Animal Breeding and Productivity Growth of Dairy Farms

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Abstract

Breeding can result in more output per unit of inputs as well as improved quality of outputs. A genetic-based technical change component is introduced into the Malmquist index, and productivity growth due to genetic and nongenetic factors is estimated for Icelandic dairy farms with quality adjusted output. Only about 4 percent of the productivity growth has been genetic-based. More than a third of this growth can be attributed to better milk quality. Adoption of new nongenetic-based technologies explains most of the productivity growth.

Key words: breeding, dairy production, Malmquist decomposition, technical change

JEL codes: D24, O33, Q12, Q16.

Genetic improvement of biological inputs is an important source of technical change in agriculture (Kerr 1984; Babcock and Foster 1991). However, breeding is a slow process and one could argue that its effects on productivity can be ignored in the short run. This argument is flawed for several reasons. First, breeders have to consider heterogeneities in production conditions while developing new genetic material. For example, attributes related to disease resistance may be the priority in one area while heat tolerance may be the priority in another. Once inputs with different genetic attributes are adopted by farmers, the genetic variation will persist at the farm level.

Second, as the literature in adoption behavior shows (e.g., Feder, Just, and Zilberman 1985), the adoption of new technologies is slow and can vary among socio-economic groups of farmers due to factors such as risk preferences, infrastructural constraints, and prices. This slow diffusion of new genetic material creates short run variation among farms depending on where each farm is in the adoption process. In addition, other farm level managerial decisions can give rise to short run variation in genetic material. For example, dairy production inherently involves a continuous transfer of genetic material either naturally or through artificial insemination. Consequently, the genetic status of dairy cows on a farm is partly determined by managerial decisions such as the choice between natural and artificial insemination, the choice of breed, the proportion of a herd selected to be parents for replacement cows, and how quickly a new generation of cows replaces the former generation. The resulting variation in the genetic technology can explain short run productivity differences among farms.

Agricultural economists have been interested in the effects of breeding on yield and its variability (e.g., Babcock and Foster 1991; Byerlee 1993; Godden and Brennan 1994; and Nalley, Barkley, and Featherstone 2010). Since variety performance data under farmer growing conditions are very rare, most of these studies used variety trial data obtained from crop research stations. For example, Babcock and Foster (1991) found that new genetic material led to annual yield gains between 0.47 and 0.67 percent in three tobacco growing regions of the U.S. between 1954 and 1987. Similarly, Nalley, Barkley, and Featherstone (2010) also found that wheat yield had increased by 0.46 percent per year due to breeding in Yaqui Valley in Mexico. While such studies provide estimates of the potential yield gains from breeding or genetic-based technical change, it is likely that the actual farm level gains will differ due to farm specific conditions including adoption and other managerial behaviors. For example, Byerlee (1993) found that research station data overestimated the effects of breeding at a farm level. He found annual yield gain of 1 percent on research station plots in Pakistan's Punjab region while average yield gain for actual farms in the area, measured by varietal improvement index, was 0.6 percent. According to the author the slow diffusion of newly released varieties is a likely reason for the yield difference.

In addition, measurement of productivity effects from breeding have frequently focused on yield levels. However, breeding can also result in changes that may not be reflected as yield increases over time. For example, yield maintenance through improved disease resistance and improving product quality (Godden and Brennan 1994; Marasas, Smale, and Singh 2003). Such improvements will be reflected as reduced expenditures on pesticides or veterinary services as well as better product prices. In a South African case, for example, Townsend and Thirtle (2001) found that the estimates of returns from livestock research were likely to be underestimated by a minimum of 50 percent when yield maintenance effects were ignored. Furthermore Saito et al. (2009) showed that wheat breeding in Japan has been quality oriented. They found that the mean wheat yield was higher for standard than new varieties while new varieties have higher protein content, which results in higher wheat prices.

We contribute to the literature in three ways. First we measure overall productivity growth on Icelandic dairy farms over the period 1997 - 2006 using the Malmquist productivity index (Malmquist 1953). The Malmquist productivity index has been frequently used to measure productivity change among dairy farms and to decompose for the sources of productivity change including technical progress (e.g., Tauer 1998; Newman and Matthews 2006). Second, we extend the decomposition of the Malmquist index by decomposing the technical change component of the index further into one genetic- and one nongenetic-based technical change components. Given that farm level indicator of genetic progress is used in the process, actual productivity change due to breeding rather than potential productivity change is measured. Consequently, we can also study the distribution of productivity change from genetic-based technical change in terms of farm level characteristics. Since we use a technology specification that allows for changes in nongenetic inputs, cost reducing yield maintenance effects from breeding are also captured. Third, accounting for quality is important for accurate measurement of productivity change. In the productivity literature, augmenting the input and output vectors with quality attributes has been used as a way of addressing the problem e.g., Fixler and Zieschang (1992) and Färe et al. (2006). However, we do not have detailed account of the attributes of inputs and outputs in our data. Therefore, we develop a hedonic approach to partially account for milk quality based on market valuation of milk. The correction for quality allows us to identify improvement in milk quality as a form of productivity growth through implicit decomposition as in Färe et al. (2006).

The Structure of Icelandic Dairy Farms

Icelandic dairy farms are usually organized as small family owned enterprises with an average herd size of 30 dairy cows. Cow milk provides more than 85 percent of the farm sales revenue while meat production is to a large extent a side production. Milk production has been subjected to supply control since 1980 using a quota system that evolved slowly towards freely tradable quota in 1992 (Johannesson and Agnarsson 2004; Bjarnadottir and Kristofersson 2008). The flexibility of this system allowed structural changes in the dairy sector towards fewer and bigger farms (Icelandic Research Fund, 2001). For example, in the period 1993 to 2006 the number of dairy farms decreased by more than 50 percent while the average number of dairy cows per farm nearly doubled (Bjarnadottir and Kristofersson 2008). Such transformation is also partly made possible by the substantial improvement in yield per cow which has increased by more than 32 percent from 1990 to 2007 (The Farmers Association of Iceland 2009). Apart from successful dairy cow breeding, several nongenetic factors are responsible for this. First, feed quality has improved significantly during this period due to better feed processing and storage methods, e.g., the introduction of round bales in late 1980s. Moreover the widespread cultivation of high quality forage (e.g., timothy), increased local production of concentrates, mainly barley, and mechanization of feeding as well as the introduction of automated milk parlors contributed for the gain in yield per cow. A combination of all these factors makes our sample period a period of substantial productivity gain for the Icelandic dairy sector.

