation decision and investment

(Random Effects Heckman Selection Estimation 2004-2014)

Dependent Variable	Dairy		Arable	
	Engage in Innovation (0/1)	Innovation Intensity	Engage in Innovation (0/1)	Innovation Intensity
Demand pull				
Environment, safety, health	0.0721 ***	0.0292	0.0562 ***	0.0282
	(0.0107)	(0.0576)	(0.0167)	(0.0347)
Regulation, standards	0.0691 **	0.0851	0.0112	0.1226 *
	(0.0299)	(0.0629)	(0.0469)	(0.0653)
Funding information	-0.0113	-0.0228	-0.1269	0.3075 ***
	(0.0485)	(0.0469)	(0.0801)	(0.1129)
Cooperation (vertical/horizontal)	0.1039	0.0017	-0.1351	0.2073
	(0.0683)	(0.1001)	(0.0837)	(0.1325)
Marketing contract	0.0523	0.0529	-0.1474 ***	0.0804
	(0.0391)	(0.0546)	(0.0346)	(0.0716)
Knowledge institutions	0.0577 ***	0.0247	0.2111 ***	-0.1603
	(0.0211)	(0.0501)	(0.0382)	(0.1095)
Product/Process development own	---	0.2817 ***	---	1.7707 ***
		(0.1083)		(0.3017)
Product/Process development other	---	-0.0103	---	-0.1105
		(0.1221)		(0.1653)
Confidence				
Short-run	0.1146 ***	0.0121	-0.3368 ***	0.3109 **
	(0.0265)	(0.0994)	(0.0383)	(0.1491)
Long-run	0.0204	0.0028	-0.0557	-0.0026
	(0.0211)	(0.0261)	(0.0393)	(0.0507)
Size				
185-318 (2nd Q)	0.0039	0.0058	0.1025 ***	-0.0107
	(0.0188)	(0.0169)	(0.0338)	(0.0568)
319-1409 (3rd Q)	0.0256	-0.0115	0.1811 ***	-0.0426
	(0.0214)	(0.0271)	(0.0366)	(0.0853)
Technology				
Milking carousel	0.0088	0.0092	---	---
	(0.0329)	(0.0302)		
Milking fishbone	0.0021	0.0032	---	---
	(0.0201)	(0.0184)		
Milking next	0.0036	0.0004	---	---
	(0.0214)	(0.0198)		
Assets	---	0.0316 *	---	0.0582 **
		(0.0175)		(0.0271)
Off-Farm income	---	0.0111***	---	-0.0011
		(0.0041)		(0.0064)
Organic	0.0233	0.0312	-0.0559	-0.0004
	(0.0266)	(0.0277)	(0.0721)	(0.0861)
Age	-0.0027 ***	-0.0009	-0.0559	0.0043
	(0.0011)	(0.0023)	(0.0721)	(0.0029)
Education				
Agricultural	0.0108	-0.0157	0.0548	0.0005
	(0.0287)	(0.0251)	(0.0411)	(0.0494)
Higher professional	0.0368	0.0105	-0.0121	-0.0035
	(0.0261)	(0.0372)	(0.0343)	(0.0335)
Lower professional	0.0218	-0.0318	-0.0376	0.0144
	(0.0235)	(0.0253)	(0.0609)	(0.0606)

Table 2. Stage I innovation decision and investment *(cont.)*

Dependent Variable	Dairy		Arable	
	Engage in Innovation (0/1)	Innovation Intensity	Engage in Innovation (0/1)	Innovation Intensity
Region				
1 - Bouwhoek en Hogeland	0.0837	0.0012	-0.0261	-0.0059
	(0.0739)	(0.0907)	(0.0421)	(0.0415)
2 - Veenkolonien en Oldambt	0.0955	0.0569	0.0111	-0.0047
	(0.0629)	(0.0934)	(0.0391)	(0.0401)
3 - Noordelijk Weidegebied	0.0725	0.0188	-0.1118	0.0513
	(0.0569)	(0.0747)	(0.1016)	(0.1128)
4 - Oost. Veehouderijgebied	0.1148 **	0.0371	-0.1468 **	0.0695
	(0.0567)	(0.1023)	(0.0671)	(0.0903)
5 - Centr. Veehouderijgebied	0.0325	0.0203	---	0.2215
	(0.0664)	(0.0596)		(0.2575)
7 - Westelijk Holland	0.1241 **	-0.0405	0.0477	0.0075
	(0.0647)	(0.1151)	(0.0934)	(0.0949)
8 - Waterland Droogmakerijen	0.0663	-0.0128	-0.1393	0.1658
	(0.0905)	(0.0902)	(0.1369)	(0.1381)
9 - Holl/Utrechts Weidegbied	0.0193	0.0089	0.0397	-0.1136
	(0.0622)	(0.0541)	(0.2199)	(0.2626)
10 - Rivierengebied	7.53e-04	0.0206	-0.0703	0.9086 ***
	(0.0683)	(0.0556)	(0.2041)	(0.2159)
11 - Zuidwest Akkerbouwgebied	-0.0227	0.0006	-0.0099	0.0039
	(0.0831)	(0.0656)	(0.0079)	(0.0087)
13 - Zuidwest Veehouderijgebied	0.0559	0.0552	0.0908	-0.0233
	(0.0578)	(0.0659)	(0.0742)	(0.0848)
14 - Zuid-Limburg	0.1269 *	0.0801	0.1134	-0.1186
	(0.0731)	(0.1169)	(0.1023)	(0.1161)
Year				
2005	-0.0031	0.0051	0.1101	-0.0598
	(0.0696)	(0.0478)	(0.0801)	(0.1182)
2006	0.0551	0.0326	0.2285 ***	-0.1359
	(0.0696)	(0.0652)	(0.0799)	(0.1375)
2007	0.0587	0.0006	0.2565 ***	-0.1997
	(0.0695)	(0.0671)	(0.0795)	(0.1452)
2008	-0.1349 *	-0.0749	0.1827 **	-0.3339 **
	(0.0757)	(0.1224)	(0.0829)	(0.1318)
2009	0.0178	0.0371	0.2441 ***	-0.1852
	(0.0695)	(0.0498)	(0.0825)	(0.1419)
2010	0.0064	0.0123	0.2226 ***	-0.1035
	(0.0691)	(0.0475)	(0.0797)	(0.1355)
2011	-0.2596 ***	-0.1145	0.1975 **	-0.2693 **
	(0.0771)	(0.2157)	(0.0827)	(0.1341)
2012	0.0719	0.0693	0.3784 ***	-0.2857
	(0.0693)	(0.0751)	(0.0826)	(0.1839)
2013	0.0698	0.0529	0.3732 ***	-0.1877
	(0.0686)	(0.0735)	(0.0804)	(0.1834)
2014	0.1899 ***	0.0518	-0.0648	0.0396
	(0.0657)	(0.1632)	(0.0754)	(0.1127)

