# Precision Livestock Agriculture and Productive Efficiency: The Case of Milk Recording in Ireland

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**Abstract**

*This paper investigates the effect of precision livestock agriculture and, in particular, milk recording, on the productive efficiency of Irish dairy farms. We use a micropanel of farms that covers the period 2008-2017 and a dynamic stochastic frontier model to account for the dependence of efficiency on past values. This allows us to distinguish between short- and long-run effects of precision livestock agriculture practices on technical efficiency. We provide evidence that the Irish dairy sector experienced fast productivity growth in the period covered by the data, which was achieved mostly through technical change and efficiency improvements, but not due to scale effects at the farm level. Furthermore, our results show that precision livestock agriculture in the form of milk recording contributed to a more efficient use of resources. Specifically, use of milk recording is found to affect positively technical efficiency in both the short and long run. Finally, we provide policy implications and directions for future research.*

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# 1 Introduction

Precision agriculture[1] describes a set of improved decision-making processes within a farm (or in the broader food system) based on a variety of data, which are collected through the use of sensors, machines, drones etc. (Klerkx et al. 2019; Eastwood et al. 2019; Janssen et al. 2017; Wolfert et al. 2017). The expected benefits from precision technologies are related to the technical optimization of agricultural production systems, transforming the productive processes in the wider agricultural supply chains (Klerkx et al. 2019). There is an emerging literature that measures the impact of precision agriculture adoption on profitability (see DeLay et al. 2021, and references therein). However, there are only a few studies to examine the impact of precision agriculture on productive efficiency, although the latter is considered a relevant indicator of competitiveness and sustainability (e.g. Färe et al. 2005; Newman and Matthews 2006; Melfou et al. 2007; Murty et al. 2012; Fuglie et al. 2016; Coomes et al. 2018; Sidhoum et al. 2019; Chambers and Serra 2018).

Precision agriculture technologies can be distinguished into embodied knowledge technologies and information intensive technologies (Griffin et al. 2017). Embodied knowledge technologies directly affect the productivity of specific inputs. Information intensive technologies deliver data that assist farmers to utilize their inputs more efficiently. For instance, detailed soil nutrient maps may increase the precise nutrient application rates, and as a result lowering the fertiliser costs while producing the same or more output (DeLay et al. 2021). Previous studies that used data from US corn farming showed that both embodied knowledge and information intensive technologies affect positively productive efficiency (DeLay et al. 2021; McFadden and Rosburg 2021).

This paper builds on the ideas of DeLay et al. (2021) and McFadden and Rosburg (2021) and examines the impact of livestock precision agriculture on farm level produc-

[1]Alternative terms to "Precision Agriculture" that have been used in the context of the agricultural sector include: "Smart Farming", "Precision Farming", "Decision Agriculture", "Digital Agriculture", "Agriculture 4.0" (Klerkx et al. 2019).

tivity in a dynamic context. Specifically, we use a Dynamic Stochastic Frontier (DSF) model to explain the impact of milk recording (as a relevant precision livestock farming technology) on farm level productive efficiency and Total Factor Productivity (TFP) growth. To the best of our knowledge this is the first empirical paper that focuses on the linkage of precision agriculture and productive efficiency in the a livestock sector.

The focus is on the EU dairy sector and in particular on the Irish dairy sector between 2008-2017. The reason is that innovation is referred to explicitly as a priority in order to promote more sustainable and competitive agricultural production in the EU Common Agricultural Policy (CAP) programme for 2014-2020 for the first time (European Commision 2016). The specific objective in the CAP 2014-2020 is: "*to foster green growth through innovation which requires adopting new technologies, developing new products, changing production processes, and supporting new patterns of demand*" (European Commission 2010, p. 7). In the next 2021-2027 CAP, one of the policy objectives is to promote digitalisation at the farm level, and in the livestock sector, the aim being to facilitate the adoption of precision livestock farming technologies (among others) that give accurate information about individual cow performance (Poppe et al. 2013; EU SCAR 2019; EIP-AGRI 2018; European Commission 2020; Lajoie-O'Malley et al. 2020). In Ireland, the strategic plan FoodWise 2025 explicitly encourages dairy farmers to use technologies that will allow them to better utilize the grass based feed system and, ultimately, become more competitive under the vision of Sustainable Intensification (SI) (DAFM 2010).[2]

Furthermore, as part of the EU dairy sector, the Irish dairy sector experienced important market reform recently (Boysen et al. 2016). In particular, the CAP Health Check in 2008 confirmed the abolition of milk quotas in 2015 (which were imposed as early as 1984). Before this end date (2015), the EU dairy sector went through a "Soft Landing" phase out period to avoid any consequences from a "Hard Landing", such as an abrupt

[2]SI is sustainable production model in agriculture, which implies that farmers produce more output volume with the same or less inputs, minimizing the environmental pressures resulting from production (Garnett et al. 2013; Godfray and Garnett 2014; Klerkx et al. 2019).

drop in milk prices arising from a sudden spike in production volume. The "Soft Landing" was the phase out period between 2009 and 2014, where quota limits were increasing annually by 1% (Creighton et al. 2011). The quota removal aimed to allow the most efficient EU dairy farms to expand production and participate in the global dairy market (Läpple et al. 2021). After the quota removal in April 2015, milk production of the Irish dairy sector increased, which was driven mainly from an expansion of the national dairy herd and higher milk yields per cow (Kelly et al. 2020). Thus, the TFP growth measurement of the Irish dairy sector could inform policy making whether productivity was in line with the SI vision (Kelly et al. 2020).

The remainder of the paper is organized as follows: Section 2 reviews previous literature regarding the impact of information on farm level productivity and efficiency and provides a conceptual framework for quantifying this impact in a dynamic context. Section 3 outlines the methodology and Section 4 presents the data and the empirical specification. Section 5 reports the results and Section 6 further discusses some of the key findings. Finally, section 7 concludes with policy implications for the Irish and a generalization to the EU dairy sector.

# 2 Background and Conceptual Framework

## 2.1 The role of information on productive efficiency

Farmers operate in a rapidly changing environment (Batte et al. 1989; Emvalomatis 2012b; Fuglie et al. 2017; Pardey and Alston 2020): global financial and agricultural markets continuously change; input prices usually rise faster than output prices; government policies continuously adjust; and new relevant and better production technologies are becoming available at the market. Within this uncertain environment, information plays a key role in decision making (Taylor and Chavas 1980; Chavas and Pope 1984): information flows enhance a farmer's inherent capability to conceptualize and solve problems in production process. In particular, information assist farmers in decision making by changing or confirming their expectations on possible outcomes (Batte et al. 1989; Wolfert et al. 2017; Klerkx et al. 2019). Hence, information allows decision making to be more consistent with respect to farmer's objective function, which results into lower technical inefficiencies (Batte and Schnitkey 1989; Finger et al. 2019; McFadden and Rosburg 2021; DeLay et al. 2021).[3]

The demand for information is conditional on the specific needs of farmers and thus, there is a variety of mediators of information available to farmers. In empirical analysis, scholars have frequently examined the impact of various mediators of information and knowledge, on productive efficiency (e.g. Kumbhakar et al. 1991; Bravo-Ureta and Evenson 1994; O' Neill et al. 1999; Dinar et al. 2007; Bravo-Ureta et al. 2012; Rao et al. 2012; Chavas 2012; Henningsen et al. 2015). These studies mostly utilized cross-sectional data to study the impact of mediators such as advisors, natural management projects and contract farming. Methodologically, the authors either (assumed) proxied the innovation (actor) variable to affect the frontier and productive efficiency; or split the sample into groups (i.e. adopters and non adopters) and estimated different frontiers, comparing differences in marginal productivities and efficiencies among groups. In another approach, Skevas (2020) used spatial data in a dynamic efficiency specification to capture the impact of knowledge spillovers of farmers' peers on efficiency.

The developments in computer and telecommunication technologies have increased significantly the quality of information that farmers can obtain. Specifically, information technologies facilitate the processing of data[4] into information, which improves measure-

[3] Of course, many more factors than information may exist such as the initial farmers' capability to solve problems, the human capital (e.g. experience, education), investment levels, subsidies etc. and in turn technical efficiency (e.g. Batte and Schnitkey 1989; Hadley 2006; Davidova and Latruffe 2007; Zhu and Oude Lansink 2010; Alvarez and del Corral 2010; Sauer and Latacz-Lohmann 2015; Skevas et al. 2018b; Martinez-Cillero et al. 2018).

[4] There is a difference between data and information (Poe et al. 1991; Schimmelpfennig and Ebel 2016; Thompson et al. 2021). Data can be seen as any set of of non-random symbols (e.g. quantities, actions,

ment, processing, and timely dissemination of information (Batte et al. 1989; Weersink et al. 2018; Klerkx et al. 2019). In this way, information technologies allow for more control of existing production technologies, and increasing potentially technical efficiency. A few empirical papers have assessed the impact of information technologies, such as precision agriculture, on productivity and technical efficiency. McFadden and Rosburg (2021) uses USDA's Agricultural Resource Management Survey (ARMS) data (for 2010 and 2016) and reports that the use of yield and soil mapping reduces technical inefficiency. DeLay et al. (2021) suggested other complementary technologies to yield and soil mapping should be taken into account in their analysis, as these technologies in total can be part of a broader precision agriculture strategy (bundle of technologies). Otherwise, neglecting these technologies may influence the results (DeLay et al. 2021): previous literature on production economics (e.g. Lambert et al. 2015; Schimmelpfennig and Ebel 2016) or agricultural adoption technology literature (e.g. Khanna 2001; Barham et al. 2004; Miller et al. 2019) usually examine precision agriculture on bundles (i.e. multiple complementary precision technologies simultaneously).