Theoretical Model

Multiple output technologies are frequently modeled by using distance (e.g., Brümmer, Glauben, and Thijssen 2002; Karagiannis, Midmore, and Tzouvelekas 2004), profit (e.g., Quiroga and Bravo-Ureta 1992), and cost functions (e.g., Mosheim and Lovell 2009). We do not have complete input prices and therefore we use an input distance function representation of the technology.[1]

Input Distance Functions

For a vector of inputs $\mathbf{x} = (x_1, x_2, ...x_N)$ and a vector of outputs $\mathbf{y} = (y_1, y_2, ...y_M)$, a multiple output dairy technology can be defined in terms of the input requirement set $V(\mathbf{y})$ such that

$$(1) \qquad V(\mathbf{y}) = \{\mathbf{x} : (\mathbf{x}, \mathbf{y}) \in T(g, t) : \mathbf{x} \text{ can produce } \mathbf{y}\}$$

where *T* represent the technology set as defined by the state of genetic-based technology *g* and non-genetic-based technology *t*. We assume that the technology satisfies the standard economic properties as discussed in Färe and Primont (1990). The input distance function $D^{t,g}(\mathbf{x}, \mathbf{y})$ defined on the technology set is given as

$$(2) \qquad D^{t,g}(\mathbf{x}, \mathbf{y}) = \max_{\lambda} \left\{ \lambda \geq 1 : \frac{\mathbf{x}}{\lambda} \in V(\mathbf{y}) \right\}$$

where λ is an input scaling factor. $D^{t,g}(\mathbf{x}, \mathbf{y})$ is nondecreasing, homogeneous of degree one, and concave with respect to inputs, and quasiconcave and nonincreasing with respect to outputs (Färe and Primont 1990). Moreover, $D^{t,g}(\mathbf{x}, \mathbf{y}) \geq 1$ if $\mathbf{x} \in V(\mathbf{y})$ and $D^{t,g}(\mathbf{x}, \mathbf{y}) < 1$ if $\mathbf{x} \notin V(\mathbf{y})$, i.e., $D^{t,g}(\mathbf{x}, \mathbf{y}) \geq 1$ indicates a feasible input mix for the arbitrarily chosen output vector and $D^{t,g}(\mathbf{x}, \mathbf{y}) < 1$ indicates an infeasible input mix.

The Malmquist Index and Genetic-Based Technical Change

The Malmquist productivity index compares productivity differences between two data points based on a given reference technology. Following Färe et al. (1992), we define the Malmquist productivity index with an input orientation as a geometric mean of Malmquist indices for two adjacent periods s and $s+1$ as

$$(3) \qquad M\left(\mathbf{x}^{s},\mathbf{y}^{s},\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)=\sqrt{\frac{D^{t^{s},g^{s}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s},g^{s}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}\times\frac{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}}.$$

Given that $D^{t,g}\left(\mathbf{x},\mathbf{y}\right)\geq 1$ for any feasible input-output mix and $D^{t,g}\left(\mathbf{x},\mathbf{y}\right)<1$ for infeasible input-output mix, $M\left(\mathbf{x}^{s},\mathbf{y}^{s},\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)$ can assume a value which is less than, equal to, or greater than unity to indicate productivity growth, stagnation, or decline, respectively. Multiplying equation (3) by one, i.e., $\left(\frac{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}\frac{D^{t^{s},g^{s}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}{D^{t^{s},g^{s}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}\right)$ and rearranging, we obtain a decomposition of the index into productivity change due to technical efficiency change ΔTE and productivity change due to technical change ΔT. Hence, equation (3) becomes

$$\begin{aligned}(4) \qquad M\left(\mathbf{x}^{s},\mathbf{y}^{s},\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)&=\frac{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s},g^{s}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}\times\\ &\quad\sqrt{\frac{D^{t^{s},g^{s}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}\times\frac{D^{t^{s},g^{s}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s},\mathbf{y}^{s}\right)}}\\ &=\Delta TE\left(\mathbf{x},\mathbf{y}\right)\times\Delta T\left(\mathbf{x},\mathbf{y}\right).\end{aligned}$$

Then, by multiplying with $\left(\frac{D^{t^s,g^{s+1}}\left(\mathbf{x}^s,\mathbf{y}^s\right)}{D^{t^s,g^{s+1}}\left(\mathbf{x}^s,\mathbf{y}^s\right)}\frac{D^{t^{s+1},g^s}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s+1},g^s}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}\right)$ and rearranging, the technical change component in equation (4) can further be decomposed into a component measuring the contribution of genetic-based technical change ΔT^g and a component measuring the contribution of nongenetic-based technical change ΔT^{ng} as

$$
\begin{aligned}
(5)\qquad \Delta T\left(\mathbf{x},\mathbf{y}\right) &= \sqrt{\frac{D^{t^s,g^s}\left(\mathbf{x}^s,\mathbf{y}^s\right)}{D^{t^s,g^{s+1}}\left(\mathbf{x}^s,\mathbf{y}^s\right)}\times\frac{D^{t^{s+1},g^s}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}}\times \\
&\quad \sqrt{\frac{D^{t^s,g^{s+1}}\left(\mathbf{x}^s,\mathbf{y}^s\right)}{D^{t^{s+1},g^{s+1}}\left(\mathbf{x}^s,\mathbf{y}^s\right)}\times\frac{D^{t^s,g^s}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}{D^{t^{s+1},g^s}\left(\mathbf{x}^{s+1},\mathbf{y}^{s+1}\right)}} \\
&= \Delta T^g\left(\mathbf{x},\mathbf{y}\right)\times\Delta T^{ng}\left(\mathbf{x},\mathbf{y}\right).
\end{aligned}
$$

Like equation (3), each of the component indices reflect positive, zero, or negative contribution to productivity change when it takes a value less than, equal to, or greater than unity, respectively.

Empirical Model

We follow Fuentes, Grifell-Tatjé, and Perlman (2001) and undertake the decomposition above parametrically. Therefore, we specify an input distance function in a symmetric translog form. Neglecting subscripts denoting farm and time periods, our specification is

$$
\begin{aligned}
(6) \qquad \ln D^{t,g}(\mathbf{x},\mathbf{y}) = {} & \alpha_0 + \sum_{i=1}^{N} \alpha_i \ln x_i + \sum_{j=1}^{M} \beta_j \ln y_j + \gamma \ln g + \theta t + \\
& \sum_{i=1}^{N} \sum_{j=1}^{M} \lambda_{ij} \ln x_i \ln y_j + \sum_{i=1}^{N} \delta_{gi} \ln g \ln x_i + \sum_{i=1}^{N} \alpha_{ti} t \ln x_i + \\
& \sum_{j=1}^{M} \phi_{gj} \ln g \ln y_j + \sum_{j=1}^{M} \beta_{tj} t \ln y_j + \gamma_{tg} t \ln g + \\
& \frac{1}{2} \left[\sum_{i=1}^{N} \sum_{n=1}^{N} \alpha_{in} \ln x_i \ln x_n + \sum_{m=1}^{M} \sum_{l=1}^{M} \beta_{ml} \ln y_m \ln y_l + \right. \\
& \left. \gamma_{gg} \ln g \ln g + \theta_{tt} t^2 \right] + \xi .
\end{aligned}
$$

Homogeneity of degree one in inputs implies $\sum_{i=1}^{N} \alpha_i = 1, \sum_{i=1}^{N} \alpha_{in} = \sum_{i=1}^{N} \lambda_{ij} = 0$ and $\sum_{i=1}^{N} \delta_{gi} = \sum_{i=1}^{N} \alpha_{ti} = 0$, while quadratic symmetry of the form $\alpha_{in} = \alpha_{ni}$ and $\beta_{ml} = \beta_{lm}$ complete the symmetry restriction. These restrictions are imposed before estimation. The error term in equation (6) is a composite error term given as $\xi = \upsilon - u$, where υ is a symmetric two-sided error term assumed to satisfy the classical assumptions, i.e., $\upsilon \overset{iid}{\sim} N\left(0, \sigma_{\upsilon}^2\right)$, while u is a one-sided nonnegative error term that measures technical inefficiency and assumed to follow a truncated normal distribution $u \overset{iid}{\sim} N^{+}\left(\mu, \sigma_{\mu}^2\right)$.[2] The two error terms are assumed to be orthogonal with each other as well as with the independent variables of the model.

