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The effect of cow longevity on dynamic productivity growth of dairy farming

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HIGHLIGHTS

- The average annual dynamic productivity growth of Dutch dairy farms over 2007-2013 was 1.1%.
- Technical change was the main source of productivity growth of farms during 2007-2013.
- Cow longevity has a positive association with productivity growth and technical change.
- Technical inefficiency change is negatively associated with cow longevity.

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ABSTRACT

Cow longevity is recognized as an important trait to improve farm economic performance while concurrently reducing environmental and social impacts. However, there is an economic trade-off between longevity and herd genetic improvement, which may influence the dairy farms' efficiency and productivity growth over time. This study used a panel data of 723 Dutch specialized dairy farms over 2007-2013 to empirically measure the effect of longevity on dynamic productivity change and its components. First, the productivity growth estimates were obtained using the Luenberger dynamic productivity indicator. Then, the estimates were regressed on longevity and other explanatory variables using dynamic panel data model. Results show that the average dynamic productivity growth was 1.1% per year, comprising of technical change (0.5%), scale inefficiency change (0.4%) and technical inefficiency change (0.2%). Longevity is found to have a statistically significant positive association with productivity growth and technical change, implying that farms with more matured cows were also those farms that recorded increased productivity through technical progress. However, it has a negative association with technical inefficiency change, which might follow from the reduced milk productivity of old cows per unit of inputs used. Dutch dairy farms have a potential to raise productivity growth by reducing technical inefficiencies associated with input utilization.

1. Introduction

The increased focus on milk productivity of modern dairy cows has been associated with a decline in the length of cow's productive life (i.e., longevity), increase in incidences of health problems, decrease in fertility, and poor animal welfare (Hare et al., 2006; Oltenacu and Algers, 2005). Recently, cow longevity has attracted a growing attention as it contributes to the (economic, environmental and social) sustainability of milk and beef production of dairy farming. Increased longevity reduces investment costs associated with the rearing of fully productive heifers. A short herd life leads to increased replacement costs as a result of the limited potential for replacement heifers selection within a farm (Heikkilä et al., 2008). The reduction in the fertility of cows is the major contributing factor to decreases in the number of parities per cow's lifetime, lifetime days in milk and longevity (Haworth et al., 2008). Subsequently, the possibility of raising own replacement heifers within a farm decreases. Moreover, farm profit increases with the number of lactations per cow's lifetime, which is positively associated with longevity (Haworth et al., 2008). It has also been reported that increased longevity reduces the environmental footprint of dairy farming since fewer replacement heifers are required to be raised (Grandl et al., 2016; Bell et al., 2015; Van Middelaar et al., 2014; Hristov et al., 2013; Garnsworthy, 2004). Van Middelaar et al. (2014), for example, showed that an increase in cow longevity by 270 days[1] leads to a reduction of

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[1] This is equal to the genetic standard deviation of longevity.

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210 kg CO_2-equivalent greenhouse gases emission per cow per year, for an income maximizing breeding objective. A reduced longevity is also an indicator of poor animal welfare (Bruijnis et al., 2013; Oltenacu and Algers, 2005), especially when cow culling is due to health and non-pregnancy problems, which are the main causes of culling (Pinedo et al., 2010; Dechow and Goodling, 2008). Specifically, cow welfare improves if the increased longevity is achieved through an improved animal health management.

However, there is an economic trade-off between increased longevity and herd genetic improvement as a result of not using genetically superior replacement heifers (De Vries, 2017). An increased longevity results in a longer genetic lag. Hence, a lower culling rate (i.e., increased longevity) implies that 'the average cow is older and has a lower genetic merit than a herd of average age' (De Vries, 2017). A farm with more old cows has lower performance (e.g., lower milk yield, and poor reproduction and health) due to the lower genetic merit of the herd. Therefore, a longer genetic lag implies higher opportunity costs associated with the forgone farm performance as a result of not using the genetically superior replacement heifers. The presence of such an economic trade-off and the heterogeneity of farms' preferences for longevity may influence dairy farms' productivity growth and resource use efficiency over time. Improving technical efficiency, i.e., producing the maximum possible outputs using the lowest possible inputs, is critical for intensive dairy farms to stay in business in the competitive global market while complying with the ever stringent environmental and societal requirements of farming.

There have been several studies in the literature about the effect of increased longevity, for example, on farm profit (e.g., Haworth et al., 2008; Heikkilä et al., 2008), on environmental footprints (e.g., Van Middelaar et al., 2014; Garnsworthy, 2004) and on animal welfare (e.g., Bruijnis et al., 2013; Oltenacu and Algers, 2005). However, to the best of my knowledge, there are no studies on the effect of cow longevity on farms' technical efficiency and total factor productivity (TFP) growth over time. A farm is said to be technically efficient if a decrease in any input or an increase in any output is not possible without increasing some other inputs or decreasing some other outputs. TFP growth (hereafter referred to as productivity growth) refers to the residual output growth not explained by the input use growth (Rungsuriyawiboon and Stefanou, 2008). Efficiency and productivity analyses have widely been used in the last two decades to measure the economic performance of dairy farms (e.g., Skevas et al., 2018; Oude Lansink et al., 2015; Atsbeha et al., 2012; Brümmer et al., 2002). TFP and efficiency analyses, unlike cost accounting analyses, take into account all farm inputs and outputs including nonmonetary inputs and outputs. However, previous studies, with very few exceptions in the agricultural economics literature (e.g., Ali et al., 2021; Serra et al., 2011), on farm productivity and efficiency analyses do not take into account the dynamic (intertemporal) nature of investment decisions associated with breeding stock. Breeding stock is a crucial quasi-fixed input in dairy farming[2]. Dynamic (intertemporal) decisions such as investment decisions in quasi-fixed inputs affect current production (e.g. milk yield) while increasing future capital stock (e.g. breeding stock), which in turn affects the level of future production (Silva and Stefanou, 2003). Farms incur adjustment costs (e.g., search, transaction and learning costs) when doing investments in quasi-fixed inputs (e.g., breeding stocks, milking robots) (Silva and Stefanou, 2003). It is costly for farmers to adjust the level of quasi-fixed inputs instantly to their optimal levels because of financial constraints and technology-specific learning costs (Penrose, 1959). As a result, investments in quasi-fixed inputs involves an intertemporal decision that affects current production while increasing future capital stock and thereby affects production in all future periods. Immediately after technology adoption (e.g., milking robot), normally, a period of adjustment follows where productivity declines, since farmers engage in learning to adjust their production system to the new technologies (Jovanovic and Nyarko, 1996; Klenow, 1998). Subsequently, the long-term impacts of technology adoption are expected to differ from their short-term impacts. The sluggish adjustments in quasi-fixed inputs because of the high adjustment costs and the resulting lag in technology adoption affect dairy farms' efficiency and productivity growth over time (e.g., Skevas, 2016). Therefore, studying the effect of cow longevity on farms' productivity growth requires a long term and dynamic perspectives since longevity involves both genetic improvement and investment in breeding stock.

