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The effect of farm genetics expenses on dynamic productivity growth

Beshir M. Ali*, Yann de Mey, Alfons G. J. M. Oude Lansink

Wageningen University & Research, Business Economics Group, Hollandseweg 1, 6706 KN, Wageningen, the Netherlands

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ABSTRACT

Genetic improvement of animals has been an important source of productivity growth in dairy farming. Studying the effect of genetic progress on productivity growth of farms requires a long-term dynamic perspective due to the long generation interval of dairy animals, and the slow, persistent and cumulative effects of genetics. It is also essential from a farm decision-making perspective to disentangle overall productivity growth in relation to each variable input and investment in quasi-fixed input while accounting for adjustment costs associated with the slow changes in quasi-fixed inputs. This paper contributes to the literature by combining input- and investment-specific dynamic productivity growth analysis with impulse response analysis. The application focuses on panel data of Dutch specialized dairy farms over 2007–2013. The results show that farms that adopt improved genetic materials, as proxied by farm *expenses on artificial insemination* and *breeding stock investment spike,* achieved higher input- and investment-specific productivity growth in the first two years after the year of the expenses/spike. That is, farms that produce more efficiently after adopting quality genetics are also those farms that utilise their resources efficiently. The positive relationships suggest a potential positive spill-over effect from using high quality genetics on managerial efficiencies.

1. Introduction

Genetic improvement of animals and plants via selective breeding has been an important source of productivity growth in agriculture, producing permanent and cumulative changes in performance (Atsbeha, Kristofersson & Rickertsen, 2012; Babcock & Foster, 1991; Roibas & Alvarez, 2012). In dairy farming, genetic improvement has been increasing both the quantity and quality of output per unit of input. Subsequently, it influences the evolution of dairy farms' productivity growth and efficiency scores. The genetic status of animals varies among farms due to differences in the rate of adoption of improved genetic materials and the type of genetic materials adopted, which depend on farmers' risk preferences, heterogeneity of production conditions (e.g. disease-resistant vs climate-tolerant genetics) and managerial decisions (e.g. choice of insemination method, breed of cows, and generation interval; Atsbeha et al., 2012). This variation in genetic status of animals may result in productivity growth and efficiency differences among farms. In addition, the genetic status of animals within a farm could also vary over time due to investment spikes in (improved) genetic materials, which influences the evolution of one farm's productivity growth and efficiency. To the best of our knowledge, only a few studies (e.g. Atsbeha et al., 2012; Roibas & Alvarez, 2010; 2012; Steine, Kristofersson & Guttormsen, 2008) have tried to measure the effect of variations in farm-level genetic status of animals on farm productivity and profitability.

Atsbeha et al. (2012) measured, using the Malmquist productivity index, the productivity growth of Icelandic dairy production over the period 1997–2006, and decomposed it into genetic- and non-genetic-based technical changes, efficiency change and scale effects. An aggregate breeding index (average of sire merit indices used on all cows in the farm weighted by the number of active milking days of a cow) was used as a measure of genetic-based technology. The genetic-based technical change accounted for 19% from the 1.6% average annual productivity growth rate. A study by Roibas and Alvarez (2010) for Spanish commercial dairy farms showed that the gross margin of dairy farms has increased by up to 12% between 1999 and 2004 due to genetic progress. In a later study, Roibas and Alvarez (2012) analysed the role of genetics in improving milk composition by considering genetic indices (i.e. breeding values of protein and fat) as allocable inputs. They reported that a herd with a high genetic status (i.e. a herd with higher breeding values relative to the population average breeding values) produces 1048 kg of fat and 742 kg of protein more

* Corresponding author.
E-mail addresses: beshir.ali@wur.nl (B.M. Ali), yann.demey@wur.nl (Y. de Mey), alfons.oudelansink@wur.nl (A.G.J.M. Oude Lansink).

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than the average genetic herd. Farms with a high genetic status herd have a 6.6% higher farm income than farms with an average genetic status herd. For the Norwegian red cattle production system, Steine et al. (2008) estimated the economic values[1] of ten breeding goal traits from a *translog* profit function using a panel data of 3259 farms (observed over 1999–2003). A weighted average of estimated breeding value (i.e. average of breeding values of all the sires used on all cows in the farm weighted by the number of active milking days of a cow per year) was used as a measure of genetic progress for each trait. Seven of the ten traits showed statistically significant effects on farm profit, with the expected magnitudes and signs.

The main shortcoming of these existing studies is the assumption that improvements in the genetic status of a herd result in changes in productivity or profit in the same period. This assumption is likely inaccurate as the return from current period genetic statuses of dairy cows or bulls, for example, usually requires several years before being realised (i.e. the lagged effects of genetic improvement on farm performance); this is because the generation interval of cows is typically more than two years. Moreover, the effect of genetic improvement on dairy farm performance (e.g. milk production) is expressed over several years (due to the persistent and cumulative nature of genetics). Therefore, studying the effect of genetic improvement on farm productivity changes requires a long-term dynamic perspective. In this study, we use an impulse response function by adopting the local projections method of Jordà (2005) to measure the effect of improvement in genetic status of animals on dynamic productivity growth.[2] The impulse response functions are estimated by the two-step Generalised Method of Moments (GMM) technique (Arellano & Bover, 1995), which uses information from both variation within a farm over time and variation among farms.

Yet another shortcoming of previous studies is that they did not account for the intertemporal linkages of farm's production decisions. Investment in quasi-fixed inputs (e.g. buildings, milking robots and breeding stock) involves an intertemporal decision that affects current production while increasing future capital stock, which in turn affects future production. It is costly for decision makers (farmers) to adjust the level of quasi-fixed inputs instantly to their optimal levels (Penrose, 1959) due to technology-specific learning costs and financial constraints. A period of adjustment follows immediately after technology adoption, where productivity declines, since producers are learning to adjust their production system to the new technology (e.g. Jovanovic & Nyarko, 1996; Klenow, 1998). As a result, the short-term impacts of technology adoption (e.g. deploying a milking robot in dairy farming) are expected to differ from their long-term impacts. The slow adjustments in quasi-fixed inputs due to the high adjustment costs and the resulting lag in adoption of technologies influence the evolutions of dairy farms' productivity and efficiency (e.g. Skevas, 2016).

It is also essential from a farm decision-making perspective to disentangle the sources of productivity growth by exploring the contribution of each factor of production to the overall growth (Kapelko, Oude Lansink & Stefanou, 2017a). Previous studies (e.g. Atsbeha et al., 2012) measured overall productivity growth without linking productivity growth to the contributions of the specific variable and quasi-fixed inputs. However, productivity growth associated with some inputs (e.g. feed) might be positive while being negative or zero for some other inputs (e.g. capital). Identifying the factors of production (e.g. feed, capital, breeding stock) that are sources of inefficiency and productivity decline is crucial to characterize and improve farm performance.

In the light of the foregoing discussion, the objectives of this study were twofold: (i) to measure the input- and investment-specific dynamic productivity growths (and their components: technical change, technical and scale inefficiency changes) of dairy farms, and (ii) to explore the effects of (lagged) farm genetics expenses on input- and investment-specific dynamic productivity growth (and its components) using an impulse response analysis. To the best of our knowledge, this study is the first to combine input/investment-specific dynamic productivity growth and its components with impulse response analysis. The study contributes to the literature in three ways. First, it assesses the long-term effect of genetic progress on productivity growth by using an impulse response analysis. Second, it accounts for the adjustment costs associated with changes in quasi-fixed inputs (i.e. capital stocks and breeding stocks) when estimating productivity growth. Third, it disentangles productivity growth in relation to each variable input and investment, and decomposes into technical change, technical and scale inefficiency changes. The empirical application focuses on panel data of Dutch specialized dairy farms over the period 2007–2013.

2. Materials and methods

2.1. Dynamic Luenberger productivity growth indicator

Distance functions are commonly used for modelling multiple input-multiple output technologies. In this study, an input distance function is used to represent the Dutch dairy farm production technology, as during the sample period (2007–2013) the milk quota gave Dutch dairy farmers more autonomy to adjust inputs rather than outputs.

The input-specific dynamic Luenberger productivity indicator of Kapelko et al. (2017a) is employed to measure productivity and inefficiency changes associated with each variable input and investment in quasi-fixed inputs. It accounts for the adjustment costs associated with investment in quasi-fixed inputs (e.g. building and machineries). Suppose J farms $(j = 1, \ldots, J)$ produce M outputs $y = (y_1, \ldots, y_M)$ by using N variable inputs $x = (x_1, \ldots, x_N)$, H fixed inputs $L = (L_1, \ldots, L_H)$, F quasi-fixed inputs $K = (K_1, \ldots, K_F)$ and F gross investments corresponding to the quasi-fixed inputs $I = (I_1, \ldots, I_F)$. Then, the dynamic production technology in time t that transforms x and I into y for a given level of L and K can be represented by an input requirement set (Serra, Lansink & Stefanou, 2011) as:

$$P_t\left(y^t : K^t, L^t\right) = \left\{\left(x^t, I^t\right) : x^t, I^t \; can\; produce\; y^t,\; given\; K^t, L^t\right\} \qquad (1)$$

where P_t is the production technology (frontier) in time t. The following properties are assumed for the input requirement set (Silva & Stefanou, 2003): $P_t(y^t : K^t, L^t)$ is a closed and non-empty set with a lower bound, is positive monotonic in variable inputs, is negative monotonic in gross investment, is a strictly convex set, output is freely disposable, and increases with capital stock and fixed inputs.

A dynamic directional input distance function ($\vec{D}$) can be used to represent the adjustment cost input requirement set:

[1] Economic values are marginal values that are derived as the change in farm profit due to a one unit change in the value of a trait while keeping all other traits unchanged.

[2] Atsbeha et al. (2012) and Roibas and Alvarez (2012) treated genetic progress, respectively, as a 'technology' and 'input' in their production function specifications. In this study, the effect of genetic progress on farm level productivity growth is measured by treating genetic progress as an explanatory variable (as described in Section 2.2). We used genetics expenses as a proxy for genetic progress (as described in Section 3). Genetics expense is excluded from variable costs during the estimation of the inefficiency scores (so not to treat it as an input). Its share in the total variable cost is small (e.g. less than 5% for the sample farms during 2007-2013). Although these farm genetics expenses are low, the sluggish resulting improvement in the genetic status of animals is expected to influence the evolutions of dairy farms' productivity and efficiency scores.

$$\vec{D}^t\left(y^t, K^t, L^t, x^t, I^t; g_x^t, g_I^t\right) = \sup\left\{\sum_{n=1}^{N}\beta_n + \sum_{f=1}^{F}\gamma_f : \left(x_n^t - \beta_n g_{xn}^t, I_f^t + \gamma_f g_{If}^t, y_m^t, K_f^t, L_h^t\right) \in P_t\right\} \quad (2)$$

where g_x^t and g_I^t refer to directional vectors for scaling variable inputs and investment, respectively; β_n and γ_f refer to input n- and investment f-specific dynamic technical inefficiencies, respectively. The dynamic directional input distance function contracts variable inputs by $\beta_n \times g_x$ while expanding gross investments by $\gamma_f \times g_I$. The values of β_n and γ_f can be estimated using Data Envelopment Analysis (DEA). The estimation of Luenberger productivity growth requires solving four linear programming models under constant returns to scale (CRS): two single-period and two mixed-period models. The two single-period models measure the performance of farms in time t (and $t+1$) relative to their respective technologies in time t (and $t+1$) (Eqs. (3) and 6). The mixed-period models measure the performance of farms in time t relative to the technology in time $t+1$ (Eq. (4)), and the performance of farms in time $t+1$ relative to the technology in time t (Eq. (5)). The four linear programming models to estimate the input- and investment-specific dynamic productivity growths are:

$$\vec{D}_i^t\left(y^t, K^t, L^t, x^t, I^t; g_x^t, g_I^t\right) = max_{\beta_n^1, \gamma_f^1, \lambda_j^1}\left(\sum_{n=1}^{N}\beta_n^1 + \sum_{f=1}^{F}\gamma_f^1\right) \quad (3)$$