Output Quality and Productivity Change

Icelandic dairy processors adjust the unit price according to the quality of milk. The adjustment depends on the nutrient composition and hygienic quality, and therefore a quota restricted farmer may upgrade milk quality to increase the unit value of the farm's milk output. Milk quality is influenced by managerial decisions such as feeding strategies, milking patterns, production level, and handling practices as well as genetic attributes of the dairy herd. Therefore, variations in managerial ability and genetic attributes of dairy herds are likely to cause differences in the milk quality and hence the unit value paid to producers. The farm (*f*) and time (*s*) specific unit value v_{fs} of milk is

$$(7) \qquad v_{fs} = p + h\left(c_{fs}\right)$$

where *p* is the average market price paid per liter of milk with average quality during the period and $h(c_{fs})$ is a hedonic adjustment that depends on the characteristics *c* of the milk. This adjustment describes the mark up (or down) per liter received by a farmer for milk quality above (or below) the average quality of milk.

The average market price *p* is the grand mean of the farm-specific prices p_{fs} paid for milk of average quality. The farm-specific price is a weighted average of the price paid for milk of average quality produced within the farm quota p_s^w and a reduced price p_s^o paid for average quality milk produced outside the farm quota.[3] Therefore, the farm specific price for average quality milk is calculated as

$$(8) \qquad p_{fs} = \left(1-\delta_{fs}\right) p_s^w + \delta_{fs} p_s^o$$

where

$$(9) \qquad \delta_{fs} = \begin{cases} 0 & \text{if } y_{fs}^{milk} \le y_{fs}^{\max} \\ \dfrac{\left(y_{fs}^{milk} - y_{fs}^{\max}\right)}{y_{fs}^{milk}} & \text{if } y_{fs}^{milk} > y_{fs}^{\max} \end{cases}$$

where y_{fs}^{milk} denotes the total production and $y_{fs}^{\max}$ the farm milk quota. Given the unit value function (7), the quality adjusted output of milk, y_{fs}^{*} is calculated as

$$(10) \quad y_{fs}^{*} = y_{fs}^{milk} \frac{v_{fs}}{p}.$$

The adjustment factor represents the market valuation of the milk output of the farm relative to the value of average quality milk. The milk output of farmers who produce milk of average quality is the observed output while for other farmers the adjustment factor will scale up (down) the observed milk output.[4] In other words, the observed milk output is recalculated to milk output of average quality.

The contribution of changes in milk quality to productivity growth can be found by estimating the input distance function using quality adjusted and unadjusted milk outputs. Malmquist indices are then computed using each of the estimates and the resulting indices are combined as in Färe et al. (2006) to obtain an implicit decomposition given as

$$(11) \quad Q\left(\mathbf{x}^{s}, \mathbf{y}^{*s}, \mathbf{x}^{s+1}, \mathbf{y}^{*s+1}\right) = \frac{M^{*}\left(\mathbf{x}^{s}, \mathbf{y}^{*s}, \mathbf{x}^{s+1}, \mathbf{y}^{*s+1}\right)}{M\left(\mathbf{x}^{s}, \mathbf{y}^{s}, \mathbf{x}^{s+1}, \mathbf{y}^{s+1}\right)}$$

where $M\left(\mathbf{x}^{s}, \mathbf{y}^{s}, \mathbf{x}^{s+1}, \mathbf{y}^{s+1}\right)$ is the Malmquist index before the quality adjustment and $M^{*}\left(\mathbf{x}^{s}, \mathbf{y}^{*s}, \mathbf{x}^{s+1}, \mathbf{y}^{*s+1}\right)$ is the index after the adjustment. $M^{*}\left(\mathbf{x}^{s}, \mathbf{y}^{*s}, \mathbf{x}^{s+1}, \mathbf{y}^{*s+1}\right)$ is also decomposed as shown for $M\left(\mathbf{x}^{s}, \mathbf{y}^{s}, \mathbf{x}^{s+1}, \mathbf{y}^{s+1}\right)$.We use the notation used in equations (4) and (5) to identify the components of $M^{*}\left(\mathbf{x}^{s}, \mathbf{y}^{*s}, \mathbf{x}^{s+1}, \mathbf{y}^{*s+1}\right)$, but we add an asterisk on the notation of each components such that, for example ΔT^{g*} represents productivity change from genetic-based technical change after we adjust for milk quality.

Data

An unbalanced panel covering the period 1997 – 2006 is used for estimation. The data is obtained from 324 dairy farms in Iceland and contains 1,255 observations. Each dairy farm is observed for 3.9 years on average. The outputs are milk and meat. The inputs are quantities of forage and concentrates, the cost of veterinarian services,[5] the number of cows adjusted for the number of days in a year that a cow was active in milk production, farm capital measured by the cost of farm capital, land size, and the farmers' own estimates of labor input. Table 1 provides the summary statistics of the included variables.

Like most data on self reported labor use, the farmers' estimates of labor input show signs of rounding error as there are high frequency of observations at multiples of six. To deal with this measurement error, we predicted the labor input using each farm's quota for milk, $y_{fs}^{\max}$, milk prices, p, and their interactions.[6] The first stage results are reported in table A1 of the supplementary appendix. About a quarter of the variation in labor input is explained by the model. The low explanatory power could have created a weak instrument problem in our second stage model. However, as suggested by Staiger and Stock (1997), the information content of instruments used to predict an endogenous variable can be obtained from the *F* value of a joint significance hypothesis for the coefficients of all instruments in the first stage regression. For a case of one endogenous variable, they suggest that if the computed *F* value exceeds 10, one needs not to worry about a weak instrument problem. In our case, the *F* value equals 80.51, and hence, we used the predicted values for labor input in the second stage model. Zero values for concentrates, meat quantities, and veterinary services were replaced by one.[7]

In addition to input and output quantities, the dataset contains detailed information on the genetic attributes of the average cow's sire in each of the farms.