Table 2. Stage I innovation decision and investment *(cont.)*

Dependent Variable	Dairy		Arable	
	Engage in Innovation (0/1)	Innovation Intensity	Engage in Innovation (0/1)	Innovation Intensity
Mills Lambda	---	0.0585 (0.1826)	---	-0.3239 * (0.1786)
Observations	2996	2741	1695	1529
Replications based on Clusters Year/Region	371	363	259	253
Wald_demand pull	67.1 ***	3.01	14.31 ***	5.28 *
Wald_development	---	6.78 **	---	34.9 ***
Wald_confidence	33.32 ***	0.02	158.33 ***	4.49 *
Wald_region	22.73 **	12.3	12.33	20.43 **
Wald_year	58.26 ***	9.39	30.47 ***	21.45 **
Wald chi2(40)/(45) - Wald chi2 (36)/(42)	186.6 ***	70.99 ***	298.85 ***	128.99 ***

Notes: Standard errors in parentheses are robust based on 340 Jackknife replications clustered by year and region. The choice of the RE estimator is based on a standard Hausman test formula. Values reported refer to marginal effects (applying the Delta method at the sample mean) for the probability of investing in innovation and for the expected value of innovation intensity conditional on investing in innovation at all, respectively. Robustness of the estimates has been further confirmed by an IV regression. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3. Stage II knowledge/innovation production functions

Random Effects Probit Estimation 2004-2014

Dependent Variable	Dairy			Arable		
	Product Innovation (0/1)	Process Innovation (0/1)	OM Innovation (0/1)	Product Innovation (0/1)	Process Innovation (0/1)	OM Innovation (0/1)
Innovation intensity	0.2028 ***	0.7494 ***	0.2321 **	0.0345 **	0.1373 **	0.0504
(estimate stage I)	(0.0672)	(0.1525)	(0.1192)	(0.0143)	(0.0783)	(0.0549)
Investment intensity	0.0005	0.0431 ***	0.0039	0.0004	0.0205 ***	0.0024
	(0.0011)	(0.0045)	(0.0031)	(0.0009)	(0.0029)	(0.0023)
Protection	0.0062	---	---	0.0179	---	-0.0359
	(0.0185)			(0.0299)		(0.0989)
Knowledge institutions	-0.0065	-0.0079	0.0326 **	8.52e-05	0.0631 **	0.0146
	(0.0051)	(0.0164)	(0.0145)	(0.0093)	(0.0304)	(0.0235)
Demand pull						
Environment, safety,	0.0067	0.1411 ***	0.0048	0.0034	0.1756 ***	0.0116
health	(0.0048)	(0.0203)	(0.0187)	(0.0104)	(0.0338)	(0.0297)
Regulation, standards	-0.0152 **	-0.1026 ***	-0.0147	-0.0024	-0.1249 ***	0.0108
	(0.0076)	(0.0251)	(0.0227)	(0.0116)	(0.0381)	(0.0327)
Confidence						
Short-run	0.0079	0.0335 *	0.0022	-0.0243 *	0.0044	-0.0249
	(0.0062)	(0.0214)	(0.0177)	(0.0137)	(0.0343)	(0.0559)
Long-run	-0.0049	-0.0321 *	0.0147	0.0284 **	0.0209	0.0161
	(0.0051)	(0.0199)	(0.0168)	(0.0147)	(0.0326)	(0.0255)
Size						
185-318 (2nd Q)	-0.0034	0.0405 **	0.0038	-0.0022	0.0326	0.0464 **
	(0.0076)	(0.0188)	(0.0139)	(0.0084)	(0.0291)	(0.0218)
319-1409 (3rd Q)	0.0121 *	0.1062 ***	0.0074	-0.0084	0.0916 ***	0.0516 **
	(0.0075)	(0.0205)	(0.0151)	(0.0097)	(0.0311)	(0.0245)
Organic	-0.0132	0.0108	0.0201	---	-0.0815	-0.0249
	(0.0122)	(0.0265)	(0.0184)		(0.0743)	(0.0559)
Replications based on Region	15	15	15	15	15	15
Log-likelihood	-42.5942	-683.7914	-529.3952	-74.6993	-458.4977	318.8221
Wald_chi2(11) / (10)	10.65	211.44 ***	22.18	12.79	115.99 ***	39.77 ***
PseudoR2	0.6663	0.1195	0.0016	0.4147	1.5904	0.3987
LR test rho=0	4.78 **	25.67 ***	8.95 ***	1.76 *	6.03 ***	3.36 **
Wald_demand pull	3.72	50.11 ***	0.52	0.11	27.09 ***	1.05
Wald_confidence	1.59	2.95	2.08	4.23 *	1.13	0.93
Wald_investment	8.99 **	116.52 ***	5.85 **	6.94 **	50.07 ***	2.05
Observations	2317	2318	2319	1181	1192	1199

Notes: Standard errors in parentheses are robust based on 14 Jackknife replications clustered by region. The choice of the RE estimator is based on a standard Hausman test formula. Values reported refer to marginal effects (applying the Delta method at the sample mean) for the probability of realising product innovations, process innovations and/or organisational/marketing innovations, respectively. Robustness of the estimates has been further confirmed by an IV regression and the test for lagged explanatory values with respect to investments.

OM: organisational-marketing; * significant at 10%, ** significant at 5%, *** significant at 1%. Due to the relatively low number of observations on product innovation, the estimates reported for this type of innovations at farm level should be interpreted with great care.