The objectives of this study were therefore (i) to measure the dynamic productivity growth of dairy farms and its components (i.e., technical change, technical inefficiency change and scale inefficiency change), and (ii) to assess the effects of cow longevity on dynamic productivity growth, technical change, technical inefficiency change and scale inefficiency change. The study contributes to the literature in two ways by introducing the concept of 'dynamic analysis' in the two stages of the analysis. First, dynamic inefficiency and productivity scores were estimated by accounting for adjustment costs associated with changes in the quasi-fixed inputs of dairy farming (i.e., breeding stock, machineries and buildings). Second, a dynamic panel data modelling is used to assess the long term effects of cow longevity on dynamic productivity growth of farms and its components. The use of a dynamic panel data model accounts for the economic trade-off between longevity and genetic improvement of the herd, which are long term phenomenon. The empirical application employs a panel data of Dutch specialized dairy farms over the period 2007-2013.

2. Materials and methods

2.1. Decomposition of Luenberger dynamic productivity change

A dynamic Luenberger productivity indicator (Kapelko et al., 2016; Oude Lansink et al., 2015) is used to measure the productivity and inefficiency changes of Dutch dairy farms. Suppose there are J farms ($j = 1, \ldots, J$) producing M outputs $y = (y_1, \ldots, y_M)$ by employing N variable inputs $x = (x_1, \ldots, x_N)$, H fixed inputs $L = (L_1, \ldots, L_H)$ and F quasi-fixed inputs $K = (K_1, \ldots, K_F)$ with F corresponding gross investments $I = (I_1, \ldots, I_F)$. The dynamic production technology (Serra et al., 2011) that shows the relationship between outputs, and inputs and investments can be written as:

$$P_t(y^t : K^t, L^t) = \{(x^t, I^t) : x^t, I^t \textit{ can produce } y^t, \textit{ given } K^t, L^t\} \tag{1}$$

where P_t is the production technology in time t. The production technology is a closed and non-empty set with a lower bound, a strictly convex set, positive monotonic in variable inputs, negative monotonic in gross investment, increases with fixed and quasi-fixed inputs, and output is freely disposable (Silva and Stefanou, 2003). In the current study, a dynamic directional input distance function (Silva and Stefanou, 2003) is used to represent the dairy farm dynamic production technology since Dutch farmers had more autonomy to adjust inputs than outputs during the sample period (2007-2013) because of the milk quota. The dynamic directional input distance function ($\overrightarrow{D}$) can be expressed as:

$$\overrightarrow{D}_i^t\left(y^t, K^t, L^t, x^t, I^t; g_x^t, g_I^t\right) = \sup\left\{\sum \beta : \left(x_n^t - \beta g_{xn}^t, I_f^t + \beta g_{If}^t, y_m^t, K_f^t, L_h^t\right) \in P_t\right\} \tag{2}$$

[2] Farm inputs can be classified into three types: variable, fixed and quasi-fixed. Variable inputs are inputs whose quantities depend on the level of output produced. Fixed inputs are inputs whose quantities cannot be adjusted in the short-term, and fixed costs are incurred regardless of the level of output. Quasi-fixed inputs are inputs whose quantities can to some extent be adjusted in the short run, but cannot be adjusted all the way to the optimal level due to constraints (adjustment costs).

where g_x^t and g_I^t are directional vectors associated with variable inputs and investments, respectively; β refers to the dynamic technical inefficiency score. For a farm to become fully efficient (i.e., to move onto the production frontier defined by the fully efficient farms), the use of variable inputs should be contracted by $\beta \times g_x$ while expanding gross investments by $\beta \times g_I$. Fig. 1 illustrates the computation of dynamic technical inefficiency. The frontier is defined by the three fully efficient farms (*A, B* and *C*). Farm *E*, which uses 5 units of variable inputs while doing 3 units investment, is inefficient compared to the other farms (i.e. it is far from the frontier). To become fully efficient (to reach to the frontier), Farm *E* has to reduce the use of variable inputs by 1.4 units while expanding its investment by 1.4 units.

Data envelopment analysis (**DEA**) is used to estimate the dynamic directional input distances (i.e., β). Four DEA models, under constant returns to scale (**CRS**), are required to estimate Luenberger productivity growth scores: two single- and two mixed-period models Kapelko et al., 2016; Oude Lansink et al., 2015). The single-period models (Eqs. 3 and (6) measure the performance of farms in time *t* (and *t+1*) relative to their respective technologies in time *t* (and *t+1*). The mixed-period models Eqs. 4 and (5), on the other hand, measure the performance of farms in time *t* (and *t+1*) relative to the technologies in time *t+1* (and *t*), respectively. The four DEA models are:

$$\overrightarrow{D}_i^t\left(y^t, K^t, L^t, x^t, I^t; g_x^t, g_I^t\right) = max_{\beta_1,\ \lambda_j^1}\beta_1 \tag{3}$$

Subject to

$$y_{mi}^t \le \sum_{j=1}^{J} \lambda_j^1 y_{mj}^t,\ m = 1,\ \ldots,\ M$$

$$\sum_{j=1}^{J} \lambda_j^1 x_{nj}^t \le x_{ni}^t - \beta_1 g_{xn}^t,\ n = 1,\ \ldots,\ N$$

$$\sum_{j=1}^{J} \lambda_j^1 L_{hj}^t \le L_{hi}^t,\ h = 1,\ \ldots,\ H$$

$$I_{fi}^t + \beta_1 g_I^t - \delta_f K_{fi}^t \le \sum_{j=1}^{J} \lambda_j^1 \left(I_{fj}^t - \delta_f K_{fj}^t\right),\ f = 1,\ \ldots,\ F$$

$$\beta_1,\ \lambda_j^1 \ge 0$$

$$\overrightarrow{D}_i^{t+1}\left(y^t, K^t, L^t, x^t, I^t; g_x^t, g_I^t\right) = max_{\beta_2,\ \lambda_j^2}\beta_2 \tag{4}$$

