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The Economics of Dairy Production: Effects of Breeding and Marketing Quotas

Økonomien i melkeproduksjonen: Effekter av avl og produksjonskvoter

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>
> Associate Professor Dadi Kristofersson at Department of Economics, University of Iceland, and
>
> Professor Rodolfo Nayga Jr. at Department of Agricultural Economics and Agribusiness, University of Arkansas.

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Contents

Dedicated to:

The People of Norway

and the

School of Business and Economics

at UMB

Abstract

This dissertation compiles four articles investigating the effects of breeding and marketing quota in dairy production. Farm level panel datasets from Norway and Iceland were used for the analysis. In the first article, the main objective was to measure the contribution of animal breeding to productivity growth on Icelandic dairy farms. An extended decomposition of the Malmquist productivity index was proposed for the task. Average productivity growth during 1997–2006 was 1.6%. Scale effects contributed the most followed by breeding, which contributed about 19% of the growth. The second article investigated the effects of broad breeding goals on production cost of dairy farms in Norway. A cost system allowing for unobserved heterogeneity was used to derive cost effects of genetic progress. Results show that genetic progress in welfare-improving traits such as health and fertility led to a 1% cumulative cost saving during 1999–2007. This corresponds to a perpetual industry-wide cost saving of NOK 160 million. The effect of Norwegian marketing quotas on milk quality, as measured by milk composition, was the objective of the third article. A theoretical model of substitution effects between milk quantity, as determined by each farm's quota, and milk components was developed and empirically estimated. The substitution effect was positive for protein and negative for fat. Given the value of components, this suggests low milk quality as quota regimes get restrictive. The fourth article investigated supply response among Icelandic dairy farms under yield uncertainty and two-price system. An existing model of supply response that assumes single input in production was generalized to a multiple input setting. Results show milk supply response to a price change in quota milk market is only a third of the supply response to equivalent and simultaneous price change in quota and surplus milk markets. Finally, statistical testing preferred results from the generalized model.

Introduction

Expanding production potential and public support in different forms have resulted in oversupply of many agricultural commodities in most developed countries. As a result, quota instruments have been widely used to restrict supply. In dairy production marketing quotas have been commonly used since the early 1980s. These instruments are still used to regulate milk supply in Canada, the EU, Norway, Iceland, and in California while some countries (e.g., Australia and Switzerland) have removed them since 2000.[1]

The primary objective of marketing quotas in dairy sectors of most developed countries is to reduce the budgetary pressures implied by milk oversupply because of subsidy programs meant to protect farmer incomes. While alternative tools such as price adjustments can be used to deal with oversupply, the application of marketing quotas could be preferred for economic and political reasons (OECD 2005a). First restricting supply by reducing prices can be politically difficult. For example, Kirke and Moss (1987) estimated that milk prices in Northern Ireland had to be reduced 14–16% to have a major impact on milk supply, which results in profit reductions of up to 25%. Second price cuts may not have a lasting effect on production incentives since technical change as well as increased cost efficiency can lead to regeneration of the oversupply problem at lower prices. Third, direct control on milk supply through marketing quotas allows subsidy programs to aim for other objectives such as promoting cultural landscape without creating an oversupply problem. Finally, marketing quotas are argued to improve the transfer efficiency of price support programs by preventing leakage to input suppliers (OECD 2005a).

However, marketing quotas also introduce economic problems to the efficient operation of the dairy sector itself, for example by restricting or delaying structural adjustment and efficient utilization of resources (Richards and Jeffrey 1997; Kumbhakar et al. 2008). Such rigidity will reduce competitiveness by keeping production costs high, which can possibly lead to welfare loss to society. Therefore, the effect of marketing quotas on the performance of dairy farms, the structure of dairy industries, and social welfare have been investigated since their introduction in the 1980s.

This dissertation consists of four articles applying neoclassical production theory to study the economic behavior of dairy producers in Norway and Iceland. Dairy sectors in both countries are operating under marketing quota systems since the early 1980s. The first article measures productivity growth on quota-constrained farms and isolate contribution of breeding to productivity growth. The second article highlights the farm level effects of broadening breeding goals to consider health and fertility traits. In the third article, the effect of marketing quotas on milk quality, as defined by nutrient composition, is investigated. Finally, milk supply response under yield uncertainty in a two-market set up resulting from the way marketing quota systems are administered is evaluated in the last article. The four articles included in the dissertation are the following:

Article 1: Animal Breeding and Productivity Growth of Dairy Farms,

Article 2: Broad Breeding Goals and Production Cost in Dairy Farming,

Article 3: The Effect of Dairy Quota on Milk Composition, and

Article 4: Milk Supply Response under Two-Price Systems.

Panel data from Iceland for the period 1997–2006 and 1998–2006 are used for analysis in articles 1 and 4, respectively. In article 1, a parametric Malmquist productivity index constructed based on input distance functions is used while in article 4 results are based on expected profit maximization framework. Articles 2 and 3 are based on panel data from Norway, covering the periods 1999–2007 and 2004–2009, respectively. Furthermore, a short-run cost function estimated through a random coefficient framework of Bjørn, Lindquist, and Skjerpen (2003) and a system of netput equations derived from a restricted profit function underlie the analysis in article 2 and 3, respectively. Article 1 and 2 are co-authored with my supervisors Kyrre Rickertsen and Dadi Kristofersson.

Although the articles can be read independently, they are closely related thematically. Either the direct response of dairy producers to the quota constraint itself or the farm level consequences of quota-induced responses elsewhere in the dairy sector, such as adjustment of breeding objectives, are highlighted. Therefore, the papers provide methodological and empirical results that contribute to the understanding of producer behavior under marketing quotas.

This introductory section presents some background concerning the dairy sectors and quota systems in Norway and Iceland. Then theoretical approaches to model producer behavior under marketing quota are briefly presented. Discussion of the research objectives, methodology, data, and findings of each article follows. Finally a brief summary of findings and contributions is presented with limitations of the dissertation.

The Structure of Dairy Industries in Norway and Iceland

This section provides a brief overview of the dairy sector in Norway and Iceland. The structure of dairy farms, breeding programs, government support policies, and consumption patterns for dairy products will be highlighted.

Norway

Norwegian dairy farms are usually small and family-operated. The farms are largely mixed farms combining milk and meat production, though the latter is mainly a by-product. As in most developed countries, the number of dairy farms has been declining and production has been concentrating to fewer farms. According to Statistics Norway, the number of dairy farms in 2010 was only 30% of the number in 1979. However, production has declined only slightly suggesting that production on existing farms has increased over time. Partly this is due to scale adjustments as average herd size per farm increased from 13 in 1999 to 21 in 2010.[2] Furthermore, the average milk yield per cow has more than doubled since the 1950s (Rauw et al.1998). Increased average herd size is the result of several factors including the introduction of tradable milk quotas in 1996 and a subsidy program favoring joint operations, which was introduced in 1998. However, structural change in the Norwegian dairy sector is slower than other Nordic countries due to government policies that favor smaller farms and their wider geographic distribution (Jervell and Borgen 2000; Flaten 2002).

As it is common for many agricultural commodities in Norway, dairy producers are organized under farmer cooperatives. The dairy cooperative, TINE SA, is a dominant player in milk processing and marketing as well as regulation of the dairy sector. It is

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estimated that TINE SA controlled 96% of the raw milk supply and more than 85% of the processed fluid milk products in 2007 (The Federation of Norwegian Agricultural Cooperatives 2008). Some competition in the fluid-milk product category is ensured by the privately-owned dairy processor Q-dairies, which collects raw milk from its own set of dairy suppliers. In addition, regulatory arrangements force TINE SA to ensure the supply of raw milk for milk processors engaged in the production of non-fluid milk dairy products such as cheese where TINE SA has a market share of 55% (The Federation of Norwegian Agricultural Cooperatives 2008).

It is estimated that 99% of the dairy cows in the country are Norwegian Red (Committee on Farm Animal Genetic Resources 2003). The average milk yield per cow in 2010 was about 7,000 kgs with 3.38% protein and 4.24% fat content. The relatively low yield is mainly due to the quota system in the country and yield from the best cows can go up to 16,000 kgs.[3] The breeding program for the Norwegian Red has been centralized under Geno, a subsidiary of the dairy cooperative. The breeding program is known for its broadness due to its consideration of traits meant to improve animal welfare. The emphasis on such traits, known as functional traits, has also increased over time to currently account for almost half of the breeding weights guiding selection. All farms that are members of the dairy cooperative are considered to be members of Geno and participate in the development of the breeding goal for the breed. Furthermore, all herds on member farms, estimated to be 98% of the dairy cows in the country, are considered to be part of the population from which selection takes place. The resulting high participation rate in the breeding program has allowed Geno to undertake high quality selection even for low heritability traits like functional traits. This has shown

itself by the growing demand for Norwegian Red semen outside Norway for cross breeding projects involving other high-production breeds like Holstein Friesian. For example, the export of NRF semen doses has increased from 22,650 in 1998 to 80,000 in 2001(Committee on Farm Animal Genetic Resources 2003).

The Norwegian government provides significant support to the agricultural sector and dairy producers are among the heavily supported farmers. Subsidy programs and border protection are the two instruments used for supporting the sector. Organization for Economic Cooperation and Development (OECD) estimates that state subsidies for agriculture in Norway are one of the highest in the world and constituted 71% of the gross farm revenues in 2002 (OECD 2003). For comparisons the percentage Producer Subsidy Estimates (%PSE) for the same year are 36% in the EU, 18% in the US, 20% in Canada, and 4% in Australia. Though Norwegian subsidy levels remained higher than the OECD average, their contribution to gross farm revenues has declined over time and during 2005–07 it was 62% of gross farm revenues (OECD 2008). State support can be product-specific or non-specific. Product-specific supports are directly related to volume of production while non-product specific supports are mainly related to input use such as acreage and headage payments. Other types of payments, such as investment supports and indirect subsidies for research and extension services, are also provided (Knutsen 2007). Border protection also has been used to protect the dairy sector from foreign competition in addition to pursuing other objectives such as prevention of animal diseases (Committee on Farm Animal Genetic Resources 2003). However after membership in the European Economic Area (EEA) and trade agreements at the World Trade Organization, some of the border protection measures are slightly relaxed.

Norwegian consumption trends for dairy products vary across products. Since the 1990s, the demand for most processed fluid milk products has declined or remained stagnant while non-fluid milk products such as cheese and yogurt saw increased demand. Such trends are caused by availability of alternative products such as juice and soft drinks, life style changes, and health concerns among consumers with respect to dairy fat consumption (Knutsen 2007). Similarly, the possibilities for dairy product exports have also diminished since 2000 following WTO trade agreements against subsidized exports (Knutsen 2007).

Iceland

Icelandic dairy farms are dominantly family-operated enterprises like their Norwegian counterparts. The average Icelandic dairy farm has a herd size of about 34 cows (Johannesson 2010), which is large compared to the average Norwegian dairy farm. However, the Icelandic dairy farm is still small relative to dairy farms in most other western countries. For example, average herd size is 62 cows in Sweden (Swedish Dairy Association 2011) and over 130 in Denmark. Structural adjustment towards fewer and bigger farms is also observed in the Icelandic dairy sector. Bjarnadottir and Kristofersson (2008) found that the number of dairy farms has been reduced by half in the decade since 1995. In addition to efficiency considerations, the free-tradability of dairy quotas since 1992 has played a key role for the structural adjustment.

Marketing of dairy products in Iceland is also dominated by farmer cooperatives to a large extent.[4] In contrast to Norway, however, there are more dairy cooperatives owned either only by the farmers themselves or together with consumers.

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The dairy breed in Iceland is a native breed called the Icelandic dairy cattle. Annual milk yield per cow is about 5,000 kgs with 3.4% protein and 4.0% fat. Despite its low yield level relative to other popular dairy breeds, the Icelandic dairy cattle is believed to have desirable characteristics such as adaptation to difficult geographic and climate conditions as well as milk composition favorable to cheese production (Johannesson 2010). The breeding program for the Icelandic dairy cattle is organized under the Farmers Association, which also collects and maintains performance records for the Icelandic dairy cattle. Like most breeding programs elsewhere, the breeding program emphasizes traits related to production (44% on protein yield) though non-production traits such as fertility are also included in the breeding program.

State intervention in agriculture is also widespread based on arguments relating to local regulatory needs of the sector as well as protection from foreign competition. Therefore, border protection using tariffs and different types of subsidies constitute the policy tools used by the state to support agriculture. OECD's estimates show that state financial support to agriculture, as measured by %PSE, was 66% during 2004–2006, which is more than twice of the OECD average for the period. Single commodity transfers (SCTs) constitute 93% of the total subsidies and milk is identified as one of the major recipients together with poultry and eggs (OECD 2007).

Consumption of dairy products in Iceland follows similar trends as in many western countries. That is the demand for fluid milk has declined over time as life styles change, health awareness improves, and alternative products are made available. For example, the consumption of milk per capita in 2007 has declined by 52.9% as compared with 1960 while consumption per capita of soft drinks has increased by more than six

folds during the same period (The Famers Association of Iceland 2009). On the other hand the consumption of other processed dairy products such as cheese and yogurt has increased over time (The Famers Association of Iceland 2009).

Dairy Marketing Quotas in Norway and Iceland

Increased potential for production on dairy farms, farm support programs, and tight marketing options for milk resulted in milk oversupply around late 1970s and early 1980s in both countries. In 1982, a year before the Norwegian quota system was introduced; excess milk supply was about 300 million liters (Jervell and Borgen 2000).

The first quota system in Norway was then introduced in 1983. Initially, the quotas were non-tradable and administered through a two-price system for milk within and outside quota. Later on subsequent adjustments were made to the quota system that increased its effectiveness in curbing oversupply as well as its transferability through market mechanisms. The first adjustment to allow transfer of quotas was made in 1996. Under this system also known as "quota buy-and-sell scheme" (Jervell and Borgen 2000), the sale of quotas was allowed. However, there were several restrictions on quota transactions. For instance, farmers who choose to sell their quota had to sell all or nothing of their quota holdings to the state at administratively set prices. The quotas purchased by the state will be made available for sale based on certain rules that included minimum amounts that could be purchased and the maximum quota size allowed after buying quota (OECD 2005b). In addition the two-price system was phased out and replaced with a levy system that penalizes oversupply.

In 2003 limited direct transfer of dairy quota (i.e., 30% of the quota to be sold) to farms that already own quota and are located in the same trading region as the seller was allowed. Subsequently the proportion allowed to be traded privately has been raised and by 2008 farmers were allowed to trade up to 50% of their quota in the private market, though some important restrictions like geographical boundaries on quota transfers still apply. In addition, quota lease markets were allowed as of 2009 only for single farms with total quota size up to 400,000 liters. Quota transactions however are quite limited and the demand for quota has always been greater than its supply. Each year only between 9% and 29% of the requested quotas have been transferred (Norwegian Agricultural Authority 2007). Additional details on the Norwegian quota system are available in Jervell and Borgen (2000) and OECD (2005).