Table 4. Stage IIIa output production

Arellano-Bond DPD Estimation 2004-2014

Dependent Variable	Dairy		Arable	
	Labor Productivity	Cow Productivity	Labor Productivity	Land Productivity
Labor productivity *(lag 1)*	0.2899 ***	---	-0.1203 ***	---
	(0.0443)		(0.0442)	
Cow productivity *(lag 1)*	---	0.0005	---	---
		(0.0359)		
Land productivity *(lag 1)*	---	---	---	-0.1906 ***
				(0.0451)
Product innovation *(estimate stage II)*	0.3239 **	0.1663 *	-0.9491	0.0108
	(0.1631)	(0.0873)	(1.0801)	(1.1787)
Product innovation *(estimate stage II, lag 1)*	0.0237	0.0598	-0.3895	-0.4974
	(0.1566)	(0.0847)	(0.9241)	(1.0064)
Product innovation *(estimate stage II, lag 2)*	-0.2221	0.2247 ***	-0.1976	0.2385
	(0.2001)	(0.0807)	(0.9442)	(1.0184)
Process innovation *(estimate stage II)*	0.0258	-0.0799	0.2141	0.1976
	(0.0934)	(0.0581)	(0.1702)	(0.1435)
Process innovation *(estimate stage II, lag 1)*	0.0471	0.0559	0.4988 ***	0.3471 ***
	(0.0897)	(0.0557)	(0.1474)	(0.1241)
Process innovation *(estimate stage II, lag 2)*	0.1945 **	-0.0306	0.3662 **	0.4749 ***
	(0.0833)	(0.0503)	(0.1476)	(0.1229)
Organisational/Marketing innovation *(estimate stage II)*	-0.6766	0.3248	0.5294	1.6595 ***
	(0.6048)	(0.3737)	(0.6396)	(0.5146)
Organisational/Marketing innovation *(estimate stage II, lag 1)*	0.7963	0.5717 *	-0.0188	0.7703
	(0.5565)	(0.3438)	(0.5967)	(0.5282)
Organisational/Marketing innovation *(estimate stage II, lag 2)*	1.8781 ***	0.5441 *	0.3519	0.7641
	(0.5653)	(0.3223)	(0.6223)	(0.5422)
Investment intensity	-2.31e-04	-0.0034	0.0135	0.0004
	(0.0059)	(0.0029)	(0.0093)	(0.0044)
Investment intensity *(lag 1)*	0.0011	-0.0002	0.0221 ***	0.0018
	(0.0059)	(0.0028)	(0.0084)	(0.0041)
Investment intensity *(lag 2)*	-6.94e-04	0.0015	0.0217 **	0.0093 *
	(0.0056)	(0.0027)	(0.0088)	(0.0041)
Land	0.1153 ***	0.0405 *	0.2078 ***	---
	(0.0386)	(0.0241)	(0.0539)	
Assets	0.0219	0.3835 ***	0.0705	0.3418 ***
	(0.0573)	(0.0274)	(0.0649)	(0.0406)
Size				
185-318 (2nd Q)	0.0169	0.0116	0.0165	-0.04837
	(0.0204)	(0.0138)	(0.0609)	(0.0526)
319-1409 (3rd Q)	0.0688 **	0.0253	0.0654	0.0336
	(0.0295)	(0.0198)	(0.0769)	(0.0641)
Organic	-0.2756**	-0.0161	-0.0643	-0.1017
	(0.1289)	(0.0813)	(0.1078)	(0.0958)
Technology				
Milking carousel	0.0555 ***	-0.0014 **	---	---
	(0.0574)	(0.0007)		
Milking fishbone	-0.0005	0.0346 **	---	---
	(0.0265)	(0.0179)		
Milking next	0.0273	0.0052	---	---
	(0.0283)	(0.0187)		

Table 4. Stage IIIa output production (*cont.*)

Dependent Variable	Dairy		Arable	
	Labor Productivity	Cow Productivity	Labor Productivity	Land Productivity
Age	-0.0013	-0.0014 **	0.0031	0.0026
	(0.0012)	(0.0007)	(0.0027)	(0.0023)
Year				
2005	0.0259 *	0.0192 **	0.0479 **	-0.0196
	(0.0155)	(0.0104)	(0.0247)	(0.0225)
2006	0.0811 ***	0.0746 ***	0.2435 ***	0.1565 ***
	(0.0163)	(0.0107)	(0.0276)	(0.0238)
2007	0.2697 ***	0.2533 ***	0.2825 ***	0.1904 ***
	(0.0171)	(0.0108)	(0.0339)	(0.0281)
2008	0.2053 ***	0.2364 ***	0.2391 ***	0.1433 ***
	(0.0216)	(0.0138)	(0.0344)	(0.0278)
2009	-0.0213	-0.0152	0.3132 ***	0.1341 ***
	(0.0245)	(0.0157)	(0.0404)	(0.0316)
2010	0.2872 ***	0.2147 ***	0.5435 ***	0.3298 ***
	(0.0262)	(0.0157)	(0.0487)	(0.0371)
2011	0.3592 ***	0.3436 ***	0.3525 ***	0.1674 ***
	(0.0310)	(0.0191)	(0.0516)	(0.0409)
2012	0.2686 ***	0.2604 ***	0.6462 ***	0.4359 ***
	(0.0319)	(0.0197)	(0.0545)	(0.0425)
2013	0.3511 ***	0.3392 ***	0.5258 ***	0.3598 ***
	(0.0335)	(0.0198)	(0.0606)	(0.0479)
2014	0.4049 ***	0.3762 ***	0.6316 ***	0.2521 ***
	(0.0384)	(0.0207)	(0.0988)	(0.0583)
Instruments	332	322	282	293
Replications based on Region	15	15	15	15
Wald chi2(32) / (29)	2725.57 ***	3429.24 ***	917.84 ***	1107.22 ***
Wald_innovation	22.03 ***	15.31 *	17.65 ***	32.21 ***
Wald_technology	1.96	3.87	---	---
Wald_size	7.46 **	1.67	1.28	5.74 **
Wald_year	650.71 ***	1311.48 ***	253.88 ***	248.9 ***
AB test (autocorrelation of order 1/2)	-4.3032/-7.3233 ***/***	-4.4152/-10.551 ***/***	-6.146/-2.7823 ***/***	-5.1223/-2.8193 ***/**
Observations	1888	1997	1019	1031

Note: Standard errors in parentheses are robust based on 14 Jackknife replications clustered by region. Values reported refer to marginal effects (at the sample mean based on the Delta method) from the AB DPD Regression. Estimates for yearly effects are not reported. As instruments the variables related to regions, education as well as all other explanatory were used. Robustness of the estimates has been further confirmed by several IV regressions. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5. Stage IIIb output production

Arellano-Bond DPD Estimation 2006-2012

Dairy		
Dependent Variable	Total Factor Productivity	
Total factor productivity *(lag 1)*	0.2313	***
	(0.0564)	
Product innovation *(estimate stage II)*	-0.0109	
	(0.0124)	
Product innovation *(estimate stage II, lag 1)*	0.0021	
	(0.0118)	
Process innovation *(estimate stage II)*	-0.1114	
	(0.0704)	
Process innovation *(estimate stage II, lag 1)*	0.1258	**
	(0.0644)	
Organisational/Marketing innovation *(estimate stage II)*	0.0055	
	(0.0369)	
Organisational/Marketing innovation *(estimate stage II, lag 1)*	-0.0332	
	(0.0291)	
Investment intensity	-0.0097	
	(0.0057)	
Investment intensity *(lag 1)*	-0.0089	
	(0.0059)	
Size		
185-318 (2nd Q)	0.0681	***
	(0.0207)	
319-1409 (3rd Q)	0.0972	***
	(0.0263)	
Organic	0.0339	
	(0.0957)	
Technology		
Milking carousel	-0.0412	
	(0.0478)	
Milking fishbone	-0.0147	
	(0.0213)	
Milking next	-0.0123	
	(0.0204)	
Age	0.0017	*
	(0.0011)	
Year		
2006	0.0258	**
	(0.0208)	
2007	0.0233	**
	(0.0233)	
2008	0.0272	***
	(0.0104)	
2009	0.0209	**
	(0.0098)	
2010	0.0256	**
	(0.0101)	
2011	0.0183	
	(0.0111)	
Instruments	204	
Replications based on Region	14	
Wald chi2(13)	87.32	***
Wald_innovation	9.85	*
Wald_technology	1.35	
Wald_size	14.93	***
Wald_year	13.34	**
AB test (autocorrelation of order 1/2)	-7.6208/1.865	***/***
Observations	1156	

Note: Standard errors in parentheses are robust based on 14 Jackknife replications clustered by region. Values reported refer to marginal effects (at the sample mean based on the Delta method) from the AB DPD Regression. Estimates for yearly effects are not reported. As instruments the variables related to regions, education as well as all other explanatory were used. Robustness of the estimates has been further confirmed by several IV regressions. * significant at 10%, ** significant at 5%, *** significant at 1%.