Subject to

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

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

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

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

$$\beta_n^1, \gamma_f^1, \lambda_j^1 \ge 0$$

$$\vec{D}_i^{t+1}\left(y^t, K^t, L^t, x^t, I^t; g_x^t, g_I^t\right) = max_{\beta_n^2, \gamma_f^2, \lambda_j^2}\left(\sum_{n=1}^{N}\beta_n^2 + \sum_{f=1}^{F}\gamma_f^2\right) \quad (4)$$

Subject to

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

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

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

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

$$\beta_n^2, \gamma_f^2, \lambda_j^2 \ge 0$$

$$\vec{D}_i^t\left(y^{t+1}, K^{t+1}, L^{t+1}, x^{t+1}, I^{t+1}; g_x^{t+1}, g_I^{t+1}\right) = max_{\beta_n^3, \gamma_f^3, \lambda_j^3}\left(\sum_{n=1}^{N}\beta_n^3 + \sum_{f=1}^{F}\gamma_f^3\right) \quad (5)$$

Subject to

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

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

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

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

$$\beta_n^3, \gamma_f^3, \lambda_j^3 \ge 0$$

$$\vec{D}_i^{t+1}\left(y^{t+1}, K^{t+1}, L^{t+1}, x^{t+1}, I^{t+1}; g_x^{t+1}, g_I^{t+1}\right) = max_{\beta_n^4, \gamma_f^4, \lambda_j^4}\left(\sum_{n=1}^{N}\beta_n^4 + \sum_{f=1}^{F}\gamma_f^4\right) \quad (6)$$

Subject to

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

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

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

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

$$\beta_n^4, \gamma_f^4, \lambda_j^4 \ge 0$$

The parameter λ_j refers to peer weights (intensity vector) and δ_f refers to the depreciation rates of quasi-fixed inputs (e.g. capital and breeding stock). When computing dynamic technical inefficiency in this study, the quasi-fixed input constraint in Eqs. (4)–(6), which is presented in terms of capital stock K_f, gross investment I_f and depreciation rate δ_f, is expressed as net investment NI_f ($NI_t = K_{t+1} - K_t$; where t is time).

The Luenberger measures of input- and investment-specific dynamic productivity changes can be derived from the input- and investment-specific dynamic technical inefficiencies under CRS as (Kapelko et al., 2017a; Oude Lansink, Stefanou & Serra, 2015):

$$L_{xn} = \frac{1}{2} * \left(\beta_n^2 - \beta_n^4 + \beta_n^1 - \beta_n^3\right), \quad n = 1, \ldots, N \quad (7a)$$

$$L_{If} = \frac{1}{2} * \left(\gamma_f^2 - \gamma_f^4 + \gamma_f^1 - \gamma_f^3\right), \quad f = 1, \ldots, F \quad (7b)$$

where L_{xn} and L_{If} refer to the Luenberger measure of input n- and investment f-specific dynamic productivity changes, respectively.

The Luenberger measure of dynamic productivity change can be decomposed into technical change, technical inefficiency change under variable returns to scale (VRS) and scale inefficiency change (Kapelko et al., 2017a; Oude Lansink et al., 2015) as presented below. The measure L_{xn} can be decomposed into input-specific dynamic technical inefficiency change under CRS ($TEIC_{xn}^{CRS}$) and input-specific dynamic technical change (TC_{xn}):

$$TEIC_{xn}^{CRS} = \beta_n^1 - \beta_n^4, \quad n = 1, \ldots, N \quad (8a)$$

$$TC_{xn} = \frac{1}{2} * \left(\beta_n^4 - \beta_n^3 + \beta_n^2 - \beta_n^1\right), \quad n = 1, \ldots, N \quad (8b)$$

Dynamic technical inefficiency change measures the change in the position of a farm relative to the frontier (which is defined by the fully-efficient firms) between two time periods, whereas dynamic technical change measures the shift of the frontier between two time periods. Similarly, the measure L_{If} can also be decomposed into investment-specific dynamic technical inefficiency change under CRS ($TEIC_{If}^{CRS}$) and investment-specific dynamic technical change (TC_{IF})

$$TEIC_{If}^{CRS} = \gamma_f^1 - \gamma_f^4, \quad f = 1, \dots, F \tag{9a}$$

$$TC_{If} = \frac{1}{2} * \left(\gamma_f^4 - \gamma_f^3 + \gamma_f^2 - \gamma_f^1\right), \quad f = 1, \dots, F \tag{9b}$$

The measures $TEIC_{xn}^{CRS}$ and $TEIC_{If}^{CRS}$ can be further decomposed into input- and investment-specific dynamic technical inefficiency changes under VRS and input- and investment-specific dynamic scale inefficiency changes, respectively. The input- and investment-specific dynamic technical inefficiency changes under VRS ($TEIC_{xn}^{VRS}$ and $TEIC_{If}^{VRS}$) are given by:

$$TEIC_{xn}^{VRS} = \beta_n^{1VRS} - \beta_n^{4VRS}, \quad n = 1, \dots, N \tag{10a}$$

$$TEIC_{If}^{VRS} = \gamma_f^{1VRS} - \gamma_f^{4VRS}, \quad f = 1, \dots, F \tag{10b}$$

The dynamic input- and investment-specific technical inefficiencies under VRS (β_n^{1VRS}, β_n^{4VRS}, γ_f^{1VRS} and γ_f^{1VRS}) can be estimated by re-running Eqs. (3) and (6) under VRS (by adding convexity restrictions $\sum_{j=1}^{J} \lambda_j^1 = 1$ in Eq. (3) and $\sum_{j=1}^{J} \lambda_j^4 = 1$ in Eq. (6)).

The input- and investment-specific dynamic scale inefficiency changes (SIC_{xn} and SIC_{If}) are given by:

$$SIC_{xn} = \left(\beta_n^1 - \beta_n^4\right) - \left(\beta_n^{1VRS} - \beta_n^{4VRS}\right), \quad n = 1, \dots, N \tag{11a}$$

$$SIC_{If} = \left(\gamma_f^1 - \gamma_f^4\right) - \left(\gamma_f^{1VRS} - \gamma_f^{4VRS}\right), \quad f = 1, \dots, F \tag{11b}$$

2.2. Impulse responses by local projections

An impulse response analysis is used to track and measure the effect of farm genetics expenses on the Luenberger dynamic productivity change indicator and its components. An impulse response function measures the responses of a system's variables to shocks. Jordà (2005) proposed the method of local projections for deriving impulse responses that overcome the shortcomings of the traditional analytical impulse responses which were multi-period-ahead projections computed using autoregressive estimation techniques as described below. Consider the following autoregressive fixed effects panel data model of order r:

$$y_{it} = \alpha_i + \sum_{r=1}^{R} \beta_r y_{i,t-r} + \sum_{l=0}^{L} \gamma_l d_{i,t-l} + v_{it} \tag{12}$$

where y_{it} is the dependent variable (e.g. productivity change) for farm i in year t; α_i is farm fixed effect for farm i; β and γ are parameters to be estimated; r denotes number of lags for y_t; d_t refers to a shock variable for a farm in year t and v_{it} is the error term that is independently and identically distributed: $v_{it} \sim \mathrm{N}(0, \sigma^2)$. Then the impulse response function of y_{it} to a shock d_t, k years after it starts can be stated as (Jordà, 2005; Teulings & Zubanov, 2014):

$$IRF(k) = E\left[y_{i,t+k} | d_{it} = d, y_{is}, d_{is}, s < t\right] - E\left(y_{i,t+k} | d_{it} = 0, y_{is}, d_{is}, s < t\right) \tag{13}$$

where IRF is the impulse response function; k refers to prediction horizon; the conditional expectation $E[.|.]$ indicates the best, mean-squared error predictor and the rest as defined above.

Traditionally, impulse response functions (Eq. (13)) are estimated analytically for each prediction horizon k by solving the conditional expectation of $y_{i,t+k}$ as a function of the estimates of the parameters of Eq. (12) (Jordà, 2005; Teulings & Zubanov, 2014). These estimation techniques are criticised for being sensitive to misspecification of the underlying model (Eq. (12)). The impulse responses become more sensitive to even slight specification errors when the model includes more lags of the dependent variable and the shock variable, and when the prediction horizon increases (Jordà, 2005; Teulings & Zubanov, 2014). They are also criticised for the complications in calculating standard errors as the standard errors are non-linear functions of estimated parameters. However, the local projection estimator of Jordà (2005) directly derives the coefficients of impulse responses for each time horizon, based on sequential regressions of the dependent variable shifted several steps ahead. Jordà (2005) demonstrated that impulse response estimates from local projections are consistent and inferences can be made using standard heteroscedastic and autocorrelation robust standard errors (e.g. as in Newy & West, 1987).

The estimates from local projection methods of Jordà (2005), however, suffer from a systematic bias which increases with the prediction horizon since the error term is correlated with current shocks (Teulings & Zubanov, 2014). Teulings and Zubanov (2014) proposed the inclusion of intermediate shocks in the model (i.e. shocks occurred between the current period t and the prediction period $t + k$) to obtain unbiased estimates of impulse response function for prediction horizon k. Several studies followed the (corrected) local projection technique for estimating impulse responses (e.g. Bernal-Verdugo, Furceri & Guillaume, 2013; Haug & Smith, 2012; Kapelko, Lansink & Stefanou, 2015; 2017b).

Following Teulings and Zubanov (2014), the corrected local projection estimator of Jordà (2005), for assessing the effect of genetic progress that occurred at time t on dynamic productivity growth and its components at time $t + k$ can be stated as[3]:

$$y_{i,t+k-1} = \alpha_{1ik} + \alpha_{2k} t + \sum_{r=1}^{R} \beta_{rk} y_{i,t-r} + \sum_{l=1}^{L} \gamma_{lk} gen_{i,t-l} + \sum_{l=1}^{k-1} \tau_l gen_{i,t+k-1-l} + v_{i,t+k}^* \tag{14}$$

where y_{it} is dynamic productivity change (and its components) for farm i ($i = 1, 2, \dots, N$) in year t ($t = 2, 3, \dots, T$); k indicates the prediction horizon; α_{1ik} is farm fixed effect for farm i; α_{2k} is a time trend common to all farms; β, γ and τ are parameters to be estimated; r denotes number of lags for y_t; l denotes the number of lags for gen_t; gen_t refers to a dummy variable for genetic progress with values 1 for genetic progress and 0 otherwise for a farm in year t; and $v_{i,t+k}^* = \sum_{m=1}^{k-1} a_m u_{i,t+k-1-m} + u_{i,t+k-1}$ is the error term. Since the error term no longer contains current values of shocks, the inclusion of intermediate shocks in Eq. (14) (the third summation) produces unbiased estimates of impulse response function for prediction horizon k (Teulings & Zubanov, 2014).