Subject to

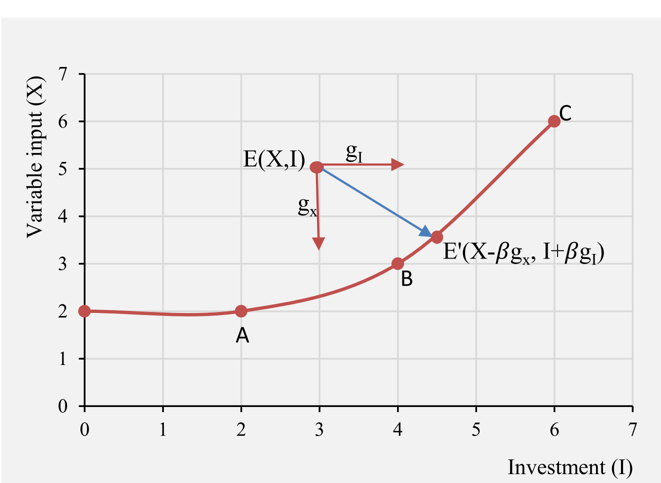

Fig. 1. Elaboration of dynamic technical inefficiency.

$$y_{mi}^t \le \sum_{j=1}^{J} \lambda_j^2 y_{mj}^{t+1},\ m = 1,\ \ldots,\ M$$

$$\sum_{j=1}^{J} \lambda_j^2 x_{nj}^{t+1} \le x_{ni}^t - \beta_2 g_{xn}^t,\ n = 1,\ \ldots,\ N$$

$$\sum_{j=1}^{J} \lambda_j^2 L_{hj}^{t+1} \le L_{hi}^t,\ h = 1,\ \ldots,\ H$$

$$I_{fi}^t + \beta_2 g_I^t - \delta_f K_{fi}^t \le \sum_{j=1}^{J} \lambda_j^2 \left(I_{fj}^{t+1} - \delta_f K_{fj}^{t+1}\right),\ f = 1,\ \ldots,\ F$$

$$\beta_2,\ \lambda_j^2 \ge 0$$

$$\overrightarrow{D}_i^t\left(y^{t+1}, K^{t+1}, L^{t+1}, x^{t+1}, I^{t+1}; g_x^{t+1}, g_I^{t+1}\right) = max_{\beta_3,\ \lambda_j^3}\beta_3 \tag{5}$$

Subject to

$$y_{mi}^{t+1} \le \sum_{j=1}^{J} \lambda_j^3 y_{mj}^t,\ m = 1,\ \ldots,\ M$$

$$\sum_{j=1}^{J} \lambda_j^3 x_{nj}^t \le x_{ni}^{t+1} - \beta_3 g_{xn}^{t+1},\ n = 1,\ \ldots,\ N$$

$$\sum_{j=1}^{J} \lambda_j^3 L_{hj}^t \le L_{hi}^{t+1},\ h = 1,\ \ldots,\ H$$

$$I_{fi}^{t+1} + \beta_3 g_I^{t+1} - \delta_f K_{fi}^{t+1} \le \sum_{j=1}^{J} \lambda_j^3 \left(I_{fj}^t - \delta_f K_{fj}^t\right),\ f = 1,\ \ldots,\ F$$

$$\beta_3,\ \lambda_j^3 \ge 0$$

$$\overrightarrow{D}_i^{t+1}\left(y^{t+1}, K^{t+1}, L^{t+1}, x^{t+1}, I^{t+1}; g_x^{t+1}, g_I^{t+1}\right) = max_{\beta_4,\ \lambda_j^4}\beta_4 \tag{6}$$

Subject to

$$y_{mi}^{t+1} \le \sum_{j=1}^{J} \lambda_j^4 y_{mj}^{t+1},\ m = 1,\ \ldots,\ M$$

$$\sum_{j=1}^{J} \lambda_j^4 x_{nj}^{t+1} \le x_{ni}^{t+1} - \beta_4 g_{xn}^{t+1},\ n = 1,\ \ldots,\ N$$

$$\sum_{j=1}^{J} \lambda_j^4 L_{hj}^{t+1} \le L_{hi}^{t+1},\ h = 1,\ \ldots,\ H$$

$$I_{fi}^{t+1} + \beta_4 g_I^{t+1} - \delta_f K_{fi}^{t+1} \le \sum_{j=1}^{J} \lambda_j^4 \left(I_{fj}^{t+1} - \delta_f K_{fj}^{t+1}\right),\ f = 1,\ \ldots,\ F$$

$$\beta_4,\ \lambda_j^4 \ge 0$$

where, λ_j is the peer weights or intensity vector for defining the reference frontier and δ_f is the depreciation rate associated with the quasi-fixed inputs. Linear programming is used to solve Eqs. 3-6. In the empirical application of the current study, the quasi-fixed input constraint in Eqs. 3-6 is rewritten as net investment *NI* (where $NI_t = K_{t+1} - K_t$). The actual values of variable inputs *x* and 20% of capital stocks *K* were used as directional vectors, i.e., $(g_x, g_I) = (x, 0.2\ \times K_f)$. The use of 20% of capital stock as a directional vector for investment in quasi-fixed inputs is a common practice in the literature (e.g., Geylani et al., 2019; Kapelko et al., 2016; Oude Lansink et al., 2015) since it approximates the actual size of farm investments and as it allows to account for heterogeneity of investment between farms (Geylani et al., 2019).

The Luenberger dynamic productivity change (**LPC**) can be calculated from the β estimates under CRS Eqs. 3-(6) as (Kapelko et al., 2016; Oude Lansink et al., 2015):

$$LPC = \frac{1}{2} * (\beta_2 - \beta_4 + \beta_1 - \beta_3) \quad (7)$$

The dynamic LPC is computed as the arithmetic average of the productivity change measured by the technology at time $t+1$ (the first two terms in Eq. 7) and the productivity change measured by the technology at time t (i.e. the last two terms in Eq. 7) (Kapelko et al., 2016). Positive (negative) value of LPC indicates growth (decline) in productivity between t and $t+1$. The *LPC* score can be decomposed into technical change[3], technical inefficiency change[4] under variable returns to scale (**VRS**) and scale inefficiency change (Kapelko et al., 2016; Oude Lansink et al., 2015)[5]. The dynamic technical inefficiency change measures the change in the position of a farm relative to the production technology (frontier) that is defined by the fully-efficient farms between two time periods whereas dynamic technical change measures the shift of the frontier between two time periods or over time. Dynamic scale inefficiency change measures the change in the optimality of the scale/size of operation between two time periods (i.e. operating at too large or too small farm size). The dynamic technical inefficiencies under VRS (i.e., $\beta_{1,VRS}$, $\beta_{4,VRS}$) can be estimated by adding a convexity restriction $\sum_{j=1}^{J} \lambda_j^1 = 1$ in Eq. 3 and $\sum_{j=1}^{J} \lambda_j^4 = 1$ in Eq. 6.