In Iceland the first dairy quota system was installed in 1980 by the Agricultural Production Committee (APC) after unsuccessful attempts to find export markets for dairy products (Agnarsson 2007). The first quota system however was not effective in curbing oversupply leading to subsequent adjustments. In 1992 the first quota system without any restrictions on quota transfer was set up after the third agreement on milk production between the state and the Farmers Association. The only restriction on quota transactions was the prohibition of quota leasing (Bjarnadottir and Kristofersson 2008). Compared to the system in Norway, the lack of restrictions on quota transfers in the Icelandic system has led to a significant re-structuring of the dairy sector with the number of dairy farms being reduced by half within a decade since 1995 (Bjarnadottir and Kristofersson 2008).

Two-price system is used to enforce the quota system and hence milk in excess of the farm quota can be sold at market determined prices according to market conditions.

There is also a requirement for dairy farms to use their quota every second year or risk

loosing it though exceptions from this requirement can be requested for (Agnarsson

2007).

Modeling Producer Behavior under Marketing Quota

In this section, a brief overview of standard approaches to model producer behavior is

provided. First approaches that can be used when producers are free to choose both their

input and output levels are presented. Then modifications resulting from the introduction

of constraints on the input-output choice, for example in the form of marketing quotas,

are presented. These modified approaches form the methodological core of the

dissertation. The discussion in this section heavily relies on Färe and Primont (1995);

Chambers, Chung, and Färe (1996; 1998) and Färe and Grosskopf (2000).

Modeling Production Technology Without Constraints

A common starting point of standard producer theory is expressing the technical

relationship between inputs and outputs or the production technology. Accordingly, let

$x \in \Re_+^N$ and $y \in \Re_+^M$ be input and output vectors, respectively. The production technology

set T can then be defined as:

$$(1) \qquad T = \left\{ (x, y) : x \text{ can produce } y \right\},$$

which represents the set of input and output combinations that are feasible. The

technology is assumed to satisfy certain properties (see Färe and Primont 1995;

Chambers, Chung, and Färe 1998).

These properties allow the technology set to be expressed in terms of functions. Several alternative functions exist to implicitly express the technology set in forms that are analytically convenient. These alternatives can be classified into primal and dual representations. One general primal representation of a production technology is the directional distance function proposed by Chambers, Chung, and Färe (1996; 1998). The directional distance function is defined as:

$$(2) \quad \vec{D}_T\left(x, y; -g_x, g_y\right) = \begin{cases} \sup\limits_{\beta}\left\{\beta \geq 0 : \left(x - \beta g_x, y + \beta g_y\right) \in T\right\}, \\ \qquad \text{if } \left(x - \beta g_x, y + \beta g_y\right) \in T \text{ for some } \beta, \\ -\infty, \text{otherwise.} \end{cases}$$

where $g = \left(g_x, g_y\right)$ is a non-zero vector that determines the direction of projection for an observed input-output vector towards the frontier of the technology. For an efficient input-output vector, $\vec{D}_T\left(x, y; g\right) = 0$ while for inefficient input-output vectors $\vec{D}_T\left(x, y; g\right) > 0$, with larger values indicating greater inefficiency. Therefore, the directional distance function is a complete characterization of the production technology as shown by Lemma 2.1 in Chambers, Chung, and Färe (1998). More formally, this can be expressed as:

$$(3) \quad \vec{D}_T\left(x, y; g_x, g_y\right) \geq 0 \quad \text{if and only if } \left(x, y\right) \in T.$$

Equivalent dual representations can be obtained by making behavioral assumptions about producers' objectives in production. The most general of such behavioral assumptions is profit maximization, which allows producers to adjust both inputs and outputs to maximize profits. Let $p \in \Re_{++}^{M}$ and $w \in \Re_{++}^{N}$ are competitive price

vectors in the output and input markets, respectively. Then the profit function can be defined as (Chambers, Chung, and Färe 1998.; Färe and Grosskopf 2000):

$$(4) \qquad \Pi(p,w) = \sup_{x,y \geq 0} \{py - wx : (x,y) \in T\}.$$

However, $(x,y) \in T$ if and only if $\vec{D}_T(x,y; g_x, g_y) \geq 0$. Therefore, the profit function can also be written as:

$$(5) \qquad \Pi(p,w) = \sup_{x,y \geq 0} \{py - wx : \vec{D}_T(x,y; g_x, g_y) \geq 0\},$$

which forms the basis for the mathematical relationship between the directional distance function and the profit function. The duality results relating the directional distance function and the profit function are shown in Chambers, Chung, and Färe (1998).

Given a functional representation of the production technology satisfying certain properties, analytical tools such as calculus can be applied to study producer behavior in the input and output markets. For example, producer behavior in the input and output markets can be studied from factor demand and output supply equations derived through Hotelling's lemma and its dual counterpart.

Modeling Production Technology with Input/Output Constraints

In practical applications, one can encounter cases where producers cannot control either the quantity of inputs or the quantity of outputs. For example, assuming farms are producing for the market; marketing quotas imply a constraint on the output combinations available to the producer. In such cases, the approaches above must be modified to allow for the constraints faced by producers.

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In terms of directional distance functions presented above, a constraint on the output side, say due to a binding marketing quotas, imply:

$$(6) \quad \vec{D}_T\left(x,y;g_x,0\right) = \begin{cases} \sup_{\beta}\left\{\beta \geq 0:\left(x-\beta g_x,y\right)\in T\right\}, \\ \qquad \text{if } \left(x-\beta g_x,y\right)\in T \text{ for some } \beta, \\ -\infty, \text{otherwise}. \end{cases} \quad .$$

i.e., the producer can only adjust input levels in the direction of g_x. Equation (6) defines the directional input distance function $\vec{D}_i\left(x,y;g_x\right)$ introduced by Chambers, Chung and Färe (1996). Similarly if the producers can not adjust their input levels, (2) reduces to:

$$(7) \quad \vec{D}_T\left(x,y;0,g_y\right) = \begin{cases} \sup_{\beta}\left\{\beta \geq 0:\left(x,y+\beta g_y\right)\in T\right\}, \\ \qquad \text{if } \left(x,y+\beta g_y\right)\in T \text{ for some } \beta, \\ -\infty, \text{otherwise}, \end{cases}$$

which is the directional output distance function $\vec{D}_o\left(x,y;g_y\right)$.

Directional distance functions depend on the direction vector that has to be pre-determined by the researcher. The usual practice is to set the direction vector with the observed input and /or output levels of producers based on the argument that it relates the directional distance functions with the widely used radial distance functions proposed by Shephard (1953; 1970). These radial distance functions can also be used as complete primal expressions of the constrained technology set. For example, the radial input distance function is given as:

$$(8) \quad D_I\left(x,y\right) = \sup_{\lambda}\left\{\lambda \geq 1:\frac{x}{\lambda}\in L\left(y\right)\right\},$$

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where $L(y)$ is the input requirement set or the set of all input combinations that can produce y. To recover $D_I(x, y)$ from the directional input distance function, we set $g = (x, 0)$, i.e. (Chambers, Chung and Färe 1996):

$$(9) \qquad \vec{D}_T(x, y; x, 0) = \sup_{\beta} \{ \beta \geq 0 : x - \beta x \in L(y) \}$$

$$= 1 - \inf \{ (1 - \beta) \in R_+ : x(1 - \beta) \in L(y) \}$$

$$= 1 - \frac{1}{D_i(x, y)}.$$

Like the directional input distance function, the input distance function is also a complete characterization of the technology set represented by $L(y)$, i.e., $D_i(x, y) \geq 1$ if and only if $(x, y) \in L(y)$. Similar relationship can be also derived between the directional output distance function and the radial output distance function (see Färe and Grosskopf 2000).

Like the profit function above, dual representations of the technology set under input/output constraints can be obtained by making behavioral assumptions about producers' objective in production under constraint. Accordingly, producers who cannot adjust their output vectors can be assumed to minimize the cost of producing the given output vector while those who cannot adjust their input vectors can be assumed to maximize their revenue. For example, under cost minimization, a dual characterization of the technology set is the cost function. As defined by Chambers, Chung and Färe (1996) the cost function is given as:

$$(10) \qquad C(w, y) = \inf_{x} \{ wx : x \in L(y), y \in \Re_+^M \},$$

or

$$(11) \qquad C(w, y) = \inf_{x} \{ wx : D_I(x, y) \geq 1, y \in \Re_+^M \},$$

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since $(x, y) \in L(y)$ if and only if $D_I(x, y) \geq 1$. The last expression also forms the basis for a duality result between the cost function and the input distance function established by Shephard (1953; 1970), provided that $L(y)$ satisfies certain regularity properties. The duality relationship between the cost function and the input distance function can also be found in Chambers, Chung, and Färe (1998). Furthermore, the application of dual approaches for modeling producer behavior under marketing quota is also discussed in more detail in Fulginiti and Perrin (1993).

From the set of functions presented above, all functions that allow producers to scale their input vectors while keeping the output vector fixed can be used to analyze producer behavior under marketing quota. The candidate functions include the input distance function and its dual, the cost function, which are used in two of the articles in the dissertation. The third article employs the restricted profit function to study quality effects of marketing quotas.[5]

So far it was assumed that producers are operating in risk-free environment with complete knowledge about prices and quantities. However, the agricultural production environment is characterized by uncertainties originating from various sources such as nature and government policies. Therefore, modified versions of the approaches discussed above have to be used to consider producer behavior under uncertainty. Accordingly, the last article uses the expected profit maximization framework to account for the effect of yield uncertainty on milk supply response by producers under marketing quotas.

Research Objectives, Literature and Contributions

The imposition of marketing quotas affects all aspects of dairying, often in manners unforeseen by policy makers (OECD 2005a). One of the earliest studies on this regard is Alston and Quilkey (1980) who provided theoretical assessment of the effects of marketing quotas on the supply behavior of dairy producers under yield uncertainty. Framed in the context of dairy production in New South Wales in Australia, Alston and Quilkey (1980) argued that producers operating under non-tradable marketing quotas have incentives to produce 'insurance milk', i.e., milk in excess of production quota. This can happen since marketing quotas create preferred markets where higher prices are paid for milk due to public support programs. Therefore, shortfalls in production caused by uncertain yield can imply substantial reductions in farm profits. Furthermore, it was showed that 'insurance milk' production leads to net social costs as prices in the less preferred market are depressed further due to excess supply caused by the precautionary behavior.

The theoretical work of Alston and Quilkey (1980) was further developed by Fraser (1986; 1995) and Babcock (1990). Fraser (1986; 1995) provided a formal mathematical framework that can be used to model producer behavior under two-price systems and risk neutrality. Babcock (1990) introduced risk aversion into the model. Later on, Borges and Thurman (1994) questioned the analogy of excess production with insurance and approached the problem as a response to exogenous forces, like prices, under uncertainty. Using data from peanut growing counties of North Carolina in the U.S, they demonstrated a way of extracting the probability that production will exceed quota.

Furthermore, they constructed measures of supply response to relative price changes in quota and surplus peanuts markets.

Though the discussion in Alston and Quilkey (1980) was in the context of dairy production, the supply effects of a two-market set up resulting from the administration of dairy marketing quotas is not empirically investigated for dairy producers. Article 4 seeks to provide such empirical results using the framework suggested by Borges and Thurman (1994), referred to as the single input approach herafter. Furthermore, the usual assumption of yield per single input that is independent of other input choices is relaxed to generalize the Borges and Thurman (1994) framework to the more realistic multiple input setting. The generalization, referred to as the aggregate input approach, is achieved through construction of an aggregate input using weights obtained from a production frontier. Estimation of a production frontier also enables objective selection of approaches to construct yield data (i.e., based on a single input or multiple inputs) through appropriate statistical testing.

The aggregate input approach is implemented using data from Icelandic dairy farms for the period 1998–2006. Due to lack of previous work to guide choice of distributional form, the flexible Johnson's distribution system (Johnson 1949) is used to estimate empirical milk yield densities required for the analysis. The empirical density function is then used to derive estimates of the probability that each farm will exceed its quota given its observed input choices. In addition, following Borges and Thurman (1994), a relative marginal supply response measure is constructed for each farm.

Results from the aggregate input approach show that the average Icelandic dairy farm will exceed its quota with a probability of 0.655. The estimate is smaller than what

Borges and Thurman (1994) found in peanuts production using the single input approach. However, the difference between the two results can be explained by the assumption underlying yield calculation in the latter. Borges and Thurman (1994) computed yield levels per acreage assuming that it is unaffected by other input choices. There is however no compelling reason for this common assumption to be valid in all cases. When the assumption is not valid, the input selected for yield computation will appear more productive than it actually is. Consequently, observed levels of the selected input would imply high planned production than when planned production is inferred from an approach taking multiple inputs in production into account. For example, when the single input approach is used to compute probability to exceed quota using yield per cow data, the average Icelandic farm is likely to exceed its quota with a probability of 0.809. This figure is close to what Borges and Thurman (1994) found for peanut farms in North Carolina. However, a Wald test of the null hypothesis that yield per cow is unaffected by all other inputs in Icelandic dairy production is rejected at 1%., providing statistical support for the aggregate input approach.

Next the relative marginal supply responses to price changes in the quota and surplus milk markets have been computed. When milk price in the quota milk market increase by 1 Icelandic Króna (ISK), the resulting relative marginal supply response is only a third of the supply response from an equivalent but simultaneous price increase in both markets.[6] Due to the high estimate of the probability for surplus production, the comparable estimate from the single input approach is lower by 60.8%.

It is therefore concluded that milk price in the surplus milk market is the price at the margin for Icelandic dairy farms. A change in this price is more likely to have a major effect on surplus milk production than equivalent price change in the quota milk market.

Another aspect of the literature on the economic effects of supply control measures is their effect on output quality. There is a rich literature in international trade investigating quality effects of quota restrictions that occur in the form of import quotas or voluntary export restraints (VER). Examples are Aw and Roberts (1986), Feenestra (1988), and Lutz (2007). This literature reports evidence of quality upgrading following restrictions on import quantities. Although there are no studies investigating the same effect for agricultural products, there are some observations of potential quality effects from quotas. For example, Alston and James (2002) hypothesized that the high quality of flue-cured tobacco exported from the US, where production is constrained by marketing quotas, relative to the quality of imported tobacco could be a partial indication of quality effects from the marketing quota. As noted by Alston and James (2002), quality change in response to quota restrictions may have implications to the welfare impacts of the quota itself and its transfer efficiency. The authors argued that following quality improvements in response to quota restrictions, the loss to consumers due to the quota will decline and the transfer efficiency of the quota will be reduced. The latter is likely due to transfers to input suppliers following resource requirements of improving output quality.