[3] Since the main objective of this study is to assess the effect of genetic progress on dynamic productivity growth, other factors or events that might possibly influenced productivity growth during the study period (e.g. the 2008 financial crisis, or milk and input prices volatility) are not considered in the analysis. For example, the 2008 financial crisis, the substantial decrease in milk prices in 2008 and 2009 from the 2007 spike, and high 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 specialised dairy farms. For example, Kapelkoa et al. (2017b) found that, one year after its occurrence, the 2008 financial crisis had a positive (1%) effect on the productivity growth of Spanish dairy processing industries. However, we have included a time trend common to all farms although a time trend does not capture the year-specific idiosyncrasies like time dummies (which were dropped due to collinearity problem). This approach has also been followed in the literature (e.g. Kapelko et al., 2015, 2017b; Teulings and Zubanov, 2014).

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

Variables	Mean	Std. dev.	Minimum	Maximum
Quantities				
Protein and fat corrected milk (kg)	725,431	318,109	116,582	2,887,738
Other output (constant 2010 €)[a]	22,293	12,489	2,079	129,379
Feed (constant 2010 €)[a]	51,441	26,861	4,214	257,999
Other variable inputs (constant 2010 €)[a]	46,929	38,283	2,379	637,537
Land (ha)	46	20	9	206
Labour (AWU)	2	1	1	13
Capital (constant 2010 €)[a]	344,259	293,194	10,954	2,495,164
Breeding stock (constant 2010 €)[a]	79,485	36,325	13,327	356,374
Net investment in capital (constant 2010 €)[a]	26,781	137,897	−1,758,952	1,625,509
Net investment in breeding stock (constant 2010 €)[a]	4,607	12,454	−115,466	174,873
Expense on genetics per cow (constant 2010 €)[a]	78	26	6	351
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
Expense on genetics	1.000	0.022	0.968	1.034

[a] Implicit quantities. $N = 8254$.

In short panel data models with a large number of observations and few time periods, it has become a standard practice to use Generalized Method of Moments (GMM) estimation and the Instrumental Variables (IV) method to obtain consistent parameter estimates (Anderson & Hsiao, 1981; Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). In the present study, Eq. (14) is estimated using the system GMM estimator, also called the two-step GMM estimator. The system GMM estimator uses the moment conditions of lagged levels as instruments for differenced equation, and the lagged differences for the equation in levels (Arellano & Bover, 1995; Blundell & Bond, 1998). These instruments are potentially good predictors of endogenous variables, even in highly persistent (autocorrelated) series (Blundell & Bond, 1998). Unlike in the first-difference GMM procedure (Arellano-Bond, 1991), the process of differencing in the system GMM does not remove the farm fixed effects α_i, all other time-invariant variables (e.g. gen_{it} in the present study), and cross-farm variations in levels. However, Windmeijer (2005), using Monte Carlo simulation, showed that the standard error estimates of a system GMM estimator suffer from downward bias in small samples. Windmeijer (2005), therefore, proposed a correction term in the weighting matrix[4] for estimating finite-sample corrected standard errors. The system GMM estimator is consistent and asymptotically efficient in the presence of heteroscedasticity.

In the present study, the impulse responses of input- and investment-specific dynamic productivity changes (and their components) to genetic progress during the period 2007–2013 (Eq. (14)) are estimated for five prediction horizons ($k = 5$). Sequential regressions using the two-step GMM estimator with robust standard errors (Windmeijer, 2005) are applied in STATA Version 13 (StataCorp LP, College Station, Texas, USA). The models are fitted using two lags for the dependent variables (i.e. dynamic productivity changes).[5] The same models are applied for the productivity change's components (i.e. technical, technical inefficiency and scale inefficiency changes). The problem of too many instruments, which is a common feature in system GMM estimator, reduces the joint validity of instruments (Roodman, 2009). In this study, we followed the suggestion of Roodman (2009) that combining instruments into smaller sets through addition reduces the number of instruments while retaining all information (as no lags are dropped from the list of instruments).[6] The Arellano–Bond test for the presence of autocorrelation, and the Hansen test of over-identifying restrictions for the joint validity of instruments are applied. To this end, the estimation of impulse response functions by the corrected local projection method of Jordà (2005), by itself, guarantees robustness. The method is more robust to misspecifications compared to the traditional analytical autoregressive models of estimating impulse responses (Jordà, 2005).

3. Empirical application

This study employs unbalanced panel data from 1317 Dutch specialised dairy farms from 2007 to 2014, which were obtained from the accountancy firm FLYNTH (www.flynth.nl). This sample size was reached based on the following criteria. First, only specialised dairy farms, where at least 85% of the total farm revenue is obtained from milk production (average over the sample period, not in each individual year), are considered. Second, only farms that are observed for at least four consecutive years are included in the sample as the impulse response analysis of productivity change requires at least four years to see the effect of lagged genetic progress. Third, complete data were available for all variables of interest (Table 1). Fourth, outliers were removed following the Banker and Chang (2006) super-efficiency procedure for identifying outliers in DEA models. The super-efficiency scores were computed for each year (2007–2013). Then, we used a screen level of 1.3 for detecting outliers (i.e. a farm with a super-efficiency score of greater than 1.3 is considered as an outlier).[7]

Two outputs (i.e. milk production and other output); two variable inputs (i.e. feed and other variable inputs), two quasi-fixed inputs (i.e. capital and breeding stock) and two fixed inputs (i.e. land and labour) are distinguished. Milk production is measured as fat and protein corrected *milk yield* in kg. This measurement accounts for the quality of milk in assessing the contribution of genetics; as genetic progress improves the quality of output in addition to yield. The second output is measured as *revenues* (in euro) from livestock and livestock products (excluding milk) and crop

[4] A weighting matrix is the inverse of an estimate of *variance*$[Z'v]$, where Z is the instrument vector and v is an error term (Roodman, 2009).

[5] The models with two lags provide the best specification in terms of serial correlation and joint validity of instrument post estimation results (Section 4).

[6] Practically, the '*collapse*' command was used in the *xtabond* command in STATA.

[7] Banker and Chang (2006, p. 1317) stated that "… 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".

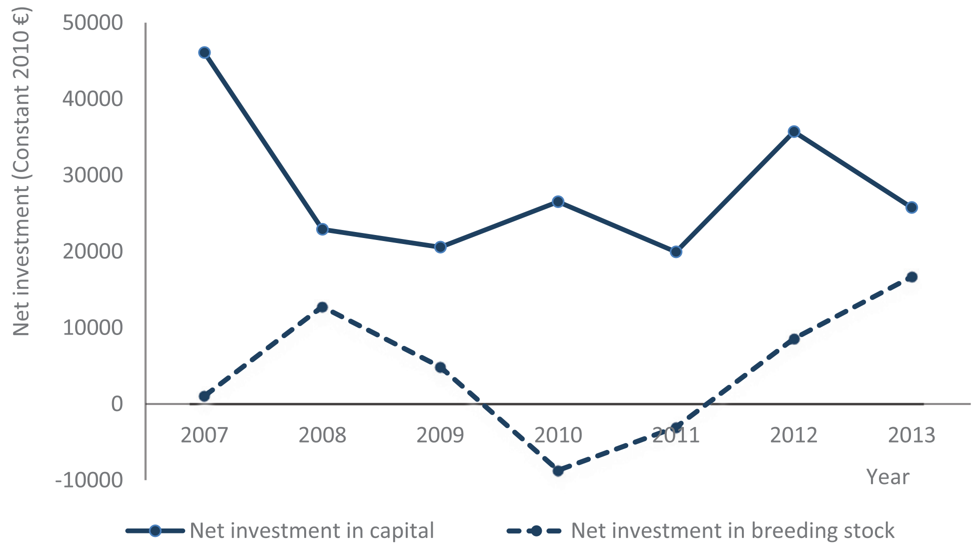

Fig. 1. Evolutions of net investments during 2007–2013 for Dutch specialised dairy farms.

production. The variable inputs *feed* and *other variable inputs* are expressed in euros. Other variable inputs are expenses of energy, veterinary, seed, fertiliser and other crop related expenses. *Capital* is measured in euros as the book value of buildings and machinery. *Breeding stock* is measured as the total value of breeding stock in euros. The *breeding stock* value is calculated as the market value of existing breeding animals *plus* the purchase value of incoming animals *minus* the sales value of exiting animals.[8] The market value of animals accounts for the changes in the values of animals following, for example, from growth (which results in an appreciation or a depreciation in the value of a breeding animal). 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). Following this formula, dynamic productivity change (and its components) are not estimated for the period 2013/14 as data on net investment is not available for the year 2014. The evolution of the average net investments in capital and breeding stock is depicted in Fig. 1. *Net investment in capital* declined between 2007 and 2009 (including during the 2008 financial crisis) until it recovered in 2010. *Net investment in breeding stock* also declined following the 2008 financial crisis until it recovered in 2011. The two fixed inputs are *land* in hectare and *labour* in annual working units (AWUs). Since a large share of labour (more than 95% in the sample farms) comes from family members, labour is considered as a fixed input.

The directional vectors used in the estimation of the directional distance functions are the actual observed value of feed and other variable inputs x. For investments in quasi-fixed inputs K, the directional vectors are set to 20% of capital stock: $(g_x, g_I) = (x, 0.2 \times K_f)$, where f refers to *capital stock* and *breeding stock*. In the dynamic productivity and efficiency literature (e.g. Dakpo & Oude Lansink, 2019; Geylani, Kapelko & Stefanou, 2019; Kapelko, 2019; Kapelko et al., 2017a 2016; Oude Lansink et al., 2015), it is a common practice to use 20% of capital stocks as a directional vector for investments in quasi-fixed inputs. As stated by Geylani et al. (2019); p.), "the application of such a directional vector for investments follows from the high heterogeneity in the investment variable, as well as its ability to approximate the usual size of investments undertaken by firms [which is about 20% of their capital stock]". Moreover, it accounts for the zero values of investments during the estimation of inefficiency scores (Dakpo & Oude Lansink, 2019). That is, given Eq. (2), the dynamic directional input distance function aims at contracting variable inputs by $\beta_n \times g_x$ while expanding gross investments by $\gamma_f \times g_I$. For zero values of investments, the potential expansion in investment would be zero for any level of inefficiency score associated with investment (i.e. γ_f).

All variables measured in monetary units are expressed in constant 2010 prices. Producer price indices (PPIs) from the EUROSTAT (2016) database are used to compute the implicit quantities as the ratio of value and PPI. For capital (buildings and machinery), a Törnqvist price index is used to compute the implicit quantity of capital. The final unbalanced panel dataset contains 8254 observations from 1317 farms (on average, a farm is observed for 6 consecutive years). Table 1 presents the descriptive statistics of the variables.

In this study, *expense on artificial insemination* (in euro per cow) is used as a measure of genetic progress (Table 1). Genetics expense is excluded from variable costs during the estimation of the inefficiency scores. Its share in the total variable cost is small (e.g. less than 5% for the sample farms during 2007–2013). We assumed that a farm experiences genetic progress (i.e. a shock to the system) in year t if its expenditure on semen per cow (in constant 2010 prices) in that year is greater than the farm's median expenditure over the study period (2007–2013).[9] It is used as a proxy for the genetic index of sires (total merit index of bulls): it is assumed to measure the genetic levels of sires used in a farm in a given year compared to the population average genetic level. We hypothesise that high expense on semen per dairy cow (compared to the median expenditure) has a positive effect on farm productivity growth as a result of the use of higher quality genetics. This measure is, however, imperfect as expenses on artificial insemination consist of two confounding components that cannot be distinguished in the dataset used in this study. First, a higher genetic expense per cow implies acquisition of higher quality semen that helps to enhance productivity. Second, (for the same or lower level

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

[9] The analogy is similar with the concept of investment spikes, which refer to abnormally high investment episodes relative to the typical investment rate of a firm (Kapelko et al., 2015).