The decomposition of *LPC* is as follow. First, *LPC* is decomposed into dynamic technical change (***TC***) and dynamic technical inefficiency change under CRS (***TIC***$_{CRS}$):

$$TC = \frac{1}{2} * (\beta_4 - \beta_3 + \beta_2 - \beta_1) \quad (8a)$$

$$TIC_{CRS} = \beta_1 - \beta_4 \quad (8b)$$

Then, TIC_{CRS} can be decomposed into dynamic technical inefficiency change under VRS (***TIC***$_{VRS}$) and dynamic scale inefficiency change (***SIC***) as:

$$TIC_{VRS} = \beta_{1,VRS} - \beta_{4,VRS} \quad (9)$$

$$SIC = TIC_{CRS} - TIC_{VRS} \quad (10)$$

2.2. System generalized method of moments estimator

A second stage dynamic panel data regression model is used to explain variations in productivity growth and inefficiency scores over time within ones farm and across farms, and specifically, to measure the effect of longevity on dynamic productivity growth and its components. The model can be written as:

$$\begin{aligned} y_{it} &= \alpha_{1i} + \alpha_{2t}t + \sum_{r=1}^{R} \gamma_{1r} y_{i,t-r} \\ &\quad + \gamma_2 L_{it} + \sum_{k=1}^{K} \gamma_{3k} Z_{k,it} + v_{it} \end{aligned} \quad (11)$$

where y_{it} is dynamic productivity growth and its components for farm i ($i = 1, 2, \ldots, N$) in year t ($t = 2, 3, \ldots, T$); α_{1i} is farm fixed effect for farm i; α_{2t} is a time dummies common to all farms; L_{it} is average cow longevity for farm i in year t; $Z_{k,it}$ is other explanatory variables (other than longevity) for farm i in year t; γ_1, γ_2 and γ_3 are parameters to be estimated; r denotes number of lags for y_t; and v_{it} is the error term that is independently and identically distributed: $v_{it} \sim N(0, \sigma^2)$. Average cow longevity is derived as (De Vries, 2017):

$$L_{it} = \text{Age at first calving}_{it} + 1/\text{Culling rate}_{it} \quad (12)$$

where *age at first calving* (years) and *culling rate* (decimal).

Other explanatory variables ($Z_{j,it}$) in Eq. 11 refer to factors that were not considered during the estimation of the inefficiency scores, yet expected to influence the economic performance of farms directly or indirectly by affecting the reproductive and production performance of cows, and animal welfare as described in the following section. The time dummies are included in the model to capture year-specific idiosyncrasies (e.g., the 2008 financial crisis, volatility of input and milk prices) that would explain some of the variations in the productivity and inefficiencies of Dutch dairy farms. For example, the 2008 financial crisis, the substantial decrease in milk prices in 2008 and 2009 from the 2007 spike, and the commodity price volatility are some of the major events occurred within the study period (2007-2013), which might have significant effect on the productivity growth of Dutch specialized dairy farms.

Eq. 11 is estimated using the two-step Generalized Method of Moments (**GMM**) estimator, also called the system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). This estimator uses the lagged differences for the equation in levels, and the moment conditions of lagged levels as instruments for differenced equation. The process of differencing does not remove farm fixed effects α_i, other time-invariant variables, and cross-farm variations in levels. However, the standard error estimates of a system GMM estimator suffer from downward bias in small samples as shown by Windmeijer (2005) using Monte Carlo simulation. Windmeijer (2005) proposed a method for estimating a finite-sample corrected standard errors. In the present study, the system GMM estimator with robust standard errors (Windmeijer, 2005) is applied in STATA Version 13 (StataCorp LP, College Station, Texas, USA). Eq. 11 is fitted with one lag for the dependent variables[6]. The Arellano–Bond test for the presence of serial correlation (autocorrelation), and the Hansen test of over-identifying restrictions for the joint validity of instruments are applied.

2.3. Empirical Application

The empirical application uses a dataset obtained from FLYNTH (www.flynth.nl), an accountancy firm. The dataset contains information on an unbalanced panel of 3,205 observations from 723 Dutch specialized dairy farms over the period 2007-2013 (where a farm is observed, on average, for at least four years). This sample size consists of only specialized dairy farms to reduce farm heterogeneity. A specialized farm is defined as a farm that obtains, on average, at least 85% of its total farm revenue from the sales of milk and milk products. Observations with complete data on all the variables of interest are considered. Since DEA models are known to be very sensitive to the presence of outliers, observations with outliers are removed from the sample by applying the Banker and Chang (2006) super-efficiency procedure of detecting outliers. For each sample year (2007-2013), the super-efficiency scores

[3] Dynamic technical change refers to the change in productivity between two time periods as a result of adoption of new technologies (innovations).

[4] A farm is said to be dynamic technically efficient if an increase in any output or an increase in any investment or a decrease in any input requires a reduction of at least one other output or investment, or an increase of at least one input.

[5] A farm is considered as (dynamic) scale inefficient if an increase in any output or an increase in any investment or a decrease in any input is possible by increasing or decreasing the scale of farm operation (i.e. farm size).

[6] The models with one lag provide the best specification in terms of serial correlation and joint validity of instrument post estimation results (see the Results section).

were estimated. Farms with a super-efficiency score of greater than 1.3 were excluded[7].

Two outputs, two variable inputs, two quasi-fixed inputs with their corresponding net investments and two fixed inputs are defined for the empirical application. The outputs are milk production and other outputs. Milk production is defined in kg as fat and protein corrected milk yield. Other output is measured as *revenues* (in euro) from other farm activities such as crop production and other livestock and livestock products (excluding milk). The two variable inputs are *feed* and *other variable inputs*, which are measured in euros. *Other variable inputs* are expenses on veterinary, energy, manure management, fertilizer, seed and other crop related expenses. The two quasi-fixed inputs are *capital* and *breeding stock* expressed in euros. *Capital* refers to the book value of machinery and buildings. *Breeding stock* refers to the value of the breeding stock, which is measured as the market value of existing animals *plus* the purchase value of incoming animals *minus* the sales value of exiting animals[8]. Net investments (**NI**) associated with quasi-fixed inputs are derived from capital stocks as $NI_t = K_{t+1} - K_t$ (where t refers to years, 2007-2014). The two fixed inputs are *labor* in annual working units and *land* in hectare. Since family members are the main source of labor in the sample farms, labor is considered as a fixed input. The variables that are measured in monetary units are deflated and expressed in constant 2010 prices. Using the EUROSTAT (2016) database, producer price indices (**PPIs**) were used to derive the implicit quantities as the ratio between value and PPI. The implicit quantity of capital is computed using a Törnqvist price index (Balk and Diewert, 2001).