Farm size shows a positive effect on innovation probability: medium and large size farms are more likely to invest in innovation (by about 10% and 18% respectively, compared to small arable farms). The type of milking technology is not significantly linked to the probability of engaging in innovation for a dairy farm. Younger dairy farmers show a higher probability of engaging in innovation activities whereas the type of education seems not to be of direct importance for the engagement in innovation activities. A strong confidence in (short-run) future business and sector developments seemingly increases the innovation probability at dairy farm level (by about 11% compared to farmers without such confidence). However, the opposite effect has been found for arable farmers. Here, short-run business confidence obviously leads to a lower probability of engaging in innovation activities at farm level. This surprising result is somewhat watered down by the positive and significant estimate for the innovation intensity effect by short-run business confidence in arable farming (see below). The regional location of the farm seems important for innovation activities with respect to dairy farms located in Westerlijk Holland, Oost. Veehouderijgebied and Zuid-Limburg. Finally, the p-values of the significance tests with respect to the joint significance of demand pull variables, product/process development variables, business confidence, regional location and time related yearly dummy variables indicate their significance for the probability to engage in innovation activities for the dairy farms in the sample considered. These statistical significances are also confirmed for arable farms with the exception of those variables linked to regional location.

The second stage of the structural model delivers estimates for the *determinants of how much farms invest in innovation* conditional on doing innovation investment at all in the period 2004 to 2014. The numbers reported in the second and fourth columns of Table 2 are again marginal effects for the expected value of the innovation intensity conditional on investing in innovation at all, respectively. Many of the explanatory variables are again binary dummy variables taking the value 1 when the factor is important to the farmer's decision or used in the farm's production process (Table A2) and the value zero if it is unimportant or not used. Therefore, the "marginal" effect relates to a change in the binary variable from 0 to 1. By interpreting the estimates it should be noted that the dependent variable (innovation intensity) is now used in logs, hence, the estimates reported for the explanatory variables represent one-unit log changes in innovation intensity for the binary dummy variables and percentage changes for the logged continuous explanatory variables (i.e. assets, off-farm income).

Innovation intensity (measured in resources invested in innovation activities in euros per cow or ha by the respective farm) is found to be significantly higher for dairy farms that develop innovative products and/or processes. Mainly developing own products and processes is resource intensive compared to sharing the cost of innovation activities. The marginal effect by demand pull factors again showed to be significant with respect to regulation and standards related to the production (by about 12% compared to other arable farms for which such aspects are not relevant, again conditional on the mean values of all other explanatory variables). Having access to information on innovation related funding possibilities further increases the probability of investing resources in innovation activities (by about 30% for arable farms). This might reflect the resource intensity of own development activities discussed above. The estimates further suggest that the level of assets (dairy and arable farming) and the level of off-farm income (only dairy farming) positively influence the amount invested in innovation at farm level. Short-run business confidence significantly increases the innovation intensity for arable farms in the sample (by about 30% ceteris paribus) On the other hand, no significant effect has been found for farm size, technology, or individual characteristics such as age and education. Arable farms located in the region Rivierengebied show a significantly higher intensity of innovation activities compared to arable farms in other regions of the Netherlands. Finally, the p-values for the significance tests with respect to the joint significance of time related yearly dummy variables, demand pull factors and process development characteristics indicate their joint significance for the level of innovation intensity. Finally, the insignificance of the estimate for the mills lambda indicates no severe misspecification due to potential selection bias with respect to the (reportedly) innovation active dairy farms in the sample. However, its estimate indicate some misspecification due to potential selection bias with respect to the (reportedly) innovation active arable farms in the sample. The inclusion of the Mills ratio corrects for such potential bias.

The third stage of the structural model gives *estimates for the knowledge or innovation production functions* reported in Table 3. The first and fourth columns show the results for production related innovation, the second and fifth for process related innovation, and the third and sixth columns show the results for organisational and marketing innovation. The numbers reported are marginal effects evaluated at the sample means (i.e. changing the value of binary dummy variables from 0 to 1). The marginal effects for innovation intensity (estimate from stage I) are statistically and economically significant for product, process and organisational-marketing (OM) related innovations for both dairy and arable farms (except OM related innovations for arable farming). They suggest that greater innovation investment (per cow or ha) leads to a higher probability of having at least one product innovation (+20% or +3%) and/or process innovation (+75% or +14%) and/or of having at least one OM innovation (+23%). Also, the marginal effects for tangible investment intensity (per cow or ha) are significant with respect to process innovations (to a lesser extent). However, product and OM innovations seem not to be significantly influenced by tangible investment related factors. These estimates indicate the essential role of investments in innovation activities for the production of actual innovative products, processes and/or organisational characteristics. Such innovations are resource intensive which is documented by the relatively high estimates for process (technology) related innovation production.

The ability to protect an innovation through formal or strategic methods (e.g. certification, trademark, plant breeders, patent) shows to be not important for the sample of dairy and arable farms participating in the survey with respect to their production of innovative products. However, one has to keep in mind that other actors which develop and market innovations that are adopted by farmers (e.g. new seeds, new production equipment, etc.) are not part of the survey. Dairy farms in the sample that co-operate with knowledge producing institutions (universities, research institutes etc.) are significantly more likely to engage in OM innovations. Arable farms that co-operate with such institutions are significantly more likely to engage in process related innovations.

Demand pull related factors - environment, safety and health related aspects - positively influence the probability of process innovations for both type of farms. This suggests that innovations in dairy and arable processes (milking, feeding etc. or sowing, harvesting etc.) are significantly initiated by management considerations related to an improvement in sustainability as well as labour cost implications of production. Regulation and standards show no positive (and significant) effect with respect to any innovation production. However, the relationship between consumer concerns on environment, safety and health on the one hand, and regulation on the other hand is likely to be a complex one: in some cases regulations are following as a reaction to consumer concerns, and in others regulation can act as a floor for performance that can trigger the search for innovative solutions. In sum, the statistically significant demand pull related effects on the production of process innovation are positive (i.e. about 4% for dairy and about 5% for arable farming). However, this does of course not imply that additional regulation simply leads to productivity gains per se. Stated short- and long-term business confidence showed again mixed effects on the probability of producing process and product related innovations. However, for dairy processes the positive short-term effect by confidence in business and sector developments/prospects slightly outweighs the negative long-term effect (ceteris paribus), whereas for arable products the negative short-term confidence related innovation production effect is outweighed by the positive effect of long-term confidence. So, keeping the findings from the first stage estimations in mind, having confidence in the dairy or arable operation’s performance might help to increase the probability of actually producing a new process or product on the farm. This suggests that a positive outlook in the short-term (dairy) or long-term (arable) is linked to a higher probability of generating sufficient means to invest in new resource-intensive products (arable) and processes (dairy).