Table 2
Decomposition of Luenberger dynamic productivity change associated with *feed* for Dutch specialised dairy farms over the period 2007 to 2013 and comparing small versus large farms.

	LPC[a]	TC[b]	TIC_VRS[c]	SIC[d]
2007/2008	0.0030	0.0025	0.0027	−0.0022
2008/2009	−0.0165	−0.0008	−0.0212	0.0055
2009/2010	0.0673	0.0162	0.0591	−0.0080
2010/2011	0.0200	0.0011	0.0077	0.0112
2011/2012	−0.0078	0.0035	0.0025	−0.0139
2012/2013	0.0142	0.0246	−0.0110	0.0007
Average	0.0130 (0.001)	0.0082 (0.001)	0.0056 (0.001)	−0.0009 (0.001)
Small	0.0094 (0.001)	0.0064 (0.001)	0.0052 (0.002)	−0.0022 (0.001)
Large	0.0166 (0.001)	0.0099 (0.001)	0.0061 (0.002)	0.0005 (0.001)
S-Z statistic[e]	6.8292***	1.5961*	5.7593***	0.4112

Note: Standard errors in parentheses.
[a] Luenberger productivity change.
[b] Technical change.
[c] Technical inefficiency change under variable returns to scale.
[d] Scale inefficiency change.
[e] ***, ** and * denote significant differences between small and large farms at the critical 1%, 5% and 10% levels, respectively.

Table 3
Decomposition of Luenberger dynamic productivity change associated with *other variable inputs* for Dutch specialised dairy farms over the period 2007 to 2013 and comparing small versus large farms.

	LPC[a]	TC[b]	TIC_VRS[c]	SIC[d]
2007/2008	0.0138	−0.0117	0.0235	0.0020
2008/2009	−0.0164	0.0566	−0.0313	−0.0417
2009/2010	0.0609	−0.0100	0.0746	−0.0038
2010/2011	−0.2028	−0.0306	−0.1658	−0.0065
2011/2012	0.1761	−0.0173	0.2000	−0.0065
2012/2013	−0.1439	−0.0252	−0.1138	−0.0049
Average	−0.0253 (0.003)	−0.0070 (0.002)	−0.0070 (0.003)	−0.0112 (0.002)
Small	−0.0251 (0.004)	−0.0067 (0.002)	−0.0119 (0.005)	−0.0065 (0.001)
Large	−0.0254 (0.004)	−0.0072 (0.002)	−0.0021 (0.004)	−0.0161 (0.003)
S-Z statistic[e]	6.9628***	0.2559	6.2031***	3.2557***

Note: Standard errors in parentheses.
[a] Luenberger productivity change.
[b] Technical change.
[c] Technical inefficiency change under variable returns to scale.
[d] Scale inefficiency change.
[e] ***, ** and * denote significant differences between small and large farms at the critical 1%, 5% and 10% levels, respectively.

of productivity) a higher expense might also be due to farm-level inefficiencies. Less fertile (unproductive) cows require several inseminations which raise semen expense (it might also be due to managerial inefficiency, for example, in detecting heat period). A cow with a longer calving interval produces less milk per year while it may require several inseminations. In that case, the expense on genetics does not lead to an improved genetic level, but it is spent to solve problems that may have their cause in other sources of inefficiency. Since expense on artificial insemination is not corrected for managerial inefficiencies, its effect on productivity growth might be understated in the present study. As a robustness check, we also used another measure of genetic progress, i.e. *breeding stock investment spike* as a proxy for the genetic index of cows (refer to Appendix A for the details).

4. Results and discussion

4.1. Decomposition of Luenberger dynamic productivity change

The results of the decomposition of the input- and investment-specific Luenberger dynamic productivity growth into technical change, technical inefficiency change and scale inefficiency change[10] for Dutch dairy farms over the period 2007–2013 are presented in Tables 2 to 5. Results of the estimation of productivity growth associated with feed input are presented in Table 2. The differences in dynamic productivity measures (i.e. productivity growth, technical and scale inefficiency changes) between 'small' and 'large' farms[11] are also assessed using the statistical test of Simar and Zelenyuk (2006) (henceforth called the S-Z test).[12] Productivity associated with feed grew on average by 1.3% per year during the sample period (Table 2). The average Luenberger dynamic productivity growth rate of 1.3% for *feed* implies that the use of feed has reduced on average by 1.3% per year during the sample period while still producing the same level of output, holding other variable inputs and *investments in capital* and *breeding stock* constant. The productivity increase might be attributable to nutritional improvements and better feed management. On average, technical change accounted for about 56% of the 1.3% productivity growth associated with *feed* while technical inefficiency change

[10] Note that throughout this results section (Tables 2–5), negative technical inefficiency change and scale inefficiency change imply a negative contribution to productivity change (i.e. an increase in inefficiency over time, following Eqs. (8a) and (11a)).

[11] In this study, the distinction between small and large farms is based on the median number of cows in the sample. A farm is categorised as 'small' and 'large' if its average number of cows during the study period (2007-2013) is less/greater than the median number of cows of the sample farms (75), respectively.

[12] Simar and Zelenyuk (2006) adapted the Li (1996) test for comparing the distributions of efficiency scores of different groups that are estimated by the DEA technique. The test is based on bootstrapping the Li (1996) statistic by smoothing the original DEA efficiency scores of the fully efficient firms (i.e. scores that are equal to one). In the present study, as implemented in Kapelko et al. (2017a), Simar and Zelenyuk's (2006) test is used without smoothing since productivity measures are not truncated.

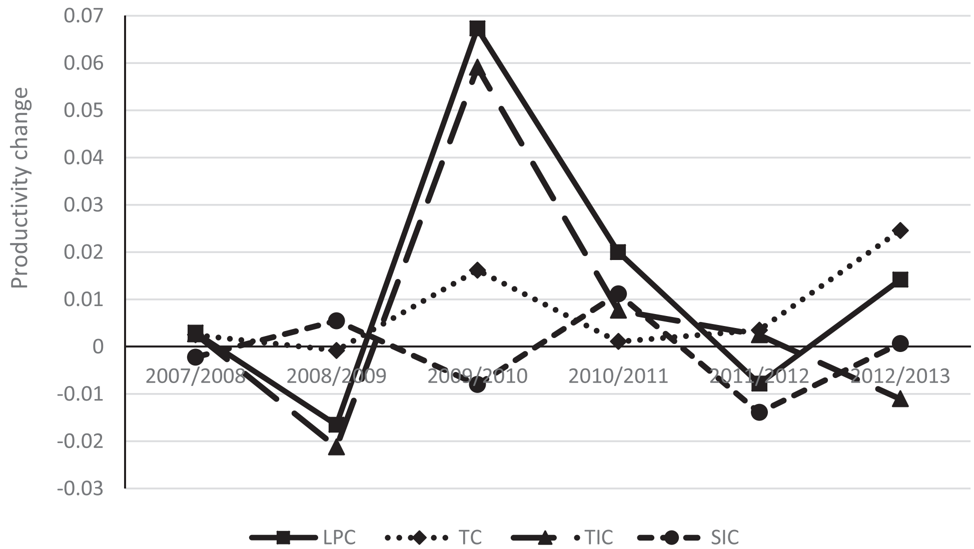

Fig. 2. Evolution of Luenberger productivity change associated with *feed* and its components over the period 2007/08 and 2012/13.

accounted for about 38% of this growth. Although technical change was, on average, the main component of the average productivity change associated with *feed* over the sample period (Table 2), fluctuation in technical inefficiency change was the main driver of the fluctuation in productivity change (Fig. 2). These fluctuations might be due to volatility of milk (Oude Lansink et al., 2015) and input prices.[13] The negative average scale inefficiency change associated with feed input (−0.09%) implies that productivity has slightly declined as a result of non-optimal scale of operation (i.e. operating either at a too small or too large scale). There is a statistically significant difference in average performance (i.e. productivity growth, technical change and technical inefficiency change) between 'small' and 'large' farms (Table 2). Productivity growth, technical change and technical inefficiency change were significantly higher for large farms than small farms as shown by the S-Z test.

The average annual dynamic productivity growth for *other variable inputs* during the sample period was negative (about −2.5% per year; Table 3). Holding *feed* and *investments in capital* and *breeding stock* constant, this implies that the use of *other variable inputs* has increased on average by 2.5% per year during the sample period while still producing the same level of output. The productivity decrease might be due to the fact that modern productive breeds require more care to obtain the maximum output from a given cow (e.g. expenses on energy and veterinary services). The main source of productivity decline associated with other variable inputs was an increase in scale inefficiency of about 1.1% per year, which implies that productivity has declined due to a non-optimal scale of operation. Technical and technical inefficiency changes also contributed negatively to productivity growth of other variable inputs by the same magnitude. This means that the efficiency of the sample farms in adopting and utilising variable inputs such as veterinary services and energy has declined. Therefore, these specialised dairy farms may improve productivity associated with other variable inputs by designing a better health and resource management system. Although scale inefficiency change was, on average, the main component of the average productivity change associated with *other variable inputs* over the sample period (Table 3), fluctuation in technical inefficiency change was the main driver of the fluctuation in productivity change (Fig. 3). These fluctuations might also be due to the milk and input prices fluctuations as stated before, and as a result of the non-parametric Luenberger indicator we used.[14] The difference in performance between 'small' and 'large' farms is negligible (Table 3). The performance difference between 'small' and 'large' farms in terms of technical change is not statistically significant (Table 3). However, the difference is statistically significant for productivity growth, technical and scale inefficiency changes.

The average annual dynamic productivity change associated with *investment in capital* (building and machineries) during the sample period was 1.5 (Table 4). This implies that the potential for doing investments in capital has increased by about 30% of the capital stock per year ($= 1.5 \times 0.2 \times 100\%$) during the sample period while producing the same level of output, for given levels of variable inputs and investment in breeding stock. This was mainly due to reduction in technical inefficiency over time. For a given level of feed, other variable inputs and investment in breeding stock, the increase in the potential for doing investments due to technical inefficiency change ($38\% = 1.9 \times 0.2 \times 100\%$) implies that the potential for doing investments in capital has increased by about 38% of the capital stock per year following from improvements in the optimal use of available capital. Technical inefficiency decreased substantially during the sample period where the highest reductions were observed in 2007/08 and 2009/10. How-

[13] 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" (Oude Lansink et al., 2015). Moreover, during the sample period (2007-2013), input (e.g. grain) price volatility was exceptionally high even after the 2008 financial crisis (e.g. Wright, 2011; Leibtag, 2009). Although we used the annual price deflator to capture annual price changes, input prices also vary within the years. Thus, the timing of purchases of individual farms within a year may had a considerable impact on farms' input prices, which cannot be corrected by the annual averages of price indices. This could explain part of the high volatility of the technical inefficiency scores.

[14] Such huge fluctuations are not uncommon in the non-parametric-based productivity and efficiency literature (e.g. Kapelko, 2019; Kapelko et al., 2017a, 2016; Oude Lansink et al., 2015, Kapelko et al., 2012). As noted by one of the reviewers, the fact that the same method has produced highly volatile components of productivity change also in other datasets implies either a weakness of the method or the strength that reveals the true variations the other methods fail to reveal. However, the volatility of the scores is not specific to the dynamic Luenberger approach. Kapelko et al. (2012) conducted a comparison between dynamic Luenberger- and static Malmquist-based components of productivity growth. They found that the scores of the dynamic approach are less volatile. Further studies are required to empirically compare competing methods, by using similar datasets, to check the evolution of inefficiency scores over time across different non-parametric and parametric methods. Furthermore, a rigorous analysis of the sources of the high volatility of technical inefficiency scores is required to draw business and policy implications.