Consequently, DeLay et al. (2021) extend the work of McFadden and Rosburg (2021) by taking into account in their analysis all available precision agriculture technologies in the ARMS dataset (again for 2010 and 2016) and compared technical efficiencies across technology bundles using a metafrontier, reporting qualitatively similar results to McFadden and Rosburg (2021). However, as DeLay et al. (2021) note, their methodological approach does not capture long-run efficiency gains, which may be more significant than their reported results. The reasons is that although the value of additional costless information may never make the decision maker worse off, and eventually can make him better

qualities, goals, etc), that result from experimentation or sampling (Davis 1963; Harsh 1978; Eisgruber 1973; Chavas and Pope 1984). Information is data that has been processed or organized into a form that is useful to the decision maker (Poe et al. 1991; Schimmelpfennig and Ebel 2016; Thompson et al. 2021). Information technologies broadly include all those developments designed to measure, store, retrieve, process and communicate data or information (Batte et al. 1989; Schimmelpfennig and Ebel 2016; Thompson et al. 2021).

off (Chavas and Pope 1984); adjustment costs with respect to the information could "disguise" the true benefits afforded by these technologies in the short run (Stefanou 2009; DeLay et al. 2021). Thus, a solution would be to assess the impact of precision agriculture technologies on productive efficiency in a dynamic context rather than a discrete, "one-shot decision" DeLay et al. (2021).

## 2.2 Assessing the impact of livestock precision agriculture in a dynamic context

We address the limitation described in the previous section by assessing the impact of precision agriculture on productive efficiency in a dynamic context. We consider milk recording as an indicative livestock precision technology in the Irish dairy sector. Milk recording provides data that can be used by farmers to improve breeding and culling decisions (Läpple et al. 2017; Balaine et al. 2020) and produce better quality and higher quantity of milk (Geary et al. 2013; Balaine et al. 2020); and enables farmers to monitor and prevent diseases, such as mastitis, through Somatic Cell Count (SCC) readings (Dillon et al. 2018). The use of cow specific information from milk recording may affect efficiency at the time period this is obtained but also in subsequent periods. For instance, there is a time lag between breeding decisions and improvement in the genetic composition of the herd: the age at first calving is between 24 and 36 months (Berry and Cromie 2009).

Furthermore, obtaining detailed data that can inform production decisions does not guarantee that the farmer will be able to reorganize fully the production process immediately in relation to the obtained information: adjustment in the short run may be too costly or even infeasible. For example, farmers may face difficulties processing the large amount of information obtained from milk recording (despite the support and training that milk recording provides) and decide to partially adjust their production processes (Hostiou et al. 2017; Schewe and Stuart 2015; Dillon et al. 2018; Balaine et al. 2020).

Given that total management time is fixed, a loss in physical output could occur if the farmer spends time learning to use the information (Stefanou 2009). As another example, information from milk recording may induce farmers to increase feed intake per cow (Balaine et al. 2020), which would require either production of more feed within the farm or purchasing feed on the market. The former approach has associated internal adjustment costs (i.e. learning how to produce a new intermediate input or with increased scale), as well as large external adjustment costs due to low land availability in Ireland (O'Donoghue and Hennessy 2015). The latter approach may not be feasible in the short run if farmers lack the required financial resources to purchase feed.

In this dynamic view of the production process, current decisions may affect, not only current, but also future production possibilities and profitability (Stefanou 2009; Emvalomatis 2012a; Skevas et al. 2017). The adjustment cost theory suggests that the source of the time interdependence of firm's production decisions is the physical or economic infeasibility of changing the levels of quasi-fixed factors in the short run (Penrose 1959; Lucas 1967; Treadway 1969; Treadway 1970; Rothschild 1971; Mortensen 1973; Stefanou 2009). Adjustment costs may cause inefficiency in the short-run, which may persist over time (Stefanou 2009; Emvalomatis 2012a; Skevas et al. 2018a). To account for the dynamic nature of a production process and its gradual adjustment to external factors, we use a DSF model (Ahn and Sickles 2000; Desli et al. 2003; Tsionas 2006; Emvalomatis 2012a; Lai and Kumbhakar 2020) to quantify the impact of milk recording on short - and long-run technical efficiency. In this model, the efficiency specification allows farmers to not only be inefficient due to suboptimal decision making, but also due to persistent inefficiency that is caused by adjustment costs in their effort to reach their long run efficiency equilibrium.

Thus, the use of DSF can addresses the limitation of DeLay et al. (2021) and McFadden and Rosburg (2021) regarding adjustment costs and can show that precision agriculture has an impact on short and long run efficiency. However, milk recording can be seen as complementary to a larger bundle of technologies, similar to other low cost technologies for dairy systems (e.g. Barham et al. 2004). Specifically, milk recording is part of the "core technologies" related to grassland management, breeding techniques and cost management, which are promoted by the Irish AIS for the SI of the Irish dairy sector (see O'Dwyer 2015; Läpple et al. 2019). This implies that, for example, farmers may use a bundle of breeding techniques. These may be applied not simultaneously but in as gradual process over the observed period, in which, the use of milk recording specifically may be applied at specific years and not sequentially in all adjacent years (Khanna 2001; Miller et al. 2019). Then, complementary technologies should be taken into account in the analysis in order to distinguish their dynamics from milk recording's impact on efficiency, following McFadden and Rosburg (2021) and DeLay et al. (2021). However, including more complementary technologies may result in high collinearity, while the farmers maybe use much more related technologies which are not observed in the dataset in a panel setting.

For this reason, after estimating the DSF, we take into account the impact of various technologies implicitly by constructing a TFP growth index and its components. The components of the TFP growth index can indicate whether productivity growth is driven by effects (such as the contribution of "core technologies") that are consistent with the vision of SI in FoodWise 2025: TFP growth should be driven by technological and efficiency gains, but not scale effects. Efficiency changes in the model are explained explicitly by adjustment costs and milk recording. Given that a number of shocks occurred in the time period under investigation (European Parliament 2018), the DSF specification could reveal abrupt changes in efficiency; and estimate more accurately adjustments in production process, and thus, the evolution of TFP growth between adjacent time periods, as it can capture (persistent) time-specific efficiency shocks (Skevas et al. 2018b).

Examples of shocks include rapid changes in input or output prices, an extreme weather event, or a disease outbreak, that may force a farm to be less efficient at a particular point in time (European Parliament 2018; Pieralli et al. 2017; Skevas et al. 2018b). For instance, an extreme weather event may lower the cows' reproductive performance or exacerbate disease outbreaks, causing a drop in output at the time of the event. However, such an event would introduce persistent effects on output as farmers slowly adjust back to normality and this slow adjustment process manifests itself in the data as persistent inefficiency (e.g. Emvalomatis et al. 2011). Hence, accounting for persistent inefficiency can provide better insights to policy makers regarding competitiveness (e.g. Heshmati et al. 2018; Filippini et al. 2018). The following section describes the construction of a Malmquist productivity index which is obtained using a DSF model.

# 3 Modelling Approach

To measure and decompose TFP growth and the effect of innovative production techniques on productivity, we first need to define a mathematical representation of the production technology. To account for the multi-output nature of the production processes employed by Irish dairy farms (e.g. Newman and Matthews 2006), we use an output distance function:[5]

$$D_o(\mathbf{x}, \mathbf{y}, t) = \min \left\{ \theta : \tfrac{\mathbf{y}}{\theta} \in \text{production possibilities set in period } t \right\} \tag{1}$$

where the input and output vectors, $\mathbf{x} \in \mathbb{R}^N$ and $\mathbf{y} \in \mathbb{R}^M$, are implicitly defined as functions of time, $t$. The output distance function takes an output-expanding approach in measuring the distance of a producer to the boundary of the production possibilities set by determining the minimum amount, $\theta \leq 1$, by which the output vector should be deflated to reach this boundary. The combinations of $\mathbf{x}$, $\mathbf{y}$ and $t$ for which the value of the distance function is equal to one define the boundary of the production possibilities set.

[5]The output-expanding view of efficiency taken here is in line with the vision of SI, in which farmers are encouraged to maximize the amount of output, given the available resources. Despite the quota scheme operating until 2014, we assume that the farmers' objectives are still consistent with output expansion, since quota was tradeable in Ireland (under some conditions) and between 2009-2014 dairy farmers were allowed to increase the amount of milk output (up to 1% annually).

Thus, the distance function itself can be used to define technical efficiency as a function of its arguments:

$$D_o(\mathbf{y}, \mathbf{x}, t) = \mathrm{TE} \tag{2}$$

Taking logs of both sides of the previous expression, totally differentiating with respect to time and rearranging gives:

$$\sum_{m=1}^{M} \frac{\partial \log D_o}{\partial \log y_m} \hat{y}_m + \sum_{n=1}^{N} \frac{\partial \log D_o}{\partial \log x_n} \hat{x}_n + \frac{\partial \log D_o}{\partial t} = \frac{\mathrm{d} \log \mathrm{TE}}{\mathrm{d}t} \tag{3}$$

where a "hat" over a variable denotes growth rate, for example $\hat{y}_m = \frac{\partial y_m}{\partial t} / y_m$.

In general, TFP growth is defined as the growth rate in the amounts of outputs that cannot be attributed to growth in input use. In a production process where multiple inputs are used to produce multiple outputs, growth rates in outputs and inputs must be aggregated. A Törqnvist index uses revenue shares (for outputs) and cost shares (for inputs) to perform this aggregation. With a profit-maximization assumption, these shares can be replaced by functions of the elasticities of the distance function with respect to the outputs and inputs, and TFP growth can be expressed as:

$$\frac{\mathrm{d} \log \mathrm{TFP}}{\mathrm{d}t} = \sum_{m=1}^{M} \frac{\partial \log D_o}{\partial \log y_m} \hat{y}_m - \sum_{n=1}^{N} \frac{\varepsilon_n}{\varepsilon} \hat{x}_n \tag{4}$$

where $\varepsilon_n = \frac{\partial \log D_o}{\partial \log x_n}$, $\varepsilon = \sum_{n=1}^{N} \varepsilon_n$. Finally by inserting (4) in (3) and rearranging we get:

$$\frac{\mathrm{d} \log \mathrm{TFP}}{\mathrm{d}t} = \frac{\mathrm{d} \log \mathrm{TE}}{\mathrm{d}t} - \frac{\partial \log D_o}{\partial t} - (1 + \varepsilon) \sum_{n=1}^{N} \frac{\varepsilon_n}{\varepsilon} \hat{x}_n \tag{5}$$

The last expression presents the usual decomposition of TFP growth into technical efficiency change, technical change and scale effects, as in Orea (2002).