Currently, the breeding goal for the Icelandic dairy cattle targets eight traits, which are summarized in table 2. The Icelandic breeding program, like most breeding programs elsewhere, gives high weights to production related traits, accounting 44 percent of the overall economic weight. The change in genetic material i.e., genetic-based technical change that has occurred at a farm level is measured through an aggregate breeding index constructed for the average sire of all cows in the herd.[8] This index is constructed by weighted aggregation of the estimated breeding values (EBVs) of the average sire for all the traits where the weights are the economic values of each trait, i.e., the increase in farm profit following a unit gain in the EBV of a trait *ceteris paribus*, as determined by the breeding organization. As shown in table 1, the mean aggregate breeding index for a dairy herd on the average farm in the sample is 99.55 and it has been improving at a rate of 0.67 percent per year between 1997 and 2006. Finally, a trend variable is included to proxy nongenetic-based technical change.

Estimation and Results

The variables were normalized to their mean values in 2006 and hence the first-order coefficients can be interpreted as elasticities at the point of normalization. Homogeneity of degree one was imposed by dividing the input quantities with the costs of veterinary services. Equation (6) was initially estimated with a time variant specification for technical inefficiency (Battese and Coelli 1992), using milk output adjusted for quality. However, the likelihood ratio test could not reject a time invariant specification (LR = 1.12, *p*-value = 0.28). Consequently, a time invariant specification was used. Moreover, we tested for restrictions on the technology and nonrejected restrictions were imposed. The results of these Wald tests are reported in table 3. The dairy technology is characterized by Hicks as well as scale neutral genetic-based technical change while nongenetic-based technical change is only Hicks neutral.[9]

The estimated parameters and the associated *p* values of the input distance function estimated before adjusting for milk quality are reported in table A2 of the supplementary appendix. We only obtain the composite error term from these estimates, and the time invariant technical efficiency score for each farm is obtained by using the conditional expectation predictor of Jondrow et al. (1982). Based on the estimates in table A2, Icelandic dairy farms exhibit high technical efficiency levels with the associated average technical efficiency score of 91 percent. This estimate is in the same level as obtained by other studies using the same methodology on a sample of specialized dairy farms. For example, from a parametrically estimated input distance function, Sipiläinen (2007) found that the mean technical efficiency score of specialized Finnish dairy farms between 1990 - 2000 is 91.3 percent.

The estimated parameters and the associated *p* values for the input distance function, using the quality adjusted milk output, are reported in table A3 of the supplementary appendix. At the point of normalization, the quality adjustment for milk output has mainly affected the parameter estimate of milk output and inputs associated with milk quality such as quantity of concentrates, breeding index and labor. Based on the estimates in table A3, the time invariant average technical efficiency score is 89 percent. The difference in the medians of the technical efficiency scores from the models with quality adjusted and unadjusted milk output is tested using Wilcoxon's sign test and the null hypothesis of equal medians is strongly rejected ($p = 0.000$). High technical efficiency scores before correcting for milk quality can then be taken as indications of improved milk quality during the sample period.

Despite the temporal invariance, there are cross sectional differences of technical efficiency in terms of farm size as measured by number of cows and the farmer's age.[10] Farms with larger herds and farms operated by younger farmers are more technically efficient than their counterparts, although the differences are quite small.[11]

The year to year average productivity growth rate after milk quality adjustment and its decomposition into genetic and non-genetic components are presented in table 4. The components were tested to determine if they were significantly different from one (e.g., H_0: $\Delta T^{g^*} = 1$) using the nonparametric Wilcoxon's signed-rank test. In all cases, the null hypothesis was rejected suggesting that the productivity contribution of each component is statistically different from zero.[12] Table 4 shows that the average productivity growth in the dairy farms was 4.86 (i.e., (1 – 0.9514) × 100) percent per year, and has been increasing at a declining rate throughout the decade. Productivity increased by 0.19 (i.e., (1 – 0.9981) × 100) percent annually on average due to genetic-based technical change. This is about 4 percent of the overall productivity growth and nongenetic-based technical change accounted the rest of the overall productivity growth. As discussed before, this is most likely due to the widespread adoption of new nongenetic-based technologies during the period.

The year to year average productivity growth rate before milk quality adjustment and its decomposition into genetic and non-genetic components are presented in table 5. The associated estimate of average productivity growth from genetic-based technical change is 0.12 (i.e., (1 – 0.9988) × 100) percent per year. Relative to what was found after milk quality adjustment; this result indicates that about 37 percent of the productivity contribution of genetic-based technical change is in the form of improved milk quality.

Although genetic-based technical change was found to be Hicks neutral, the productivity gains from genetic-based technical change appear to be nonlinearly related to feeding strategy as measured by the concentrate-to-forage ratio. As shown in figure 1, at very low levels of concentrate use, the productivity gain from genetic-based technical change responds negatively to increases in concentrate use, but the productivity gain increases rapidly as the share of concentrates in the feed ration increases. [13]

Figure 2 shows the trends in productivity growth from genetic- and nongenetic-based technical change. The trend of productivity change from genetic-based technical change shows a clear drop during 2001 to 2003. The most likely cause of this drop is a reduction in the use of concentrates, which strongly affects the productivity growth from genetic sources. The reduction in concentrate use was caused by an increase in the relative price of concentrates during these years. The relative price increase was the result of a decline in the exchange rate of the Icelandic Króna (ISK) after the Central Bank of Iceland changed the exchange rate regime from fixed-floating to floating in 2001. The exchange rate improved slowly until 2006, lowering the relative price of concentrates again. This explanation is supported by a statistically significant pair wise correlation ($\rho = -0.74$, p-value $= 0.024$) between the yearly average exchange rate index for the ISK and the productivity growth from genetic-based technical change. Figure 3 shows the monthly averages of the exchange rate index for the ISK. The index shows a similar pattern as the productivity growth from genetic-based technical change in figure 2.

The productivity contribution of genetic-based technical change to productivity growth can be highlighted further by classifying the farms into farms with high and low genetic quality dairy cows. We define farms with high genetic quality dairy cows as farms where the EBV of the average sire of cows in the herd is greater than 100, which is the population average. The rest of the farms are classified as farms with low genetic quality dairy cows. The productivity contribution of genetic-based technical change is as high as 6.2 percent $\left(\Delta T^{g^*}=0.9970\right)$ and as low as 2.3 percent $\left(\Delta T^{g^*}=0.9989\right)$ of the average overall productivity growth per year among farms with high genetic quality dairy cows and with low genetic quality dairy cows, respectively. The significance of the difference between the distributions of productivity gains from genetic sources for the two groups was tested using the nonparametric Mann-Whitney two sample test. It was found that the underlying distributions of productivity gains from genetic sources are different for the two groups ($z=-9.778,\ p\text{-value}=0.000$). We have also tested for differences in productivity contribution of genetic-based technical change based on the proportion of unregistered cows on the farm or cows from unknown sires.[14] For farms with less than half of the dairy herd consisting of unregistered cows, the productivity contribution of genetic-based technical change ($\Delta T^{g^*}=0.9978$) is four times bigger compared to farms with more than half of the dairy herd consisting of unregistered cows ($\Delta T^{g^*}=0.9995$). The null hypothesis of identical distributions of productivity gains from genetic sources for the groups defined based on proportion of unregistered cows is also rejected ($z=-6.163,\ p\text{-value}=0.000$).