In the second stage regression (Eq. 11), only factors that are related to the reproductive and production performance of cows, and animal welfare are included as explanatory variables. These factors were not included during the estimation of the inefficiency scores. However, they are expected to influence the economic performance of cows. The following explanatory variables were used in the model (Eq. 11): longevity, time dummies, automated milking system (**AMS**), calving interval (**CI**), death rate of cows, death rate of calves within two weeks after birth and access to grazing. Due to lack of data, other socio-economic variables (e.g., farming experience, subsidies, education level, off-farm income) are not included in the model. The effects of these omitted variables on productivity growth is captured by the error term. Subsequently, the problem of endogeneity due to omitted-variable bias is taken into account by the use of system GMM estimator.

Longevity may have both a positive and negative effect on farm's economic performance: (i) it reduces replacement cost and increase the number of cow's lactation per cow's lifetime (positive effect), and (ii) it increases the opportunity cost of herd genetic improvement following from the forgone performance from not replacing old cows with genetically superior heifers (negative effect). Moreover, an increased longevity is associated with improved animal welfare and reduced environmental footprints, which may have a positive association with farm performance through reducing health and environmental management costs. The average longevity across farms and years is 5.93 years for the sample Dutch specialized dairy farms. For an average Holstein Friesian Dutch dairy cow in 2013, the average actual age (i.e., a proxy for longevity) was 5.89 years (CRV, 2012). The natural logarithm of longevity is used in the empirical application. A longer CI increases the unproductive days of a cow and probably expenses associated with unsuccessful mating. As a result, a longer CI is expected to raise farms' inefficiency and reduce farm's productivity. Lawson et al. (2004) showed that, using a 1998 dataset for Danish dairy farms, an increase in CI by 1 month increases the technical inefficiency of farms by 0.01. Allendorf and Wettemann (2015) also reported that a longer CI increases the technical inefficiency of German dairy farms. The average CI across farms and years is 414 days per cow for the sample Dutch specialized dairy farms. AMS is included since it influences cows' performance and welfare. Jacobs and Siegford (2012) stated that AMS has "the potential to increase milk production by up to 12%, decrease labor by as much as 18%, and simultaneously improve dairy cow welfare by allowing cows to choose when to be milked". The use of AMS is often combined with sensors. These sensors and data analysis programs in AMS improves farm management and performance via detection of estrus, abnormal milk, mastitis and other health parameters (Jacobs and Siegford, 2012). Moreover, the use of AMS is also positively associated with farmers' job satisfaction (Hansen and Stræte, 2020). In the application, a dummy variable with values of 1 for the use of AMS and 0 otherwise is used. On average, about 15% of the observations (per year across farms) used AMS during the sample period. The loss of calves is expected to negatively affect farm's productivity and efficiency since it reduces 'other farm outputs' and raises replacement cost. The loss of female calves affects rearing of replacement within a farm, and thereby increase replacement cost. The average death rate of calves across the sample farms and years was about 10% for the Dutch specialized dairy farms. Loss of cows reduces farm productivity per cow (i.e., it increases cost of production per cow while reducing farm revenue per cow). Loss of a cow at its prime production life time is a huge loss for farms. Moreover, it raises replacement investment and thereby affects farm's performance. Allendorf and Wettemann (2015) reported that a higher death rate of cows and a higher replacement rate increase the technical inefficiency of German farms. The average death rate of cows across the sample farms and years was 3.3% for the Dutch specialized dairy farms. Access to pasture is regarded as very relevant to improve animal welfare. Access to longer grazing periods is associated with improved cow welfare through reduced lameness and leg injuries (Meul et al., 2012; von Keyserlingk et al. 2009). Meul et al. (2012) reported that the percentage of cows with lesions and lame cows was negatively associated with the duration of grazing period for Flemish dairy farms. In the present study, a dummy with values 1 for access to grazing, and 0 for zero-grazing is used. On average, about 81% of the sample Dutch dairy farms had access to grazing during the sample period. Table 1 presents the descriptive statistics of all the variables used in the analysis.

3. Results and discussion

3.1. Dynamic technical inefficiency scores

The average dynamic technical inefficiency scores over the period 2007-2013 is presented in Table 2 under both CRS and VRS technologies. The average dynamic technical inefficiency score under the VRS technology is 27% per year. This implies that if the farms were fully efficient over the sample period in the use of variable inputs and doing investments, *ceteris paribus*, they would have reduced the use of *feed* and *other variable inputs* by 27% while expanding their *investments in capital* and *breeding stocks* by 5.4% of the values of the capital stocks ($= 0.2 \times 27\%$). That is, farms could have produced the same levels of outputs (i.e., *fat and protein corrected milk* and *other outputs*) by using the same amounts of fixed inputs (i.e., land and labor) while reducing the amounts of variable inputs needed (by 27%) and simultaneously increasing investments in quasi-fixed inputs (by 5.4% of the capital stocks).

The average technical inefficiency scores of this study are within the available scores in the literature. Skevas and Oude Lansink (2020)

[7] According to Banker and Chang (2006, p. 1317), '… the use of a more stringent screen level such as 1 is likely to misclassify many uncontaminated efficient observations as outliers, while the use of a less stringent screen level such as 1.6 or greater may fail to remove many contaminated observations'.

[8] It is assumed that the livestock value represent the value of the breeding stock since the sample farms are specialised dairy farms, where at least 85% of the total farm revenue is obtained from milk production.

Table 1
Descriptive statistics of variables for Dutch specialized dairy farms over the period 2007-2014.