Equation (5) makes clear that, before we construct and decompose TFP growth, we need to retrieve the parameters from an empirical counterpart of the distance function, as presented in (1). The distance function itself is defined as an implicit function of observable quantities. However, by definition, it is homogeneous of degree one in outputs: multiplying all outputs by a positive constant $\lambda$ results to the value of the distance function also being multiplied by the same constant. Linear homogeneity in outputs can be imposed by dividing all outputs and the value of the distance function by the amount of the normalizing output, $y^m$. After taking the natural logarithm of both sides of the resulting expression, rearranging and appending an error term we obtain (see for example Coelli and Perelman 1999):

$$-\log y_{it}^m = \log D_o \left( \mathbf{x}_{it}, \frac{\mathbf{y}_{it}}{y_{it}^m}, t \right) + v_{it} + u_{it}^+ \tag{6}$$

where $y_{it}^m$ is the amount of normalizing output for farm $i$ in period $t$, $v_{it}$ is a linear error term that accounts for statistical noise[6], assumed to be normally distributed with mean zero and variance $\sigma_v^2$, and $u_{it}^+ \equiv -\log(\mathrm{TE}_{it})$ is the one sided technical inefficiency term for the same observation. Denoting the dependent variable in (6) by $y_{it}$ and using a specification for the logarithm of the distance function that is linear in the parameters, the following empirical counterpart to the output distance function is obtained:

$$y_{it} = \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + v_{it} + u_{it}^+ \tag{7}$$

where $y_{it}$ is minus the logarithm of the normalizing output and $\mathbf{x}_{it}$ is a vector of covariates (functions of the arguments of $\log D_o$). $\boldsymbol{\beta}$ is a vector of parameters to be estimated and, given this setup, the parameters associated with outputs should be positive (*ceteris paribus*, increasing the amount of an output brings the farm closer to the frontier), while

[6]Statistical noise is assumed to capture random shocks, such as weather events. However, the notion of statistical noise does not reflect the degree of preparedness of farmers for future shocks. Being prepared for shocks is a management decision that leads to resilience. In the event of a shock, a more resilient farmer will also be more efficient relative to peer farmers. For this reason, SFA distinguishes between inefficiency and statistical noise and neglecting the latter may lead to biased efficiency estimates (Karagiannis 2014; Kumbhakar et al. 2018).

the parameters associated with inputs negative (*ceteris paribus*, increasing the amount of an input moves the farm farther from the frontier). $\alpha_i$ is a a random effect that captures time invariant (farm specific) unobserved heterogeneity and it is assumed to be normally distributed with mean zero and variance $\sigma_\alpha^2$.

We specify the distance function as translog in inputs and outputs, and we include also a time trend and its square, as well as interactions between the time trend and the remaining variables to capture the effect of technical progress. Model specification is complete once a distributional assumption is imposed on the inefficiency term in (7). To account for the persistence of inefficiency over time, we use a DSF model in which an autoregressive process is imposed on farm-specific technical efficiency (Tsionas 2006). $\mathrm{TE}_{it}$ is treated as a random variable bounded on the unit interval and a one-to-one transformation of $\mathrm{TE}_{it}$ is used to project it from the unit interval to the real line. This is done to avoid complications related to a specification of an autoregressive process on a variable that can assume values only in a restricted interval. The inverse of the logistic function is used for the transformation, $s_{it} = \log\left(\frac{\mathrm{TE}_{it}}{1-\mathrm{TE}_{it}}\right)$, as in Emvalomatis 2012a, and the following autoregressive process is assumed for $s_{it}$:

$$s_{it} = \mathbf{z}_i'\boldsymbol{\delta} + \rho s_{i,t-1} + \xi_{it}, \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2) \tag{8}$$

$$s_{i1} = \frac{\mathbf{z}_i'\boldsymbol{\delta}}{1-\rho} + \xi_{i1}, \qquad \xi_{i1} \sim \mathcal{N}(0, \sigma_{\xi_1}^2) \tag{9}$$

where $\mathbf{z}$ is a vector of a constant term and milk recording, $\boldsymbol{\delta}$ is a vector of parameters to be estimated and $\rho$ is the inefficiency persistence parameter. $\xi_{it}$ is a two-sided error term that accounts for statistical noise and $\sigma_{\xi_1}^2 = \frac{\sigma_\xi^2}{1-\rho^2}$, along with the the specification of $s_i$ in the initial period, impose stationarity on the $s$ series. Stationarity is necessary from an econometric and theoretical standpoint. Econometrically, $\mathbf{s}$ requires an initial distribution because it is an unobserved quantity (Wooldridge 2005). Theoretically, stationarity of $\mathbf{s}$

will rule out cases where the expected value, conditional on the sign of the term $\mathbf{z}_i'\boldsymbol{\delta}$, will approach either positive or negative infinity, in which case technical efficiency will approach either unity or zero. Observing fully efficient farms is something rare, while fully inefficient farms should exit the market before they reach such a point. Technical efficiency is obtained as $\frac{e^{s_{it}}}{1+e^{s_{it}}}$, by inverting the transformation from $\text{TE}_{it}$ to $s_{it}$. Given the specification of the model, a positive coefficient associated with a variable in $\mathbf{z}$ implies a positive effect of the variable on technical efficiency.[7]

The persistence parameter, $\rho$, is an elasticity that measures the percentage change in the efficiency to inefficiency ratio that is carried from one period to the next (Emvalomatis 2012a). Stationarity of the $\mathbf{s}$ series ensures that $\rho$ is bounded between -1 and 1. Moreover, in the estimation approach $\rho$ is restricted on the unit interval, since a negative autocorrelation in inefficiency is not realistic. A value of $\rho$ close to 1 implies high adjustment costs or a limited effect of learning by doing. Given the one-to-one transformation from $s$ to TE, the steady-state value of $s$ can be transformed into a measure of Long-Run Technical Efficiency (LRTE). An estimate of this can be obtained by inserting the unconditional expected value of $s$ into the transformation from TE to $s$, which leads to $[1+\exp\{-\mathbf{z}_i'\boldsymbol{\delta}/(1-\rho)\}]^{-1}$ (Emvalomatis 2012a; Skevas et al. 2018b). LRTE is interpreted as the expected value of efficiency that will prevail in the sector in the long run. In this paper LRTE is farm specific due to the farm specific variables in $\mathbf{z}$ and despite the fact the $\rho$ is treated as a parameter common to all farms.[8] Firm specific covariates in (8) and (9) could, instead, be modelled as time varying (e.g. Tsionas 2006; Lambarraa et al. 2016; Galán et al. 2015; Lai and Kumbhakar 2020). This approach, however, would not allow estimation of LRTE, as the expectation of $s_{it}$ unconditional on $s_{i,t-1}$ would depend on the values of the variables in $\mathbf{z}_{it}$.

[7]The derivative of technical efficiency with respect to the $\ell^{th}$ explanatory variable in $\mathbf{z}$ is given by: $\frac{\partial \text{TE}_{it}}{\partial z_\ell} = \frac{\delta_\ell \times e^{\mathbf{z}_i'\boldsymbol{\delta}}}{(1+e^{\mathbf{z}_i'\boldsymbol{\delta}})^2}$, whose sign is the same as the sign of $\delta_\ell$.

[8]This assumption can be relaxed, assuming that farmers face different adjustment costs that result in different inefficiency persistence across farms (Skevas et al. 2018a).

All the parameters in the specified DSF model above (eq. 6-9) are estimated simultaneously. Estimation of the model can be performed using non-linear Kalman filtering (Emvalomatis et al. 2011). This approach, however, is computationally intensive and, as a result, Bayesian inference techniques have become the norm in the estimation of DSF models (Tsionas 2006; Emvalomatis 2012a; Galán et al. 2015; Skevas et al. 2018a; Skevas et al. 2018b). For a Bayesian procedure to be applied the specification of prior distributions for the model's parameters is required. These can be found in Appendix A.

# 4 Data and Empirical Specification

The data used in this study are taken from Teagasc's National Farm Survey (NFS) and cover a sample of Irish dairy farms for the period between 2008 and 2017. The original dataset contains a total of 3740 observations on 486 specialist dairy farms, with cases of farms reported between 1 and 10 years. In order to model dynamic effects, only data from farms that are observed for at least five consecutive years are used, which results into an unbalanced panel of 2323 observations from 277 farms. In this reduced dataset farms remain in the sample for an average of 8.7 years.

Two categories of outputs are defined, the main output, which is milk and it is measured as the total revenue from milk production ($y_1$) and other output, that consists of aggregate revenues from beef, pigmeat, other meat products, crops and other minor commodities ($y_2$). Four input categories are defined: capital ($K$) comprises of the value of machinery and buildings, total livestock ($LU$) is measured in units and comprises the number of cattle, pigs, sheep or other animals owned by the farms (multiplied by ther respective coefficients, e.g. dairy cows by 1, suckling cows by 0.9, working horses by 1.5 etc.), labor ($L$) is measured in total labour units working on the farm, both unpaid and paid, land ($A$) is the utilized agricultural area, measured in hectares ($A$). Materials ($M$) include expenditures in the following subcategories: seeds and plants, fertilizers, crop protection, energy, contract work and purchased feed (includes purchased concentrates and bulky feed), upkeep of buildings, machinery hire and upkeep of land. For outputs, as well as for capital and materials, which are measured in monetary terms, a Törnqvist index was constructed for each aggregate, using price indexes from EUROSTAT with 2010 as the base year. Then, each aggregate variable was deflated accordingly. Summary statistics for the input and output variables are presented in Table 1.