Finally, the contribution of milk quality changes to productivity growth can be computed by combining the Malmquist indices in table 4 and 5 as discussed before. Accordingly, improved milk quality led to a productivity growth of about 1.5 percent per year on average. Both genetic and nongenetic sources have contributed for the quality gain during the period.

Conclusions

Most previous research has used data from research stations to measure the effects of breeding. Research station data neglects farm specific managerial behavior that may affect the actual gains from breeding. We measured the productivity contribution of breeding from farm level data using the multifactor Malmquist productivity index extended with a genetic-based technical change component. This index provides an improved measurement of productivity gains due to changes in genetic material as compared to other indices that neglect changes in other inputs use, such as the varietal improvement index. Moreover, we demonstrated that the emphasis on yield only can lead to underestimation of productivity gains when product quality improving effects of breeding are ignored. Our results show evidence of significant productivity growth in the Icelandic dairy sector. The average productivity growth was 4.86 percent per year. However, genetic-based technical change has contributed only about 4 percent of this growth or 0.19 percent annually. About 37 percent of the contribution from genetic-based technical change was in the form of better milk quality.

Furthermore, the productivity growth from genetic-based technical change is smaller for farms with high proportion of unregistered cows and it is also sensitive to concentrate intensity in the feed ration of the dairy cows. Concentrates are largely imported from abroad, and as a result the productivity growth from genetic-based technical change exhibits a pattern that closely follows fluctuations in the exchange rate of the ISK. Promoting local production of concentrates may therefore lead to stability of returns from breeding.

Footnotes

[1] Distance functions can be input or output oriented and the two orientations are equivalent only under constant returns to scale (Coelli et al. 2005). Farm specific milk quotas are determined each year by a committee of stakeholders including farmers' representatives and the government and are based on past production levels. Although tradable, the allocated milk quota will to a large extent determine the output level of each dairy farm, and therefore we believe an input distance function is the most appropriate representation of dairy technology in the Icelandic case.

[2] Other frequently used distributional assumptions for the inefficiency term are half normal, exponential, and gamma distributions. Coelli, Rao, and Battesse (2005) argue that there are no á priori reason to prefer one of them since each distribution has its own pros and cons.

[3] The price of milk of average quality produced within the farm level quota is determined by the government and the reduced price paid for average quality milk produced outside the quota is determined by market conditions.

[4] Since more than 85 percent of the total value of farm output is milk, meat output is considered to be a byproduct and no quality adjustment was made for the meat quantity.

[5] The cost of veterinary services can be considered to be a weighted aggregation, where market prices are used as the weights of different veterinary services that otherwise cannot be aggregated.

[6] The choice of predictors is based on the fact that quota is the most important determinant of farm scale, while quota and prices together determine revenue. The farms ability to employ the farmer and his family is to a large extent determined by these factors.

[7] The parameter estimates of the input distance function were stable when alternative replacements to zero observations (0.95 and 1.5) were used.

[8] Given that the true genetic quality of a dairy bull is unobservable, the construction of the breeding index for each bull by the breeding organization involves estimation of breeding values (EBVs) from performance data collected from the daughters of the bull, their relatives and herd mates. Together with á priori information on heritability and correlations between different traits, a prediction is made about the genetic quality of the bull after allowing for the contribution of environmental factors. The EBVs of the average sire in a herd is then constructed through a weighted aggregation of the EBVs of each cow's sire for each trait using weights such as number of days a cow is active in milk production during a year.

[9] The quadratic term for the breeding index and its interaction with the trend variable were also insignificant and are dropped in the final specification.

[10] The plots showing the technical efficiency scores for different herd sizes and ages of farmers is presented in figure A1 of the supplementary appendix.

[11]Experience is expected to improve farmer's performance and one possible explanation for our result is that larger farms are operated by younger farmers. Alternatively it could also be a result of higher education among young than old farmers, which can compensate for lack of experience.

[12] The rate of productivity change due to the different sources in tables 4 and 5 is computed by subtracting the values for each source from one and a test for statistical difference from one is the appropriate test. For example, based on table 4, the average productivity growth per year on the average farm is $(1 - 0.9514) \times 100 = 4.86$ percent.

[13] High concentrate intensity in the feed maximizes the energy intake of high yielding dairy cows and the maximum energy intake is achieved when the concentrate intensity is 75 percent (Hardarson 2002).

[14] The proportion of cows with unknown sires determines the state of genetic-based technical change on the farm as cows with unknown sires tend to be genetically inferior compared to cows that originated from proven bulls in the breeding program. For example, Norman et al. (2003) found that milk yields for daughters of proven bulls can be 366 – 444 kilograms higher than daughters of natural service bulls.

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Table 1. Descriptive Statistics of Variables

Variable	Mean	Std. Dev.	Min.	Max.
Breeding index	99.55	2.47	94.73	109.63
Concentrates (feed units)	23,339.76	19,135.73	0	144,470.30
Forage (feed units)	168,713.70	74,104.41	20,000.00	582,500.00
Capital ('000 ISK)	2,996.94	2,236.64	288.45	20,039.25
Veterinary services ('000 ISK)	236.19	176.14	0	1,256.63
Milk quota (liters)	137,868.50	65,609.88	30,657.00	562,263.00
Land (hectares)	46.57	17.83	13.00	138.00
Number of cows (cow years)	31.73	12.75	4.50	119.00
Labor (months / year)	24.34	4.16	15.95	46.06
Milk (liters)	140,979.10	66,682.34	29,249.00	520,137.00
Meat (kgs.)	3,497.30	10,165.85	0	283,941.70

Table 2. Weights for Groups of Traits Used in the Icelandic Cattle Breeding Program

Traits	Economic Weights
Production	44
Udder, teats, and mastitis resistance	24
Milking behavior and temperament	16
Fertility	8
Longevity	8

Source: The Farmers Association of Iceland (www.bondi.is).