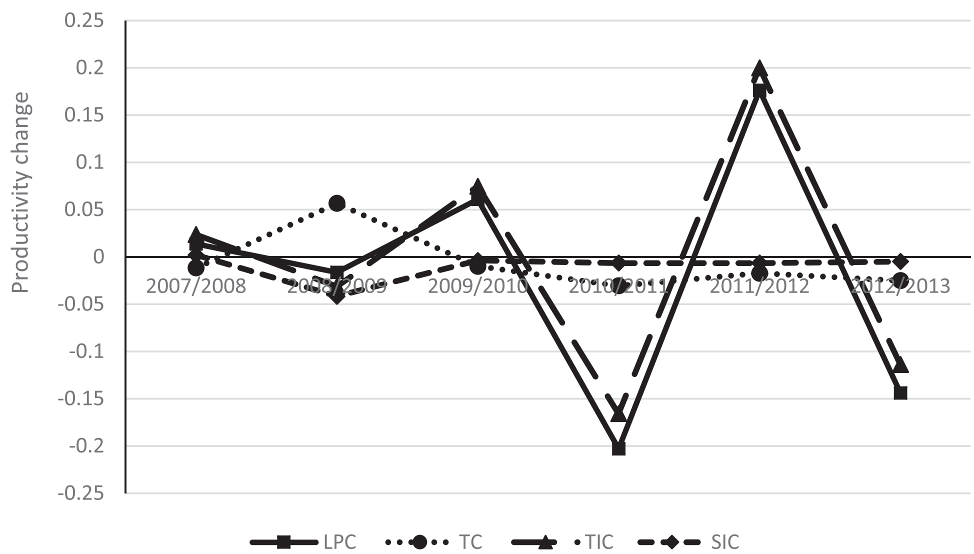

Fig. 3. Evolution of Luenberger productivity change associated with *other variable inputs* and its components over the period 2007/08 and 2012/13.

Table 4
Decomposition of Luenberger dynamic productivity change associated with *investment in capital* for Dutch specialised dairy farms over the period 2007 to 2013 and comparing small versus large farms.

	LPC[a]	TC[b]	TIC_VRS[c]	SIC[d]
2007/2008	6.4366	−3.6773	10.0856	0.0283
2008/2009	0.0756	−0.6932	1.2154	−0.4466
2009/2010	10.3872	1.5526	6.9085	1.9260
2010/2011	−3.3257	−2.2015	−0.7551	−0.3691
2011/2012	0.1331	−0.3537	−0.2648	0.7516
2012/2013	−0.0589	−0.1350	−0.0481	0.1241
Average	1.4860 (0.101)	−0.7119 (0.101)	1.8755 (0.126)	0.3224 (0.034)
Small	1.7623 (0.167)	−0.7569 (0.161)	2.5318 (0.211)	−0.0127 (0.025)
Large	1.2035 (0.111)	−0.6660 (0.123)	1.2045 (0.136)	0.6650 (0.063)
S-Z statistic[e]	9.3782***	6.2980***	10.5907***	3.2332***

Note: Standard errors in parentheses.
[a] Luenberger productivity change.
[b] Technical change.
[c] Technical inefficiency change under variable returns to scale.
[d] Scale inefficiency change.
[e] ***, ** and * denote significant differences between small and large farms at the critical 1%, 5% and 10% levels, respectively.

ever, the dairy farms experienced a technical regress of about 14% per year during the sample period ($-14\% = -0.71 \times 0.2 \times 100\%$). Although the efficiency of farmers increased in the utilisation of technologies (i.e. positive average technical inefficiency change) over the sample period, they were not successful in adopting new technologies for bringing in technical progress. This might be due to higher costs to comply with environmental regulations such as manure disposal and emission reducing measures, which impose higher costs on dairy farms, but do not add directly to production. Over the sample period, productivity associated with investment in capital has increased by 6.4% of the capital stock ($= 0.32 \times 0.2 \times 100\%$) as a result of improvement in scale of operation associated with capital (i.e. following from production technology movement from VRS towards CRS). The high average technical inefficiency change (38%) and technical change (−14%) results suggest that farmers were forced to utilise their available capital efficiently rather than investing in new technologies for achieving productivity growth (30%) during the sample period, which might be due to constraining capital for doing productive investments, the 2008 financial crisis, the milk quota, and fluctuations of input and milk prices. The fluctuation in technical inefficiency change was the main driver of the fluctuation in productivity change (Fig. 4). There is a statistically significant difference in average performance between 'small' and 'large' farms (Table 4). On average, small farms achieved higher productivity growth associated with capital compared to large farms as a result of technical inefficiency change during the sample period.

The average annual dynamic productivity change associated with investment in breeding stock during the sample period was negative (−0.05; Table 5). This suggests that the potential for doing investments in breeding stock has declined on average by about 1.0% per year ($= -0.05 \times 0.2 \times 100\%$) during the sample period, for a given level of feed, other variable inputs and investment in capital. The main source of productivity decline associated with investment in breeding stock was technical regress (i.e. an average technical regress of about 2.6% per year ($= -0.13 \times 0.2 \times 100\%$)). This might be due to the fact that investment in improved breeding stock need to be accompanied by an expansion of other inputs (e.g. feed, veterinary services, labour) and an investment in capital assets (e.g. a new milking robot) or expansion of output. The optimization with respect to the quasi-fixed *breeding stock* is conditional on the level of the other quasi-fixed input, i.e. *capital*. Accordingly, the optimized *breeding stock* may not be optimal if the *capital stock* is not optimal. The average technical inefficiency change is positive and the highest change was observed in 2012/13. This suggests that over the sample period, the efficiency of farms in utilising the available breeding stock has increased. Over the sample period, productivity associated with investment in breed-

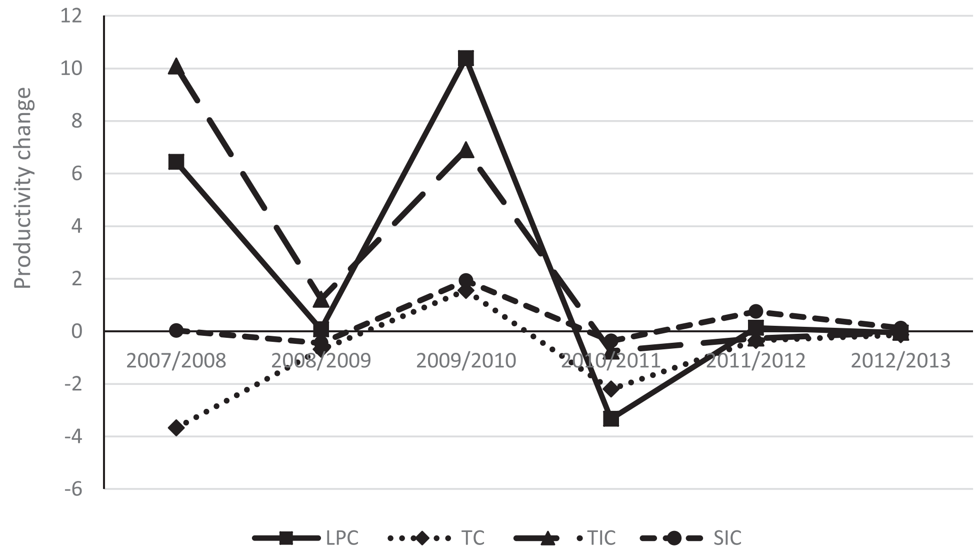

Fig. 4. Evolution of Luenberger productivity change associated with *investment in capital* and its components over the period 2007/08 and 2012/13.

Table 5
Decomposition of Luenberger dynamic productivity change associated with *investment in breeding stock* for Dutch specialised dairy farms over the period 2007 to 2013 and comparing small versus large farms.

	LPC[a]	TC[b]	TIC_VRS[c]	SIC[d]
2007/2008	−0.4029	−0.6426	0.0933	0.1463
2008/2009	0.8035	0.3315	0.4155	0.0565
2009/2010	0.5397	0.4510	0.0591	0.0297
2010/2011	−0.9971	−0.1914	−0.7325	−0.0732
2011/2012	−0.3549	−0.4362	−0.0095	0.0908
2012/2013	0.1476	−0.4334	0.5851	−0.0041
Average	−0.0510 (0.014)	−0.1308 (0.009)	0.0511 (0.015)	0.0288 (0.005)
Small	−0.0382 (0.020)	−0.1231 (0.014)	0.0766 (0.022)	0.0084 (0.003)
Large	−0.0641 (0.020)	−0.1387 (0.013)	0.0250 (0.021)	0.0496 (0.010)
S-Z statistic[e]	36.6395***	50.3151***	117.6238***	118.7675***

Note: Standard errors in parentheses.
[a] Luenberger productivity change.
[b] Technical change.
[c] Technical inefficiency change under variable returns to scale.
[d] Scale inefficiency change.
[e] ***, ** and * denote significant differences between small and large farms at the critical 1%, 5% and 10% levels, respectively.

ing stock has increased by about 0.6% ($= 0.03 \times 0.2 \times 100\%$) as a result of improvement in the scale of operation associated with breeding stock (i.e. following from the shift/movement in the production technology from VRS to CRS). The performance difference between 'small' and 'large' farms in terms of productivity growth associated with investment in breeding stock is statistically significant (Table 5). Technical inefficiency changes were significantly higher for small farms than large farms as shown by the S-Z test, whereas scale inefficiency changes were higher for large farms.

The input- and investment-specific productivity change results (Tables 2–5) suggest that technical inefficiency change associated with *feed* and *other variable inputs* showed a similar pattern over the sample period, whereas a similar pattern is observed for technical changes associated with *investment in- capital* and *breeding stock*. Moreover, the results also suggest that size-specific dynamic productivity growth and its components for *feed*, *other variable inputs* and *investment in breeding stock* show similar patterns over the sample period for small and large farms, whereas a different pattern is observed for investment in capital. However, the average values of the productivity change and its components are very sensitive to the inclusion or exclusion of a year from the sample period (i.e. the average scores would be very different if, for example, the first or last year is removed from the series; Figs. 2–4). From the decompositions of investment-specific dynamic productivity growths associated with *investments in capital and breeding stock* (Tables 4 and 5), we observe that the average technical changes are negative for Dutch dairy farms over the period 2007–2013. This implies that, for producing the same level of output, the potential for doing investments in capital (e.g. milking robots) and breeding stocks to achieve technical progress has declined over the sample period for a given level of variable inputs. This might be due to higher costs to comply with environmental regulations (e.g. manure disposal and emission reducing measures), which impose higher costs but do not add directly to production. Over the sample period, Dutch dairy farms rather improved their productivity associated with investments by a better utilisation of available capital and breeding stocks (i.e. by reducing technical inefficiency) and to some extent by improving the scale of their operations. Farmers might have also been discouraged to make investments in modern technologies and breeds as a result of the milk quota system that posed an upper limit on milk production during the sample period.[15] Therefore, there is a potential to improve productivity growth of Dutch dairy farms via technical progress. Further research is required to study the causes behind lack of investments and to make business and policy recommendations accordingly.

[15] Note that the quota system was abolished in April 2015 in the Netherlands.