Table (1)

Summary Statistics, Irish dairy farms 2008-2017

| **Variable** | **Mean** | **Std. Dev** | **Min** | **Max** |
|---|---|---|---|---|
| Milk (1000 €) | 115.41 | 79.39 | 1.13 | 623.69 |
| Other Output (1000 €) | 50.33 | 37.70 | 1.18 | 424.06 |
| Capital (1000 €) | 161.93 | 126.341 | 0 | 774.63 |
| Livestock (Units) | 118.8 | 65.93 | 10.69 | 485.56 |
| Labor (AWU) | 1.59 | 0.65 | 0.5 | 6.93 |
| Area (Ha) | 54.01 | 28.97 | 3.7 | 222.61 |
| Materials (1000 €) | 69.10 | 47.89 | 4.67 | 383.43 |

The data on milk recording provide information on whether or not a farmer used milk recording in a particular year, but do not describe the extent or way in which information obtained by milk recording was utilized in farm management decisions (Balaine et al. 2020). Hence the farmer may use the obtained information at any time period, $t+j$, after the initial application of the practice in period, $t$. The possibility that the farmer did not use the obtained information from milk recording cannot be dismissed, particularly since the technology is not associated with high installation or running costs: the individual farmer remains the one who is responsible for deciding whether they adjust their production with respect to the obtained information (Berckmans 2014; Hostiou et al. 2017). However, there is evidence that the vast majority of farmers, who obtain information through the use of precision agriculture, use eventually this information (e.g. Thompson et al. 2021), as part of their wider bundle of technologies; while, the vast majority of

Irish dairy farmers indicated that will manage SCCs through the use of milk recording as part of their breeding management technologies (Läpple et al. 2017). Therefore, it is expected the bulk of Irish dairy farmers, who used milk recording, to actually use the obtained information. Even if farmers do not use the information, we expect that farmers will be eventually better off, because they can form more accurate expectations regarding the possible outcomes of the overall technology bundles (e.g total breeding management techniques or feeding) (as argued in subsection 2.1). It is also possible that farmers may not reorganize production with respect to information of milk recording from a purely production purpose. For instance, farmers may be more concerned about animal welfare (see Hansson et al. 2018); in this case again, adjustment costs will occur slowing down efficiency.

Table 2 provides the average use of milk recording across the sample, which is 0.51, with the average use on individual years across farms ranging between 0.48 and 0.53. Out of the 277 farmers in the sample, 101 farmers never used milk recording. Another 176 farmers used milk recording for at least some time during the period under consideration, but not necessarily in consecutive time periods: out of these 176 farmers, 5 of them used milk recording all years, while the rest 171 farmers may have used milk recording in year $t$, not in period $t+1$, and then again in year $t+2$ or $t+3$ etc, in a similar manner as explained in the conceptual framework of this paper.

Table (2)

Milk recording use over time across Irish dairy farms, 2008-2017

| **Use of milk recording over time** | **No of farmers** |
|---|---|
| Not at all | 101 |
| At least once, but less than half, of their observed years | 50 |
| More than the half of their observed years | 126 |
| Average milk recording use of all farmers | 0.51 |

To turn the time-varying indicator of milk recording application into a time invariant variable, as the econometric model requires, we use the average number of years in which the practice was used relative to the number of years for which a farm is observed. Thus, if a farmer has used milk recording for all the years for which data are observed, then the time invariant milk recording variable has a value of one.

# 5 Results and Discussion

## 5.1 Frontier estimates

Table 3 reports the posterior means and the 90% credible intervals of the parameters associated with the first order terms in the specification of the DSF. The full set of results of the model can be found in Table 6 of Appendix B. The results in these tables are obtained from 10 Markov Chain Monte Carlo (MCMC) chains and using data augmentation techniques. Each chain had a burn-in phase of 50,000 iterations to reduce the influence of the initial values, and another 100,000 draws, out of which 1 out of every 10 was retained, to remove any potential autocorrelation. The total number of retained draws from the posterior distribution is, therefore, 100,000.[9]

Prior to estimation, the data for inputs and outputs were normalized by their geometric mean, allowing us to interpret the parameters associated with the first-order terms directly as distance elasticities, evaluated at the geometric mean of the data. The estimated distance elasticity of $y_2$ in the DSF shows that, if the farmer produces 1% more of other output (holding inputs and milk output fixed), then the value of the distance function is increased by 0.213%, moving the farmer closer to the frontier. Regarding input elasticities,

[9]In a similar fashion, we also estimated three alternative models with different aggregation in the inputs: Model 2 (M2) in which livestock value (instead of livestock units) is aggregated to capital (similar to Newman and Matthews (2006)); Model 3 (M3) where feeds is a separate variable from materials and livestock value is aggregated to capital, and; Model 4 (M4) where livestock units is accounted and feeds are a separate variable from materials. We used Bayes factors to compare the performance of these three models with the main Model 1 (M1) presented in this section. The Bayes factors favoured M1 compared to the rest of the models. A short description of the concept of Bayes factor and the results of M2, M3 and M4 can be found in Tables 7, 8, 9 respectively, Appendix C.

an increase in utilized area by 1%, while holding other inputs and outputs fixed, leads to a reduction in the value of the distance function by 0.062%, thus moving the farmer farther away from the frontier. The estimated output elasticities differ from the study of Newman and Matthews (2006) (due to the differences in input aggregation), but it is evident that livestock units and materials have the highest effect on production, similar to studies on the Dutch, UK and German dairy sectors (Emvalomatis et al. 2011; Skevas 2020; Areal and Tiffin 2012; Skevas et al. 2018a; Skevas et al. 2017). The model shows slightly decreasing returns to scale at the geometric mean of the data: $-\sum_n \varepsilon_n = 0.976$.

The average short run technical efficiency (TE) score, across both farms and years, is 0.85. This is higher than the 70% efficiency score reported by Newman and Matthews (2006) (approximately 70%) for the period 1985-2000. Compared to studies in other EU dairy sectors, the reported TE is slightly higher than in the Dutch and UK dairy sectors (Emvalomatis et al. 2011; Areal and Tiffin 2012; Skevas 2020), and much higher than the average efficiency of German dairy farms (Skevas et al. 2017). These difference may be attributed to the efficiency specification used in the respective empirical analyses (Skevas et al. 2017), but also to the abolition of the quota system in the period covered by our data, which allowed for much more flexibility in decision making at the farm level.

Average long run technical efficiency (LRTE) across farms is estimated at 0.87. The marginal difference between the short and long run efficiency scores indicates that Irish dairy farmers have almost reached, in the period covered by the data, their respective equilibrium efficiency levels. This finding is similar to Skevas (2020), who found that the average TE and LRTE of the Dutch dairy sector between 2009-2016 was 0.843 and 0.845. Our study and Skevas (2020) are probably the only to report such a small difference between TE and LRTE: given the period of investigation of both studies, it seems that the abolition of milk quotas possibly facilitated a more efficient EU dairy production. Furthermore, the estimate of the inefficiency persistence parameter ($\rho$) is approximately equal to 80% (Table 3), indicating the existence of high adjustment costs. This implies that a high percentage of inefficiency in period $t$ is carried to period $t+1$.

Finally, this is the first study that examines the evolution of TFP in the Irish dairy sector using a DSF model. It should be noted that the persistence of inefficiency is estimated in this paper to be noticeably lower than what was reported for the Dutch and German dairy sectors by Emvalomatis et al. (2011), Skevas et al. (2018a), and Skevas et al. (2018b)[10] for the years before the "Soft Landing". A possible explanation is that the abolition of the quota system may have provided additional incentives to invest at the farm level (Levi and Chavas 2018), which resulted in lower external adjustment costs, thus reducing their persistent inefficiency. Another possible explanation is the effect of the AIS on reducing internal adjustment costs. As Ireland has the strongest and most integrated AIS in EU (EIP-AGRI 2018) that creates considerable knowledge flows (Renwick et al. 2014; Läpple et al. 2016; Läpple et al. 2019), it could reduce learning costs that result from the application of new technologies and the reorganization of the production process. Instead, the German AIS cannot be characterized as well-functioning from a national perspective (Paul et al. 2014). In the Netherlands, the privatization of extension services has created competition, where advisors are sometimes hesitant to share knowledge (EU SCAR 2012). We leave this for further investigation.

Table (3)

Posterior summaries of key parameters of the DSF

| **Variable** | **Mean** | **95% Credible Interval** |
|---|---|---|
| constant | -0.129 | [ -0.173, -0.088] |
| $\log K$ | -0.083 | [-0.101, -0.066] |
| $\log LU$ | -0.585 | [-0.628, -0.542 ] |
| $\log L$ | -0.021 | [-0.049, 0.006] |

[10]Emvalomatis et al. (2011) estimated the persistence parameter at 95% and 98% for dairy farmers in Germany and the Netherlands, respectively, between 1995 and 2006. Skevas et al. (2018a) and Skevas et al. (2017) estimated the parameter at 95% for the German dairy sector between 2001 and 2007.

| | | |
|---|---|---|
| $\log A$ | -0.062 | [-0.096, -0.028] |
| $\log M$ | -0.225 | [-0.250, -0.201] |
| $\log y_2$ | 0.213 | [ 0.202, 0.224] |
| $t$ | -0.015 | [ -0.017, -0.012] |
| $\sigma_v$ | 0.072 | [0.067, 0.077] |
| $\sigma_a$ | 0.133 | [0.119, 0.147] |
| $\rho$ | 0.80 | [0.719, 0.873] |
| RTS | 0.976 | |
| Average TE | 0.85 | |
| Average LRTE | 0.87 | |

Table 4 presents the estimates of the parameters that appear in the specification of the dynamic equation that describes the evolution of efficiency. A positive coefficient in $z_i$, i.e. milk recording implies a negative impact of the firm specific time-invariant covariates on technical inefficiency.[11] Thus, the positive coefficient associated with milk recording (0.191) indicates that application of the practice has a negative effect on inefficiency, i.e. a positive effect on long and short run efficiency. Hence, farmers using milk recording are able to produce more output with given inputs, which of course is aligned with the SI concept.

We estimate additional models in order to provide robustness checks regarding the positive effect of milk recording, as many more factors could affect inefficiency. We first estimate a model (Model 5 -M5) with stocking density as an additional factor in the specification of the hidden-state equation, which is associated with more intensive production methods (Alvarez and del Corral 2010). Similarly to Alvarez and del Corral (2010) and

[11]The marginal effects of the $l^{th}$ explanatory variable in $\boldsymbol{z}$ on technical efficiency is given by: $\frac{\partial TE_{it}}{\partial z_l} = \frac{\delta_l \times \exp\{\mathbf{z}_i' \boldsymbol{\delta}\}}{(1+\exp\{\mathbf{z}_i' \boldsymbol{\delta}\})^2}$.