Variables	Mean	Std. dev.	Minimum	Maximum
Quantities				
Protein and fat corrected milk (kg)	735003	329625	116582	2887738
Other output (constant 2010 €)†	22145	11763	2424	97146
Feed (constant 2010 €)†	51328	26923	4214	257999
Other variable inputs (constant 2010 €)†	43986	32459	2379	368217
Land (ha)	46	20	9	194
Labour (AWU)	1.7	0.6	0.8	5.0
Capital (constant 2010 €)†	352020	295165	12493	2214533
Breeding stock (constant 2010 €)†	79818	36435	13825	356374
Net investment in capital (constant 2010 €)†	24201	127204	-869903	1439531
Net investment in breeding stock (constant 2010 €)†	4400	11612	-76891	90824
Cow (#)	83	36	16	387
Prices				
Other output	1.081	0.101	0.898	1.202
Feed	1.192	0.152	0.997	1.378
Other variable inputs	1.055	0.046	0.989	1.097
Capital	0.987	0.011	0.972	1.000
Breeding stock	1.126	0.107	1.000	1.288
Second-stage variables				
Calving interval (days)	414.02	29.91	356.00	996.00
Automatic milking robot; dummy (Yes=1, No=0)	0.15	0.36	0.00	1.00
Death rate of calves within two weeks after birth (%)	9.91	5.29	0.00	46.00
Death rate of cows (%)	3.30	2.81	0.00	30.00
Grazing; dummy (Yes=1, No=0)	0.81	0.39	0.00	1.00
Culling rate (%)	26.24	7.13	2.00	61.00
Age at first calving (years)	2.02	0.07	1.09	3.05
Longevity‡	5.93	1.70	3.38	52.08

† Implicit quantities.‡Estimated within the dataset from *age at first calving* (years) and *culling rate* (decimal) using Eq. 12.

Table 2
Average dynamic technical inefficiency (TI) scores over 2007-2013 for Dutch specialized dairy farms.

	Dynamic TI under CRS technology †		Dynamic TI under VRS technology ‡	
Year	Mean	Std. dev.	Mean	Std. dev.
2007	0.2596	0.1174	0.2362	0.1170
2008	0.2630	0.1205	0.2408	0.1203
2009	0.2873	0.1050	0.2617	0.1142
2010	0.3283	0.0915	0.3140	0.1012
2011	0.2837	0.1205	0.2733	0.1247
2012	0.2721	0.1125	0.2661	0.1159
2013	0.2711	0.1029	0.2622	0.1069
Average	0.2830	0.1109	0.2691	0.1158

† CRS, Constant returns to scale.

‡ VRS, Variable returns to scale.

reported an average dynamic technical inefficiency score of 22% per year for Dutch specialized dairy farms[9] over the period 2009-2016. Skevas et al. (2018), using a Stochastic Frontier Analysis (SFA) technique, reported an average annual dynamic technical inefficiency score of 35% for German dairy farms over the period 2001-2009. Both our sample period (2007-2013) and average inefficiency score (27%) are within the sample periods and average inefficiency scores of Skevas et al. (2018), and Skevas and Oude Lansink (2020). Steeneveld et al. (2012) reported an average static[10] technical inefficiency score of 24% and 22%, respectively, for Dutch dairy farms with and without AMS for the production year 2010. In the present study, the 2010 average dynamic technical inefficiency score is 31% (under VRS). The difference from the current study's result might be due to differences in sample farms and the models employed (dynamic vs static). Serra et al. (2011) measured the inefficiency of Dutch dairy farms over the period 1995-2005 using the SFA method, and reported an average annual dynamic technical inefficiency score of 10.4%. The lower inefficiency scores of Serra et al. (2011) compared to the results of the current study could be explained by the differences in the sample periods (1995-2005 vs 2007-2013) and the models used (SFA vs DEA).

3.2. Decomposition of Luenberger dynamic productivity change

Table 3 presents the results of the decomposition of the Luenberger dynamic productivity change into technical change, technical inefficiency change and scale inefficiency change. The average productivity growth of Dutch specialized dairy farms was 1.0% per year during the sample period (Table 3). This growth is comprised of technical change of 0.5% per year, scale inefficiency change of 0.4% per year and technical inefficiency change of 0.2% per year. The average dynamic productivity growth rate of 1.0% implies that, *ceteris paribus,* the use of *feed* and *other variable inputs* has reduced on average by 1.0% per year while expanding annual *investments in capital* and *breeding stock* by 0.2% of the capital stocks during the sample period. On average, technical change accounted for about 47% of the 1% annual productivity growth while scale inefficiency change accounted for about 39% of this growth. The average scale inefficiency change of 0.4% per year implies that productivity has increased as a result of improvement in the optimal scale of operation (by increasing or decreasing the farm size). The contribution of technical inefficiency change (0.2%) to productivity growth (1.0%) is very small despite the average technical inefficiency of Dutch specialized dairy farms being close to 30% per year. This implies that Dutch dairy farms have a potential to raise productivity growth by reducing technical inefficiency through improved management and utilization of available resources.

The main driver of the fluctuation in productivity change was fluctuation in technical change during the sample period (Figure 2). This might be due to volatility of milk and input prices. For example, Oude Lansink et al. (2015) stated that milk price fluctuations 'may explain the difficulties of producers to allocate resources efficiently from a technical and economic point of view in the long-run'. The negative correlation between milk price fluctuation and dynamic productivity growth[11] implies that 'farmers are conservative (pessimistic) regarding price expectations and they devise production structures that are optimal in low price frameworks' (Oude Lansink et al., 2015). As a result, farmers' behavior is more conducive for achieving productivity growth during low milk price years than high price years.

The result of the current study for the average productivity growth (1.0% per year) is lower compared to results in the literature. By using the Luenberger dynamic productivity indicator as in the current study, Oude Lansink et al. (2015) reported an average productivity growth of 1.5% per year for Dutch dairy farms over 1995-2005. Skevas et al.

[9] In Skevas and Oude Lansink (2020), a specialised dairy farm refers to a farm whose revenues from sales of milk, milk products, and turnover and growth of cattle account for at least 67% of its total revenues, whereas in our study it is defined as a farm that obtains at least 85% of its total farm revenue from sales of milk and milk products.

[10] Unlike dynamic inefficiency scores, static scores are derived without accounting for the intertemporal linkages of farm decisions and the associated adjustment costs of investments in quasi-fixed inputs.

[11] In the present study, the correlation between dynamic productivity growth and milk price index was -33% during the sample period.

Table 3
Decomposition of Luenberger dynamic productivity change for Dutch specialized dairy farms over the period 2007 to 2013.

	LPC[†]		TC[‡]		TIC_VRS[§]		SIC[¶]	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
2007/2008	-0.0578	0.050	-0.0369	0.105	-0.0279	0.119	0.0070	0.036
2008/2009	0.0407	0.051	0.0461	0.097	-0.0181	0.099	0.0128	0.025
2009/2010	0.1203	0.046	0.0751	0.098	0.0394	0.111	0.0058	0.027
2010/2011	-0.0603	0.041	-0.0519	0.106	-0.0088	0.110	0.0004	0.021
2011/2012	-0.0328	0.042	-0.0184	0.101	-0.0148	0.110	0.0004	0.014
2012/2013	0.0354	0.040	0.0087	0.103	0.0258	0.110	0.0009	0.013
Average	0.0101	0.076	0.0047	0.110	0.0015	0.111	0.0039	0.022

[†] Luenberger productivity change.