Article 3 evaluates quality effects of a quota restriction in dairy production when milk quality is defined by milk composition. The definition of milk quality in terms of its nutrient composition is informed by the fact that the dairy processing sector in most

developed countries encourages better milk composition through component pricing schemes. A quality effect of marketing quotas can therefore be modeled as a response of component supply to changes in quota level. In particular a quality-related response may arise in the form of substitution towards high-value milk components (e.g., protein). There are two reasons why component supply is likely to respond to quota change. First, restrictive quota regimes attach a shadow value to the price of milk (Falvey 1979; Lutz 2007). This shadow value measures the profit lost due to the quota. Augmenting milk composition therefore provides a way of minimizing this shadow value. Second, feed adjustment is the most likely alternative to respond for quota changes in the short-run. However, feeding regimes are one of the determinants of milk composition (Jenkins and McGuire 2006) and therefore changes in feeding regimes following quota changes are likely to affect milk composition as well.

To investigate the relationship between milk composition and quota, a theoretical model of quality effects from dairy quota is developed. The effect of a change in quota levels on milk composition is then derived from elasticities of intensities, which measure the percentage change in component supply for a percentage change in quota. Given that total component supply is component per liter multiplied by total milk produced, the elasticity of intensity with respect to quota is decomposed into scaling and substitution effects. Scaling effect reflects what happens to total component supply when quota changes keeping component level per liter constant. Substitution effects reflect what happens to total component supply when component level per liter changes in response to the quota change.

A system of netputs including component supply functions is derived from a restricted variable component profit function by Hotelling's lemma. The profit function is specified in a Symmetric Normalized Quadratic form (Diewert and Wales 1987; Kohli 1993). Iterative Feasible Generalized Nonlinear Least Squares (IFGNLS) is then used to estimate curvature-corrected netput system. Data from Norwegian dairy farms, covering the period 2004–2009, is used for empirical analysis. Apart from facing marketing quotas, Norwegian dairy farms also get rewarded for better milk composition through component premiums. For each 1% increase in protein and fat content per liter, milk price increase by NOK 1.0 and NOK 0.15, respectively. Furthermore, penalties as high as the milk price are applied for milk deliveries outside quota.[7]

Results show that the substitution effect is positive for protein and negative for fat. That is a reduction of quota will decrease protein content per liter while it increases fat content per liter. Given that protein is valued more than six times than fat in Norwegian dairy market, the sign of the substitution effects is unexpected. Two factors can however explain this result. First, the dairy technology may exhibit cost complementarity between milk quantity and its protein content; i.e., the marginal cost of producing protein declines as more milk is produced and vice versa. If this is the case, a quota reduction will reduce the profitability of the component premium paid for protein. One indicator of cost complementarity between milk quantity and protein content is the change in feeding regime following quota change. Empirical results show that the demand for concentrates decrease more than forage following a quota reduction, suggesting that concentrate-to-forage ratio will decline after a quota reduction, ceteris

paribus. This will depress not only milk yield per cow but also protein content per liter (Jenkins and McGuire 2006).

Second, cost complementarity between protein production and milk quantity also increases the importance of producing within quota over increasing milk revenue through component premiums. This is due to severe penalties for milk deliveries outside milk quota and relatively low component premiums. Unlike previous results, therefore, it was concluded that restrictive quota regimes reduce milk quality in Norwegian dairy farming.

The effects of imposing supply control measures like marketing quotas are not, however, limited to dairy farms themselves. Other stakeholders in the dairy sector are also likely to be affected. For example, in participatory dairy cow breeding programs where dairy farmers actively participate in defining breeding objectives, genetic traits that are directly related to production cost such as health-related traits are likely to receive more breeding emphasis than other traits such as milk yield.

As mentioned above, the Norwegian breeding program is one such example of participatory program where 46% of the breeding weight is assigned to functional traits, traits that affect profitability through their impact on production cost rather than increasing yield (Groen et al. 1997).[8] Such emphasis on functional traits is likely to become a global trend in the future due to the adverse side effects of selection emphasizing yield traits. As shown by Rauw et al. (1998), the emphasis of breeding goals on milk yield has resulted in dairy cows that suffer physiological, behavioral, and immunological problems due to negative genetic correlation between production traits and functional traits. The consequent negative effects on animal health and longevity can result in high production costs to the dairy farms. Furthermore, emphasizing yield traits

may also endanger attractiveness of dairy products to consumers that are increasingly getting sensitive to animal welfare and sustainability issues.

Accordingly, breeding programs around the world are increasingly broadening their breeding goals by considering traits that improve animal welfare. Given that the cow is a key factor in dairy production, the broadening of breeding goals is likely to cause genetic-based technical change on dairy farms as replacement cows are introduced into dairy herds. Articles 1 and 2 seek to evaluate the implication of such genetic-based technical change on farm level outcomes.

In article 1, the main objective is to measure the contribution of genetic-based technical change to productivity growth. For this purpose, the Malmquist productivity index (Caves, Christensen, and Diewert 1982) has been used. Unlike previous applications of the index in productivity measurement for dairy farms, an extended decomposition of the index is implemented. The extension of the decomposition is related to extracting the productivity effects of breeding and other forms of technical change. Accordingly, the technical change component of the index is decomposed further into genetic-based and nongenetic-based technical change components.

To construct and decompose the index, an input distance function augmented with a farm level indicator of genetic status of dairy cows is specified. The input distance function is then estimated by maximum likelihood using data from Icelandic dairy farms, covering the period 1997–2006. The breeding program for the Icelandic dairy cattle emphasizes production traits and mainly traits related to milk composition. Therefore, allowing for milk quality differences across farms and over time is important for accurate measurement of productivity growth from breeding. To achieve this, a milk quality

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correction procedure is implemented based on unit values and farm level milk composition data.

Furthermore, although artificial insemination is the most commonly used insemination method in Iceland, unregistered bulls are also used on heifers. This is likely to have an implication to productivity growth from breeding since daughters of unregistered bulls tend to be less productive than daughters of proven bulls (Norman et al. 2003). This is controlled by introducing the proportion of cows from unregistered bulls as a control variable in the input distance function.

A parametric specification of the Malmquist productivity index proposed by Orea (2002) is used to measure and decompose productivity growth. This approach has the advantage that it allows for scale effects (i.e., productivity growth caused by operating close to the Most Productive Scale Size, or MPSS) without the need to compute scale efficiencies. Based on the estimated input distance function productivity growth is measured and decomposed into four sources: technical efficiency change, genetic-based technical change, nongenetic-based technical change, and scale effects.

Results show that productivity has increased by 1.6% per year and by 14.5% cumulatively during 1997–2006. Scale effects are the major source of this growth. This is as expected given the quota trade reform in 1992 that has resulted in significant structural adjustment in Icelandic dairy farms. Genetic-based technical change is the second most important source of productivity growth. On average productivity has increased by 0.3% due to genetic-based technical change that has cumulated to a 2.5% productivity growth during 1997–2006. As expected, productivity growth from genetic-based technical change declines as the proportion of cows from unregistered bulls increase. The

productivity growth from genetic-based technical change on farms with high proportion of cows from unregistered bulls was only 25% of the comparable figure for farms with low proportions.

Finally article 2 focuses on the effect of broadening breeding goals by considering functional traits on production cost of dairy farms. Data from Norwegian dairy farms for the period 1999–2007 is used for the empirical work. There are two reasons why the Norwegian experience is of broader relevance in this respect. First, functional traits are known to have low heritability (Groen et al. 1997). Consequently high quality selection over several cow generations is required to ensure genetic progress in these traits. Norway adopted broad breeding goals in dairy cow breeding since the 1970s. The early start then allows for sufficient time to observe the effects of the broad breeding goals at the farm level. Second, the breeding program is based on almost the entire dairy cow population in the country. The resulting high participation rate ensures high quality selection, for example by increasing the number of daughters for progeny testing per tested bull, as well as by allowing problems of practical relevance to dairy farms to be addressed.

For this purpose a short-run variable cost function is specified in a translog form (Christensen, Jorgenson, and Lau 1973). The cost function is augmented with indices representing genetic status of dairy cows. Two specifications are used to measure the cost effects of genetic progress. First, an aggregate breeding index representing over all genetic status is included in the cost function to measure the cost effects of over all genetic progress. Second, three sub-indices are introduced into the cost function to represent genetic status in production (milk and meat), functional (health and fertility)

and conformation (udder and legs) traits. To ensure efficient estimation, the cost function is estimated together with cost share equations for each variable input. A random coefficient framework of Bjørn, Lindquist, and Skjerpen (2003) is used to estimate the resulting cost system by allowing for unobserved heterogeneity. A maximum likelihood estimator implemented in the –xtmixed- module of STATA® version 11 (StataCorp. 2009) is used to estimate the system. Cost effects are then derived as cost elasticities with respect to genetic indices.

Estimated cost elasticities show that genetic progress is cost-reducing. According to these elasticities, a 1% increase in the aggregate breeding index from its level in 2007 leads to a variable cost reduction of 0.53%. This implied that increasing the aggregate breeding index by one standard deviation from its level in 2007 will reduce the farm level variable cost of producing the average output on the same year by NOK 3,436. This figure is about 1% of the expected variable cost of production in 2007.

In the second specification with sub-indices of genetic status, the same story is confirmed: a 1% increase in the genetic sub indices of production and functional traits from their levels in 2007 will reduce variable costs by 0.14% and 0.29%, respectively. Conformation traits did not have a statistically significant effect on variable costs. These results show that the Norwegian breeding program was able to ensure the cost reducing effects of functional traits without causing the cost-increasing deterioration in production traits as implied by the negative genetic correlation between the two groups of traits. The related cost savings of producing the average output in 2007 from a 1 standard deviation increase in the sub-indices of production and functional traits from their 2007 levels are NOK 1,290 and NOK 1,952, respectively. These figures correspond to 0.4% and 0.6% of

the expected variable cost in 2007. Given that genetic progress is cumulative and permanent, estimates of cumulative and perpetual cost savings are also provided in the article. Based on the discounted perpetual cost saving estimate for the average farm, the discounted industry wide perpetual cost saving from a 1 standard deviation genetic progress in functional traits relative to their level in 2007 is estimated to be approximately NOK 160 million.

It was then concluded that broadening of breeding goals have a cost reducing effect for dairy farms. The results also show that it is possible to achieve cost reducing genetic progress in production and functional traits despite the negative genetic correlation between the two traits.

Summary of Contributions, Findings, and Limitations

The articles compiled in this dissertation highlight aspects of dairy production under marketing quota that have not been addressed before. Both methodological and empirical contributions are made to the literature. Methodologically an extended decomposition of the widely used Malmquist productivity index is proposed and implemented to account for genetic-based technical change caused by breeding. In addition a theoretical framework to model producer response to quota restrictions in the form of product quality change is outlined and empirically tested. Finally, a framework proposed by Borges and Thurman (1994) to study supply response under yield uncertainty from yield data is generalized to a multiple input setting.

The empirical results in article 1 show that breeding can increase the productivity of dairy farms operating under marketing quota. Furthermore, broadening of breeding

goals to account for traits that improve animal welfare and ensure sustainability of production improve current farm profitability by cutting production cost. The issue of milk quality, as defined by nutrient composition, is also evaluated with respect to changes in the quota regime. Results show that restrictive quota regimes are likely to result in the substitution of high-value protein with low-value dairy fat. To the extent that milk quality can be reduced to nutrient composition, it can be concluded that restrictive quota regimes reduce milk quality. Finally, price changes in the surplus milk market are shown to be relatively stronger determinants of milk supply by Icelandic dairy producers. It was also found that studying supply response based on yield per single input data tends to overstate the probability of surplus production and consequently undermine supply response to prices changes in a quota milk market.

Due to data related problems, there are two areas of limitation for articles included in this dissertation. These are:

1. Selection into panel

In all articles unbalanced panel data is used to study the respective topics. However, there was no information with respect to why non-response occurs in the panel. Accordingly, there was no option but to assume selection into the panel is random or ignorable (Baltagi 2005 p220, Baltagi and Song 2006), i.e., non-response is independent of endogenous variables in an econometric model. This may not however be necessarily valid. For example if non-response is caused by farms exiting production and those exiting production are systematically different from those remaining, non-random or non-ignorable selection will arise. In this case, econometric analysis of the unbalanced panel

using standard panel data methods or without considering selection may result in inconsistent estimates (Baltagi and Song 2006).

2. Missing labor data

Dairy production is a labor intensive production process and therefore labor cost is a major cost component. However, labor data was unavailable in the Norwegian dataset used for article 2 and 3. Therefore, weak separability of non-labor inputs from labor inputs is assumed. As shown by Fuss (1977), this assumption implies a two stage production process where the optimal mix of non-labor inputs is selected first. Given the optimal mix, the aggregate of non-labor inputs is selected together with labor inputs in a second stage. There is no reason to believe that weak separability is a necessarily valid assumption, and therefore it has to be recognized as a limitation of the analysis in the abovementioned articles.

Footnotes
[1] The EU proposed the removal of dairy marketing quotas by 2015 and quotas are planned to be increased slowly each year until then to allow 'soft-landing' of the dairy sector.

[2] http://www.ssb.no/stjord_en/

[3] www.genoglobal.no

[4] http://www.landbunadur.is/landbunadur/wgbi.nsf/key2/mhhr5ajd7s.html

[5] Note that restricted profit function collapses to the cost function when producers cannot influence their revenues in anyway.

[6] 1 USD = 127.58 ISK on March 15,2012. Source: http://www.sedlabanki.is, Acessed 18, March 2012.

[7] 1 USD = 5.75 NOK on March 15, 2012. Source: http://www.norges-bank.no/en/, Acessed 18, March 2012.

[8] The breeding program for the Icelandic dairy cattle also started to increase the ephasis on non production related traits since 1993 following farmer complaints about health and physical propoerties of dairy cows. In 1993, the breeding weight on production traits was reduced to accomodate such concerns. In 2005, the emphasis on production traits was reduced further to introduce longevity as a selection trait (Sigurdsson 1993; Sigurdsson and Jonmundsson 2011).

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Paper I

Animal Breeding and Productivity Growth of Dairy Farms

Daniel Muluwork Atsbeha, Dadi Kristofersson, and Kyrre Rickertsen

Abstract

We introduce genetic-based technical change into Malmquist productivity index and measure productivity growth caused by animal breeding. Breeding is likely to affect milk quality, and therefore milk quantities are adjusted for quality change. We use panel data from Icelandic dairy farms for the period 1997–2006 to estimate an input distance function. The parametric Malmquist productivity index and its decomposition show that average annual productivity growth has been 1.6%. Scale effects are the most important source, but 19% of the productivity growth is due to breeding. If quality effects are ignored, productivity growth would be reduced by 83%.

Key words: breeding, dairy production, Malmquist productivity index, technical change.

JEL codes: D24; O33; Q12; Q16.