Table 3. Wald Tests of Restrictions on the Technology

Restriction	χ^2	*p*-value
Cobb-Douglas technology	1334.25	0.000
Genetic-based technical change		
Hicks neutral	4.98	0.547
Scale neutral	0.81	0.668
Non genetic-based technical change		
Hicks neutral	9.01	0.173
Scale neutral	203.57	0.000

Table 4. Productivity Decomposition for Iceland Dairy Farms, 1997 – 2006: After Milk Quality Adjustment

Year	Genetic-Based Technical Change (ΔT^{g*})	Non Genetic-Based Technical Change (ΔT^{ng*})	Malmquist Index (M^{*})
1997	-	-	-
1998	0.9984	0.9191	0.9177
1999	0.9976	0.9295	0.9273
2000	0.9981	0.9365	0.9346
2001	0.9993	0.9416	0.9410
2002	1.0002	0.9436	0.9437
2003	0.9997	0.9584	0.9581
2004	0.9977	0.9706	0.9684
2005	0.9965	0.9799	0.9765
2006	0.9971	0.9889	0.9860
Mean	0.9981	0.9532	0.9514
S.D.	0.0027	0.0296	0.0291
Min.	0.9878	0.8886	0.8877
Max.	1.0069	1.0477	1.0466

Table 5. Productivity Decomposition for Iceland Dairy Farms, 1997 – 2006: Before Milk Quality Adjustment

Year	Genetic-Based Technical Change (ΔT^{g})	Non Genetic-Based Technical Change (ΔT^{ng})	Malmquist Index (M)
1997	-	-	-
1998	0.9990	0.9437	0.9427
1999	0.9985	0.9516	0.9502
2000	0.9988	0.9569	0.9557
2001	0.9996	0.9604	0.9600
2002	1.0001	0.9607	0.9608
2003	0.9998	0.9708	0.9706
2004	0.9986	0.9789	0.9775
2005	0.9978	0.9857	0.9835
2006	0.9982	0.9918	0.9900
Mean	0.9988	0.9675	0.9663
S.D.	0.0017	0.0223	0.0220
Min.	0.9924	0.9186	0.9175
Max.	1.0043	1.0434	1.0442

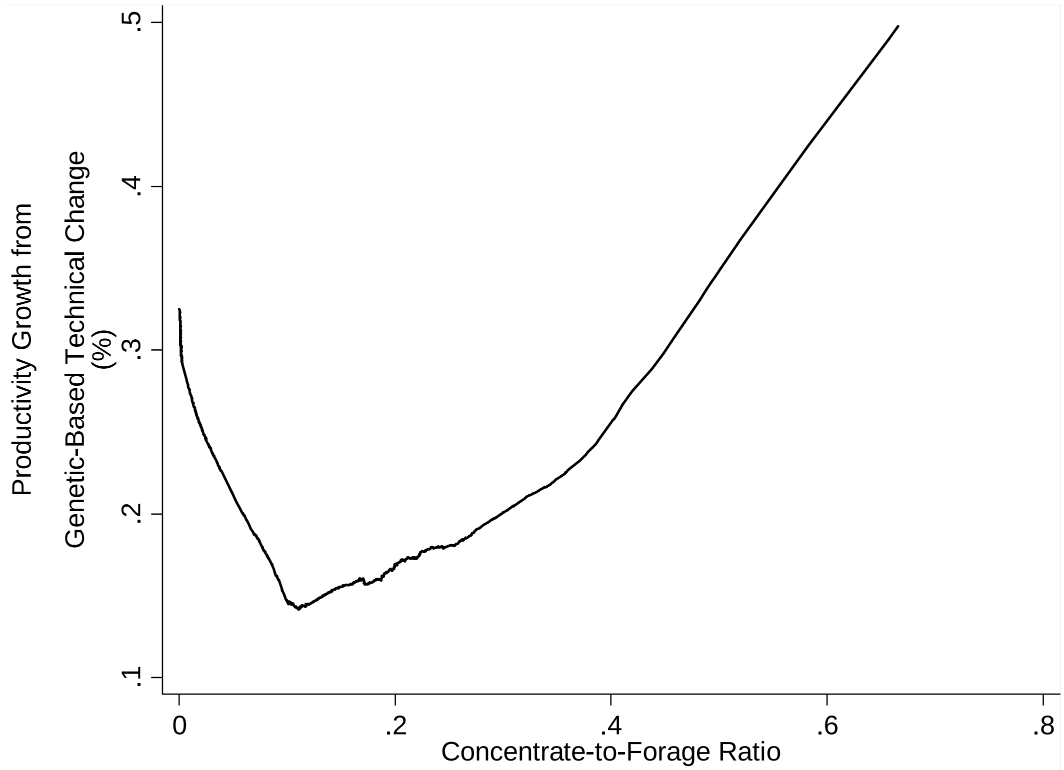
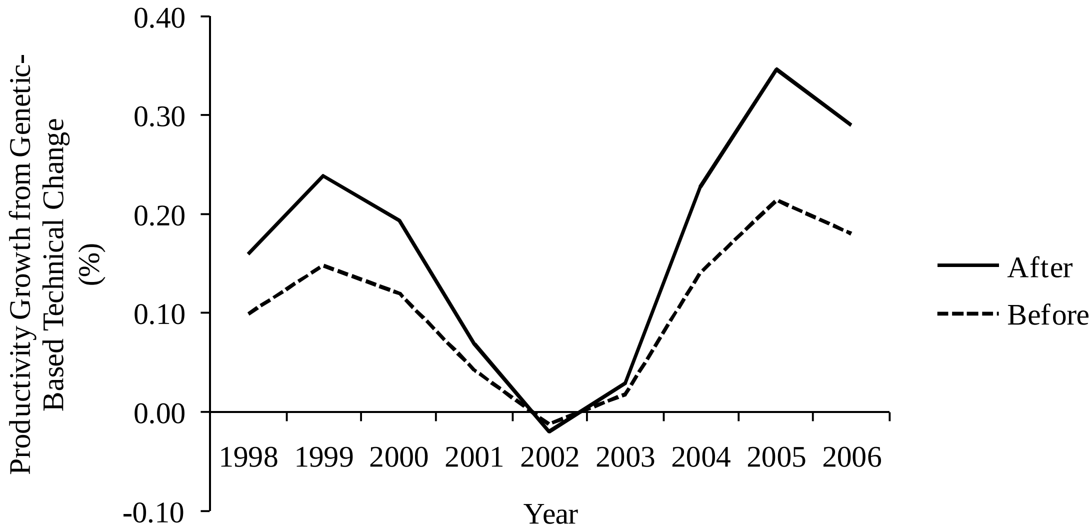


Figure 1. Productivity growth from genetic-based technical change and concentrates –to-forage ratio



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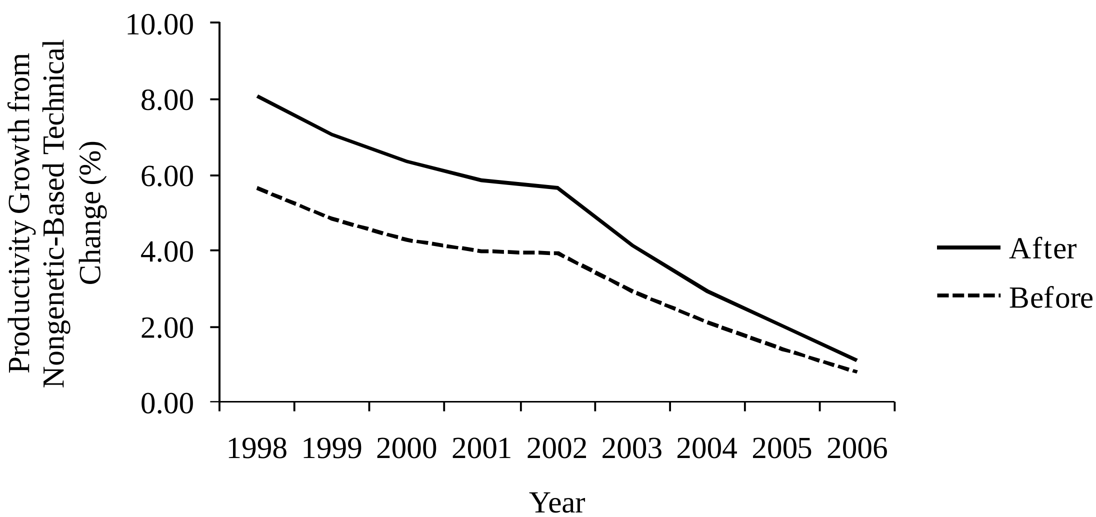