[‡] Technical change.

[§] Technical inefficiency change under variable returns to scale.

[¶] Scale inefficiency change.

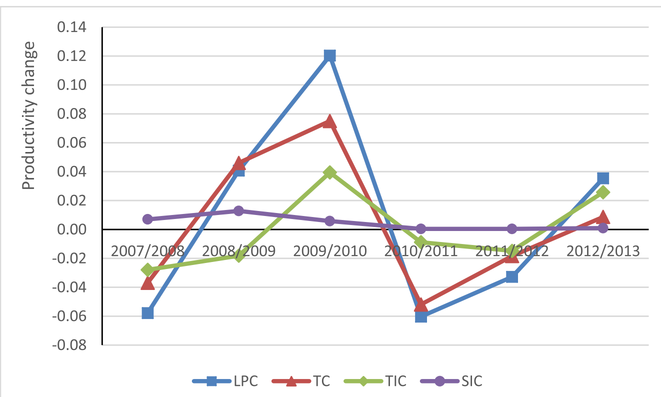

Fig. 2. Decomposition of Luenberger productivity change over the period between 2007/08 and 2012/13.

(2018), by employing a dynamic SFA, reported an average annual productivity growth of 1.7% (technical change of 1.9%, technical efficiency change of -0.2% and scale effect of 0.1%) for German dairy farms over 2001-2009. Brümmer et al. (2002) also reported an average productivity growth of 2.9% per year for Dutch dairy farms over the period 1991-1994 using a static model. This growth was as a result of technical change of 0.5%, technical efficiency change of 0.6% and scale effect of 0.2%, whereas the respective values from the current study's dynamic model for Dutch dairy farms over the period 2007-2013 are 0.5%, 0.2% and 0.4%. These differences between the results of Brümmer et al. (2002) and the current study could be explained by the differences in the models used (static vs dynamic) and the sample periods (1991-1994 vs 2007-2013). Moreover, in the current study, the sample consists of only specialized dairy farms, where at least 85% of farm's revenue is from milk. This could also be one of the reasons for the lower average productivity growth of the current study compared to the results from the literature.

3.3. Effect of cow longevity on dynamic productivity change and its components

Table 4 presents the estimation results of the two-step GMM for measuring the effect of cow longevity on dynamic productivity change and its components. Table 4 also reports the post estimation diagnostic test results (i.e., Wald test for the joint significance of the explanatory variables included in the model, the Arellano–Bond test for the presence of first- and second-order autocorrelation, and the Hansen test for the

Table 4
Effect of cow longevity on dynamic productivity change and its components over 2007-2013 for Dutch specialized dairy farms[a].

	LPC[†]	TC[†]	TIC_VRS[†]	SIC[†]
Farm fixed effect	-0.0308	-0.5824**	0.4903*	0.0477*
First lag of dependent variable	-0.3872***	-0.5224***	-0.5107***	-0.2028***
Dummy_2009	-0.0077**	0.0308***	-0.0573***	0.0125***
Dummy_2010	0.1163***	0.1155***	0.0012	0.0056***
Dummy_2011	-0.0354***	-0.0076	-0.0090	-0.0005
Dummy_2012	-0.0769***	-0.0496***	-0.0304***	-0.0006
ln(longevity)	0.0133***	0.0474***	-0.0353***	-0.0009
Calving interval	0.0047	0.0795	-0.0651	-0.0075*
Automatic milking system	0.0011	-0.0009	-0.0010	0.0019*
Death rate of calves	0.0002	0.0003	-0.0001	0.0000
Death rate of cows	0.0008**	0.0019**	-0.0011	0.0001
Access of grazing	-0.0026	0.0061	-0.0078	-0.0001
Post estimation diagnostic test results[‡]				
Wald Test[§]	6082.840***	1386.110***	781.600***	83.420***
Arellano-Bond Test for AR(1)[¶]	0.000	0.000	0.000	0.001
Arellano-Bond Test for AR(2)[¶]	0.236	0.000	0.000	0.380
Hansen Test[¶]	0.825	0.309	0.347	0.981

[a] The models are fitted using one lag for dynamic productivity change and its components (i.e., the dependent variable) and estimated using system GMM with Windmeijer (2005) corrected standard errors. ***, ** and * denote statistical significance at the critical 1%, 5% and 10% levels, respectively.

[†] LPC, Luenberger productivity change. TC, Technical change. TIC_VRS, Technical inefficiency change under variable returns to scale. SIC, Scale inefficiency change.

[‡] The number of observations, farms and instruments used in the models are 2078, 659 and 13, respectively.

[§] The null hypothesis of the Wald test: the coefficients of the explanatory variables in the model are equal to zero.

[¶] In the Arellano-Bond test for first- (AR(1)) and second-order autocorrelation (AR(2)), and for the Hansen test of the joint validity of instruments, p-values are reported. The null hypotheses of the Arellano-Bond test for is: no autocorrelation. The null hypothesis of the Hansen test is: overidentifying restrictions are jointly valid.

joint validity of instruments). The Wald chi-squared test results show that longevity and the other explanatory variables included in the models are statistically significant, at the critical 1% level, in jointly explaining the variations in dynamic productivity change and its components. Although the Arellano–Bond test results show that there is a first-order autocorrelation, the null hypothesis of no second-order autocorrelation is not rejected at the critical 10% level (i.e., there is no problem of second-order serial correlation) for dynamic productivity change[12]. The Hansen test results also show that the instruments used in the model are jointly valid.

The first lag of dynamic productivity growth is statistically significant in explaining the variations in dynamic productivity growth, implying the persistent nature of productivity. That is, farms with a productivity decline last year would observe more productivity decline in the current production period. Similarly, farms that were inefficient last year would become more inefficient in the current production period. All, but the 2010, time dummies have negative associations with productivity growth (i.e., farms' productivity growth declined by about 0.008 to 0.077 in each year compared to the 2007 reference year). However, the 2010 time dummy has a positive association with productivity growth and its components (i.e., compared to the 2007 reference year, farms' productivity growth increased by 11.6% in 2010, mainly attributed to technical progress). This might be due to the increase in milk price in 2010 from the 2009 drop, which could have encouraged farms to invest in technologies (that led to technical progress) and to adjust their size of operations (that led to reduced scale inefficiency).