The size of the dairy or arable operation showed a statistically significant positive effect on the probability of producing innovations whereas organically producing farms are not more likely to produce innovations compared to conventional farms. The p-values for the significance tests with respect to the joint significance of demand pull related variables indicate a joint significance with respect to process innovations only. Those for the joint significance test of the business confidence related variables indicate such joint significance to a lesser extent for product related innovations. And the p-values for the significance tests with respect to the joint significance of investment related variables in general indicate varying levels of significance for all three dimensions of innovation production and both farm types. Overall, the significance of the second stage estimations is highly satisfactory for process innovation production and to a much lesser extent for product and OM innovation production given the datasets available. This might be related to the essential importance of production technology in primary industries.

Finally, *estimates of the link between innovation and productivity from the output production or productivity functions* are presented (Table 4 and Table 5). The coefficients summarised in Tables 4 and 5 represent elasticities or semi-elasticities since the dependent variables are specified in log form (i.e. the log of output per labour, the log of output per cow, the log of output per ha land, and the log of total factor productivity). To account for the likely endogeneity of production decisions a dynamic estimation procedure is applied allowing for the incorporation of lagged values of the performance related dependent variable. Further it allows considering lagged effects and likely endogeneity with respect to innovation production related explanatory variables. The lagged values of the dependent partial and total performance indicators are highly significant and positive in the case of diary labour productivity and total factor productivity, however, statistically significant and negative for arable related labour and land productivity. This suggests a strong upward trend in dairy farms' productivity but a downward trend in arable farms' productivity over the period investigated (2004-14). The intensity of tangible investments (to control for farms' capital stock) shows the expected significant and positive effects on arable farms' performance measured by labour and land related productivity, however, a slight negative impact on dairy farms' performance measured by total factor productivity.

Product related innovation shows to increase partial productivity per labour and per cow for dairy farming. Process related innovation has been found to increase labour productivity for both farming types with a certain time lag as well as to increase land productivity of arable farming (lag 1 and lag 2 estimates) and total factor productivity of dairy farming (lag 1 estimate). OM related innovation obviously increases all partial productivity measures: arable farming related land productivity in the current year, dairy farming related labour and cow productivity with a certain time lag. The elasticities of the performance related indicators with respect to innovation production estimates (from the second modelling stage) show a mixed statistical and economic significance throughout the different performance measures tested. Overall, it is evident that process and OM related innovation production lead to the highest productivity gains: dairy farms' productivity most significantly benefits from organisational and marketing innovations, arable farms' productivity most significantly benefits from process related innovation production. In the case of dairy farming labour related partial productivity is most significantly increased by innovation production, whereas for arable farming land related partial productivity is most significantly increased by innovation production.

Other farm and farmer related characteristics are also examined (e.g. size, production system, technology and age of the farm manager). In terms of dairy production technology: the carousel based milking technique increases farms' labour productivity significantly keeping all other factors constant, and the fishbone based milking technique significantly increases farms' cow related productivity. Finally, the elasticities for farm size confirm the existence of economies of scale only to a relative extent. The p-values for the significance test with respect to the joint significance of innovation production related variables indicate such a joint significance for all productivity models. The Wald test with respect to the joint significance of the farm size related variables show a high significance for labour and total productivity (dairy farming) and land productivity (arable farming). Hence, these test results indicate an overall statistical significance of innovation production for modelling dairy and arable farms' economic performance. However, the mixed results with respect to product, process and OM innovation for dairy and arable output production suggest a considerable sensitivity of the performance measure applied with respect to the effect of innovation investment and production as measured by stages I and II.

6. Conclusions and recommendations

This study delivers empirical evidence on the link between innovation and economic performance at farm level for a comprehensive sample of dairy and arable farms in the Netherlands. Based on an original unbalanced sample for the period 2004 to 2014 which has been generated by a comprehensive annual survey, microeconometric techniques are used to identify and estimate a multi-stage structural model consisting of the innovation decision, the innovation intensity, the innovation production and the output production. Potential selectivity and simultaneity bias is corrected by using a Heckman correction routine and aim to capture dynamics by estimating a dynamic panel data model using lags of the dependent and independent variables. Product, process and organisational or marketing related innovations at farm level, and approximate farm level performance by partial and total productivity indicators depending on the type of production (labour, cow and land based productivity indicators as well as total factor productivity) are considered.

The main empirical findings can be summar ised as follows: demand pull factors mainly due to standards have a strong effect on the farms' innovation engagement and intensity. Environment, safety and health related aspects specifically increase the probability of producing process related innovations at farm level. To co-operate with knowledge producing institutions significantly helps to engage farms in innovation activities. Co-operating dairy farms in the sample are significantly more likely to engage in organisational and marketing innovations. Co-operating arable farms are significantly more likely to engage in process related innovations. Hence, the findings reflect the notion in the relevant literature that the socio-economic environment the firm is operating in is likely to be significant for its innovation behaviour in terms of access to finance, institutional support, cultural values, cooperation with research entities etc.

If farms pursue their own product and process related development activities it can be concluded that these farms are more likely to be engaged in innovation activities as well as show a higher innovation intensity in terms of resources invested in innovation activities. A positive effect of size on the probability to innovate and the probability of actually producing innovations is confirmed by the findings. However, no size effect has been found with respect to the intensity of such engagement. Overall, the study reveals a more positive role of size compared to the literature that states an ambiguous size effect on innovation activities. Further, the age of the farmer matters, but the type of education does not, with respect to innovation engagement and intensity. Finally, overall confidence in business and sector developments increases the innovation intensity at farm level. In addition, such confidence obviously helps to increase the probability of successfully producing process or product innovations.

Regarding the core hypotheses investigated for this empirical study reveals that indeed a greater innovation investment per unit leads to a higher probability of producing at least one successful product, process and organisational and marketing innovation. Parts of the literature that conclude on an essential role of investments in innovation activities (innovation input) for the actual production of innovations (innovation output) are confirmed. Furthermore, the study shows that the production of process and organisational and marketing innovation leads to significant productivity gains adding additional empirical proof for a positive and significant relationship between innovation and farm performance mostly stated in the relevant literature.

With regard to policy implications, it can be concluded that the effective communication of business and sector confidence, and the support of knowledge dissemination by knowledge producing institutions, as well as the support of co-operation of individual farms with such institutions, are primary fields of activity. Furthermore, the building up and communication of demand pull situations based on environmental, safety and health concerns should lead to strong incentives to engage in innovation at farm level. Financial incentives for investing in productivity increasing process and organisational or marketing innovations promise highest productivity gains.

The OECD review on the innovation system in the Netherlands with respect to food and agriculture (OECD, 2015) stresses that the policy environment is one of the most favourable to investment worldwide which holds also with respect to innovation to increase productivity and sustainability. However, scope for further improvement exists in areas such as access to capital, transaction costs related to regulatory procedures, and available funding resources. The empirical findings with respect to the future role of innovation policy in the agricultural sector empirically complements those concerns and reflects the crucial need for evidence based policy making in this area.