(2b)

Figure 2. Productivity growth from genetic- (2a) and nongenetic-based (2b) technical change: before and after quality adjustment

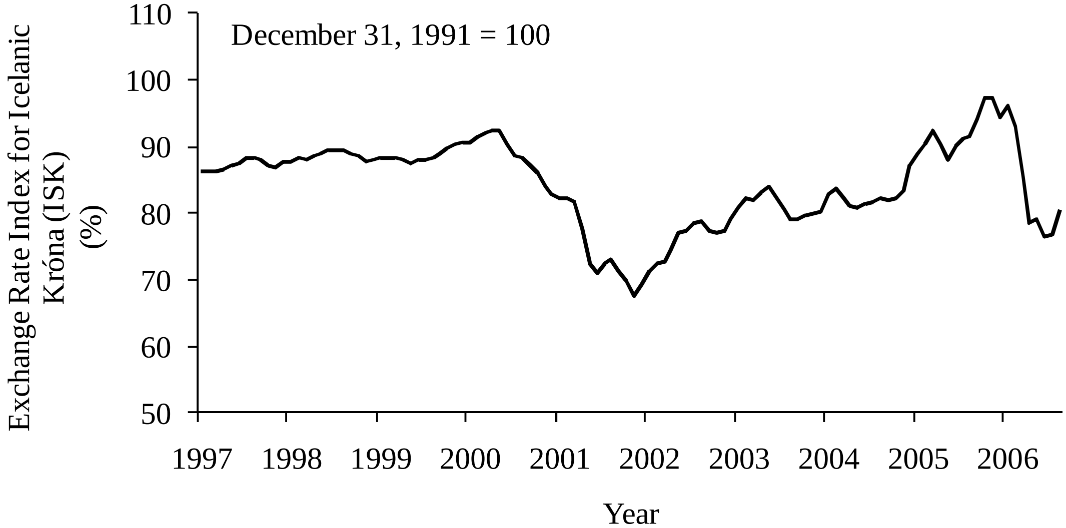


Figure. 3 The monthly averages of the exchange rate index for the ISK between January 1, 1997 and December 31, 2006

Note: To facilitate the reading of the figure, the index is transformed as (100 / Exchange rate index) × 100. Therefore, a smaller value for the exchange rate index represents a weaker ISK.

Table A1. Ordinary Least Squares Regression for Predicting Labor Input Use

Variables	Coef.	p values
Milk Quota $\left(y_{fs}^{\max}\right)$	0.0003***	0.000
Milk Price (p)	-2.3019***	0.001
$p \times y_{fs}^{\max}$	-6.72E-06***	0.000
p^2	0.0699***	0.000
$\left(y_{fs}^{\max}\right)^2$	3.85E-11	0.486
Constant	50.6237***	0.000

Note: Significance codes '***' 0.01, '**' 0.05, '*' 0.10

Adjusted $R^2 = 0.2406$

H_0: $\beta_i = 0$

$F(5, 1250) = 80.51$

$p > F = 0.000$

Table A2. Estimation Results for Input Distance Function Before Adjustment for Milk Quality

Variable	Coefficient	*p*-value	Variable	Coefficient	*p*- value
Breeding Index (γ)	0.180**	0.01	λ_{12}	0.000	0.59
Concentrates (α_1)	0.007**	0.02	α_{22}	0.003	0.82
Forage (α_2)	-0.003	0.76	α_{23}	-0.003	0.73
Capital (α_3)	0.004	0.63	α_{24}	-0.021	0.14
Land (α_4)	0.005	0.53	α_{25}	0.065**	0.02
No. of cows (α_5)	-0.036**	0.03	α_{26}	-0.042	0.12
Labor (α_6)	1.028***	0.00	λ_{21}	-0.045**	0.01
Milk (β_1)	-0.224***	0.00	λ_{22}	0.003	0.11
Meat (β_2)	-0.007***	0.00	α_{33}	-0.007	0.34
Time (θ)	0.008***	0.00	α_{34}	0.001	0.90
α_{11}	0.001	0.51	α_{35}	-0.011	0.47
α_{12}	-0.004*	0.07	α_{36}	0.024	0.15
α_{13}	-0.001	0.60	λ_{31}	0.036***	0.00
α_{14}	0.005**	0.02	λ_{32}	0.001	0.67
α_{15}	0.006	0.21	α_{44}	-0.025	0.27
α_{16}	-0.005	0.30	α_{45}	-0.045	0.13
λ_{11}	0.006*	0.06	α_{46}	0.080**	0.01

continued

Table A2. Continued

Variable	Coefficients	*p*-value
λ_{41}	0.031*	0.08
λ_{42}	-0.002	0.31
α_{55}	-0.201***	0.00
α_{56}	0.217***	0.00
λ_{51}	0.155***	0.00
λ_{52}	0.002	0.56
α_{66}	-0.312***	0.00
λ_{61}	-0.224***	0.00
λ_{62}	-0.005	0.27
β_{11}	-0.409***	0.00
β_{12}	-0.005**	0.02
β_{t1}	0.042***	0.00
β_{22}	-0.002***	0.00
β_{t2}	0.000	0.47
θ_{tt}	-0.009***	0.00
α_0	-0.077	0.96

Note: Significance codes: '***' 0.01 ,'**' 0.05 ,'*' 0.10

Table A3. Estimation Results for Input Distance Function After Adjusting for Milk Quality