Introduction

Genetic improvement of biological inputs by breeding is an important source of technical change in agriculture (Babcock and Foster 1991). Breeding is a slow process, and some may argue that its effects on productivity can be ignored in the short-run. However, this argument is flawed for two reasons. First, breeders have to consider heterogeneities in production conditions when they develop new genetic material. For example, attributes related to disease resistance may be the priority in one area while attributes related to heat tolerance may be the priority in another area. Consequently, once farmers have adopted animals with specific genetic attributes, the genetic variation in these attributes 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 socioeconomic groups of farmers because of factors such as risk preferences, infrastructural constraints, and prices. Depending on where each farm is in the adoption process, the slow diffusion of new genetic material reinforces short-run variation between farms. In addition, other managerial decisions can give rise to short-run variations in genetic material. For example, dairy production involves a continuous transfer of genetic material, either naturally or through artificial insemination. Therefore, managerial decisions such as choices of insemination method, breed of cows, and generation interval will partly determine the genetic status of dairy cows on a farm. This genetic variation may result in short-run productivity differences among farms.

Agricultural economists have long been interested in the effects of plant breeding on yield per acre and its variability (e.g., Babcock and Foster 1991; Byerlee 1993;

Godden and Brennan 1994; Nalley, Barkley, and Featherstone 2010). However, there are few studies measuring productivity effects of breeding in livestock production, and these studies use proxy variables such as expenditure on livestock research to measure the effects of breeding (e.g., Townsend and Thirtle 2001). In studies of productivity growth from plant breeding, variety-trial data obtained from crop research stations are commonly used. For example, Babcock and Foster (1991) used research station data from three regions that cultivate tobacco in North Carolina, and they found that new genetic material led to an annual yield gain of 0.54% between 1954 and 1987. Similarly, Nalley, Barkley, and Featherstone (2010) found that breeding increased wheat yield by 0.46% per year on test plots in Mexico's Yaqui Valley between 1990 and 2002. While such studies provide estimates of potential yield gains from breeding, it is also likely that actual farm-level gains will differ because of farm-specific conditions including technology adoption and other managerial behavior. For example, Byerlee (1993) found annual yield gain of 1% on research station plots in Pakistan's Punjab region even though the average yield gain for actual farms in the area, as measured by varietal improvement index, was only 0.6%.[1] According to Byerlee (1993), the slow diffusion of newly released varieties was one likely reason for this difference.

Measurement of productivity gain from breeding has frequently focused on yield levels. However, breeding may also result in other benefits. Such benefits include yield maintenance through improved disease resistance and improved product quality (Godden and Brennan 1994; Marasas, Smale, and Singh 2003). These improvements may either result in cost reductions or higher product prices. Townsend and Thirtle (2001) found that the returns from South African livestock research were underestimated by at least 50% when yield maintenance effects were ignored. Furthermore, Saito et al. (2009) found that

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the mean wheat yields were higher for standard varieties than for new varieties. However, new varieties had higher protein content that leads to higher prices.

We contribute to the literature in four ways. First, the effect of animal breeding on the productivity of dairy farms is measured. Several studies have measured productivity growth on dairy farms (e.g., Brümmer, Glauben, and Thijssen 2002; Newman and Matthews 2006; Sipiläinen 2007). However, none of these studies have investigated the effects of animal breeding. Furthermore, contrary to the studies of plant breeding that are discussed above, we use farm level data and estimate actual rather than potential productivity effects.

Second, we measure total productivity growth using Malmquist productivity index. This index has frequently been used to measure and decompose productivity growth in dairy production (e.g., Newman and Matthews 2006; Sipiläinen 2007). We extend the decomposition of the Malmquist index and decompose its technical change component further into genetic- and nongenetic-based technical change components. Unlike other indices that are used to measure productivity effects of breeding, the Malmquist index allows for variations in the use of nongenetic inputs such as veterinary expenses, and yield maintenance effects are thereby taken into account.

Third, accounting for quality is important for accurate measurement of productivity growth. Coelli et al. (2005) point out different approaches that can be used to consider the effects of quality changes in productivity analysis. We use milk composition and unit values data to adjust the quantities of milk to standard quality milk that can be compared across farms and over time.

Fourth, insemination of dairy cows can be done either artificially by using semen from proven bulls or naturally by using unregistered bulls on the farm. Artificial

insemination is the most common method in Icelandic dairy production, but natural insemination is also practiced mainly on heifers (Ministry of Agriculture of Iceland 2003). We then investigate the productivity effects of these insemination methods.

Dairy Production and Policy in Iceland

Icelandic dairy farms have traditionally been small family-owned enterprises. Milk production has provided more than 85% of sales revenues and meat output has largely been a by-product. During the 1970s, there were significant increases in milk production and by the late 1970s, production exceeded domestic demand. Production quotas were introduced at the farm level in the early 1980s. The quotas were initially non-tradable. Such quotas are likely to slow down productivity growth significantly by preventing farms from operating at optimal size and, thereby, making efficient utilization of available resources difficult (Richards and Jeffrey 1997; Kumbhakar et al. 2008). To facilitate efficiency, the quota system evolved towards a system with freely tradable quotas in 1992 (Johannesson and Agnarsson 2004; Bjarnadottir and Kristofersson 2008). However, quota trade was limited until new agreement was signed between The Farmers Association of Iceland and the government in 1997. This agreement secured stable subsidies and market conditions for dairy farms, and the late 1990s were characterized by large quota trade and subsequent reduction in the number of farms (Bjarnadottir and Kristofersson 2008).[2]

During the period 1995–2007, the number of dairy farms was reduced by 50%, and the average milk production per farm more than doubled (Bjarnadottir and Kristofersson 2008). Several changes in dairy technology made this large increase in

output possible (The Farmers Association of Iceland 2009). For example, feed quality

improved significantly because of better feed processing and storage methods such as the

introduction of round hay bales in the late 1980s. Moreover, the widespread cultivation of

high-quality forage (e.g., timothy grass), increasing local production of concentrates

(mainly barley), mechanization of feeding, and the introduction of automated milk parlors

contributed to the output growth.

Theoretical Model

Multiple output technologies are frequently modeled using distance, profit, or cost

functions. Because we do not have complete input prices, the radial input distance

function is used to model production technology (Shephard 1953; 1970).[3]

Input Distance Functions

For a vector of inputs $\mathbf{x} = (x_1, x_2, ... x_J)$ and a vector of outputs $\mathbf{y} = (y_1, y_2, ... y_M)$, a

multiple output dairy technology can be defined by an input requirement set L such that:

(1) $L(\mathbf{y}; g, a) = \{\mathbf{x} : (\mathbf{x}, \mathbf{y}) \in P(g, a) : \mathbf{x} \text{ can produce } \mathbf{y}\}$,

where P represents the technology set as defined by the states of genetic-based, g, and

nongenetic-based technology, a. We assume that the technology satisfies the properties

discussed in Färe and Primont (1990). The input distance function $D_I(\mathbf{x}, \mathbf{y}; g, a)$ defined

on the technology set is given as:

(2) $D_I(\mathbf{x}, \mathbf{y}; g, a) = \max_{\lambda} \left\{ \lambda \geq 1 : \dfrac{\mathbf{x}}{\lambda} \in L(\mathbf{y}; g, a) \right\}$,

where λ is an input scaling factor. $D_I(\mathbf{x}, \mathbf{y}; g, a)$ is nondecreasing, homogeneous of degree one, and concave with respect to inputs as well as quasiconcave and nonincreasing with respect to outputs (Färe and Primont 1990). Moreover, $D_I(\mathbf{x}, \mathbf{y}; g, a) \geq 1$ if $\mathbf{x} \in L(\mathbf{y}; g, a)$, i.e., the input mix is feasible, and $D_I(\mathbf{x}, \mathbf{y}; g, a) < 1$ if $\mathbf{x} \notin L(\mathbf{y}; g, a)$, i.e., the input mix is infeasible.

The Malmquist Index and Genetic-Based Technical Change

The Malmquist productivity index proposed by Caves, Christensen, and Diewert (1982) measures productivity growth that occurred between two periods based on a given reference technology. The reference technology can be represented by the technology of one of the periods, as constructed from observed input-output data, or by some combination of technologies from both periods. For example, Färe et al. (1992) defined the input-oriented Malmquist productivity index, M_I^{CCD}, as the geometric mean of Malmquist indices for two adjacent periods, t and $t+1$, as:

$$(3) \quad M_I^{CCD}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}\right) = \left[\frac{D_I\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}; g^t, a^t\right)}{D_I\left(\mathbf{x}^t, \mathbf{y}^t; g^t, a^t\right)} \times \frac{D_I\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}; g^{t+1}, a^{t+1}\right)}{D_I\left(\mathbf{x}^t, \mathbf{y}^t; g^{t+1}, a^{t+1}\right)} \right]^{0.5}.$$

Given that $D_I(\mathbf{x}, \mathbf{y}; g, a) \geq 1$ for any feasible input–output mix and $D_I(\mathbf{x}, \mathbf{y}; g, a) < 1$ for any infeasible input–output mix, $M_I^{CCD}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}\right)$ can be less than, equal to, or greater than unity to indicate productivity growth, stagnation, or decline, respectively. Furthermore, the index can be decomposed parametrically (e.g., Fuentes, Grifell-Tatjé, and Perelman 2001) or nonparametrically (e.g., Färe et al. 1992) to reflect the contribution of technical efficiency change (i.e., a catch-up effect implying a

producer is approaching the best-practice frontier) and technical change (i.e., a shift in the best-practice frontier) to total productivity growth. Given the technology set specification above, one can also isolate the contribution of genetic- and nongenetic-based technical change to productivity growth over time.

However, the decomposition of the index in equation (3) does not allow for productivity growth associated with scale effects. Scale effects refer to productivity growth that will arise as a result of a producer getting closer to the most productive scale size, MPSS (Färe et al. 1994). However, scale effects can be introduced by using different methods, for example, through the enhanced decomposition discussed by Färe et al. (1994) for nonparametric decomposition or the method proposed by Balk (2001) for the parametric decomposition. In both cases, measurement of productivity growth due to scale effects requires computation of scale efficiencies for adjacent periods. However, as discussed by Orea (2002), computing scale efficiencies can be problematic for certain types of technologies such as globally increasing, decreasing, or constant returns to scale technologies.

Therefore, Orea (2002) proposed a parametric decomposition of the Malmquist productivity index that enables measurement of scale effects without the need to compute scale efficiencies. For a translog representation of an output distance function, Orea (2002) defined the parametric Malmquist productivity index as the weighted difference between the average growth rates of output and inputs. Accordingly, using distance elasticities as weights, the parametric Malmquist productivity index can be defined as:

$$(4) \quad \ln M_I = -\frac{1}{2}\sum_{m=1}^{M}\left(\varepsilon_m^{t+1} + \varepsilon_m^t\right)\ln\left(y_m^{t+1}/y_m^t\right) - \frac{1}{2}\sum_{j=1}^{J}\left(\varepsilon_j^{t+1} + \varepsilon_j^t\right)\ln\left(x_j^{t+1}/x_j^t\right),$$

where the distance elasticity for output m is $\varepsilon_m^t = \dfrac{\partial \ln D_I(t)}{\partial \ln y_m}$, the distance elasticity for

input j is $\varepsilon_j^t = \dfrac{\partial \ln D_I(t)}{\partial \ln x_j}$, and $D_I(t) = D_I\left(\mathbf{x}^t, \mathbf{y}^t; g^t, a^t\right)$. Since the input distance

function is homogeneous of degree one in input quantities, the input weights sum to one.

However, the output weights do not sum to one except under constant returns to scale.

This violates the proportionality property that equation (4) needs to satisfy to be a total

factor productivity index (Orea 2002). To ensure the proportionality property, we follow

Orea (2002) and define the output weights as elasticity shares. This results in the

generalized parametric Malmquist productivity index:

$$(5) \qquad \ln G_I = -\frac{1}{2} \sum_{m=1}^{M} \left(\left(\varepsilon_m^{t+1} \Big/ \sum_{m=1}^{M} \varepsilon_m^{t+1} \right) + \left(\varepsilon_m^t \Big/ \sum_{m=1}^{M} \varepsilon_m^t \right) \right) \ln\left(y_m^{t+1} / y_m^t \right) -$$
$$\frac{1}{2} \sum_{j=1}^{J} \left(\varepsilon_j^{t+1} + \varepsilon_j^t \right) \ln\left(x_j^{t+1} / x_j^t \right).$$

By rearranging equation (5), Saal, Parker, and Weyman-Jones (2007) showed that the

generalized parametric Malmquist productivity index can also be written as:

$$(6) \qquad \ln G_I = \ln M_I + \frac{1}{2} \sum_{m=1}^{M} \left(\left(\varepsilon_m^{t+1} SF_I^{t+1} \right) + \left(\varepsilon_m^t SF_I^t \right) \right) \ln\left(y_m^{t+1} / y_m^t \right),$$

where $SF_I^t = \left(\left(\sum_{m=1}^{M} \varepsilon_m^t + 1 \right) \Big/ \sum_{m=1}^{M} \varepsilon_m^t \right) = 1 - RTS^t$ is a scale factor and $RTS^t = -1 \Big/ \sum_{m=1}^{M} \varepsilon_m^t$ is a

measure of scale elasticity from the input distance function. Therefore, under constant

returns to scale $RTS^t = 1$, $SF_I^t = 0$, and equation (6) reduces to equation (4).