Confidence in business related matters (i.e. output and input price developments, security of policy support, animal and crop health issues, probability of external shocks, etc.) should be periodically surveyed and monitored by trustworthy and independent institutes or companies based on transparent and clear categories following peer-reviewed survey techniques. The results of such confidence monitoring should be timely and effectively communicated to farmers and related dairy and arable supply chain actors (e.g. by market outlook briefs). It might be therefore a primary policy option to build up and maintain such a survey and documentation system for different agricultural and food sectors helping to encourage investments in innovations at farm level by transparently documenting perceived future investment and innovation gains as considered by the majority of sectoral players at a given point in time. The OECD 2015 Dutch innovation system review report stresses the need for policy to strengthen incentives for innovation by continuing to provide information on current and future opportunities and challenges in the agri-food sectors.

Knowledge producing institutions (e.g. universities, basic and applied research institutes, technology supplier related R&D departments, etc.) should be supported in the process of disseminating their innovation related findings and recommendations. Publicly funded research institutes should be required to spend a significant amount of their overall budget on dissemination related output periodically evaluated by independent experts in the field. Private R&D departments at firm level should be able to compete for additional public funding for such dissemination related actions. Furthermore, co-operation of individual farms with such knowledge producing institutions has to be considered at the centre of the innovation knowledge dissemination process. Specific programmes managed by public agencies to maintain an ongoing dialogue between innovation users (farms, firms) and innovation designers (universities, basic and applied research institutes, and private consulting companies) should be established. Periodic conferences and workshops based on innovation networks would help to accelerate such co-operative innovation efforts. These recommendations are in line with the latest OECD review of the Dutch agricultural innovation system (OECD, 2015) where the further improvement of capacities and services for innovation especially with respect to facilitating labour mobility and on-the-job training as well as strengthening linkages between educational systems is highlighted.

Demand side pressure with respect to the introduction and consideration of environmental, safety and health concerns related to products, processes and organisational or marketing innovations seem to significantly stimulate innovation engagement and activities at farm level. A crucial role for policy engagement therefore might be to effectively support the communication of such concerns to the farm business community. This relates to the channelling of such discussions (e.g. animal welfare considerations) via the organisation and financial support of discussion forums and the active engagement of farmers and industry focused interest associations. The OECD report (2015) concludes that the capacity of farmers to participate in the agricultural innovation system (farm advisory, producer groups etc.) has to be further increased. Policy should therefore strengthen the links between agriculture-specific innovation systems and related areas (health, environment). However, policy support should predominantly focus on market oriented measures aiming at increasing transparency. This notion is empirically supported by the insignificance of regulation push based factors with respect to farms’ innovation engagement and innovation intensity revealed by the quantitative analyses. The OECD report on the Dutch agricultural innovation system (2015) also stresses that the existing policy mix of regulation, financial incentives, and market-based mechanisms has to be improved to foster also eco-innovation. Further, a crucial role of the government is seen in shaping the research agenda towards an increasing consideration of longer-term and public good concepts.

Finally and crucially, the survey and documentation of innovation behaviour at farm level in different sectors is the base for the production of empirical evidence based on quantitative methods. The OECD report (2015) concludes that innovation adoption should be continuously monitored and evaluated. However, to be useful for evidence based policy making such robust empirical insights are crucial and should be produced by state-of-the-art statistical instruments. Such surveys should be based on the general guidelines of the Oslo Manual and be conducted periodically to enable analysts to shed comparative empirical light on the relationship between innovation engagement, intensity and economic performance in a dynamic perspective.

The availability of longitudinal data on innovation will allow researchers to more effectively control for unobserved heterogeneity at farm and firm level and also allow for separate estimations of innovation models for different groups of farms/firms (e.g. along size considerations). However, structural dynamic models of innovation adopting the CDM framework are currently the gold standard of empirical innovation research based on microeconomic concepts and microeconometric tools. Principles and recommendations as well as concrete advice on questionnaire design with respect to good practice based innovation surveys can be found in Mairesse and Mohnen (2010). They nevertheless stress that a gap between more sophisticated innovation survey data and policy needs will remain. There are promising attempts in this direction as e.g. the key findings of the recently completed FLINT project show (see, for example, Poppe et al., 2016). However, statistical and econometric modelling and analyses should be regarded as the primary candidate able to – at least partly – close this gap in the near future in order to foster evidence based policy making.

Annex A.

Supplementary tables

Table A1. Literature review on dairy farms' performance and drivers

	Article title (Journal)	Year	Country	Driving forces
1.	A Production Model with firm-specific temporal Variation in Technical Inefficiency: with application to Spanish dairy Farms (JPA)	2000	Spain	Technical change
2.	Decomposition of Productivity Growth Using Distance Functions: the Case of dairy Farms in three European Countries (AJAE)	2002	Germany, Netherlands, Poland	Ger.: Technical change NL: Allocative components PL: Technical change
3.	Economic Effects of U.S. Dairy Policy and alternative Approaches to Milk Pricing (USDA)	2004	United States	Policy
4.	Sources of Productivity Growth and Stochastic Dominance Analysis of Distribution of Efficiency (MTT Reports)	2004	Finland	Technical change
5.	The productivity performance of Irish dairy farms 1984–2000: a multiple output distance function approach (JPA)	2006	Ireland	Technical change Scale economies Intensification
6.	Productivity growth in Australian broad acre and dairy industries (ABARE)	2008	Australia	Policy Intensification
7.	Components of Productivity Growth in Finnish Agriculture (MTT Reports)	2008	Finland	Technical change
8.	Scale Economies and Inefficiency of U.S. Dairy Farms (AJAE)	2009	United States	Scale economies
9.	Organic Farming in Scandinavia - Productivity and Market Exit (EE)	2009	Denmark	Investments Subsidies Debt, Off-Farm Income
10.	Farm innovation in the broad acre and dairy industries (ABARE)	2009	Australia	Innovation Adoption
11.	Technology Adoption and technical efficiency: organic and conventional farms in the US (AJAE)	2010	United States	Technical change
12.	Deregulation and Dairy Production Systems: A Bayesian Distance Function Approach (JPA)	2010	Denmark	Policy Deregulation
13.	Productivity growth: Trends, drivers and opportunities for broad acre and dairy industries (ABARE)	2010	Australia	Innovation Management
14.	Scale Efficiency in Danish agriculture: an input distance-function approach (ERAE)	2010	Denmark	Technical change Scale economies
15.	Identifying different technologies using a latent class model: extensive versus intensive dairy farms (ERAE)	2010	Spain	Intensification

Table A1. Literature review on dairy farms' performance and drivers (*cont.*)

	Article title (Journal)	Year	Country	Driving forces
16.	Productivity and efficiency scores of dairy farms: the case of turkey (QualQuant)	2010	Turkey	Scale economies Extension services
17.	A reduced-form model for dynamic efficiency measurement: application to dairy Farms in Germany and the Netherlands (AJAE)	2011	Germany, Netherlands	Policy Technical change
18.	Animal Breeding and Productivity Growth of dairy farms (AJAE)	2012	Iceland	Genetic improvement Technical change
19.	Performance of dairy farms in Finland and Norway (ERAE)	2014	Finland, Norway	Policy
20.	Potential effects of climate change on the productivity of U.S dairies (AJAE)	2014	United States	Climate change
21.	Investment, Technical Change and Efficiency: Empirical Evidence from German Dairy Production (ERAE)	2014	Germany	Investments Education Policy
22.	Efficiency and Regulation: A Comparison of Dairy Farms in Ontario and New York State	2016	United States	Allocative Decisions Prices