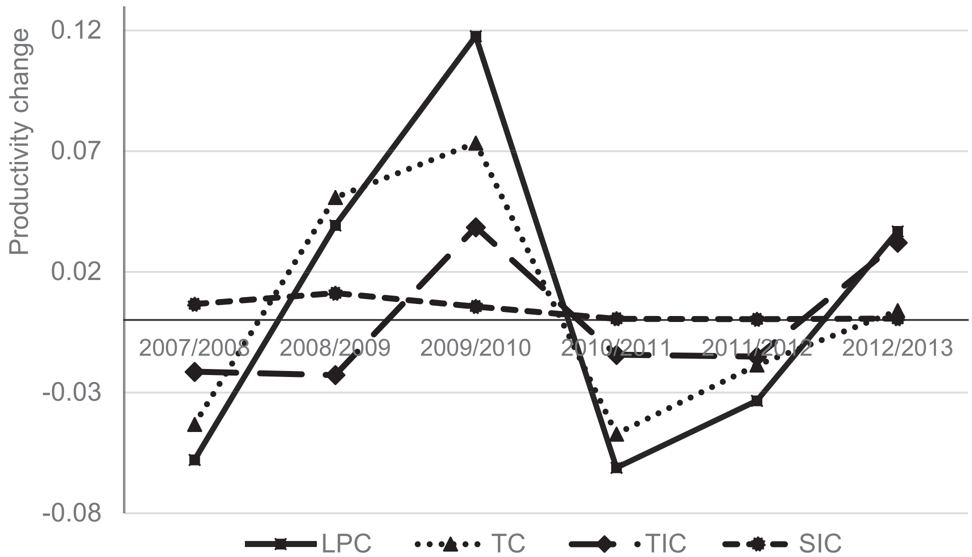

Fig. 5. Evolution of Luenberger overall productivity change and its components over the period 2007/08 and 2012/13.

Table 6
Correlation between overall and input-specific annual productivity changes.

Inputs/Investments	Productivity change and its components			
	LPC	TC	TIC	SIC
Feed	0.59	0.35	0.57	0.16
Other variable input	0.16	0.56	−0.07	−0.65
Investment in capital	0.53	0.79	0.05	−0.11
Investment in breeding stock	0.85	0.86	0.32	0.44

We have also computed the overall (total factor) productivity change and its components[16] (Fig. 5), by solving Eq. (2) such that $\beta_{feed} = \beta_{other\,variable\,inputs} = \gamma_{investment\,in\,capital} = \gamma_{investment\,in\,breeding\,stock}$. The overall average productivity change over the sample period is 0.85% per year (Fig. 5), mainly as a result of technical change (0.44% per year) and scale inefficiency change (0.36% per year). The contribution of technical inefficiency change to average productivity growth is very low during the sample period (0.05% per year), even though it was the second main driver of the fluctuations in productivity change next to technical change (Fig. 5). The differences between the input-specific and overall productivity change scores (i.e. 1.3% for *feed*, −2.5% for *other variable input*, 30% for *investment in capital* and −1.0 for *investment in breeding stock* vs 0.85% for the overall productivity change) underline the importance of computing input-specific productivity change (and its components) for improving farm decision-making. The correlation between the overall- and input-specific average annual productivity changes are given in Table 6. Overall productivity and technical changes have a strong positive correlations (85–86%) with productivity and technical changes associated with *investment in breeding stock*. On the other hand, overall technical inefficiency change has a very low association with technical inefficiency changes associated with- *investment in capital* (5%) and *other variable inputs* (−7%). These correlations suggest that the calculation of overall (total factor) productivity change and its components does not provide full information regarding the actual level of inefficiency in relation to each factor of production.

The input-specific (dynamic) productivity change results of the present study are not directly comparable with other studies as there are no studies on input-specific (dynamic) productivity growth for dairy farms. As a result, here we compare the overall productivity change results. Brümmer et al. (2002) measured the productivity growth of Dutch dairy farms over 1991–1994 using a static model. They found an average annual productivity growth of 2.88%, technical change of 0.53%, technical efficiency change of 0.58% and scale effect of 0.22%. The respective values from our dynamic model for Dutch dairy farms over the period 2007–2013 are 0.85%, 0.44%, 0.05% and 0.36%. The differences in the sample period (1991–1994 vs 2007–2013) and the models used (static vs dynamic) could explain the difference between the results. The result of our study for the average productivity growth (0.85% per year) is also lower than the result of Oude Lansink et al. (2015) who found an average productivity growth of 1.5% per year for the Dutch dairy farms over the period 1995–2005 using the Luenberger dynamic productivity indicator. In Oude Lansink et al. (2015), technical change accounts for about 80% of the productivity growth whereas it accounts for 52% in our study. The fluctuation in technical and technical inefficiency changes are the main drivers of the fluctuation in the overall productivity change in the present study, whereas it was the fluctuation in technical inefficiency change in Oude Lansink et al. (2015). Skevas, Emvalomatis and Brümmer (2018), using a dynamic stochastic frontier model, measured the productivity growth of German dairy farming over the period 2001–2009. The authors decomposed the productivity growth of 1.73% into technical change of 1.88%, technical efficiency change of −0.20% and scale effect of 0.05%. Atsbeha et al. (2012) also measured the productivity growth (1.63%) of Iceland dairy farming over the period 1997–2006, and decomposed it into technical change of 0.43%, technical efficiency change of −0.61% and scale effect of 1.81% using a static model. The respective values from our dynamic model for Dutch dairy farms over the period 2007–2013 are 0.85%, 0.44%, 0.05% and 0.36%. The consideration of only specialised dairy farms in our sample, where at least 85% of farm's revenue is from milk, could also be one of the reasons

[16] This is mainly as a robustness check and for comparing the overall productivity change results of the present study with other studies since there are no studies on input-specific (dynamic) productivity growth for dairy farms.

Table 7
Impulse responses of input- and investment-specific Luenberger dynamic productivity changes and their components to genetic progress using the measure of expense on artificial insemination[a].

Years after expenditure (k)	LPC[b]	TC[c]	TIC[d]	SIC[e]
Feed				
1	−0.0123**	0.0027	−0.0144	−0.0150**
2	0.0209***	0.0111**	0.0168	0.0117***
3	0.0509	−0.0262	−0.0482	0.0170
4	0.0034	0.0028	0.0069	−0.0066*
5	0.0062	−0.0025	−0.0018	0.0073**
Other variable inputs				
1	0.1421***	−0.0088	0.2612***	0.0088
2	−0.0350**	0.0131	−0.0913*	−0.0048
3	0.0441	0.0259	0.0710*	0.0105
4	0.0160	−0.0101	0.0103	−0.0148
5	−0.0083	0.0104	−0.008	0.0029
Investment in capital				
1	4.5633***	1.0631	4.6907***	0.7255***
2	−0.8688	0.0424	−1.2297*	−0.4544***
3	−1.6036	−3.9218	1.4326**	0.4541
4	−0.7256*	−0.2245	−0.3694	0.0748
5	0.0352	−0.2168	−0.1912	−0.1309
Investment in breeding stock				
1	1.4213***	−0.3188***	1.7793***	0.1625***
2	0.1266*	0.1124	0.1894*	−0.0296
3	−0.0642	−0.9609***	−0.0043	0.1023
4	−0.2510***	0.1772*	−0.2032*	0.0455
5	0.0391	0.0193	0.0084	0.0620

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.
[a] According to this measure, if a farm's expense on artificial insemination per cow in constant 2010 prices in a given year is greater than its median expenditure over 2007–2013, a farm is assumed to experience genetic progress in that year.
[b] Luenberger productivity change.
[c] Technical change.
[d] Technical inefficiency change under variable returns to scale.
[e] Scale inefficiency change.

for the lower average productivity growth result the present study compared to results from the literature.

4.2. Effect of genetic progress on dynamic productivity growth and its components

The results of the impulse response analysis for measuring the effect of genetic progress on input- and investment-specific dynamic productivity growths and their components are presented in Table 7. 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 of over-identifying restrictions for the joint validity of instruments) as well as the number of instruments and observations used in each sequential regression are reported in Appendix B (Tables B1–B4). The Wald chi-squared test results showed that the explanatory variables included in each model are statistically significant, at the critical 1% level, in jointly explaining the variations in productivity changes and their components. Although the Arellano–Bond test results show that there is a first-order autocorrelation, in almost all the models, the null hypothesis of no second-order autocorrelation is not rejected at the critical 5% level (i.e. there is no problem of second-order serial correlation). The Hansen test results also showed that the instruments in the model are jointly valid (i.e. there is no problem of overidentification).

Spending greater than the median farm genetics expenses is positively related with productivity growths (and their components) associated with- *other variable inputs*, and *investments in capital and breeding stock* one year after the time of spending at the critical 1% level; whereas it is negatively related for *feed* (Table 7). Thereafter, these expenses have mixed relations with most input- and investment-specific productivity growths and their components from the second year onwards. The statistically significant results in the first two years (Table 7) suggest that the effect of using purchased quality semen starts one year after its application. This effect is not attributable to better efficiency of the progenies as the generation interval of dairy cows is longer than two years. The positive relationship suggests a potential positive spill-over from using high quality genetics to efficient use of inputs. That is, farms that produce more efficiently after adopting quality genetics are also those farms that utilise their resources efficiently. Moreover, the statistically significant positive relations in the first two years could also partly be due to the genetic status variations amongst farms (e.g. Atsbeha et al., 2012).

When a farm spends more than its median expenditure on artificial insemination, productivity change associated with *feed* decreases by 1.23% and increases by 2.09% after one and two years from the spending time, respectively. Holding output, other variable inputs and investments constant, these results imply that spending more than the median expenditure leads to an increase and a decrease in the use of feed by 1.23% and 2.09% per year after one and two years from the time of spending, respectively. The second year effect is mainly attributed to the effect on technical change and scale inefficiency change, suggesting that farmers that adopt high quality genetics are also those farmers that undertake steps to improve their technical progress and scale of operation. Spending greater than the median expenditure on artificial insemination is negatively and positively related with scale inefficiency change associated with feed after three and four years, respectively.

One year after spending more than the median expenditure, productivity growth associated with investment in capital increases by 4.56. This implies that, holding output, feed and investment in breeding stock constant, spending more than the median expenditure is associated with a greater potential for doing investments in capital. After one year, this potential for doing investments increased by 91% of the capital stock (as $g_I = 0.2 \times K$). This effect is mainly attributed to the effect of spending on technical inefficiency change. This implies that farms that use improved genetics have a larger efficiency in utilising available resources (i.e. buildings and machineries). This relation might be due to the spill-over effect of using improved genetics on managerial efficiencies that allow farms to use the under-utilised capital resources.

The results of the impulse response analyses using the measure of *breeding stock investment spike* are also comparable to the results of expense on artificial insemination (Appendix A, Table A1). The effects of genetics expenses on productivity growth and its components are also robust to the inclusion of farm size (in Eq. (14)) during the estimation of the impulse responses.[17] The results show that the effects of genetics expenses on productivity growth and its components do not depend on farm size (i.e. no scale effect). The results of the impulse response analyses suggest that expense on genetics, using the measures of *expenses on artificial insemination* (Table 7) and *breeding stock investment spike* (Appendix A, Table A1), has the potential to improve productivity of dairy farms.[18] Productivity growth associated with inputs and investments increases following from higher expense on genetics in the first two years and then productivity starts to grow slowly (with very few exceptions). The negative coefficients do not imply a reduction in productivity as a result of genetics expenses. They rather imply that productivity growth declines, i.e. the productivity in time $t+1$ is lower than the productivity in time t. The benefits of using a high quality genetics in the first two years could be attributed to the spill-over effect on managerial efficiency, and the increase in revenues following from sales of (at least 50% of) the calves born in the first two years. The less statistically significant results for later prediction horizons (i.e. $k \geq 3$) might also partly be due to the small sample sizes (Appendix B) remained for distant prediction horizons after the differencing procedure in the system GMM estimator.