Increased longevity has a positive and statistically significant, at the critical 1% level, association with dynamic productivity growth of Dutch specialized dairy farms. A 1% increase in average longevity is associated with a 0.013 increase in dynamic productivity growth, due to the positive relationship between longevity and technical change. A 1% increase in average longevity is associated with a 0.047 increase in dynamic technical change, implying that farms with increased longevity are also those farms that achieved technical progress during the sample period. However, increased longevity has a statistically significant negative, at the critical 1% level, association with dynamic technical inefficiency change during the sample period. This implies that farms with more old cows are less efficient in utilizing their resources. This might follow from the reduced milk productivity of old cows per unit of inputs (e.g., feed, energy) used. Although Lawson et al. (2004) found a positive relationship between replacement rate (which implies reduced longevity) and static technical inefficiency scores for Danish dairy farms, the relationship was not statistically significant. However, Allendorf and Wettemann (2015) reported that a 1% increase in average replacement rate (which implies reduced longevity) led to a 0.0087 increase in the static technical inefficiency scores for German dairy farms. Both results are not directly comparable with the current study due to differences in the modelling approach (dynamic vs static) and sample periods used. In the current study, the association between longevity and scale inefficiency change was not statistically significant.

An increase in CI has a statistically significant negative, at the critical 10% level, association with scale inefficiency change. An increase in CI by 1-d is associated with a 0.008 decrease in dynamic scale inefficiency change (i.e., CI is positively associated with scale inefficiency). Although statistically insignificant, CI has also a negative association with technical inefficiency change (i.e., a 1-d increase in average CI is associated with a 0.065 increase in technical inefficiency). Similarly, Lawson et al. (2004) did not found a statistically significant relationship between CI and static technical inefficiency of Danish dairy farms. However, Allendorf and Wettemann (2015) reported that an increase in average CI by 1-d led to a 0.0016 increase in the static technical inefficiency of German dairy farms during 2007/08-2011/12. Both results are not directly comparable with current study due to differences in the modelling approach (dynamic vs static) and sample periods used.

The use of AMS has a positive, although not statistically significant, effect on dynamic productivity growth of Dutch specialized farms during the sample period. This positive association was the result of its positive effect on scale inefficiency change. Farms that use AMS are more likely to operate in an optimal scale of operation (i.e., scale inefficiency of farms with AMS is lower by 0.002 than farms without AMS). The use of AMS does not have a statistically significant effect on dynamic technical change and technical inefficiency change. In line with our result, Steeneveld et al. (2012) reported, using a 2010 dataset, the absence of a statistically significant difference in the static technical inefficiency of Dutch dairy farms with and without AMS although the farms with AMS had a slightly higher technical inefficiency (24% vs 22%).

The loss of cows has a positive association with dynamic productivity growth and technical change of Dutch specialized dairy farms during the sample period. An increase in cow death rate by 1% is associated with a 0.001 and 0.002 increase in productivity growth and technical change, respectively. This positive association might be attributable to the use of genetically superior replacement heifers (in place of the dead cows) that would led to technical progress. Although statistically insignificant, an increase in cow death rate is associated with an increase in dynamic technical inefficiency. Allendorf and Wettemann (2015) also reported that a 1% increase in the death rate of cows increases the mean static technical inefficiency of German dairy farms by 0.012 and 0.015 under CRS and VRS technologies, respectively. The results of Allendorf and Wettemann (2015) are not directly comparable with the current study due to differences in the modelling approach (dynamic vs static) and sample periods used.

The results also show that access to grazing has a negative association with dynamic productivity growth and technical inefficiency change even though the associations are not statistically significant (Table 4). Farms with access to grazing have higher technical inefficiency (0.008) than farms with zero-grazing. This may imply the trade-off between economic performance and animal welfare (since access to grazing is associated with reduced lameness, leg injuries, and improved animal welfare (e.g., Meul et al., 2012)). Similarly, Allendorf and Wettemann (2015) did not found a statistically significant difference in the technical efficiency scores of German dairy farms with and without access to grazing.

The current study employed a seven years panel data, which is too short to fully capture the effect of longevity on farm productivity and inefficiency changes by accounting for the economic trade-off between increased longevity and herd genetic improvement. Future studies could implement the procedure using long panel data and by including socio-economic variables in the second stage regression analysis to precisely estimate the effect of longevity.

4. Conclusions

Improving technical efficiency, i.e., producing the maximum possible outputs with the lowest possible inputs, is critical for farms to compete in the global market and comply with the ever stringent environmental and societal requirements of farming. Cow longevity is recognized as an important trait to improve farm economic performance while concurrently reducing environmental and societal impacts. However, there is an economic trade-off between longevity and herd genetic improvement. Increased longevity increases genetic lag that implies higher opportunity costs associated with the forgone farm performance as a result of not using genetically superior replacements. This economic trade-off and the heterogeneity of farms' preferences for longevity may influence dairy farms' productivity growth and

[12] The same model structure used for the dynamic productivity change is fitted for its components (i.e., technical change, and technical and scale inefficiency changes). As a result, the post-estimation results show the presence of second-order autocorrelation for technical change and technical inefficiency change models (Table 4).

inefficiency over time. This study used a panel data of 723 Dutch specialized dairy farms over 2007-2013 to empirically measure the effect of longevity on dynamic productivity change and its components (technical change, and technical and scale inefficiency changes). The productivity growth estimates were, first, obtained and decomposed using the Luenberger dynamic productivity measure. Then, the estimates were regressed on longevity and other explanatory factors using dynamic panel data model (i.e., system GMM). Results show that the average dynamic productivity growth of Dutch specialized farms was 1.1% per year, comprising of technical change (0.5%), scale inefficiency change (0.4%) and technical inefficiency change (0.2%). The contribution of technical inefficiency change to productivity growth is very small despite the average technical inefficiency of Dutch specialized dairy farms being close to 30% per year. This implies that Dutch dairy farms have a potential to raise productivity growth by reducing technical inefficiency through improved management and utilization of resources. Increased longevity is found to have a positive and statistically significant association with productivity growth and technical change, implying that farms with more matured cows are also those farms that recorded increased productivity through technical progress. However, increased longevity has a negative association with technical inefficiency change, which might follow from the reduced milk productivity of old cows per unit of inputs used.

Author statement

Beshir Ali: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing- Original draft preparation, Writing-Reviewing and Editing.

Declaration of Competing Interest

The author has no conflicts of interest to declare.

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