Table A2. Variables used in the structural estimation models, 2004 to 2014

Variable	Description	Mean (Stdev)		Min/Max	
		Dairy	Arable	Dairy	Arable
1 - Knowledge/Innovation/Output					
innovation engagement	binary variable [1 - yes, 0 - no activities] farm reports engagement in innovation/R&D activities	0.1474 (0.3545)	0.4098 (0.4919)	0 / 1	0 / 1
innovation intensity	continuous variable $[0; \infty]$ resources invested in innovation activities per cow (per ha land) [in Euro]	5.0783 (8.0686)	80.6579 (156.8845)	0.0005 / 731.8404	0.7404 / 867.8295
product innovation	binary variable [1 - yes, 0 - no activities] farm reports having introduced new or significantly improved products	0.0094 (0.0964)	0.0154 (0.1232)	0 / 1	0 / 1
process innovation	binary variable [1 - yes, 0 - no activities] farm reports having introduced new or significantly improved production processes	0.1179 (0.3226)	0.1801 (0.3844)	0 / 1	0 / 1
organisational / marketing innovation	binary variable [1 - yes, 0 - no activities] farm reports having introduced new or significantly improved organisational and/or marketing structures	0.0604 (0.2383)	0.0771 (0.2668)	0 / 1	0 / 1
labor productivity	continuous variable $[0; \infty]$ revenue per labor [in Euro]	75.7802 (38.2189)	109.4675 (64.6443)	4.7656 / 346.7992	8.1261 / 795.978
cow productivity	continuous variable $[0; \infty]$ revenue per cow [in Euro]	356.3845 (89.2556)	---	21.5606 / 1135.533	---
land productivity	continuous variable $[0; \infty]$ revenue per ha [in Euro]	---	4442.354 (2137.904)	---	1033.145 (16973.54)
total factor productivity (06-12)	continuous variable $[0; \infty]$ productivity points	1.3224 (0.3307)	---	0.1545 (3.3914)	---
milk output	continuous variable $[0; \infty]$ total milk sales per farm [in Euro]	273429.6 (209791.5)	---	0 / 1937557	---
crop output	continuous variable $[0; \infty]$ total crop sales per farm [in Euro]	---	458553 (448268.6)	---	16662.59 / 4753613
investment intensity	continuous variable $[0; \infty]$ gross investments in tangible goods per cow (per ha land) [in Euro]	119.1959 (232.2931)	1477.25 (2580.406)	0 / 4889.808	0 / 30342.03

Table A2. Variables used in the structural estimation models, 2004 to 2014 (*cont.*)

Variable	Description	Mean (Stdev)		Min/Max	
		Dairy	Arable	Dairy	Arable
2 - Demand Pull					
environmental, health and safety aspects	binary variable [1 - yes, 0 - no activities] *"if environmental, health or safety aspects were of high relevance"*	0.1724 (0.3777)	0.1239 (0.3295)	0 / 1	0 / 1
regulation and standards	binary variable [1 - yes, 0 - no activities] *"if regulation or standards were of relevance"*	0.1187 (0.3235)	0.0993 (0.2992)	0 / 1	0 / 1
3 - Sources of Information					
product or process development own	binary variable [1 - yes, 0 - no activities] *"own product development"*	0.0036 (0.0601)	0.0019 (0.0439)	0 / 1	0 / 1
product or process development seperate	binary variable [1 - yes, 0 - no activities] *"product development in separate company"*	0.0003 (0.0181)	0.0005 (0.0219)	0 / 1	0 / 1
product or process development mainly other	binary variable [1 - yes, 0 - no activities] *"product development mainly by others"*	0.0029 (0.0543)	0.0058 (0.0758)	0 / 1	0 / 1
product or process development cooperation	binary variable [1 - yes, 0 - no activities] *"product development in cooperation"*	0.0019 (0.0443)	0.0024 (0.0491)	0 / 1	0 / 1
product or process development only other	binary variable [1 - yes, 0 - no activities] *"product development exclusively by others"*	0.0013 (0.0362)	0.0072 (0.0847)	0 / 1	0 / 1
knowledge institutions	binary variable [1 - yes, 0 - no activities] *"cooperation with knowledge institutions"*	0.8201 (0.3842)	0.8843 (0.3199)	0 / 1	0 / 1
4 - Cooperation/Contracts/Protection					
cooperation	binary variable [1 - yes, 0 - no activities] *"any form of cooperation along supply chain"*	0.0602 (0.2378)	0.0391 (0.1938)	0 / 1	0 / 1
marketing contracts	binary variable [1 - yes, 0 - no activities] *"any form of marketing contract"*	0.0231 (0.1501)	0.2473 (0.4316)	0 / 1	0 / 1
protection	binary variable [1 - yes, 0 - no activities] *"farm uses form of protection for innovation (e.g. certification, trademark, plant breeders, patent)"*	0.0016 (0.0405)	0.0048 (0.0693)	0 / 1	0 / 1
5 - Public Support					
funding information	binary variable [1 - yes, 0 - no activities] *"well informed about funding opportunities"*	0.0224 (0.1479)	0.0236 (0.1519)	0 / 1	0 / 1
6 - Business Confidence					
confidence short-run	binary variable [1 - yes, 0 - no activities] *"a lot or some confidence in short-term business development"*	0.6253 (0.4841)	0.4566 (0.4982)	0 / 1	0 / 1
confidence long-run	binary variable [1 - yes, 0 - no activities] *"a lot or some confidence in long-term business development"*	0.5489 (0.4977)	0.3905 (0.4879)	0 / 1	0 / 1

Table A2. Variables used in the structural estimation models, 2004 to 2014 (cont.)