Table (4)

Determinants of transformed efficiency, $s$

| **Variable** | **Mean** | **95% Credible Interval** |
|---|---|---|
| Constant | 0.401 | [0.252, 0.586] |
| Milk Recording | 0.191 | [0.122, 0.276] |

Skevas et al. (2017), we find that farms with higher stocking density are also more efficient. Additionally, we use the farm operator's age as an additional factor in the specification (Model 6 -M6) and we find that older operators are less efficient (e.g. Hadley 2006), although the magnitude of the coefficient is relatively small. Finally, including both age and stocking density as additional factors produces very similar results (Model 7 -M7). The results of M5, M6 and M7 can be found in Table 10, 11, 12 respectively, Appendix D. We maintain M1 and further discuss because this model is favoured by the data when compared to M5, M6, M7 using Bayes factors.

## 5.2 TFP growth results

Table 5 presents the Technical Change (TC), Technical Efficiency (TE) change, Scale Effect (SE) and the aggregate TFP growth for the 2008-2017 period. On average, the estimated TFP growth rate is 1.31%. This is driven primarily by the technical change effect, which is 1.49%, on average, per annum.

Between 2008-2009, farmers experienced negative technical progress, which is referred to in the literature as technical regress (Tsionas and Kumbhakar 2004; Kumbhakar et al. 2008). Between 2013 and 2017 technical progress started to grow at an accelerated rate. The results pertaining to technical regress in the earlier time period can be aligned with the final phase of the milk quota regime, which begins with the EU Common Agricultural Policy (CAP) Health Check of 2006: since 2007, dairy farmers proceeded with significant on-farm investments in infrastructure and livestock, preparing for the post quota era, Table (5)

TFP growth rate and decomposition (%)

| **Year** | **TC** | **TE** | **SE** | **TFP growth** |
|---|---|---|---|---|
| 2008-2009 | -0.139 | -0.517 | 0.029 | -0.627 |
| 2009-2010 | 0.216 | 0.846 | -0.030 | 1.033 |
| 2010-2011 | 0.626 | 0.318 | 0.021 | 0.965 |
| 2011-2012 | 1.012 | -0.670 | 0.058 | 0.401 |
| 2012-2013 | 1.319 | -0.042 | -0.305 | 0.971 |
| 2013-2014 | 1.732 | 0.633 | -0.310 | 2.055 |
| 2014-2015 | 2.237 | 0.436 | -0.203 | 2.470 |
| 2015-2016 | 2.700 | -0.585 | -0.291 | 1.823 |
| 2016-2017 | 3.102 | 0.025 | -0.904 | 2.223 |
| Average | 1.499 | 0.040 | -0.226 | 1.313 |

guided by dairy advisors (O'Dwyer 2015); approximately €2 billion was invested between 2007 and 2013 in infrastructure, while there was a remarkable increase of 0-1 year old replacement heifers, from 250,000 in the mid-2000s, to over 350,000 in 2014 (O'Dwyer 2015). Thus, across the period 2008-2010 farmers increased their investments, while output was allowed to increase annually only by 1%. As a result, technical regress in our results reflects that the growth rate of inputs was possibly higher than of outputs in this period[12]. After the abolition of the quota system, the technical change component exhibits a fast growth, reaching a rate of approximately 3.1% in the last year of observation.

The average efficiency change in the period is 0.04%, and the pattern that efficiency displays within this period is particularly interesting. In particular, the results indicate a decline in efficiency between 2011 and 2013. Between 2011 and 2012, the price of milk declined by 9%, and at the same time unfavourable weather conditions and high feed prices led to an increase in total production costs by 13% (Teagasc 2012). This may have resulted in a reduction in efficiency, as farmers had to adjust input use to levels beyond their usual experience. In the following year, inclement weather conditions resulted in a 8% rise in

[12]Technical regress was also found for Swedish farmers between 1960 to 1988 and 1976 to 2005 (Kumbhakar and Heshmati 1995; Kumbhakar et al. 2008) and Irish beef farmers in 1984 to 2000 and then 2000 to 2013 (Newman and Matthews 2007; Martinez-Cillero et al. 2018).

production costs, which was over compensated by a 23% spike of the average Irish farm gate milk price (Teagasc 2013). However, due to adjustment costs farmers possibly could not adjust fully their production process that resulted in small, but negative, efficiency change in that period.

Given the shocks that occurred in the period under investigation, which are also possibly reflected in the efficiency change component of TFP growth, the positive impact of milk recording on TE may also indicate that milk recording enhances (albeit partially) farmers' resilience.[13] Resilience reflects the capacity of a system to absorb and recover quickly from negative shocks (Walker et al. 2003; Folke 2006; Fuglie et al. 2016; Coomes et al. 2018). As specified in DSF model, the use of milk recording in period $t$ can have a positive effect on TE of period $t$, but also in period $t+1$. This implies that between two farmers who experienced the same shock in period $t$, the one who used milk recording in period $t$, may have lower losses in period $t$. Even if these two farmers have the same adjustment costs, the farmer who used milk recording in period $t$ can use this information to restore the production process in period $t+1$ closer to its initial state (before the shock) and, hence, to adjust and become more efficient in period $t+1$ compared to the peer farmer. However, further analysis is required to examine the precise impact of shocks on efficiency, and the contribution of milk recording to the shock recovery. Last, from a methodological perspective, the positive impact of milk recording use on both short and long run efficiency in this paper indicates that neglecting to take into account the lagging effect of information on farm level productivity and efficiency may result in a misspecified empirical model; the extent to which such a misspecification affects results requires further research.

The average scale effect (-0.226%) is also negative implying farmers are operating on a smaller scale in relation to the optimal scale of the technology they employ.While farm

[13] Resilience is recognized as an essential condition for competitiveness and sustainability by the recent Farm to Fork strategy (European Commission 2020).

specific investments allowed farmers to enjoy TFP growth improvements due to positive scale effects between 2007-2011, from 2012 negative scale effects are observed. This result could possibly indicate that Irish dairy farmers increased the size of their cow herd but low land mobility (and given that the grass based feed system is the main source of competitiveness of Irish dairy farmers) prevent farmers from increasing sufficiently the amount of feeds of the herd (O'Donoghue and Hennessy 2015). Nevertheless, this result is consistent with the SI of the Irish dairy sector, i.e. scale adjustments should not drive TFP growth.

# 6 Conclusions

This paper extends the work of DeLay et al. (2021) and McFadden and Rosburg (2021) in order to examine the impact of livestock precision agriculture on productive efficiency. Specifically, we examine the impact of milk recording, as an indicative technology of livestock precision agriculture, on the Irish dairy farm level productive efficiency, using a Dynamic Stochastic Frontier (DSF). This model accounts for the time-interdependence of efficiency between adjacent production periods, attributed to adjustment costs. Specifically, the obtained short and long run efficiency scores in this paper are expressed as function of the application of milk recording use and persistent inefficiency that reflects adjustment costs. Differences in intensity of milk recording use across farms explain farm specific discrepancies in efficiency. While we do not assess the impact of milk recording as a bundle similar to DeLay et al. (2021) and McFadden and Rosburg (2021), we estimate a Total Factor Productivity growth (TFP) index. The index can capture implicitly the impact of technology "bundles" on the productivity growth, as an overall indication of competitiveness under the concept of Sustainable Intensification (SI).

Overall, the average growth rate of TFP is approximately 1.3% approximately between 2008-2017 and is in line with the SI vision of FoodWise 2025 strategic plan: technical change is the main driver (1.4%); overall efficiency change is almost 0.04%, which implies that given the estimated high technical progress rate, Irish dairy farmers had important catch up effects through better use of the new technologies that were acquired, and; negative scale effects slowed down TFP growth, possibly due to low land availability (O'Donoghue and Hennessy 2015). The average short run efficiency was found to be 0.85%. Average short and long run efficiency scores are very close in magnitude, reflecting that dairy farmers have almost reached their equilibrium efficiency in the period 2008-2017. The results also reveal the presence of inefficiency persistence, due to adjustment costs, that forces Ireland's dairy farmers to remain inefficient over time. Despite the high persistent inefficiency, milk recording is found to affect positively short and long run TE: this finding extends the literature on precision agriculture and productive efficiency (see DeLay et al. 2021).

Persistent inefficiency has important implications for policies that aim to increase productive efficiency of farmers. Specifically, the results indicate that inefficiency is not necessarily resulting purely from poor management but also from high adjustment costs. Hence, the role of Agricultural Innovation System (AIS) actors is important for providing knowledge and inputs, assisting farmers to reorganise their production process faster, i.e. eliminating their inefficiency by reducing adjustment costs. The role of AIS for reducing inefficiency might be more important than promoting the uptake of relevant technologies such as milk recording. The reason is that farmers may adjust production factors for wider purposes (e.g animal welfare) than purely maximizing productivity. As a result part of inefficiency might be "rational" but it is erroneously considered as poor management ("rational inefficiency hypothesis", see Bogetoft and Hougaard 2003; Hansson et al. 2018).[14] In this light, similar to the arguments of Hansson et al. (2018), policy and

[14]This may explains the relatively low uptake of policy and advisory measures, such as milk recording, that target to increase productive efficiency at the farm level for a more sustainable production. From an Irish perspective, policy makers aim foster the uptake of milk recording (Balaine et al. 2020), which is lower compared to other key EU dairy sectors such as Germany and France (ICAR 2018).

advisory measures should be better adjusted to increase efficiency conditional on whether inefficiencies arise from poor management arguments, adjustment costs but also the aims of farmers, e.g. whether farmers aim to increase productivity only.

Finally, there are three crucial general findings from a EU policy perspective. First, technical progress appeared to grow faster towards and after the abolition of the quota system. This suggests that policy changes (e.g. soft landing, abolition of quotas) indeed helped farmers become more competitive by improving their technology at a faster rate. Second, negative efficiency changes were observed at periods when shocks occurred. It appears that, apart from policy changes, shocks may also have a large impact on the evolution of productivity (as argued also in  Frick and Sauer 2017), affecting efficiency, not only in the period of the shock, but also in subsequent periods (i.e. through persistent inefficiency). Third, precision livestock agriculture assists farmers to use their production factors more efficiently and, thus, to become more competitive. Thus, precision livestock agriculture can facilitate a more sustainable EU dairy farming in line with the vision of CAP 2021-2028 and the recent EU Farm to Fork strategy.

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# Appendices

## Appendix A

Following previous papers (van den Broeck et al. 1994; Emvalomatis 2012a; Skevas et al. 2017), the priors used in this paper are the following:

- Multivariate normal densities are used for $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$. In both cases prior means are set equal to conformable vectors of zeros, while the prior covariance matrices are diagonal with a value of 1000 on the diagonal entries.