Orea (2002) used the quadratic identity (approximation) lemma of Diewert (1976)

to decompose equation (6) into the different components contributing to productivity

growth. As shown in Diewert (1976), the quadratic identity lemma states that if $F(\mathbf{s})$ is a

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quadratic function of its argument $\mathbf{s}$, which is a vector of dimension R, then

$$F\left(\mathbf{s}^1\right) - F\left(\mathbf{s}^0\right) = \sum_{r=1}^{R} \frac{1}{2}\left[F_r\left(\mathbf{s}^1\right) + F_r\left(\mathbf{s}^0\right)\right]\left[\mathbf{s}^1 - \mathbf{s}^0\right], \text{ where the superscripts on } \mathbf{s} \text{ represent}$$

certain data points, say specific years, and $F_r = \dfrac{\partial F}{\partial s_r}$. Then $F_r\left(\mathbf{s}^1\right)$ and $F_r\left(\mathbf{s}^0\right)$ represent

the evaluation of F_r at the two data points. Since the translog functional form is quadratic

in the natural logarithms of its arguments, the difference between evaluations of the input

distance function at two data points can be written as:

$$(7) \quad -\left[\ln D_I\left(t+1\right) - \ln D_I\left(t\right)\right] \equiv -\frac{1}{2}\sum_{m=1}^{M}\left(\varepsilon_m^{t+1} + \varepsilon_m^{t}\right)\ln\left(y_m^{t+1}/y_m^{t}\right) -$$

$$\frac{1}{2}\sum_{j=1}^{J}\left(\varepsilon_j^{t+1} + \varepsilon_j^{t}\right)\ln\left(x_j^{t+1}/x_j^{t}\right) - \frac{1}{2}\left(\varepsilon_g^{t+1} + \varepsilon_g^{t}\right)\ln\left(g^{t+1}/g^{t}\right) - \frac{1}{2}\left(\varepsilon_a^{t+1} + \varepsilon_a^{t}\right)$$

where $\varepsilon_g^{t} = \dfrac{\partial \ln D_I\left(t\right)}{\partial \ln g}$ and $\varepsilon_a^{t} = \dfrac{\partial \ln D_I\left(t\right)}{\partial a}$. Using equation (4) and the fact that

$-\ln D_I\left(t\right) = \ln TE\left(t\right)$ (Saal, Parker, and Weyman-Jones 2007), where TE denotes

technical efficiency, equation (6) can be rewritten as:

$$(8) \quad \ln G_I = \left[\ln TE\left(t+1\right) - \ln TE(t)\right] + \frac{1}{2}\left(\varepsilon_g^{t+1} + \varepsilon_g^{t}\right)\ln\left(g^{t+1}/g^{t}\right) +$$

$$\frac{1}{2}\left(\varepsilon_a^{t+1} + \varepsilon_a^{t}\right) + \frac{1}{2}\sum_{m=1}^{M}\left(\left(\varepsilon_m^{t+1}SF_I^{t+1}\right) + \left(\varepsilon_m^{t}SF_I^{t}\right)\right)\ln\left(y_m^{t+1}/y_m^{t}\right).$$

Therefore, in our case, equation (6) is decomposed into four sources of productivity

growth namely: technical efficiency change $\Delta TE = \ln TE\left(t+1\right) - \ln TE(t)$, genetic-based

technical change $\Delta G = \dfrac{1}{2}\left(\varepsilon_g^{t+1} + \varepsilon_g^{t}\right)\ln\left(g^{t+1}/g^{t}\right)$, non genetic-based technical change

$\Delta A = \dfrac{1}{2}\left(\varepsilon_a^{t+1} + \varepsilon_a^{t}\right)$, and scale effects $\Delta S = \dfrac{1}{2}\sum_{m=1}^{M}\left(\left(\varepsilon_m^{t+1}SF_I^{t+1}\right) + \left(\varepsilon_m^{t}SF_I^{t}\right)\right)\ln\left(y_m^{t+1}/y_m^{t}\right)$. A

similar decomposition of the Malmquist index in equation (3) is also provided in the
supplementary appendix of this article.

Empirical Model

The translog input distance function is:

$$
(9) \quad \ln D_I\left(\mathbf{x}_f^t, \mathbf{y}_f^t; g_f^t, a_f^t, z_f^t\right) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln x_{fj}^t + \sum_{m=1}^{M} \beta_m \ln y_{fm}^t + \kappa \ln g_f^t + \theta \ln a_f^t +
$$

$$
\sum_{j=1}^{J}\sum_{m=1}^{M} \varphi_{jm} \ln x_{fj}^t \ln y_{fm}^t + \sum_{j=1}^{J} \delta_{gj} \ln g_f^t \ln x_{fj}^t + \sum_{j=1}^{J} \alpha_{aj} \ln a_f^t \ln x_{fj}^t +
$$

$$
\sum_{m=1}^{M} \phi_{gm} \ln g_f^t \ln y_{fm}^t + \sum_{m=1}^{M} \beta_{am} \ln a_f^t \ln y_{fm}^t + \kappa_{ag} \ln a_f^t \ln g_f^t + \varpi z_f^t +
$$

$$
\frac{1}{2}\left[\sum_{j=1}^{J}\sum_{k=1}^{J} \alpha_{jk} \ln x_{fj}^t \ln x_{fk}^t + \sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} \ln y_{fm}^t \ln y_{fn}^t + \kappa_{gg}\left(\ln g_f^t\right)^2 + \theta_{aa}\left(\ln a_f^t\right)^2 \right],
$$

where x_{fj}^t and y_{fm}^t denote input j and output m used and produced by farm f at time

period t, respectively. As above, g_f^t and a_f^t are farm and time-specific indices

representing genetic- and non genetic-based technical change. In our empirical

implementation, a trend variable is used to capture non genetic-based technical change.[4]

The variable z refers to a control variable for insemination technology, and it is defined

as the proportion of cows on each farm that are sired by unregistered bulls.[5] The vector

$\psi = [\alpha, \beta, \kappa, \theta, \varphi, \delta, \phi, \varpi]$ is a vector of parameters to be estimated.

Homogeneity of degree one in inputs implies $\sum_{j=1}^{J} \alpha_j = 1,\ \sum_{j=1}^{J} \varphi_{jm} = \sum_{j=1}^{J} \delta_{gj} = \sum_{j=1}^{J} \alpha_{aj} =$

$\sum_{j=1}^{J} \alpha_{jk} = 0,$ while quadratic symmetry implies $\alpha_{jk} = \alpha_{kj}$ and $\beta_{mn} = \beta_{nm}$. We impose these

restrictions before estimation. The homogeneity restrictions are imposed by the ratio

method due to Lovell et al. (1994). This method involves dividing the quantity of all inputs with the quantity of one of the inputs. This division also allows estimation of the input distance function because it implies that equation (9) can be written as:

$$(10) \quad -\ln x_{fJ}^t = TL\left(x_{fj}^t \big/ x_{fJ}^t, y_{fm}^t; g_f^t, a_f^t, z_f^t, \psi\right) - \ln D_I,$$

where $TL(\ )$ refers to the right-hand side of equation (9) and $\ln D_I = u_f^t$ is a nonnegative error term capturing the effects of technical inefficiency.[6] A white noise error term υ_f^t is added to allow for random measurement error in equation (10) such that we have a composite error term $\xi_f^t = \upsilon_f^t - u_f^t$. The term υ_f^t is symmetric and assumed to satisfy the classical assumptions, i.e., $\upsilon_f^t \overset{iid}{\sim} N\left(0, \sigma_\upsilon^2\right)$.

We allow technical inefficiency to vary over time using the Battese and Coelli (1992) time-varying decay specification for technical inefficiency, i.e., u_f^t is defined as $u_f^t = \exp\{-\eta(t-T)\} \cdot u_f$, where η is a decay parameter, T is the terminal period in the data, and the nonnegative u_f is assumed to follow the truncated normal distribution or $u_f \overset{iid}{\sim} N^+\left(\mu, \sigma_u^2\right)$. Other possible distributions are the half-normal, exponential, and gamma distributions.[7] Furthermore, υ_f^t and u_f^t are assumed to be orthogonal to each other as well as to the independent variables of the model.

Adjustment for Output Quality

Icelandic dairy processors determine the unit price of milk according to its nutrient content and hygienic quality, and a quota-restricted farmer may try to reduce the effects of the quota by increasing the quality of milk. Milk quality can be influenced by

managerial decisions including feeding strategies, milking patterns, and handling

practices as well as by breeding. Therefore, ignoring milk quality differences is likely to

cause incorrect measurement of productivity growth (Coelli et al. 2005). The effect of

unaccounted quality changes on productivity growth measurement is illustrated

graphically in figure A1 of the supplementary appendix of this article.

Two ways can be used to translate quality into quantity. First, milk quantity can

be expressed in terms of physical properties such as energy content (e.g., Energy

Corrected Milk). Second, one can use the value of attributes to construct quality indices.

We choose the latter alternative since attribute value directly affects managerial

decisions.

Let y_f^t denote total milk output in liters and v_f^t the corresponding unit value of

milk for farm f in time period t. The observed unit value is calculated as total revenue

from milk sales divided by total milk production. In Iceland, the unit value is a function

of quality attributes, prices of these attributes, and quota holdings of a farm. The

relationship may be specified as:

$$(11) \quad v_f^t = \left(1 - \delta_f^t\right) h_w^t \left(c_f^t\right) + \delta_f^t h_o^t \left(c_f^t\right),$$

where c_f^t is a vector of quality attributes and $h_w^t(\cdot)$ and $h_o^t(\cdot)$ are hedonic price functions

for milk produced within and outside quota, respectively. The weight δ_f^t is calculated as:

$$(12) \quad \delta_f^t = \begin{cases} 0 & \text{if } y_f^t \leq \overline{y}_f^t \\ \dfrac{\left(y_f^t - \overline{y}_f^t\right)}{\overline{y}_f^t} & \text{if } y_f^t > \overline{y}_f^t \end{cases},$$

where $\overline{y}_f^t$ denotes milk quota of the farm. The hedonic price function may be linear in

some attributes and non linear in other attributes. In the Icelandic case, it is linear in

protein content c_1, fat content c_2, and close to linear (i.e., thresholds) in somatic cell

count c_3. On the other hand it is non linear in germ count and antibiotic residues. For the

non linear attributes, increasing price deductions are applied when milk quality fails to

meet certain minimum standards with respect to each attribute.

We apply two separate adjustments for the linear and non linear attributes. First,

to correct for quality attributes with a linear effect on the unit values in equation (11),

ordinary least squares is used to estimate:

$$(13) \qquad v_f^t = \beta_0 + \beta_1 c_{1f}^t + \beta_2 c_{2f}^t + \beta_3 c_{3f}^t + \varepsilon_f^t,$$

where ε_f^t is assumed to be a white noise error term. Equation (13) will provide the

predicted unit value $\hat{v}_f^t$ for each farm in each time period. Second, unit value for average

quality milk is calculated as $\overline{v} = \hat{\beta}_0 + \hat{\beta}_1 \overline{c}_1 + \hat{\beta}_2 \overline{c}_2 + \hat{\beta}_3 \overline{c}_3$, where $\overline{c}_1$, $\overline{c}_2$, and $\overline{c}_3$ are the

average values of related attributes across all farms. Then we compute the ratio $\hat{v}_f^t / \overline{v}$ as

a quality index, which takes account of attributes affecting unit values in a linear way.

The quality index will take a value of one for a farm producing milk of average quality,

more than one for a farm producing high-quality milk, and less than one for a farm

producing low-quality milk.

In a second adjustment, we correct for quality attributes affecting unit values non

linearly. A quota-weighted and quality-corrected average milk price p_f^t is calculated by

only taking account of attributes affecting unit values in a linear way, or:

$$(14) \qquad p_f^t = (1 - \delta_f^t) \sum_{i=1}^{3} p_{iw}^t c_{if}^t + \delta_f^t \sum_{i=1}^{3} p_{io}^t c_{if}^t,$$

where p_{iw}^t and p_{io}^t are observed average prices of attributes paid for milk within and outside quota in a given year, respectively. The ratio v_f^t / p_f^t may be interpreted as another quality index, reflecting the value of attributes with non linear effects on unit values. For a farm producing milk of minimum quality with respect to the non linear attributes, this index will take a value of one.

We use the two quality indices calculated above to construct quantity of quality-adjusted milk as:

$$(15) \quad \tilde{y}_f^t = \frac{\hat{v}_f^t}{\bar{v}} \frac{v_f^t}{p_f^t} y_f^t.$$

The adjustment factors in equation (15) transform observed milk quantity into quantity of constant quality milk.[8]

Data

Unbalanced panel data, covering the period 1997–2006, is used for estimation.[9] The data contain 1,252 observations from 324 dairy farms, combining farm management, milk quality, and breeding data. The farm management data are collected by the Agricultural Economics Institute (Hagþjónusta landbúnaðarins). Farmers contribute their data to the Institute on a voluntary basis.[10] The Institute analyzes how representative the data are and their results suggest that the dataset is representative of Icelandic farms (Hagþjónusta landbúnaðarins 2010). The milk quality data are collected by the milk cooperative in Iceland, and it is based on weekly measurements of quality attributes of the milk each farm delivers to the cooperative. The breeding data are collected by The Farmers Association of Iceland. Almost all farms participate in the breeding program, and all the

participating farms are included in the data. On average, each dairy farm is observed for 3.9 years.

The outputs are milk and meat. The inputs are cost of concentrates, cost of farm capital, land size, number of cows adjusted for the number of days in a year that the average cow on a farm was active in milk production, cost of veterinarian services, and labor input. All cost based measures are expressed in 1997 prices using consumer price index for farm products. The costs of capital and veterinary services can be considered as composite inputs constructed through weighted aggregations of different capital equipments and veterinary services that could not have been aggregated otherwise.[11]

Table 1 provides descriptive statistics of variables in the model. Labor use has declined by 0.35% per year, while the application of all other inputs has increased. The largest annual increases are for capital and concentrates, which increased by 13.4% and 7.1% per year, respectively. The annual growth rate of other inputs range between 1.2% for land and 6.1% for veterinary services. The average milk quota was about 138,000 liters, and it increased annually by 5.6%. The binding nature of the quota is reflected in an average milk output of about 141,000 liters, which corresponds to almost 142,000 liters of quality adjusted milk.

The breeding goal for the Icelandic dairy cattle targets eight traits. Traits related to milk and meat production account for 44% of the total breeding goal. The breeding weight on milk emphasizes protein percentage and protein yield (Sigurdsson 1993; Sigurdsson and Jonmundsson 2011), suggesting that milk quality effects are important when measuring the contribution of breeding to productivity. The emphasis on production traits used to be higher in the past; however, their importance was reduced in 1993. The reduction reflected farmers' complaints about physical properties of cows such

as udder and teat attributes as well as longevity (Sigurdsson 1993). In 2005, longevity was included as one trait of selection and the emphasis on production traits was reduced further (Sigurdsson and Jonmundsson 2011).

We measure genetic-based technical change using an aggregate breeding index.[12] This index is a weighted aggregate of estimated breeding values (EBVs) of the average sire of all cows in the herd. The weights used for aggregation are the breeding weights of each trait as determined by the breeding organization. The index for each farm is interpreted relative to the population average, which is normalized to 100 with a standard deviation of 10. Accordingly, index values of more than 100 represent increasingly better animals while values less than 100 represent increasingly worse animals relative to the performance of the population average. As shown by table 1, the average value of the breeding index is 99.54, and the rate of genetic progress is about 0.66% per year between 1997 and 2006.

For the average farm in our sample, the proportion of cows sired by unregistered bulls is about 30%. However, daughters of unregistered bulls are likely to have inferior production potential as compared to daughters of proven bulls. For example, for daughters of proven bulls in the U.S, Norman et al. (2003) found that annual milk yield was 366–444 kilograms higher than for daughters of unregistered bulls.[13] This yield difference suggests that farms with high proportion of cows from unregistered bulls may be operating under inferior genetic technology as compared with other farms. Therefore, the proportion of cows from unregistered bulls, on each farm, is introduced as a control variable in the input distance function.