5. Conclusions

This study measured the input- and investment-specific Luenberger dynamic productivity growth indicators and their components for Dutch specialised dairy farms over the period 2007–2013. The average yearly input-specific productivity changes are 1.3% for *feed*, −2.5% *for other variable inputs*, 30% for *investment in capital* and −1.0% for *investment in breeding stock*. Technical change is the main component of productivity changes associated with-*feed* (positively) and *investment in breeding stock* (negatively). On the other hand, technical and scale inefficiency changes are the main components of productivity changes associated with- *investment in capital* (positively) and *other variable inputs* (negatively). The fluctuations in technical inefficiency changes were the main drivers of the fluctuations in the input- and investment-specific productivity changes during the sample period. The negative productivity growth associated with *breeding stock* (−1.0%) suggests that, holding output, variable inputs and investment in capital constant, the potential for doing investments in breeding stock has declined by 1.0% per year over the sample period. The negative technical changes for investments in capital and breeding stocks suggest that there is potential for Dutch dairy farms to increase productivity by raising technical progress (e.g. by doing productive investments on top of unproductive investments that are done to comply with environmental regulations such as manure disposal and emission reducing measures). Furthermore, the optimization with respect to the quasi-fixed *breeding stock* is conditional on the level of the other quasi-fixed input, i.e. *capital*. Accordingly, the optimized *breeding stock* may not be optimal if the *capital stock* is not optimal.

This study also measured the effect of genetic progress—as proxied by farm *expenses on artificial insemination* and *breeding stock investment spike*—on input- and investment-specific dynamic productivity growth indicators and their components using an impulse response analysis. The results of the impulse response analyses show that farm genetics expenses have the potential to improve productivity of dairy farms. The results suggest that productivity growth associated with inputs and investments increases following from higher expense on genetics in the first two years after expense and then productivity starts to grow slowly (with very few exceptions). The benefits of using a high quality genetics in the first two years could be attributed to the spill-over effects of using improved genetics on managerial efficiencies and increases in revenues from sales of (at least 50% of) the calves born in the first two years.

The combination of input-specific dynamic productivity growth indicators with impulse response analysis is a promising method for measuring the contribution of the farm level genetic status of dairy cows to productivity growth associated with each variable input and investments. However, a long panel dataset and a good measure of genetic progress are required. The present study used a seven-years panel data, which is quite short to fully capture the effects of genetic progress on farm performance in dairy farming. A long panel dataset (e.g. 20 years) is required to fully capture the long-term (i.e. cumulative and persistent) effects of genetic progress in dairy farming. This study used expense on artificial insemination as a proxy for genetic progress. As already stated, this measure is imperfect as expenses on artificial insemination consist of two confounding components that cannot be distinguished in the dataset used in this study. First, a higher genetic expense per cow implies acquisition of higher quality semen that helps to enhance productivity. Second, (for the same or lower level of productivity) a higher expense might also be due to farm-level inefficiencies. Less fertile (unproductive) cows require several inseminations which raise semen expense (it might also be due to managerial inefficiency, for example, in detecting heat period). Since expense on artificial insemination is not corrected for managerial inefficiencies, its effect on productivity growth is understated in the present study. The negative effects of expense on artificial insemination on productivity and efficiency changes for some of the inputs and investments might also be due to the outweigh of expenditure following farm inefficiencies over expenditure on quality genetics. A cow with a longer calving interval produces less milk per year while it requires several inseminations. In this case, the expense on genetics does not lead to an improved genetic level, but it is spent to solve problems that may have their cause in other sources of inefficiency.

Future research may use the total merit index of a herd as a measure of genetic levels at farm level using longer panel datasets (e.g. 20 years). The total merit index (also known as aggregate genotype) is a linear function of economically important traits (Miesenberger & Fuerst, 2006). It is a weighted average of breeding goal traits (i.e. estimated breeding values of traits such as milk yield, fat and protein contents, disease resistance and calving difficulty weighted by their respective economic values). Obtaining farm level long panel data on total merit index and socio-economic variables requires collaborative efforts amongst breeding companies and other institutions that collect socio-economic data (e.g. accountancy firms). In the Netherlands, for example, CRV (a cattle

[17] Results are not reported.

[18] However, these results of the impulse response analysis might not be generalizable due to the high volatility of the components of productivity change (Figs. 2–4) and the short sample period (2007-2013), which is too short to capture the full effects of genetics. Further studies could implement the procedure using long panel data (and other methods for estimating the components of productivity change).

breeding company) records farm level data on genetics (total merit index) and FLYNTH (the accountancy firm) collects socio-economic data. Normally, an overlap is expected in the two datasets that can be used for measuring the long-term effects of genetic progress on farm productivity growth. Estimated breeding values of traits have already been employed in assessing the contribution of genetic progress to farm productivity and profit using static models (in other countries), with the assumption that a high genetic herd in the current period results in higher productivity or profit in the same period (e.g. Atsbeha et al., 2012; Roibas & Alvarez, 2012; 2010; Steine et al., 2008). A long-term perspective with a dynamic approach is required to better capture the effect of genetic progress on farm performance.

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Appendix A. The effect of breeding stock investment spike on productivity change

Breeding stock investment spike is also used as a proxy for genetic progress of farms. In this study, a spike is defined as a year in which a farm's net investment rate (i.e. net investment in breeding stock divided by total breeding stock) is greater than two times the farm's median net investment rate of breeding stock over the study period (2007–2013). Previous studies (e.g. Geylani & Stefanou, 2013; Kapelko et al., 2015) defined investment spikes as a year in which the gross investment rate (i.e. gross investment divided by capital stock) is greater than 2.5 times the firm's median gross investment rate. This relative definition of spike avoids the effect of potential size differences. We assumed that a farm experiences genetic progress (i.e. uses cows with high genetic level compared to the population average genetic level, which is a shock to the system) in year t if an investment spike occurs in that year. This measure is used as an alternative proxy for the genetic index of cows (total merit index of cows). We hypothesise that a high net investment rate of breeding stock has a positive effect on farm productivity growth as a result of the use of cows with better genetic potential.

The results of the impulse response analysis are presented in Table A1. The impulse responses of input- and investment-specific dynamic productivity changes (and their components) to genetic progress using the measure of *breeding stock investment spike* during the period 2007–2013 are estimated for five prediction horizons ($k = 5$). The results show that genetic progress results in a statistically significant increase in productivity change associated with inputs and investments, and then it leads to a decline in productivity change in the third year.

Appendix B. Post estimation test results

Table A1
Impulse responses of input- and investment-specific Luenberger dynamic productivity changes and their components to genetic progress using the measure of breeding stock investment spike[a].

Years after spike (k)	LPC[b]	TC[c]	TIC[d]	SIC[e]
Feed				
1	0.0227***	0.0162***	0.0062	0.0010
2	0.0098**	0.0169***	−0.0028	−0.0002
3	−0.0027	0.0012	−0.0117**	0.0047
4	−0.0146*	−0.0077	−0.0018	−0.0022
5	0.0116	−0.0005	−0.0090	0.0072
Other variable inputs				
1	0.0047	0.0141*	−0.0851***	0.0076
2	0.1254***	0.0145	0.0728**	−0.0143
3	−0.1856***	−0.0107	−0.1846***	0.0049
4	0.0620**	0.0191	0.1214***	−0.0072
5	−0.0014	−0.0101	−0.0871	0.0079
Investment in capital				
1	2.6704***	1.5269***	1.7948***	0.3405***
2	5.5527***	1.0308*	4.6775***	0.5210***
3	−3.6718***	−1.0954**	−3.0863***	−0.6146***
4	0.1655	0.3424	−0.6544	0.1723
5	−0.8050	−0.7979	−0.4077	−0.0416
Investment in breeding stock				
1	0.7318***	0 0.4602***	0.4704***	−0.0085
2	0.4386***	0.0948	0.7550***	−0.0078
3	−0.2199	0.2150***	−0.7376***	−0.0673**
4	0.1193	−0.0728	0.1518	0.0650*
5	−0.1425	0.3717**	−0.1039	−0.0290

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.
[a] According to this measure, if a farm's net investment rate of breeding stock in a given year is greater than two times the farm's median net investment rate in 2007–2013, a farm is assumed to experience genetic progress in that year.
[b] Luenberger productivity change.
[c] Technical change.
[d] Technical inefficiency change under variable returns to scale.
[e] Scale inefficiency change.

Table B1
Post estimation diagnostic test results for the impulse responses of input- and investment-specific Luenberger dynamic productivity change associated with *feed* to genetic progress.

k	Tests	LPC [b]	TC [c]	TIC [d]	SIC [e]
1	Wald Test	363.06***	129.03***	481.42***	142.74***
	AR(1) in first differences	0.000	0.000	0.022	0.015
	AR(2) in first differences	0.132	0.072	0.064	0.659
	Hansen Test	0.195	0.522	0.191	0.109
	Number of instruments	6	6	6	6
	Number of observations	2655	2655	2655	2655
	Number of farms	1057	1057	1057	1057
2	Wald Test	410.81***	120.37***	447.03***	144.96***
	AR(1) in first differences	0.031	0.000	0.108	0.094
	AR(2) in first differences	0.655	0.121	0.088	0.329
	Hansen Test	0.254	0.472	0.255	0.122
	Number of instruments	7	7	7	7
	Number of observations	1932	1932	1932	1932
	Number of farms	761	761	761	761
3	Wald Test	18.09***	75.81***	40.49***	17.63***
	AR(1) in first differences	0.433	0.232	0.656	0.397
	Hansen Test	0.578	0.424	0.466	0.194
	Number of instruments	8	8	8	8
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
4	Wald Test	38.28***	75.08***	36.69***	32.01***
	AR(1) in first differences	0.107	0.000	0.243	0.168
	Hansen Test	0.271	0.545	0.826	0.876
	Number of instruments	10	10	10	10
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
5	Wald Test	34.40***	40.95***	44.67***	89.14***
	Hansen Test	0.214	0.828	0.779	0.870
	Number of instruments	11	11	11	11
	Number of observations	546	546	546	546
	Number of farms	284	284	284	284

The models are fitted using two lags for the dependent variables and estimated using system GMM with Windmeijer (2005) corrected standard errors.
The null hypothesis of the Wald test is Ho: the coefficients of the explanatory variables in the model are equal to zero. *** Significant at 1%; ** Significant at 5%; * Significant at 10%.
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 hypothesis of the Arellano-Bond test for autocorrelation is Ho: no autocorrelation. The null hypothesis of the Hansen test is Ho: overidentifying restrictions are valid.

Table B2
Post estimation diagnostic test results for the impulse responses of input- and investment-specific Luenberger dynamic productivity change associated with *other variable inputs* to genetic progress.

k	Tests	LPC [b]	TC [c]	TIC [d]	SIC [e]
1	Wald Test	4387.89***	193.44***	1787.92***	224.60***
	AR(1) in first differences	0.343	0.000	0.148	0.015
	AR(2) in first differences	0.905	0.524	0.293	0.488
	Hansen Test	0.781	0.732	0.982	0.804
	Number of instruments	6	6	6	6
	Number of observations	2655	2655	2655	2655
	Number of farms	1057	1057	1057	1057
2	Wald Test	2541.50***	172.50***	2116.42***	224.93***
	AR(1) in first differences	0.388	0.003	0.136	0.006
	AR(2) in first differences	0.927	0.758	0.433	0.841
	Hansen Test	0.497	0.376	0.839	0.914
	Number of instruments	7	7	7	7
	Number of observations	1932	1932	1932	1932
	Number of farms	761	761	761	761
3	Wald Test	2275.52***	92.41***	838.86***	127.40***
	AR(1) in first differences	0.985	0.000	0.546	0.752
	Hansen Test	0.595	0.842	0.935	0.104
	Number of instruments	8	8	8	8
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
4	Wald Test	2624.79***	113.45***	1497.91***	77.33***
	AR(1) in first differences	0.880	0.000	0.873	0.771
	Hansen Test	0.051	0.815	0.329	0.461
	Number of instruments	10	10	10	10
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
5	Wald Test	1238.54***	104.62***	872.55***	185.37***
	Hansen Test	0.073	0.680	0.371	0.506
	Number of instruments	11	11	11	11
	Number of observations	546	546	546	546
	Number of farms	284	284	284	284

The models are fitted using two lags for the dependent variables and estimated using system GMM with Windmeijer (2005) corrected standard errors.
The null hypothesis of the Wald test is Ho: the coefficients of the explanatory variables in the model are equal to zero. *** Significant at 1%; ** Significant at 5%; * Significant at 10%.
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 hypothesis of the Arellano-Bond test for autocorrelation is Ho: no autocorrelation. The null hypothesis of the Hansen test is Ho: overidentifying restrictions are valid.