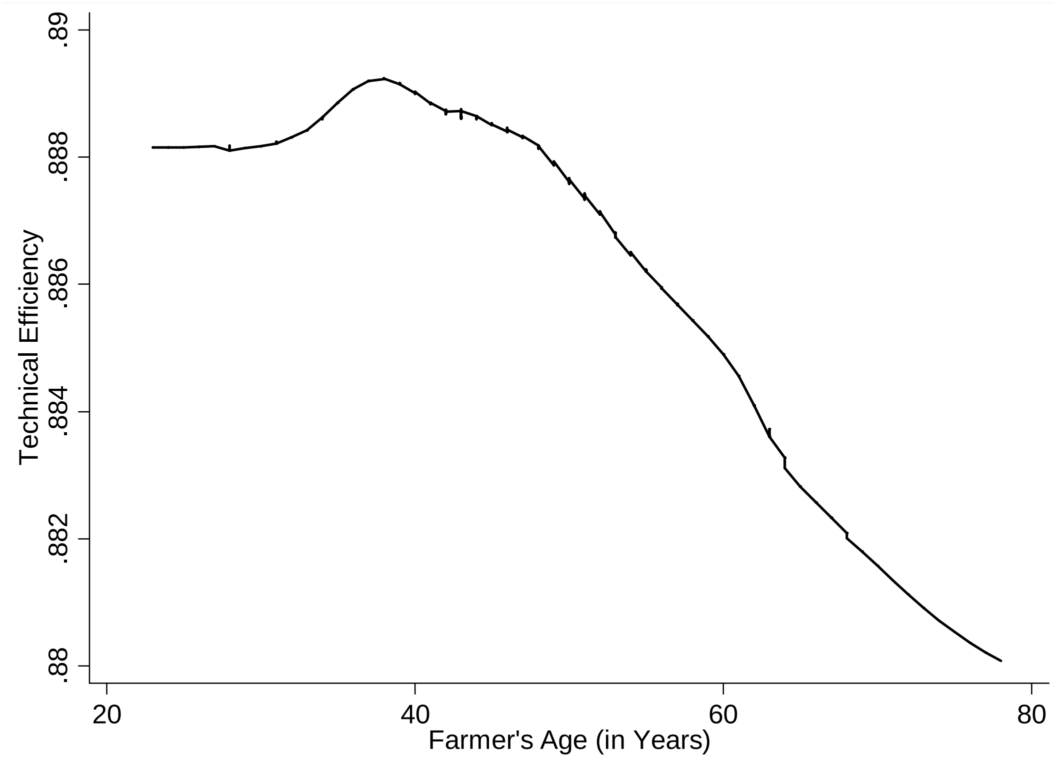
Variable	Coefficient	*p*- value	Variables	Coefficient	*p*-value
Breeding Index (γ)	0.290***	0.00	λ_{12}	0.000	0.60
Concentrates (α_1)	0.012***	0.00	α_{22}	-0.014	0.34
Forage (α_2)	0.000	0.97	α_{23}	0.012	0.19
Capital (α_3)	0.010	0.21	α_{24}	-0.032**	0.04
Land (α_4)	0.024**	0.01	α_{25}	0.061*	0.05
No. of cows (α_5)	0.029	0.13	α_{26}	-0.022	0.52
Labor (α_6)	0.924***	0.00	λ_{21}	-0.033*	0.07
Milk (β_1)	-0.276***	0.00	λ_{22}	0.002	0.25
Meat (β_2)	-0.011***	0.00	α_{33}	-0.015	0.10
Time (θ)	0.010***	0.00	α_{34}	0.000	0.99
α_{11}	0.003**	0.01	α_{35}	0.016	0.41
α_{12}	-0.002	0.52	α_{36}	-0.006	0.80
α_{13}	-0.002	0.39	λ_{31}	0.030**	0.02
α_{14}	0.007***	0.00	λ_{32}	-0.003*	0.07
α_{15}	0.004	0.44	α_{44}	-0.018	0.48
α_{16}	-0.010	0.11	α_{45}	-0.038	0.26
λ_{11}	0.004	0.25	α_{46}	0.067*	0.06

continued

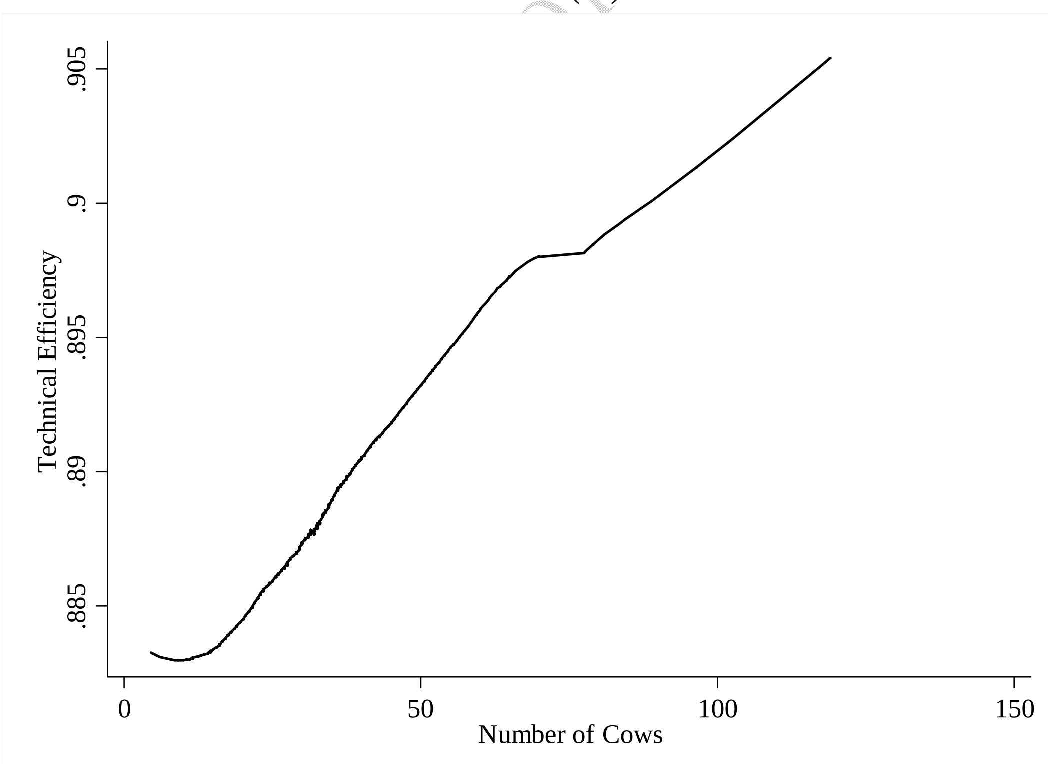
Table A3. Continued

Variable	Coefficient	*p*-value
λ_{41}	0.030	0.13
λ_{42}	-0.003	0.23
α_{55}	-0.176**	0.02
α_{56}	0.128*	0.06
λ_{51}	0.063	0.10
λ_{52}	-0.001	0.82
α_{66}	-0.155*	0.07
λ_{61}	-0.109**	0.01
λ_{62}	0.005	0.39
β_{11}	-0.301***	0.00
β_{12}	0.002	0.44
β_{t1}	0.048***	0.00
β_{22}	-0.002***	0.00
β_{t2}	0.000	0.91
θ_{tt}	-0.015***	0.00
α_{0}	-0.113	0.93

Note: Significance codes: '***' 0.01 ,'**' 0.05 ,'*' 0.10



(1a)



(1b)

Figure A1. Technical efficiency scores, farmer's age, and herd size