Estimation and Results

All variables are normalized so that the first-order parameters can be interpreted as distance elasticities at the geometric mean.[14] A maximum likelihood estimator, as implemented in the STATA 11[®] module xtfrontier (StataCorp 2009), is used to estimate equation (10). All parameters related to the breeding index are insignificant at the 5% level of significance. However, flexible functional forms such as the translog are known to be vulnerable to multicollinearity. To choose a more parsimonious specification, various tests are conducted. According to test results reported in table 2, restrictions for constant returns-to-scale, Cobb-Douglas technology, time-invariant technical inefficiency, and half-normal distribution for technical inefficiency are rejected at the 5% level of significance. On the other hand, restrictions for Hicks and scale neutrality of genetic- and non genetic-based technical change cannot be rejected.[15] The non rejected restrictions are imposed on equation (10) and a restricted model is estimated. The parameter estimates of the restricted model are reported in table 3, and subsequent computations of productivity growth are based on this restricted model.[16] The parameter estimates of the unrestricted model are provided in the supplementary appendix of this article.

Parameter Estimates

As shown in table 3, the first-order parameters of inputs and outputs have the expected signs and are statistically significant at the 5% level of significance. As discussed above, these parameters are distance elasticities at the geometric mean. Low distance elasticities are found for capital (0.04) and veterinary services (0.03). However, the coefficients of

variation of these inputs' elasticities are also as high as 95% and 154%. The combination of low and significantly varying distance elasticity for capital is also reported in Brümmer, Glauben, and Thijssen (2002) for Polish dairy farms.[17] The highest distance elasticity is found for number of cows (0.57) followed by labor (0.14). Concentrates and land, which can be considered as proxy variable for forage, have similar distance elasticities (0.12). The distance elasticities of milk and meat are −0.63 and −0.02, respectively.

The distance elasticity for the breeding index (0.47) and the coefficient of the trend variable (0.007) are both positive and significant at the 5% level of significance. These positive values suggest genetic- as well as non genetic-based technical progress during the study period, i.e., the input requirement set of producing a given level of output expands when the breeding index or trend variable increase. Given the Hicks and scale neutrality of non genetic-based technical change reported in table 2, the statistically significant and negative quadratic term for the trend suggest that non genetic-based technical progress has slowed down over time.

The estimated distance function is nondecreasing in input quantities and nonincreasing in output quantities so it satisfies the monotonicity property at the point of normalization. As noted by Orea (2002), monotonicity with respect to inputs of the output distance function has to be satisfied at all data points to avoid biased estimate of scale effects. The equivalent requirement for an input distance function is that monotonicity with respect to outputs has to be satisfied at all data points. However, the translog function does not satisfy monotonicity globally (Orea 2002), and at data points where monotonicity with respect to outputs is violated, estimated scale effects could be biased. We found that the percentage of violations with respect to inputs range between 0% and

24% of the observations. Violations with respect to milk and meat are 0% and 7.9% of the observations, respectively.[18] To evaluate the effect of violations with respect to meat on scale elasticity, we calculated the average scale elasticity (*RTS*) for all observations as well as for those observations that satisfy monotonicity with respect to both outputs. The violations with respect to meat have negligible impact on the scale elasticity estimate. The average scale elasticity is 1.57, suggesting increasing returns to scale. Our estimate is close to the value reported by Sipiläinen (2007) for Finnish dairy farms while it is larger than values reported in Brümmer, Glauben, and Thijssen (2002) and Newman and Matthews (2006), who reported scale elasticities ranging from 0.99 to 1.08 in four different European countries.[19]

Technical Efficiency

The time-varying technical efficiency scores of each farm are obtained from the composite error term using the conditional expectation predictor of Jondrow et al. (1982). The parameter γ in table 3 shows that technical inefficiency constitutes the largest share of total error variance, suggesting the appropriateness of the frontier approach as opposed to least squares. As shown by table 4, the average technical efficiency score is 76.0% with a standard deviation of 0.07. This figure implies that Icelandic dairy farms can reduce the input requirement of producing the average output by 24% if their operation becomes technically efficient. The estimate is close to what was found by Newman and Matthews (2006) for non-specialist Irish dairy farms, but it is lower than the estimates obtained by Brümmer, Glauben, and Thijssen (2002) for three other European countries.

As shown by the statistically significant decay parameter η in table 2, technical efficiency has been declining over time. The average technical efficiency score declined from approximately 77.4% in 1997 to 74.2% at the end of the sample period. This decline indicates the difficulty faced by the average farm to keep up with the best-performers in the industry that are innovating at 0.7% per year as shown by the trend parameter in table 2. The temporal decline in technical efficiency may, at least partly, be explained by the managerial challenges of a transition from quite small to larger farms as well as the learning curve associated with optimally employing new technologies. In figures 1a and 1b, technical efficiency scores are plotted against quota size and farmer's age. Technical efficiency increases with quota size, while it increases with age up to around 40 years and declines thereafter. Larger farms are operated by younger and possibly better educated farmers. The combination of increased farm size and better education may have then facilitated better use of modern technologies and best farming practices, resulting in higher technical efficiency scores for these farms.

Productivity Growth and Its Sources

Table 4 presents the yearly average productivity growth rates and their decomposition into different components. We also report average and cumulative productivity growth during the period 1997–2006. Productivity has increased by 1.6% per year. This estimate is in line with the average productivity growth reported for non-specialist Irish dairy farms during the period 1984–1990 (Newman and Mathews 2006). Sipiläinen (2007) reported a lower growth rate of 1.1% for Finnish dairy farms during the period 1990–2000. On the other hand, Brümmer, Glauben, and Thijssen (2002) found an annual

productivity growth of 6% for German and 3% for Dutch dairy farms. Furthermore, productivity growth has declined over time for Icelandic dairy farms. In the period 1997–2001, average annual productivity growth was about 3% while it declined to 0.2% in the period 2002–2006. The cumulative productivity growth during the period 1997–2006 was 14.5%.

The decomposition in table 5 shows that the productivity decline over time is mainly driven by nongenetic-based technical change. Productivity has increased by 0.1% per year due to nongenetic-based technical change. During the period 1997–2001, this figure was 1.5% while it declined to –1.3% per year during the period 2002–2006. This decline can, at least, partially be explained by the high stillbirth problem on Icelandic dairy farms after 2002. Benjamínsson (2007) report that the stillbirth rate for the Icelandic dairy cattle has increased from 10% in the 1990s to an all time high of over 15% in 2005. The cumulative productivity growth from nongenetic-based technical change was 1.3% for the period 1997–2006.

The temporal decline in technical efficiency led to productivity decline of 0.6% per year, cumulating to a decline of 5.4% during the period 1997–2006. Similar results are reported in Sipiläinen (2007) for Finnish dairy farms.

Productivity increased by 1.8% per year due to scale effects, which have been positive throughout the period. The cumulative productivity growth due to scale effects is 16.3%, which is the largest of all other sources.

Genetic-Based Technical Change

Productivity growth that is due to genetic-based technical change has been 0.3% per year. This is about 19% of the annual productivity growth during the period. Our estimate is close to what Townsend and Thirtle (2001) found for livestock production in South Africa but somewhat lower than estimates reported in Babcock and Foster (1991) and Nalley, Barkley, and Featherstone (2010) for plant breeding. However, estimated productivity returns for breeding are likely to be lower in our study than in these studies for two reasons. First, the genetic merit of biological inputs is observed through their offspring, and this requires more time for livestock than plants. This means genetic progress is likely to be slower for the former. Second, the above studies are based on research station data where the performance of new varieties is measured under ideal production conditions. We use data from actual farms, where farmers may take suboptimal decisions that reduce productivity gain from new genetic material.

Breeding contributed less to productivity growth during the first than the second part of our study period. During the period 1997–2001, the annual productivity growth due to breeding was 0.28%, while it was 0.4% during the period 2003–2006.[20] The cumulative productivity growth from breeding was 2.5% during the period 1997–2006.

To further highlight productivity differences due to breeding, we classify farms based on genetic quality of their herd. We define high and low genetic quality herds as herds with an average breeding index in the highest and lowest quartile of the index, respectively. Other herds are considered as medium quality herds. There are substantial differences in productivity growth due to breeding among these herd quality classes. Median annual productivity growth due to genetic-based technical change is 0.1%, 0.3%,

and 0.6% for low, medium, and high quality herds, respectively. The statistical significance of these differences is tested using a K-sample nonparametric test of equal medians. Under a null hypothesis of equal medians, the Pearson Chi-square test statistic is 63.9 (d.f. = 2, p-value = 0.001), and we reject the null hypothesis of identical returns for the three groups.

A related issue is the productivity effects of using cows sired by unregistered bulls. Table 3 shows a statistically significant and negative parameter estimate for the proportion of cows sired by unregistered bulls. This negative parameter implies that farms with a high proportion of cows sired by unregistered bulls operate under inferior genetic technology. This can also be shown by predicting the genetic merit of unregistered bulls. To achieve this, we compute the value the breeding index must take in order to have a distance elasticity at the geometric mean equivalent to the effect of having all cows from unregistered bulls (i.e., $\kappa \ln\left(g \middle/ \overline{g}\right) = 100 \times \varpi$). The implied genetic merit of unregistered bulls is 80.6, about two standard deviations lower than the population average.

To further investigate the consequent effects on productivity growth, we classified farms into farms with low, medium, and high proportion of cows from unregistered bulls. Farms in the highest and lowest quartiles were classified as high and low proportion farms and the remaining farms as medium proportion farms. The median productivity growth associated with genetic-based technical change is 0.4%, 0.3%, and 0.1% for low, medium, and high proportion farms, respectively. For high proportion farms, these figures suggest that productivity growth from genetic-based technical change is about 25% of the comparable figure for low proportion farms. Again, the difference in the

medians was tested by using the *K*-sample nonparametric test of equal medians. The null

hypothesis of equal medians is rejected given the Pearson Chi-square test statistic of 30.4

(d.f. = 2, *p*-value = 0.001).

Effects of Quality Adjustment

To demonstrate the effects of our quality adjustment on the results, we have estimated the

restricted input distance function without quality adjustment of milk quantities. The

parameter estimates of this model are reported in table A2 of the supplementary

appendix. Compared to the parameter estimates in table 3, the distance elasticities for all

inputs and outputs do not change much. However, the distance elasticity for the breeding

index and the coefficient for the trend variable are lower in magnitude and they are

statistically insignificant at any conventional level of significance. We also computed

productivity growth and its decomposition based on these parameters. The results are

provided in table A3 of the supplementary appendix. Average productivity growth is

reduced by 83% and productivity growth due to genetic-based technical change is

reduced by 71%. As expected, the nongenetic-based technical change component is the

most affected when quality adjustments are ignored. Productivity growth due to

nongenetic-based technical change is lower for all years relative to the figures in table 4

and negative on average. However, statistical indicators in the forms of log likelihoods,

Akaike (AIC), and Bayesian (BIC) information criteria show that the model that adjusts

for milk quality is preferred statistically.

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Conclusions

Genetic improvement of biological inputs through breeding is an important source of productivity growth in agriculture. Previous studies measuring and decomposing productivity growth of dairy farms have not studied effects of breeding specifically. We measured productivity growth due to breeding using Malmquist productivity index and extended its decomposition to include a genetic-based technical change component. Furthermore, we used farm level genetic data for our analysis. Unlike experimental data, farm level genetic data allow farm-specific factors, such as management, to be considered when productivity growth from breeding is measured. Possible effects of breeding on milk quality were also taken into account.

Productivity growth was 1.6% per year. This growth rate is similar to the growth rate found for Irish dairy farms (Newman and Mathews 2006), while it is lower than annual productivity growth rates reported for other European countries (e.g., Brümmer, Glauben, and Thijssen 2002). The cumulative productivity growth was 14.5% during the period 1997–2006 for which scale effects contributed the most.

Productivity growth due to genetic-based technical change was about 0.3% per year. This was about 19% of the annual productivity growth during the period. Our estimate was close to the annual productivity growth estimate found in Townsend and Thirtle (2001) for livestock production, while it was somewhat lower than the 0.5% annual productivity growth rate reported for plant breeding in Babcock and Foster (1991) and Nalley, Barkley, and Featherstone (2010). However, these studies used research station rather than farm level data. Furthermore, the rate of genetic progress in livestock breeding is likely to be slower than in plant breeding due to longer intervals between

generations. The corresponding cumulative productivity growth due to genetic-based technical change was 2.5%.

As expected, a high proportion of dairy cows sired by unregistered bulls led to a suboptimal genetic technology that reduced productivity growth. On farms with high proportion of cows from unregistered bulls, productivity growth from breeding was only 25% of the productivity growth on farms with low proportion of cows from unregistered bulls.

Finally, it was important to account for quality when productivity growth is measured. A model that neglected milk quality differences resulted in the rejection of technical change of any form. No technical change seems implausible given the actual changes observed in the Icelandic dairy sector, and the quality unadjusted results were also rejected by statistical criteria.

Footnotes

[1] The varietal improvement index is constructed as a weighted sum of new varieties' yields relative to the yields of standard varieties. The weights used in the index are the proportion of land planted by the different varieties. The index is appropriate in situations where other inputs are held constant as in experimental data. The constancy of other inputs implies that input use is not optimized according to the specific needs of each variety and therefore the cost differences between varieties cannot be compared in a meaningful way (Pardey et al. 2004).

[2] The production, pricing, and subsidization of dairy products are set out in periodic agreements between the Ministry of Agriculture and The Farmers Association of Iceland

(Bjarnadottir and Kristofersson 2008). The first agreement was signed for the period 1985–1987 while the current agreement is for the period 2005–2012.

[3] Farm specific milk quotas are determined each year based on past production levels by a committee of stakeholders including farmers' representatives and the government. The farm-specific milk quota will, to a large extent, determine the output level of each dairy farm. Therefore, an input distance function is used to represent dairy technology.

[4] The trend variable will also capture other changes that are not accounted for in the model.

[5] The main reason for using unregistered bulls is the difficulty to monitor heat time to heifers that have limited daily contact with the farmer. The difficulty to monitor heat time, and thus the proportion of cows sired from unregistered bulls may, however, be a function of farm specific variables such as herd size, availability of labor, and managerial ability. Consequently, we tested whether the proportion of cows from unregistered bulls could be treated as an exogenous variable by using a two-stage least squares approach after a within transformation of the data. The instrument set included the right-hand-side variables of equation (10) and debt-to-asset ratio. The latter variable was included as a proxy variable for managerial ability and as an exclusion variable. The Durbin-Wu-Hausman test was used to test for endogeneity. Under the null hypothesis of exogenous regressor, the value of the Chi-square test statistic was 6.78 (d.f. = 1, p-value = 0.01). Therefore, the proportion of cows from unregistered bulls was treated as an exogenous variable.

[6] We found no significant differences in parameter and technical efficiency estimates by using different inputs as the normalizing input.

[7] The half-normal distribution is a special case of the truncated normal distribution with $\mu = 0$. Therefore, one can use nested hypothesis testing to test whether the former is an appropriate simplification of a model. The other distributions cannot be written as special cases of the truncated normal and, hence, no similar tests can be conducted.