Variable	Description	Mean (Stdev)		Min/Max	
		Dairy	Arable	Dairy	Arable
7 - Economic/Financial Characteristics					
assets	continuous variable $[0;\infty]$ *gross assets per cow [in Euro]*	3643.681 (1459.699)	43956.49 (23550.09)	231.2519 / 14158.01	1249.876 / 188242.5
off-farm income	continuous variable $[0;\infty]$ *total off-farm income per cow [in Euro]*	21.0671 (57.9732)	233.2135 (759.5867)	0 / 1360.714	0 / 7312.031
size 1st Q	binary variable [1 - yes, 0 - no activities] *farm size in standard output > 0 to 185 TEuro*	0.3333 (0.4674)	0.3333 (0.4674)	0 / 1	0 / 1
size 2nd Q	binary variable [1 - yes, 0 - no activities] *farm size in standard output > 185 to 318 TEuro*	0.3333 (0.4674)	0.3333 (0.4674)	0 / 1	0 / 1
size 3rd Q	binary variable [1 - yes, 0 - no activities] *farm size in standard output > 318 to 1409 TEuro*	0.3333 (0.4674)	0.3333 (0.4674)	0 / 1	0 / 1
8 - Technology/Land					
organic	binary variable [1 - yes, 0 - no activities] *if farm is producing organically*	0.1092 (0.3119)	0.0379 (0.1911)	0 / 1	0 / 1
milking carousel	binary variable [1 - yes, 0 - no activities] *if milking system is carousel type*	0.0664 (0.2491)	---	0 / 1	---
milking robotic	binary variable [1 - yes, 0 - no activities] *if milking system is robotic type*	0.1493 (0.3555)	---	0 / 1	---
milking fishbone	binary variable [1 - yes, 0 - no activities] *if milking system is fishbone type*	0.6362 (0.4812)	---	0 / 1	---
milking next	binary variable [1 - yes, 0 - no activities] *if milking system is next type*	0.2608 (0.4392)	---	0 / 1	---
land	continuous variable $[0;\infty]$ *utilized agricultural area in ha*	58.7629 (36.3195)	101.0887 (76.1679)	8.45	8.45 / 302.96
9 - Individual Characteristics					
age	continuous variable $[0;\infty]$ *age of farm manager in years*	46.9331 (7.6497)	48.563 (8.6162)	24.78 / 93	19-01-1993
education agricultural	binary variable [1 - yes, 0 - no activities] *farmer has agricultural education*	0.9076 (0.2897)	0.7517 (0.4321)	0 / 1	0 / 1
education primary	binary variable [1 - yes, 0 - no activities] *farmer has lower professional education*	0.0168 (0.1284)	0.0227 (0.1489)	0 / 1	0 / 1
education lower professional	binary variable [1 - yes, 0 - no activities] *farmer has lower professional education*	0.1694 (0.3752)	0.0588 (0.2354)	0 / 1	0 / 1
education medium professional	binary variable [1 - yes, 0 - no activities] *farmer has medium professional education*	0.6731 (0.4692)	0.4537 (0.4979)	0 / 1	0 / 1
education higher professional	binary variable [1 - yes, 0 - no activities] *farmer has higher agricultural education*	0.0937 (0.2915)	0.2184 (0.4133)	0 / 1	0 / 1

Table A2. Variables used in the structural estimation models, 2004 to 2014 (cont.)

Variable	Description	Mean (Stdev)		Min/Max	
		Dairy	Arable	Dairy	Arable
10 - Location/Time					
region 1 - Bouwhoek en Hogeland	binary variable [1 - yes, 0 - no activities] *farm is located in region 1*	0.0273 (0.1629)	0.1514 (0.3595)	0 / 1	0 / 1
region 2 - Veenkolonien en Oldambt	binary variable [1 - yes, 0 - no activities] *farm is located in region 2*	0.0562 (0.2213)	0.1837 (0.3873)	0 / 1	0 / 1
region 3 - Noordelijk Weidegebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 3*	0.2414 (0.4280)	0.0275 (0.1635)	0 / 1	0 / 1
region 4 - Oost. Veehouderijgebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 4*	0.2112 (0.4082)	0.0448 (0.2071)	0 / 1	0 / 1
region 5 - Centraal Veehouderijgebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 5*	0.0559 (0.2298)	0.0024 (0.0491)	0 / 1	0 / 1
region 6 - Ijsselmeerpolders	binary variable [1 - yes, 0 - no activities] *farm is located in region 6*	0.0158 (0.1247)	0.1413 (0.3484)	0 / 1	0 / 1
region 7 - Westelijk Holland	binary variable [1 - yes, 0 - no activities] *farm is located in region 7*	0.0398 (0.1955)	0.0183 -0.1341	0 / 1	0 / 1
region 8 - Waterland Droogmakerijen	binary variable [1 - yes, 0 - no activities] *farm is located in region 8*	0.0138 (0.1167)	0.0096 -0.0977	0 / 1	0 / 1
region 9 - Holl/Utrechts Weidegebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 9*	0.0878 (0.2831)	0.0024 (0.0491)	0 / 1	0 / 1
region 10 - Rivierengebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 10*	0.0483 (0.2145)	0.0029 -0.0537	0 / 1	0 / 1
region 11 - Zuidwest Akkerbouwgebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 11*	0.0221 (0.1468)	0.5448 (0.9228)	0 / 1	0 / 1
region 12 - Zuidwest Brabant	binary variable [1 - yes, 0 - no activities] *farm is located in region 12*	0.0053 (0.0724)	0.0106 (0.1025)	0 / 1	0 / 1
region 13 - Zuidwest Veehouderijgebied	binary variable [1 - yes, 0 - no activities] *farm is located in region 13*	0.1503 (0.3574)	0.0299 (0.1703)	0 / 1	0 / 1
region 14 - Zuid-Limburg	binary variable [1 - yes, 0 - no activities] *farm is located in region 14*	0.0273 (0.1629)	0.0169 (0.1288)	0 / 1	0 / 1

Table A2. Variables used in the structural estimation models, 2004 to 2014 (cont.)

Variable	Description	Mean (Stdev)		Min/Max	
		Dairy	Arable	Dairy	Arable
year 2004	binary variable [1 - yes, 0 - no activities] *observation is in 2004*	0.0842 (0.2777)	0.0588 (0.2354)	0 / 1	0 / 1
year 2005	binary variable [1 - yes, 0 - no activities] *observation is in 2005*	0.0839 (0.2772)	0.0588 (0.2351)	0 / 1	0 / 1
year 2006	binary variable [1 - yes, 0 - no activities] *observation is in 2006*	0.0832 (0.2763)	0.0708 (0.2567)	0 / 1	0 / 1
year 2007	binary variable [1 - yes, 0 - no activities] *observation is in 2007*	0.0858 (0.2802)	0.0811 (0.2729)	0 / 1	0 / 1
year 2008	binary variable [1 - yes, 0 - no activities] *observation is in 2008*	0.0908 (0.2874)	0.0791 (0.2699)	0 / 1	0 / 1
year 2009	binary variable [1 - yes, 0 - no activities] *observation is in 2009*	0.0937 (0.2915)	0.0834 -0.2766	0 / 1	0 / 1
year 2010	binary variable [1 - yes, 0 - no activities] *observation is in 2010*	0.0947 (0.2929)	0.0902 -0.2865	0 / 1	0 / 1
year 2011	binary variable [1 - yes, 0 - no activities] *observation is in 2011*	0.0977 (0.2969)	0.0863 -0.2809	0 / 1	0 / 1
year 2012	binary variable [1 - yes, 0 - no activities] *observation is in 2012*	0.0967 (0.2938)	0.0868 -0.2816	0 / 1	0 / 1
year 2013	binary variable [1 - yes, 0 - no activities] *observation is in 2013*	0.0954 (0.2938)	0.0892 -0.2851	0 / 1	0 / 1
year 2014	binary variable [1 - yes, 0 - no activities] *observation is in 2014*	0.0937 (0.2915)	0.2155 -0.4113	0 / 1	0 / 1

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