- Inverse gamma densities are used for $\sigma_\xi^2$, $\sigma_v^2$ and $\sigma_\alpha^2$. The shape and scale hyper-parameters for $\sigma_\xi^2$ are set equal to 0.1 and 0.01; for $\sigma_v^2$ are set equal to 0.001 and 0.001; and for $\sigma_\alpha^2$ are set equal to 0.01 and 0.001.

- A beta prior is used for $\rho$ with shape parameters, $\alpha$ and $\beta$, equal 4 and 2, respectively.

All priors except for $\rho$ are conjugate. Additionally, the priors imposed on the parameters that appear in the observed equation, (7), are vague and have minimal impact on the results. More informative priors are used for $\rho$ and $\sigma_\xi^2$, as these two parameters affect the hidden-state equation, (8).

## Appendix B

Table (6)

Complete set of parameters estimates

| **Variable** | **Mean** | **Std. dev.** | **95% CI** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| constant | -0.129 | 0.025 | [-0.173, -0.088] |
| $\log K$ | -0.083 | 0.010 | [-0.101, -0.066] |
| $\log LU$ | -0.585 | 0.026 | [-0.628, -0.542] |
| $\log L$ | -0.021 | 0.017 | [-0.049, 0.006] |
| $\log A$ | -0.062 | 0.020 | [-0.096, -0.028] |
| $\log M$ | -0.225 | 0.015 | [-0.250, -0.201] |
| $\log y_2$ | 0.213 | 0.006 | [0.202, 0.224] |
| $t$ | -0.015 | 0.001 | [-0.017, -0.012] |
| $\log K \cdot \log K$ | -0.019 | 0.010 | [-0.036, -0.002] |
| $\log K \cdot \log LU$ | 0.001 | 0.041 | [-0.066, 0.070] |
| $\log K \cdot \log L$ | -0.013 | 0.025 | [-0.055, 0.029] |
| $\log K \cdot \log A$ | 0.021 | 0.032 | [-0.032, 0.070] |
| $\log K \cdot \log M$ | 0.008 | 0.027 | [-0.035, 0.074] |
| $\log K \cdot t$ | 0.001 | 0.002 | [-0.001, 0.005] |
| $\log L \cdot \log L$ | -0.005 | 0.034 | [-0.061, 0.051] |
| $\log L \cdot \log LU$ | -0.094 | 0.074 | [-0.216, 0.027] |
| $\log L \cdot \log M$ | 0.053 | 0.044 | [-0.135, 0.040] |
| $\log L \cdot \log A$ | -0.047 | 0.053 | [-0.135, 0.040] |
| $\log L \cdot t$ | 0.006 | 0.003 | [-0.000, 0.012] |
| $\log LU \cdot \log LU$ | -0.047 | 0.065 | [-0.156, 0.060] |
| $\log LU \cdot \log A$ | 0.011 | 0.083 | [-0.124, 0.148] |
| $\log LU \cdot \log M$ | 0.155 | 0.075 | [0.030, 0.279] |
| $\log LU \cdot t$ | -0.026 | 0.006 | [-0.036, -0.016] |
| $\log A \cdot \log A$ | -0.021 | 0.037 | [-0.084, 0.040] |
| $\log A \cdot \log M$ | 0.024 | 0.051 | [-0.060, 0.109] |
| $\log A \cdot t$ | 0.010 | 0.004 | [0.002, 0.018] |

| | | | |
|---|---|---|---|
| $\log M \cdot \log M$ | -0.094 | 0.032 | [-0.151, -0.037] |
| $\log M \cdot t$ | 0.012 | 0.004 | [0.004, 0.019] |
| $\log y_2 \cdot \log K$ | 0.027 | 0.012 | [0.006, 0.047] |
| $\log y_2 \cdot \log LU$ | -0.094 | 0.074 | [-0.216, 0.027] |
| $\log y_2 \cdot \log L$ | -0.011 | 0.020 | [-0.045, 0.022] |
| $\log y_2 \cdot \log A$ | -0.27 | 0.021 | [-0.062, 0.008] |
| $\log y_2 \cdot \log M$ | -0.080 | 0.022 | [-0.117, -0.043] |
| $\log y_2 \cdot \log y_2$ | 0.082 | 0.006 | [0.071, 0.094] |
| $\log y_2 \cdot t$ | -0.001 | 0.002 | [-0.005, 0.001] |
| $t * t$ | -0.002 | 0.000 | [-0.003, -0.001] |
| $\sigma_v$ | 0.072 | 0.002 | [0.067, 0.077] |
| $\sigma_a$ | 0.133 | 0.008 | [0.119, 0.146] |
| $\sigma_\xi$ | 0.411 | 0.048 | [0.336, 0.496] |
| $\rho$ | 0.80 | 0.047 | [0.821, 0.924] |
| $Log.Marg.Likelihood$ | 1398.22 | | |
| **Inefficiency effects** | | | |
| constant | 0.401 | 0.102 | [0.252, 0.586] |
| Milk recording | 0.191 | 0.047 | [0.122, 0.276] |

# Appendix C

The Bayes Factor (BF) summarizes "*the evidence provided by the data in favor of one scientific theory, represented by a statistical model, as opposed to another*" (Kass and Raftery 1995, p. 777). The model comparison between two competing models is conducted by simply calculating the logarithm of the marginal likelihood density. The logarithm of marginal likelihood density is approximated using the Laplace-Metropolis estimator (Lewis and Raftery 1997).

Table (7)

Model 2 (M2): Livestock value is added to Capital

| **Variable** | **Mean** | **Std. dev.** | **95% Credible Interval** |
|---|---|---|---|
| constant | -0.045 | 0.008 | [-0.063, -0.028] |
| $\log K$ | -0.285 | 0.016 | [-0.317, -0.253] |
| $\log L$ | -0.043 | 0.018 | [-0.079, -0.007] |
| $\log A$ | -0.240 | 0.019 | [-0.278, -0.201] |
| $\log M$ | -0.317 | 0.016 | [-0.349, -0.285] |
| $\log y_2$ | 0.195 | 0.007 | [0.180, 0.209] |
| $t$ | -0.021 | 0.001 | [-0.023, -0.019] |
| $\log K * \log K$ | -0.050 | 0.026 | [-0.102, 0.001] |
| $\log K * \log L$ | -0.093 | 0.042 | [-0.177, -0.010] |
| $\log K * \log A$ | 0.058 | 0.046 | [-0.033, 0.150] |
| $\log K * \log M$ | 0.081 | 0.046 | [-0.009, 0.171] |
| $\log L * \log L$ | -0.065 | 0.033 | [-0.132, 0.000] |
| $\log L * \log M$ | 0.077 | 0.043 | [-0.007, 0.162] |
| $\log L * \log A$ | -0.060 | 0.045 | [-0.150, 0.028] |
| $\log A * \log A$ | -0.075 | 0.032 | [-0.138, -0.012] |
| $\log A * \log M$ | 0.085 | 0.049 | [-0.010, 0.182] |
| $\log M * \log M$ | -0.090 | 0.032 | [-0.154, -0.026] |
| $\log y_2 * \log K$ | 0.042 | 0.018 | [0.005, 0.079] |
| $\log y_2 * \log L$ | -0.008 | 0.021 | [-0.051, 0.033] |
| $\log y_2 * \log A$ | -0.011 | 0.020 | [-0.051, 0.028] |
| $\log y_2 * \log M$ | -0.062 | 0.023 | [-0.108, -0.015] |

| | | | |
|---|---|---|---|
| $\log y_2 * \log y_2$ | 0.083 | 0.007 | [0.069, 0.097] |
| $\log K * t$ | -0.005 | 0.003 | [-0.011, 0.000] |
| $\log L * t$ | 0.003 | 0.003 | [-0.002, 0.009] |
| $\log A * t$ | 0.000 | 0.003 | [-0.005, 0.007] |
| $\log M * t$ | 0.007 | 0.003 | [0.000, 0.015] |
| $\log y_2 * t$ | -0.003 | 0.000 | [-0.004, -0.003] |
| $t * t$ | -0.002 | 0.001 | [-0.006, 0.000] |
| $\sigma_v$ | 0.007 | 0.007 | [0.006, 0.008] |
| $\sigma_a$ | 0.150 | 0.012 | [0.130, 0.170] |
| $\sigma_\xi$ | 0.298 | 0.002 | [0.204, 0.423] |
| $\rho$ | 0.886 | 0.005 | [0.821, 0.924] |
| $Log.Marg.Likelihood$ | 1228.32 | | |

Table (8)

Model 3 (M3): feeds is a separate variable from materials

| **Variable** | **Mean** | **Std. dev.** | **95% CI** |
|---|---|---|---|
| constant | -0.209 | 0.044 | [-0.284,-0.139] |
| $\log K$ | -0.305 | 0.017 | [-0.334,-0.276] |
| $\log L$ | -0.063 | 0.019 | [ -0.095, -0.032] |
| $\log A$ | -0.246 | 0.020 | [-0.279, -0.212] |
| $\log F$ | -0.121 | 0.008 | [-0.136, -0.107] |
| $\log M$ | -0.169 | 0.015 | [-0.196, -0.143] |
| $\log y_2$ | 0.191 | 0.007 | [0.179, 0.203] |
| $t$ | -0.018 | 0.001 | [ -0.020,-0.016] |
| $\log K \cdot \log K$ | -0.029 | 0.028 | [-0.075, 0.017] |