[8] Our adjustment may be sensitive to changing price parameters in the nonlinear part of the hedonic price function. However, if the nonlinear parameters are relatively stable over time, our adjustment should provide a good approximation. Furthermore, as correctly pointed out by a referee, our approach may not be applicable in situations where price differences are caused by other factors than milk quality, for example, transportation costs. However, in the Icelandic case, other factors are less important. There is a single common farm-gate milk price set by the government. This price is based largely on protein and fat content for milk produced within the quota. Milk processors can also make adjustments to the government set price according to other quality attributes as discussed above. Prices for milk produced above the quota are determined by market conditions. However, the processors are organized into cooperatives and there only are minor price differences. Price variations between farms in Iceland can therefore mainly be explained by quality differences and quota holding.

[9] We do not have information about farms that exit the sample and, therefore, we assume that selection bias into the panel is ignorable.

[10] The raw data contains farm level financial information that is sensitive, and its use is subject to strict confidentiality agreements. The data can therefore not be made publicly available.

[11] There were 78 zero values for meat quantities. Since logarithm of zero is not defined, these zero values are replaced by one. Parameter estimates of the input distance function were stable when alternative replacements to the zero observations (0.95 and 1.5) were used.

[12] Given that the true genetic quality of a bull is unobservable, the construction of aggregate breeding index for each bull involves the calculation of estimated breeding values (EBVs). EBVs are estimated based on performance data that are collected from the daughters of the bull, their relatives, and herd mates. Together with á priori information on the heritability and correlations between different traits, a prediction is made about the genetic merit of each bull after correcting for the contribution of environmental factors. The EBVs of the average sire in a herd is constructed through a weighted aggregation of the EBVs of each cow's sire for each trait. The number of days that a cow has been active in milk production is used as weight.

[13] Furthermore, daughters of proven bulls produced 10–13 kilograms more fat and 9–11 kilograms more protein than daughters of unregistered bulls. When the proportion of cows sired by unregistered bulls is 30%, the estimated annual income loss for U.S. dairy producers is $259 million (Norman et al. 2003).

[14] We divided all logged variables by their geometric mean values before taking their logarithms. For the non-logged variables (the proportion of cows from unregistered bulls and trend), the geometric mean values are subtracted from the observed values.

[15] Hicks-neutral technical change implies that the marginal rate of substitution between each pair of inputs remain unaffected after technical change; see Blackorby, Lovell, and Thursby (1976) for more details.

[16] The quadratic term of the breeding index and its interaction with the trend variable were also insignificant and hence dropped from the model. This restricted model is also preferred over the unrestricted model based on the Akaike (AIC) and Bayesian (BIC) information criteria, which are reported along with the parameter estimates.

[17] Brümmer, Glauben, and Thijssen (2002) argue that high variability can arise from input quality differences or from restrictions in input markets that prevent transfer of inputs towards more productive farms. We measure capital and veterinary services as composite inputs by aggregating different capital inputs and veterinary services in terms of their monetary values. The former explanation is therefore more likely in our case.

[18] The percentage of violations are 0.5% for concentrates, 12.9% for capital, 6.0% for land, 0.0% for the number of cows, 24.1% for veterinary services, 9.8% for labor, 0.0% for milk, and 7.9% for meat. Using eigenvalue decomposition of the Hessian matrix, we also found that curvature properties are violated at the geometric mean. However, these violations may arise for several reasons. For example, Sauer, Frohberg, and Hockmann (2006) show that violation of theoretical conditions is common in flexible functional forms, partly due to the tradeoff between flexibility and theoretical consistency. O'Donnell and Coelli (2005) propose a Bayesian approach for imposing regularity conditions on distance functions when panel data are used and inefficiency is assumed to be time-invariant. However, we have a time-varying specification for technical inefficiency and did not pursue their approach.

[19] For all comparisons made in this article, we recognize that our results may not be directly comparable to results in other studies due to differences in data type, study period, estimation methods, and production environments.

[20] One possible explanation of the lower productivity returns from breeding during the period 1997–2001 is the change in the breeding goal in 1993. As discussed above, the importance of traits related to milk and meat production was reduced in 1993 to increase the importance of traits that focus on physical attributes and longevity. The productivity effects of these changes will be reflected with time lag due to the time it takes to observe the effects of the new genetic composition at the farm level. Consequently, the first years of our sample can be considered to be a transition period from the productivity effects of the old breeding goal to the productivity effects of the new breeding goal.

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Table 1. Descriptive Statistics of Model Variables

Variable	Symbol	Mean	Std. Dev.	Minimum	Maximum
Breeding index	g	99.54	2.47	94.73	109.63
Concentrates (1,000 ISK)	x_1	1132.77	654.50	40.11	5598.05
Capital (1,000 ISK)	x_2	2,539.95	1,770.25	282.64	16,595.73
Land (hectares)	x_3	46.49	17.75	13.00	138.00
No. of cows (cow years)	x_4	31.68	12.67	4.50	119.00
Vet. services (1,000 ISK)	x_5	202.46	142.10	2.69	964.61
Labor (months / year)	x_6	24.41	8.36	4.00	74.00
Milk (liters) [a]	y_1	141,704.90	67,716.00	27,911.82	568,964.40
Meat (kilograms)	y_2	3,499.46	10,181.55	1.00	283,941.70
Trend (1 = 1997)	t (=ln a)	5.59	2.95	1.00	10.00
Cows from unregistered bulls (%)	z	29.8	19.9	0.00	100.00

Note: Monetary values are deflated to 1997 prices. 1 USD = 115.56 ISK (www.sedlabanki.is accessed October 17, 2011).
[a] Quality-adjusted.

Table 2. Properties of the Dairy Technology

Restriction	Parametric Restriction	Wald Test Statistic	p-value
Constant returns-to-scale	$H_0: \sum_{m=1}^{M} \beta_m = -1, \sum_{m=1}^{M} \varphi_{jm} = \sum_{n=1}^{M} \beta_{mn} = 0$	563.0	0.001
Cobb-Douglas technology	H_0: All interaction terms equal to zero	291.5	0.001
Time-invariant technical inefficiency	$H_0: \eta = 0$	7.6	0.006
Half-normal distribution for technical inefficiency	$H_0: \mu = 0$	35.5	0.001
Genetic-based technical change			
Hicks-neutral	$H_0: \delta_{g1} = \cdots = \delta_{gJ} = 0$	4.0	0.546
Scale-neutral	$H_0: \phi_{g1} = \cdots = \phi_{gM} = 0$	1.2	0.551
Non genetic-based technical change			
Hicks-neutral	$H_0: \alpha_{a1} = \cdots = \alpha_{aJ} = 0$	7.6	0.171
Scale-neutral	$H_0: \beta_{a1} = \cdots = \beta_{aM} = 0$	3.7	0.154

Table 3. Parameter Estimates of the Restricted Input Distance Function, 1997–2006

Variables		$\ln x_1$	$\ln x_2$	$\ln x_3$	$\ln x_4$	$\ln x_5$	$\ln y_1$	$\ln y_2$	t
Constant	−0.268*** (0.001)								
$\ln g$	0.474** (0.030)								
$\ln x_1$	0.118*** (0.001)	0.061*** (0.001)							
$\ln x_2$	0.036*** (0.001)	0.002 (0.852)	0.011 (0.582)						
$\ln x_3$	0.116*** (0.001)	−0.044* (0.065)	0.065*** (0.001)	0.104** (0.041)					
$\ln x_4$	0.569*** (0.001)	−0.003 (0.922)	−0.030 (0.230)	−0.205*** (0.001)	0.475*** (0.001)				
$\ln x_5$	0.026*** (0.001)	−0.016 (0.178)	−0.009 (0.302)	0.028* (0.095)	−0.042** (0.047)	−0.001 (0.880)			
$\ln y_1$	−0.625*** (0.001)	0.006 (0.770)	0.003 (0.869)	−0.041 (0.240)	−0.096** (0.023)	0.083*** (0.001)	−0.048 (0.245)		
$\ln y_2$	−0.019*** (0.001)	0.005 (0.100)	−0.009*** (0.001)	−0.007 (0.100)	0.005 (0.430)	0.001 (0.711)	0.012*** (0.003)	−0.005*** (0.001)	
t	0.007*** (0.019)								−0.005*** (0.001)
z	−0.001*** (0.004)								
μ	0.289*** (0.001)			$\gamma = \dfrac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} = 0.679$			AIC = -2,325.3		
η	−0.022*** (0.006)			Log lik.= 1,206.7			BIC = -2,099.5		

Note: Significance codes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level; p-values reported in parentheses.

Table 4. Technical Efficiency and Productivity Growth of Icelandic Dairy Farms, 1997–2006

Year	Technical Efficiency	Efficiency Change	Technical Change Genetic Based	Technical Change Non Genetic Based	Scale Effect	Productivity Growth
1997	77.4	–	–	–	–	–
1998	77.2	–0.58	0.26	2.33	2.10	4.12
1999	76.2	–0.59	0.39	1.78	1.99	3.58
2000	76.2	–0.60	0.32	1.24	2.40	3.36
2001	76.5	–0.60	0.11	0.69	0.59	0.79
2002	75.4	–0.62	–0.03	0.14	2.15	1.63
2003	75.9	–0.63	0.05	–0.41	1.57	0.58
2004	75.4	–0.62	0.37	–0.95	0.28	–0.93
2005	75.3	–0.62	0.57	–1.50	1.30	–0.26
2006	74.2	–0.65	0.46	–2.05	3.90	1.66
Average	76.0	–0.61	0.31	0.12	1.81	1.63
Cumulative		–5.51	2.50	1.27	16.28	14.54

.
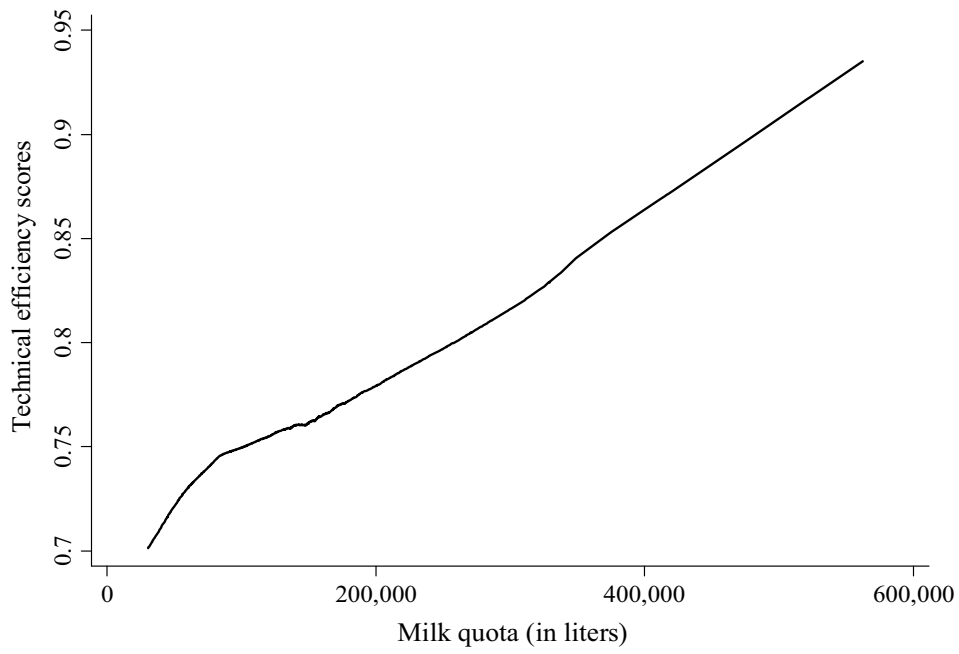
(a)

(b)

Figure 1. Technical efficiency of Icelandic dairy farms, 1997–2006

Paper II

Broad Breeding Goals and Production Costs in Dairy Farming

Daniel Muluwork Atsbeha, Dadi Kristofersson, and Kyrre Rickertsen

Abstract

Production traits have been emphasized in breeding goals of dairy cows across the world. However, long-term economic considerations by dairy farmers as well as consumers' concerns for animal welfare have resulted in a growing emphasis on functional traits such as health and fertility. We examine cost effects of genetic progress in different traits. A short-run cost function including variables measuring genetic and nongenetic technical change was estimated using Norwegian data. Our results show that a one standard deviation genetic progress in production and functional traits reduced variable costs with 0.4% and 0.6%, respectively. The cumulative effect of genetic progress in functional traits was a 1% reduction in variable costs for the average farm during 1999–2007. The discounted industry-wide perpetual cost reduction from genetic progress in functional traits amounts to NOK 160 million.

Key words: Breeding; Cost Function; Dairy Production; Functional Traits.

JEL classification: D24, O33, Q12, Q16

Introduction

Breeding and other biotechnological developments have resulted in significant productivity improvements among dairy farms in the developed world (Bauman 1992; Rauw et al. 1998). However, there are growing concerns about the implications of breeding programs' high emphasis on production traits, i.e., genetic traits related to milk and meat yield (Rauw et al. 1998; Nielsen, Christensen, and Groen 2005). These concerns are motivated by three factors. First, a selection process that emphasizes production traits tends to result in animals that are highly susceptible for physiological, behavioral, and immunological problems due to the negative genetic correlation between production and functional traits, i.e., traits related to animal health and fertility (Rauw et al. 1998; Willam et al. 2002). The resulting poor animal welfare status leads to increased maintenance costs and shorter productive life spans (Groen et al. 1997; Rauw et al. 1998), which in turn affect farm profitability adversely.

Second, breeding goals that emphasize production traits are more likely to risk sustainability of food production due to loss of genetic diversity, for example, through inbreeding (Rauw et al. 1998; Miglior, Muir, and Van Doormaal 2004; Boettcher 2005).

Third, consumers are getting increasingly interested in how their food is produced and the welfare of animals in the production process (Rauw et al. 1998; Tonsor, Olynk, and Wolf 2009). Such concerns from consumers are likely to get stronger as income increases and the costs of acquiring and distributing information continue to be reduced. Therefore, breeding goals that improve animal welfare can also boost farm profitability by increasing consumer acceptance of products and facilitating the creation of niche markets (Olsson, Gamborg, and Sandøe 2006).

Breeding organizations therefore are increasingly including functional traits such as mastitis resistance, calving ease, and longevity in their breeding goals. However, functional traits are also known to have low heritability (Groen et al. 1997; Boettcher 2005), and indirect selection through correlated traits known to have better heritability is commonly used.[1]

The farm level effects of broad breeding goals are expected to be mainly in the form of reduced production costs (Groen et al. 1997; Boettcher 2005). Therefore, we evaluate the economic effects of broad breeding goals using a cost function approach on Norwegian panel data for the period 1999–2007. To allow for unobserved heterogeneity in natural conditions as well as farmers' characteristics, a cost system is estimated under the random coefficient framework for unbalanced panel data suggested by Biørn, Lindquist, and Skjerpen (2003).