Table B3
Post estimation diagnostic test results for the impulse responses of input- and investment-specific Luenberger dynamic productivity change associated with *investment in capital* to genetic progress.

k	Tests	LPC [b]	TC [c]	TIC [d]	SIC [e]
1	Wald Test	685.97***	64.77***	175.97***	187.91***
	AR(1) in first differences	0.446	0.000	0.010	0.002
	AR(2) in first differences	0.008	0.546	0.625	0.141
	Hansen Test	0.118	0.389	0.779	0.461
	Number of instruments	6	6	6	6
	Number of observations	2655	2655	2655	2655
	Number of farms	1057	1057	1057	1057
2	Wald Test	999.15***	68.82***	173.12***	272.09***
	AR(1) in first differences	0.016	0.000	0.048	0.019
	AR(2) in first differences	0.003	0.548	0.020	0.231
	Hansen Test	0.073	0.139	0.168	0.264
	Number of instruments	7	7	7	7
	Number of observations	1932	1932	1932	1932
	Number of farms	761	761	761	761
3	Wald Test	134.64***	99.79***	37.99***	87.04***
	AR(1) in first differences	0.139	0.175	0.000	0.001
	Hansen Test	0.055	0.968	0.402	0.343
	Number of instruments	8	8	8	8
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
4	Wald Test	196.95***	96.16***	38.69***	127.79***
	AR(1) in first differences	0.011	0.002	0.000	0.048
	Hansen Test	0.069	0.978	0.272	0.808
	Number of instruments	10	10	10	10
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
5	Wald Test	54.41***	29.50***	32.99***	341.48***
	Hansen Test	0.042	0.365	0.228	0.098
	Number of instruments	11	11	11	11
	Number of observations	546	546	546	546
	Number of farms	284	284	284	284

The models are fitted using two lags for the dependent variables and estimated using system GMM with Windmeijer (2005) corrected standard errors.
The null hypothesis of the Wald test is Ho: the coefficients of the explanatory variables in the model are equal to zero. *** Significant at 1%; ** Significant at 5%; * Significant at 10%.
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 hypothesis of the Arellano-Bond test for autocorrelation is Ho: no autocorrelation. The null hypothesis of the Hansen test is Ho: overidentifying restrictions are valid.

Table B4
Post estimation diagnostic test results for the impulse responses of input- and investment-specific Luenberger dynamic productivity change associated with *investment in breeding stock* to genetic progress.

k	Tests	LPC [b]	TC [c]	TIC [d]	SIC [e]
1	Wald Test	903.44***	919.06***	475.24***	224.98***
	AR(1) in first differences	0.000	0.000	0.000	0.002
	AR(2) in first differences	0.567	0.169	0.314	0.483
	Hansen Test	0.055	0.860	0.122	0.924
	Number of instruments	6	6	6	6
	Number of observations	2655	2655	2655	2655
	Number of farms	1057	1057	1057	1057
2	Wald Test	877.54***	1037.00***	711.14***	239.79***
	AR(1) in first differences	0.000	0.000	0.000	0.011
	AR(2) in first differences	0.577	0.961	0.078	0.827
	Hansen Test	0.091	0.816	0.015	0.971
	Number of instruments	11	7	7	7
	Number of observations	1932	1932	1932	1932
	Number of farms	761	761	761	761
3	Wald Test	1407.86***	203.63***	650.61***	138.76***
	AR(1) in first differences	0.002	0.000	0.001	0.090
	Hansen Test	0.024	0.313	0.056	0.845
	Number of instruments	8	8	8	8
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
4	Wald Test	1227.13***	112.58***	680.17***	77.55***
	AR(1) in first differences	0.001	0.000	0.000	0.490
	Hansen Test	0.153	0.753	0.836	0.203
	Number of instruments	10	10	10	10
	Number of observations	1171	1171	1171	1171
	Number of farms	625	625	625	625
5	Wald Test	945.06***	106.56***	497.00***	24.17***
	Hansen Test	0.021	0.278	0.911	0.042
	Number of instruments	11	11	11	11
	Number of observations	546	546	546	546
	Number of farms	284	284	284	284

The models are fitted using two lags for the dependent variables and estimated using system GMM with Windmeijer (2005) corrected standard errors.
The null hypothesis of the Wald test is Ho: the coefficients of the explanatory variables in the model are equal to zero. *** Significant at 1%; ** Significant at 5%; * Significant at 10%.
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 hypothesis of the Arellano-Bond test for autocorrelation is Ho: no autocorrelation. The null hypothesis of the Hansen test is Ho: overidentifying restrictions are valid.

References

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association, 76*(375), 598–606.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29–51.

Atsbeha, D. M., Kristofersson, D., & Rickertsen, K. (2012). Animal breeding and productivity growth of dairy farms. *American Journal of Agricultural Economics, 94*(4), 996–1012.

Banker, R. D., & Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research, 175*(2), 1311–1320.

Babcock, B. A., & Foster, W. E. (1991). Measuring the potential contribution of plant breeding to crop yields: Flue-cured tobacco, 1954–87. *American Journal of Agricultural Economics, 73*(3), 850–859.

Bernal-Verdugo, L. E., Furceri, D., & Guillaume, D. (2013). Banking crises, labor reforms, and unemployment. *Journal of Comparative Economics, 41*(4), 1202–1219.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143.

Brümmer, B., Glauben, T., & Thijssen, G. (2002). Decomposition of productivity growth using distance functions: the case of dairy farms in three European countries. *American Journal of Agricultural Economics, 84*(3), 628–644.

Dakpo, K. H., & Lansink, A. O. (2019). Dynamic pollution-adjusted inefficiency under the by-production of bad outputs. *European Journal of Operational Research, 276*(1), 202–211.

EUROSTAT (2016). Price indices of agricultural products. Retrieved on 16 January 2018 from: http://ec.europa.eu/eurostat/data/database.

Geylani, P. C., Kapelko, M., & Stefanou, S. E. (2019). Dynamic productivity change differences between global and non-global firms: A firm-level application to the US food and beverage industries. *Operational Research*, 1–23.

Geylani, P. C., & Stefanou, S. E. (2013). Linking investment spikes and productivity growth. *Empirical Economics, 45*(1), 157–178.

Haug, A. A., & Smith, C. (2012). Local linear impulse responses for a small open economy. *Oxford Bulletin of Economics and Statistics, 74*(3), 470–492.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review, 95*(1), 161–182.

Jovanovic, B., & Nyarko, Y. (1996). Learning By Doing and the Choice of Technology. *Econometrica, 64*, 1299–1310.

Kapelko, M. (2019). Measuring productivity change accounting for adjustment costs: Evidence from the food industry in the European Union. *Annals of Operations Research, 278*(1–2), 215–234.

Kapelko, M., Lansink, A. O., & Stefanou, S. E. (2015). Analyzing the impact of investment spikes on dynamic productivity growth. *Omega, 54*, 116–124.

Kapelko, M., Oude Lansink, A., & Stefanou, S. E. (2012). Analysis of static and dynamic productivity growth in the Spanish meat processing industry. *Problems of World Agriculture: Scientific Journal. Warsaw University of Life Sciences, 12*(3), 24–36.

Kapelko, M., Oude Lansink, A., & Stefanou, S. E. (2016). Investment age and dynamic productivity growth in the Spanish food processing industry. *American Journal of Agricultural Economics, 98*(3), 946–961.

Kapelko, M., Oude Lansink, A., & Stefanou, S. E. (2017a). Input-Specific dynamic productivity change: Measurement and application to European dairy manufacturing firms. *Journal of Agricultural Economics, 68*(2), 579–599.

Kapelko, M., Oude Lansink, A., & Stefanou, S. E. (2017b). The impact of the 2008 financial crisis on dynamic productivity growth of the Spanish food manufacturing industry. An impulse response analysis. *Agricultural Economics, 48*(5), 561–571.

Klenow, P. J. (1998). Learning curves and the cyclical behavior of manufacturing industries. *Review of Economic Dynamics, 1*(2), 531–550.

Leibtag, E. (2009). How much and how quick? Pass through of commodity and input cost changes to retail food prices. *American Journal of Agricultural Economics, 91*(5), 1462–1467.

Li, Q. (1996). Nonparametric testing of closeness between two unknown distribution functions. *Econometric Reviews, 15*(3), 261–274.

Miesenberger, J., & Fuerst, C. (2006). Experiences in selecting on a total merit index in the Austrian Fleckvieh breed. *Biotechnology in Animal Husbandry, 22*(1–2), 17–27.

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777–787.

Oude Lansink, A., Stefanou, S., & Serra, T. (2015). Primal and dual dynamic Luenberger productivity indicators. *European Journal of Operational Research, 241*(2), 555–563.

Penrose, E. T. (1959). *The theory of the growth of the firm*. New York: Wiley.

Roibas, D., & Alvarez, A. (2010). Impact of genetic progress on the profits of dairy farmers. *Journal of Dairy Science, 93*(9), 4366–4373.

Roibas, D., & Alvarez, A. (2012). The contribution of genetics to milk composition: Evidence from Spain. *Agricultural Economics, 43*(2), 133–141.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics, 71*(1), 135–158.

Serra, T., Lansink, A. O., & Stefanou, S. E. (2011). Measurement of dynamic efficiency: A directional distance function parametric approach. *American Journal of Agricultural Economics, 93*(3), 756–767.

Silva, E., & Stefanou, S. E. (2003). Nonparametric dynamic production analysis and the theory of cost. *Journal of Productivity Analysis, 19*(1), 5–32.

Simar, L., & Zelenyuk, V. (2006). On testing equality of distributions of technical efficiency scores. *Econometric Reviews, 25*(4), 497–522.

Skevas, I. (2016). *A Bayesian Approach to Dynamic Efficiency and Productivity Measurement*. Germany: Georg-August-Universität Göttingen.

Skevas, I., Emvalomatis, G., & Brümmer, B. (2018). Productivity growth measurement and decomposition under a dynamic inefficiency specification: The case of German dairy farms. *European Journal of Operational Research, 271*(1), 250–261.

Steine, G., Kristofersson, D., & Guttormsen, A. G. (2008). Economic evaluation of the breeding goal for Norwegian Red dairy cattle. *Journal of Dairy Science, 91*(1), 418–426.

Teulings, C. N., & Zubanov, N. (2014). Is economic recovery a myth? Robust estimation of impulse responses. *Journal of Applied Econometrics, 29*(3), 497–514.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics, 126*(1), 25–51.

Wright, B. D. (2011). The economics of grain price volatility. *Applied Economic Perspectives and Policy, 33*(1), 32–58.