| | | | |
|---|---|---|---|
| $\log K \cdot \log L$ | -0.07 | 0.044 | [-0.143, 0.002] |
| $\log K \cdot \log A$ | 0.024 | 0.050 | -0.058, 0.106] |
| $\log K \cdot \log F$ | 0.015 | 0.025 | [-0.026, 0.056] |
| $\log K \cdot \log M$ | 0.053 | 0.041 | [-0.014. 0.122] |
| $\log K \cdot t$ | -0.007 | 0.002 | [-0.013, -0.001] |
| $\log L \cdot \log L$ | -0.005 | 0.036 | [-0.066, 0.054] |
| $\log L \cdot \log F$ | 0.022 | 0.025 | [-0.019, 0.054] |
| $\log L \cdot \log M$ | 0.036 | 0.045 | [-0.041, 0.030] |
| $\log L \cdot \log A$ | -0.071 | 0.050 | [-0.153, 0.011] |
| $\log L \cdot t$ | 0.004 | 0.004 | [-0.002, 0.011] |
| $\log A \cdot \log A$ | -0.039 | 0.033 | [-0.094, 0.015] |
| $\log A \cdot \log M$ | 0.029 | 0.046 | [-0.047, 0.105] |
| $\log A \cdot t$ | 0.003 | 0.004 | [-0.004, 0.010] |
| $\log F \cdot \log F$ | -0.024 | 0.010 | [-0.041, -0.007] |
| $\log F \cdot \log A$ | 0.049 | 0.027 | [0.004, 0.094] |
| $\log F \cdot \log M$ | -0.026 | 0.026 | [-0.070, 0.016] |
| $\log M \cdot \log M$ | -0.021 | 0.031 | [-0.072, 0.0306] |
| $\log M \cdot t$ | 0.000 | 0.004 | [-0.007, 0.007 ] |
| $\log y_2 \cdot \log K$ | 0.045 | 0.018 | [0.015, 0.075] |
| $\log y_2 \cdot \log L$ | -0.0005 | 0.021 | [-0.041, 0.030] |
| $\log y_2 \cdot \log A$ | 0.005 | 0.020 | [-0.028, 0.040] |
| $\log y_2 \cdot \log M$ | -0.061 | 0.023 | [-0.099, -0.023] |
| $\log y_2 \cdot \log F$ | -0.018 | 0.012 | [-0.040, 0.002] |
| $\log y_2 \cdot \log y_2$ | 0.089 | 0.006 | [0.078, 0.101] |
| $\log y_2 \cdot t$ | -0.001 | 0.002 | [-0.005, 0.002] |
| $t * t$ | -0.003 | 0.000 | [-0.004, -0.003] |

| | | | |
|---|---|---|---|
| $\sigma_v$ | 0.076 | 0.003 | [0.070, 0.081] |
| $\sigma_a$ | 0.154 | 0.011 | [0.135, 0.1726] |
| $\sigma_\xi$ | 0.301 | 0.044 | [0.237, 0.382] |
| $\rho$ | 0.84 | 0.044 | [0.765, 0.906] |
| $Log.Marg.Likelihood$ | 1385.92 | | |
| **Inefficiency effects** | | | |
| constant | 0.228 | 0.075 | [0.124, 0.368] |
| Milk recording | 0.117 | 0.033 | [0.068, 0.178] |

Table (9)

Model 4 (M4): feeds is a separate variable from materials and livestock units is separate from capital

| **Variable** | **Mean** | **Std. dev.** | **95% CI** |
|---|---|---|---|
| constant | 3.758 | 31.605 | [-48.318, 55.609] |
| $\log K$ | -1.615 | 31.62 | [-53.649, 50.330] |
| $\log LU$ | -1.761 | 31.66 | [-53.857, 50.278] |
| $\log L$ | -0.021 | 31.64 | [-47.963, 56.084] |
| $\log A$ | 106.88 | 30.66 | [56.726, 156.826] |
| $\log F$ | 0.572 | 0.020 | [0.375, 0.768] |
| $\log M$ | 1.896 | 0.015 | [1.674,2.118] |
| $\log y_2$ | 0.126 | 0.082 | [-0.009, 0.263] |
| $t$ | 0.659 | 31.629 | [-51.209, 52.438] |
| $\log K \cdot \log K$ | 4.89 | 31.62 | [-47.18, 56.86] |
| $\log K \cdot \log LU$ | 3.82 | 33.44 | [-48.93, 54.32] |

| | | | |
|---|---|---|---|
| $\log K \cdot \log L$ | -0.461 | 31.6642 | [-52.632, 51.632] |
| $\log K \cdot \log A$ | -25.890 | 27.742 | [-71.502, 19.758] |
| $\log K \cdot \log M$ | 0.107 | 0.027 | [-0.000, 0.215] |
| $\log K \cdot t$ | -4.222 | 31.182 | [-55.444 , 47.201 ] |
| $\log L \cdot \log L$ | 5.037 | 31.509 | [-46.872, 56.816] |
| $\log L \cdot \log F$ | -0.038 | 0.041 | [ -0.105, 0.0299] |
| $\log L \cdot \log M$ | -0.089 | 0.050 | [-0.173,-0.006] |
| $\log L \cdot \log A$ | 102.631 | 25.60 | [ 60.462 144.723] |
| $\log L \cdot t$ | -4.780 | 31.31 | [-56.244, 46.841] |
| $\log F \cdot \log F$ | 0.000 | 0.000 | [ 0.000, 0.000] |
| $\log F \cdot \log A$ | 0.003 | 0.001 | [0.001, 0.006] |
| $\log F \cdot \log M$ | 0.000 | 0.000 | [0.000, 0.000] |
| $\log F \cdot \log t$ | -0.002 | 0.009 | [-0.004, -0.001] |
| $\log A \cdot \log A$ | -0.223 | 0.729 | [-0.975, 1.426] |
| $\log A \cdot \log M$ | -0.003 | 0.001 | [-0.006, -0.000] |
| $\log A \cdot t$ | 7.397 | 7.865 | [-5.537, 20.331] |
| $\log M \cdot \log M$ | 0.000 | 0.000 | [0.000, 0.000] |
| $\log M \cdot t$ | 0.006 | 0.011 | [-0.011, 0.024] |
| $\log LU \cdot \log LU$ | 1.327 | 31.627 | [-50.616, 53.265] |
| $\log LU \cdot \log A$ | -50.869 | 30.578 | [-101.187, -0.652] |
| $\log LU \cdot \log M$ | 1.033 | 0.151 | [ 0.783,1.282] |
| $\log LU \cdot t$ | 7.852 | 31.476 | [-43.910, 59.725] |
| $\log y_2 \cdot \log K$ | 0.101 | 0.042 | [0.032, 0.170] |
| $\log y_2 \cdot \log LU$ | 0.256 | 0.099 | [0.092, 0.419] |
| $\log y_2 \cdot \log L$ | 0.085 | 0.031 | [0.033,0.136] |
| $\log y_2 \cdot \log A$ | -0.002 | 0.000 | [-0.004, -0.001] |

| | | | |
|---|---|---|---|
| $\log y_2 \cdot \log F$ | 0.000 | 0.000 | [0.000, 0.000] |
| $\log y_2 \cdot \log M$ | 0.000 | 0.000 | 0.000, 0.000] |
| $\log y_2 \cdot \log y_2$ | 0.000 | 0.000 | [0.000, 0.000] |
| $\log y_2 \cdot t$ | 0.009 | 0.006 | [ -0.001, 0.020] |
| $t * t$ | -0.002 | 0.000 | [-0.003, -0.001] |
| $\sigma_v$ | 15940.9 | 268.126 | [ 15507, 16389.2] |
| $\sigma_a$ | 31827.6 | 1555.68 | [ 29369.1 34480.9] |
| $\sigma_\xi$ | 1.668 | 2.580 | [0.105, 8.499] |
| $\rho$ | 0.487 | 0.155 | [0.239, 0.741] |
| $Log.Marg.Likelihood$ | -26270.5 | | |
| **Inefficiency effects** | | | |
| constant | 0.512 | 6.040 | [-5.724, 12.598] |
| Milk recording | 2.600 | 6.746 | [-6.959,13.301] |

# Appendix D

Table (10)

Model 5 (M5): density (LU per ha) as an additional factor in $s$ specification

| **Variable** | **Mean** | **Std. dev.** | **95% CI** |
|---|---|---|---|
| constant | -0.177 | 0.030 | [-0.228, -0.131] |
| $\log K$ | -0.081 | 0.011 | [-0.099, -0.063] |
| $\log LU$ | -0.553 | 0.028 | [-0.599, -0.507] |
| $\log L$ | -0.021 | 0.017 | [-0.050, 0.007] |
| $\log A$ | -0.090 | 0.020 | [-0.130, -0.051] |

| | | | |
|---|---|---|---|
| $\log M$ | -0.224 | 0.015 | [-0.250, -0.198] |
| $\log y_2$ | 0.211 | 0.006 | [0.199, 0.222] |
| $t$ | -0.015 | 0.001 | [-0.017, -0.013] |
| $\log K \cdot \log K$ | -0.017 | 0.010 | [-0.035, -0.000] |
| $\log K \cdot \log LU$ | -0.010 | 0.045 | [-0.083, 0.064] |
| $\log K \cdot \log L$ | -0.014 | 0.025 | [-0.056, 0.028] |
| $\log K \cdot \log A$ | 0.019 | 0.031 | [-0.032, 0.072] |
| $\log K \cdot \log M$ | 0.014 | 0.028 | [-0.030, 0.062] |
| $\log K \cdot t$ | 0.002 | 0.002 | [-0.001, 0.006] |
| $\log L \cdot \log L$ | -0.000 | 0.033 | [-0.056, 0.054] |
| $\log L \cdot \log LU$ | -0.104 | 0.076 | [-0.232, 0.020] |
| $\log L \cdot \log M$ | 0.059 | 0.042 | [-0.008, 0.127] |
| $\log L \cdot \log A$ | -0.044 | 0.055 | [-0.134, 0.047] |
| $\log L \cdot t$ | 0.006 | 0.003 | [-0.000, 0.012] |
| $\log LU \cdot \log LU$ | -0.055 | 0.065 | [-0.162, 0.054] |
| $\log LU \cdot \log A$ | 0.042 | 0.086 | [-0.101, 0.186] |
| $\log LU \cdot \log M$ | 0.158 | 0.076 | [0.031, 0.283] |
| $\log LU \cdot t$ | -0.028 | 0.006 | [-0.038, -0.017] |
| $\log A \cdot \log A$ | -0.035 | 0.037 | [-0.097, 0.025] |
| $\log A \cdot \log M$ | 0.025 | 0.054 | [-0.063, 0.113] |
| $\log A \cdot t$ | 0.011 | 0.004 | [0.003, 0.019] |
| $\log M \cdot \log M$ | -0.100 | 0.034 | [-0.156, -0.042] |
| $\log M \cdot t$ | 0.012 | 0.004 | [0.004, 0.020] |
| $\log y_2 \cdot \log K$ | 0.028 | 0.012 | [0.009, 0.049] |
| $\log y_2 \cdot \log LU$ | 0.055 | 0.029 | [0.008, 0.106] |
| $\log y_2 \cdot \log L$ | -0.007 | 0.020 | [-0.041, 0.027] |

| | | | |
|---|---|---|---|
| $\log y_2 \cdot \log A$ | -0.028 | 0.021 | [-0.062, 0.007] |
| $\log y_2 \cdot \log M$ | -0.077 | 0.022 | [-0.115, -0.039] |
| $\log y_2 \cdot \log y_2$ | 0.084 | 0.006 | [0.073, 0.095] |
| $\log y_2 \cdot t$ | -0.001 | 0.002 | [-0.005, 0.001] |
| $t * t$ | -0.002 | 0.000 | [-0.003, -0.001] |
| $\sigma_v$ | 0.071 | 0.03 | [0.066, 0.076] |
| $\sigma_a$ | 0.129 | 0.009 | [0.113, 0.144] |
| $\sigma_\xi$ | 0.332 | 0.038 | [0.269, 0.393] |
| $\rho$ | 0.81 | 0.037 | [0.742, 0.868] |
| $Log.Marg.Likelihood$ | | | |
| **Inefficiency effects** | | | |
| constant | 0.195 | 0.067 | [0.098, 0.320] |
| Milk recording | 0.151 | 0.038 | [0.096, 0.221] |
| Density | 0.061 | 0.024 | [0.025, 0.104] |

Table (11)

Model 6 (M6): with age as an additional factor in $s$ specification

| **Variable** | **Mean** | **Std. dev.** | **95% CI** |
|---|---|---|---|
| constant | -0.165 | 0.033 | [-0.228,-0.120] |
| $\log K$ | -0.080 | 0.010 | [-0.098, -0.062] |
| $\log LU$ | -0.578 | 0.027 | [-0.623, -0.534] |
| $\log L$ | -0.025 | 0.017 | [-0.053, 0.003] |
| $\log A$ | -0.066 | 0.021 | [-0.103, -0.031] |
| $\log M$ | -0.225 | 0.016 | [-0.252, -0.198] |
| $\log y_2$ | 0.212 | 0.006 | [0.200, 0.223] |

| | | | |
|---|---|---|---|
| $t$ | -0.015 | 0.001 | [-0.017, -0.013] |
| $\log K \cdot \log K$ | -0.018 | 0.010 | [-0.036, -0.001] |
| $\log K \cdot \log LU$ | -0.002 | 0.045 | [-0.075, 0.072] |
| $\log K \cdot \log L$ | 0.009 | 0.025 | [-0.052, 0.033] |
| $\log K \cdot \log A$ | 0.017 | 0.032 | [-0.034, 0.070] |
| $\log K \cdot \log M$ | 0.010 | 0.028 | [-0.034, 0.058] |
| $\log K \cdot t$ | 0.002 | 0.002 | [-0.001, 0.005] |
| $\log L \cdot \log L$ | -0.006 | 0.034 | [-0.064, 0.049] |
| $\log L \cdot \log LU$ | -0.114 | 0.074 | [-0.237, 0.007] |
| $\log L \cdot \log M$ | 0.063 | 0.042 | [-0.004, 0.132] |
| $\log L \cdot \log A$ | -0.038 | 0.054 | [-0.128, 0.051] |
| $\log L \cdot t$ | 0.005 | 0.003 | [-0.000, 0.012] |
| $\log LU \cdot \log LU$ | -0.046 | 0.066 | [-0.155, 0.060] |
| $\log LU \cdot \log A$ | 0.016 | 0.083 | [-0.116, 0.153] |
| $\log LU \cdot \log M$ | 0.150 | 0.076 | [0.025, 0.274] |
| $\log LU \cdot t$ | -0.027 | 0.036 | [-0.036, -0.017] |
| $\log A \cdot \log A$ | -0.024 | 0.036 | [-0.086, 0.034] |
| $\log A \cdot \log M$ | 0.030 | 0.052 | [-0.057, 0.116] |
| $\log A \cdot t$ | 0.010 | 0.004 | [0.002, 0.018] |
| $\log M \cdot \log M$ | -0.097 | 0.034 | [-0.154, -0.040] |
| $\log M \cdot t$ | 0.012 | 0.004 | [0.005, 0.019] |
| $\log y_2 \cdot \log K$ | 0.026 | 0.012 | [0.005, 0.046] |
| $\log y_2 \cdot \log LU$ | 0.055 | 0.030 | [0.007, 0.105] |
| $\log y_2 \cdot \log L$ | -0.008 | 0.020 | [-0.042, 0.024] |
| $\log y_2 \cdot \log A$ | -0.026 | 0.021 | [-0.061, 0.007] |
| $\log y_2 \cdot \log M$ | -0.078 | 0.022 | [-0.111, -0.040] |

| | | | |
|---|---|---|---|
| $\log y_2 \cdot \log y_2$ | 0.083 | 0.006 | [0.072, 0.094] |
| $\log y_2 \cdot t$ | -0.002 | 0.000 | [-0.003, -0.001] |
| $t * t$ | -0.002 | 0.000 | [-0.003, -0.001] |
| $\sigma_v$ | 0.072 | 0.003 | [0.067, 0.077] |
| $\sigma_a$ | 0.129 | 0.008 | [0.115, 0.143] |
| $\sigma_\xi$ | 0.344 | 0.037 | [0.282, 0.402] |
| $\rho$ | 0.82 | 0.030 | [0.767, 0.870] |
| $Log.Marg.Likelihood$ | 1387.31 | | |
| **Inefficiency effects** | | | |
| constant | 0.389 | 0.083 | [0.259, 0.532] |
| Milk recording | 0.158 | 0.033 | [0.105, 0.216] |
| Age | -0.002 | 0.001 | [-0.003, -0.001] |

Table (12)

Model 7 (M7): with both age and density as additional factors in $s$ specification

| **Variable** | **Mean** | **Std. dev.** | **95% CI** |
|---|---|---|---|
| constant | -0.174 | 0.045 | [-0.269,-0.111] |
| $\log K$ | -0.080 | 0.010 | [-0.098, -0.063] |
| $\log LU$ | -0.549 | 0.028 | [-0.596, -0.502] |
| $\log L$ | -0.020 | 0.017 | [-0.049, 0.007] |
| $\log A$ | -0.090 | 0.022 | [-0.126, -0.054] |
| $\log M$ | -0.224 | 0.015 | [-0.249, -0.200] |
| $\log y_2$ | 0.211 | 0.007 | [0.200, 0.223] |
| $t$ | -0.015 | 0.001 | [-0.017, -0.013] |
| $\log K \cdot \log K$ | -0.017 | 0.010 | [-0.033, -0.000] |

| | | | |
|---|---|---|---|
| $\log K \cdot \log LU$ | -0.012 | 0.041 | [-0.080, 0.057] |
| $\log K \cdot \log L$ | -0.014 | 0.026 | [-0.056, 0.028] |
| $\log K \cdot \log A$ | 0.023 | 0.033 | [-0.032, 0.079] |
| $\log K \cdot \log M$ | 0.011 | 0.027 | [-0.033, 0.055] |
| $\log K \cdot t$ | 0.002 | 0.002 | [-0.001, 0.005] |
| $\log L \cdot \log L$ | -0.001 | 0.034 | [-0.056, 0.054] |
| $\log L \cdot \log LU$ | -0.100 | 0.073 | [-0.225, 0.022] |
| $\log L \cdot \log M$ | 0.058 | 0.044 | [-0.014, 0.129] |
| $\log L \cdot \log A$ | -0.049 | 0.053 | [-0.137, 0.039] |
| $\log L \cdot t$ | 0.006 | 0.003 | [-0.000, 0.012] |
| $\log LU \cdot \log LU$ | -0.056 | 0.064 | [-0.164, 0.045] |
| $\log LU \cdot \log A$ | 0.055 | 0.082 | [-0.080, 0.192] |
| $\log LU \cdot \log M$ | 0.145 | 0.078 | [0.014, 0.273] |
| $\log LU \cdot t$ | -0.028 | 0.006 | [-0.038, -0.017] |
| $\log A \cdot \log A$ | -0.040 | 0.038 | [-0.103, 0.022] |
| $\log A \cdot \log M$ | 0.022 | 0.053 | [-0.064, 0.109] |
| $\log A \cdot t$ | 0.011 | 0.004 | [0.003, 0.019] |
| $\log M \cdot \log M$ | -0.091 | 0.034 | [-0.148, -0.033] |
| $\log M \cdot t$ | 0.012 | 0.004 | [0.004, 0.020] |
| $\log y_2 \cdot \log K$ | 0.029 | 0.012 | [0.010, 0.049] |
| $\log y_2 \cdot \log LU$ | 0.053 | 0.029 | [0.005, 0.103] |
| $\log y_2 \cdot \log L$ | -0.006 | 0.020 | [-0.040, 0.027] |
| $\log y_2 \cdot \log A$ | -0.031 | 0.021 | [-0.067, 0.003] |
| $\log y_2 \cdot \log M$ | -0.075 | 0.022 | [-0.111, -0.039] |
| $\log y_2 \cdot \log y_2$ | 0.085 | 0.006 | [0.074, 0.095] |
| $\log y_2 \cdot t$ | -0.001 | 0.002 | [-0.005, 0.001] |

| | | | |
|---|---|---|---|
| $t * t$ | -0.002 | 0.000 | [-0.003, -0.001] |
| $\sigma_v$ | 0.072 | 0.002 | [0.068, 0.077] |
| $\sigma_a$ | 0.129 | 0.011 | [0.109, 0.146] |
| $\sigma_\xi$ | 0.331 | 0.057 | [0.237, 0.425] |
| $\rho$ | 0.80 | 0.049 | [0.709, 0.873] |
| $Log.Marg.Likelihood$ | 1385.57 | | |
| **Inefficiency effects** | | | |
| constant | 0.261 | 0.112 | [0.101, 0.467] |
| Milk recording | 0.147 | 0.046 | [0.077, 0.230] |
| Density | 0.63 | 0.028 | [0.024, 0.116] |
| Age | -0.001 | 0.000 | [-0.002, 0.000] |