The Norwegian case is of broader relevance for two reasons. First, the breeding program for the Norwegian Red (NRF) started to target health and fertility traits in the early 1970s, and sufficient time has passed to observe the effects of the broad breeding goal at the farm level. Furthermore, a significant proportion of the dairy cow population is included in the breeding program. This enables selection based on large daughter groups for each test bull, which in turn increases the quality of the selection process. In addition, high participation rate in the breeding program provides a rich dataset making it possible to detect farm level cost saving effects of genetic progress, even for traits that change very slowly due to low heritability.

Second, there is a growing export of NRF semen to countries like the U.S., Ireland, Australia, New Zealand, Canada, and the Netherlands due to the superior functional performance of the breed. The semen is used for crossbreeding with dairy breeds that are primarily selected for high milk yield such as the Holstein Friesian.

Therefore, the farm level cost effects of the genetic makeup of the NRF is of interest to farmers and breeding organizations in these countries.

Dairy Cattle Farming and Breeding in Norway

The Norwegian dairy sector is characterized by small family-operated farms with an average herd size of 21 dairy cows producing both milk and meat. More than 85% of the gross revenue on Norwegian dairy farms is obtained from milk sales. Each farm faces a production quota for milk, and the average quota for the period 1999 to 2007 was 109,468 liters. Reflecting the restrictiveness of the quota, the milk output of the average farm was 99.4% of its quota during the period.

The quota system was introduced in 1983 under a two-price system where farms received a high price for production within quota and a low price for excess production. Until 2003, private trading of quotas was not allowed, and the government bought quotas from farmers who wanted to reduce or quit production for a relatively low and fixed prices. The purchased quotas were either removed from the market or sold to other farmers depending on market conditions. In 2003, a limited private trade in quotas was allowed, and between 2003 and 2007 the annual private sales of quotas varied between 30% and 60% of total sales. The rest was purchased by the government and redistributed. The private transactions of quotas have to be within the same county, and no farm can purchase quota that corresponds to a total annual production higher than 400,000 liters of milk. Annual sales of quotas have varied between 1.4% and 4.2% of the production volume. The demand for quotas have always been higher than the supply and only between 9% and 29% of the requested quotas was transferred each year (Norwegian Agricultural Authority 2007).

Breeding of dairy cattle has been organized under farmer owned cooperatives with a high degree of farmer participation both in the collection of performance data and the definition of breeding goals (Committee on Farm Animal Genetic Resources 2003). Currently breeding activities are centralized under one breeding organization, Geno, owned by the dominant dairy cooperative, TINE SA. Geno is responsible for the selection process, insemination services as well as the distribution of semen domestically and to export markets.

High quality selection is made possible by a dairy herd recording system that involved 98% of the dairy cow population in 2007. The high participation rate has enabled Geno to address the most important problems of dairy farmers as well as to use large daughter groups in bull selection. The progeny testing for the NRF currently involves 250 to 300 daughter groups per tested bull for low heritability traits such as fertility and health.

Table 1 shows the traits included in the breeding goal during the period 1999–2007 and their associated breeding weights. The traits are grouped in production, functional, and conformation traits. Production traits count about one-third of the total weight and include milk and meat yield, functional traits count almost half of the weight and include mastitis resistance and fertility, while conformation traits count about 20% of the weight. Conformation traits are udder and legs conformation and are used for indirect selection of functional performance.

As shown in figure 1, the emphasis on production-related traits has declined over time. The consequent increase in functional traits emphasis has enabled Geno to breed high yielding dairy cows without compromising their overall functionality. For example, Walsh et al. (2008) found that the cumulative milk yield of the NRF was not different from that of Holstein Friesian, which is primarily selected for milk yield. However, they found that the NRF had favorable attributes such as superior

reproductive efficiency, better udder health, moderate size, and high survival rate. Furthermore, Østerås et al. (2007) found that incidences of the most common dairy production diseases in Norway was reduced by more than 50% in 2002 relative to the 1990s.

Theoretical Model

The production of milk is constrained by an exogenously determined quota for milk at the farm level, and we assume that farmers are short-run cost minimizers. Let the multi-output production technology be described by an input requirement set $\mathrm{V}\left(\boldsymbol{y}; \boldsymbol{z}, \boldsymbol{g}, t\right) = \left\{\boldsymbol{x} : \boldsymbol{x} \text{ can produce } \boldsymbol{y}\right\}$, where $\boldsymbol{y}$ is an $K \times 1$ vector of outputs, $\boldsymbol{z}$ is a $L \times 1$ vector of quasi-fixed inputs that cannot be adjusted in the short run, $\boldsymbol{g}$ is a $M \times 1$ vector of genetic traits that are targeted for selection, t is time period, and $\boldsymbol{x}$ is an $J \times 1$ vector of variable inputs. The two conditioning variables $\boldsymbol{g}$ and t control for genetic and nongenetic components of the dairy technology at a given period. Consequently, the input requirement set is the set of all input combinations $\boldsymbol{x}$ that can produce a given output vector $\boldsymbol{y}$ given quasi-fixed inputs $\boldsymbol{z}$ and the genetic state of dairy cows $\boldsymbol{g}$ at time period t.

If $\mathrm{V}\left(\boldsymbol{y}; \boldsymbol{z}, \boldsymbol{g}, t\right)$ satisfies some regularity conditions (Diewert 1971), then for a nonnegative variable input price vector $\boldsymbol{w}$, a true cost function C^* can be defined as a dual representation of this technology. The true cost function is given as:

(1) $C^*\left(\boldsymbol{y}, \boldsymbol{w}; \boldsymbol{z}, \boldsymbol{g}, t\right) = \min_{x} \left\{\boldsymbol{w}'\boldsymbol{x} : \boldsymbol{x} \in \mathrm{V}\left(\boldsymbol{y}; \boldsymbol{z}, \boldsymbol{g}, t\right)\right\}.$

The regularity conditions imply that certain properties (Diewert 1971) have to hold for the true cost function. The true cost function has to be continuous, and non-negative, as well as positively linearly homogeneous, nondecreasing, and concave

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with respect to w; nondecreasing and quasiconvex with respect to y; and

nonincreasing and convex with respect to z.

The true cost function is unknown, and we use the translog form (Christensen,

Jorgenson, and Lau 1973) as a second-order approximation. Our specification of the

variable cost function C for $j = 1, \cdots, J$ variable inputs, $k = 1, \cdots, K$ outputs,

$l = 1, \cdots, L$ quasi-fixed inputs, and $m = 1, \cdots, M$ genetic traits is:

$$
(2) \quad \ln C = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln w_j + \sum_{k=1}^{K} \beta_k \ln y_k + \sum_{l=1}^{L} \phi_l \ln z_l + \sum_{m=1}^{M} \delta_m \ln g_m + \gamma t +
$$

$$
\frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \alpha_{jj'}^{w} \ln w_j \ln w_{j'} + \sum_{j=1}^{J} \sum_{k=1}^{K} \alpha_{jk}^{y} \ln w_j \ln y_k + \sum_{j=1}^{J} \sum_{l=1}^{L} \alpha_{jl}^{z} \ln w_j \ln z_l +
$$

$$
\sum_{j=1}^{J} \sum_{m=1}^{M} \alpha_{jm}^{g} \ln w_j \ln g_m + \sum_{j=1}^{J} \alpha_{jt}^{t} t \ln w_j + \frac{1}{2} \sum_{k=1}^{K} \sum_{k'=1}^{K} \beta_{kk'}^{y} \ln y_k \ln y_{k'} +
$$

$$
\sum_{k=1}^{K} \sum_{l=1}^{L} \beta_{kl}^{z} \ln y_k \ln z_l + \sum_{k=1}^{K} \sum_{m=1}^{M} \beta_{km}^{g} \ln y_k \ln g_m + \sum_{k=1}^{K} \beta_{kt}^{t} t \ln y_k +
$$

$$
\frac{1}{2} \sum_{l=1}^{L} \sum_{l'=1}^{L} \phi_{ll'}^{z} \ln z_l \ln z_{l'} + \sum_{l=1}^{L} \sum_{m=1}^{M} \phi_{lm}^{g} \ln z_l \ln g_m + \sum_{l=1}^{L} \phi_{lt}^{t} t \ln z_l.
$$

Linear homogeneity in input prices is imposed by the restrictions $\sum_{j=1}^{J} \alpha_j = 1$ and

$$
\sum_{j=1}^{J} \alpha_{jj'}^{w} = \sum_{j=1}^{J} \alpha_{jk}^{y} = \sum_{j=1}^{J} \alpha_{jl}^{z} = \sum_{j=1}^{J} \alpha_{jm}^{g} = \sum_{j=1}^{J} \alpha_{jt}^{t} = 0 \text{ for each } j', k, l, \text{ and } m. \text{ Symmetry}
$$

implies $\alpha_{jj'}^{w} = \alpha_{j'j}^{w}$, $\beta_{kk'}^{y} = \beta_{k'k}^{y}$, and $\phi_{ll'}^{z} = \phi_{l'l}^{z}$ for all $j, j', k, k', l,$ and l'. Given equation

(2), the conditional factor demand equations are derived in cost share (s) form by

using Shephard's lemma as follows:

$$
(3) \quad s_j = \frac{\partial \ln C}{\partial \ln w_j} = \frac{w_j x_j}{C} = \alpha_j + \sum_{j'=1}^{J} \alpha_{jj'}^{w} \ln w_{j'} + \sum_{k=1}^{K} \alpha_{jk}^{y} \ln y_k + \sum_{l=1}^{L} \alpha_{jl}^{z} \ln z_l +
$$

$$
\sum_{m=1}^{M} \alpha_{jm}^{g} \ln g_m + \alpha_{jt}^{t} t.
$$

Since $\sum_{j=1}^{J} s_j = 1$, the cost share equations must satisfy the adding-up property.

However, this property implies the same restrictions as linear homogeneity in the

costs function, and we impose both properties by dividing all input prices by one of the input prices. Then, the left-hand side of equation (2) is re-defined to $\ln C = \ln\left(C / w_J\right)$, and all input prices are re-defined as $\ln w_j = \ln\left(w_j / w_J\right)$. This approach also implies that one of the share equations has to be dropped while the parameters of the dropped equation can be recovered from the homogeneity restrictions above.

We estimate equation (2) simultaneously with the $J-1$ share equations shown in equation (3). The cost effects of genetic progress are recovered by calculating cost elasticities, e_m, as the first derivatives of equation (2) with respect to the mth genetic trait, or:

$$(4) \qquad e_m = \frac{\partial \ln C}{\partial \ln g_m} = \delta_m + \sum_{j=1}^{J} \alpha_{jm}^g \ln w_j + \sum_{k=1}^{K} \beta_{km}^g \ln y_k + \sum_{l=1}^{L} \phi_{lm}^g \ln z_m.$$

Genetic progress is cumulative and any associated cost saving will accumulate over time. Therefore, we also compute the cumulative variable cost saving for the average farm (ΔC_m^T) caused by genetic progress as:

$$(5) \qquad \Delta C_m^T = C\left(\tilde{w}_j, \tilde{y}_k; \tilde{z}_l, \tilde{g}_{m-1}, g_m^T, \tilde{t}\right) - C\left(\tilde{w}_j, \tilde{y}_k; \tilde{z}_l, \tilde{g}_{m-1}, g_m^1, \tilde{t}\right),$$

where $C\left(\tilde{w}_j, \tilde{y}_k; \tilde{z}_l, \tilde{g}_{m-1}, g_m^T, \tilde{t}\right)$ and $C\left(\tilde{w}_j, \tilde{y}_k; \tilde{z}_l, \tilde{g}_{m-1}, g_m^1, \tilde{t}\right)$ are the predicted variable costs obtained by evaluating equation (2) with the index value of the mth genetic trait at the end of the sample period $\left(g_m^T\right)$ and at the beginning of the sample period $\left(g_m^1\right)$, respectively, while $\tilde{w}_j, \tilde{y}_k, \tilde{z}_l, \tilde{g}_{m-1}$, and $\tilde{t}$ refer to the value of the other variables fixed at some data point (e.g., the mean).

Genetic progress is also permanent and it gets transferred to subsequent generations. Therefore, cost saving from genetic progress will continue indefinitely. Assuming a constant and indefinite annual cost savings from a percentage genetic

gain as measured by equation (4), the present value of perpetual variable cost savings $\left(\Delta C_m\right)$ can be computed as a present value of perpetuity as:[2]

$$(6) \qquad \Delta C_m = \left[\frac{e_m \Delta g_m}{100} \times C\left(\tilde{w}_j, \tilde{y}_k; \tilde{z}_l, \tilde{g}_m, \tilde{t}\right)\right]\frac{1}{r}$$

where e_l is given by equation (4), $\Delta g_m = \left(\ln g_{m,t} - \ln g_{m,t-1}\right) \times 100$ is the annual genetic gain for the mth trait in percentage terms, $C\left(\tilde{w}_j, \tilde{y}_k;, \tilde{z}_l, \tilde{g}_m, \tilde{t}\right)$ is the predicted variable cost at some data point, and r is the discount rate.

Econometric Specification

Biørn, Lindquist, and Skjerpen (2003) utilized the random coefficient framework to model unobserved heterogeneity under a translog cost system from unbalanced panel data, and we follow their econometric specification. Farms' entry and exit to the panel are assumed to be unrelated to the endogenous variables of the model. Then farms are organized into groups based on the number of times they are observed in the panel. There will be $p = 1,...,P$ observations for each farm, and these observations are neither required to be from consecutive years nor from the same years for all farms in the group. Let N_p be the number of farms which are observed for p periods and let subscript (ip) denotes the ith farm among farms observed for p periods ($i = 1,...,N_p; p = 1,..., P$). Let $t = 1, \cdots, p$ represent the sequence of observations for the ith farm. The total number of farms in the panel is $N = \sum_{p=1}^{P} N_p$ and the total number of observations is $n = \sum_{p=1}^{P} N_p p$. This organization of the data allows each sub-panel N_p to be treated as a balanced panel where each farm is observed p times.

In our case, there are four variable inputs so our system consists of the cost function and three costs share equations. This system can be written as:

(7) $\quad y_{(ip)t} = X_{(ip)t}\beta_{(ip)} + u_{(ip)t}, \quad p = 1,\dots,P, \quad i = 1,\dots,N_p, \text{ and } t = 1,\dots,p,$

where $y' = \begin{bmatrix} \ln C & s_1 & s_2 & s_3 \end{bmatrix}$, X is the design matrix, β is a parameter vector, and

u is an error vector given as $u' = \begin{bmatrix} u_C & u_{s_1} & u_{s_2} & u_{s_3} \end{bmatrix}$. As an illustration, in a

specification including 2 variable inputs, 1 output, 1 genetic trait, and 1 quasi-fixed

input, our design matrix and corresponding parameter vector would be:

$$
X' = \begin{bmatrix}
1 & 0 \\
\ln w_1 & 1 \\
\ln y & 0 \\
\ln z & 0 \\
\ln g & 0 \\
t & 0 \\
0.5(\ln w_1)^2 & \ln w_1 \\
\ln w_1 \ln y & \ln y \\
\ln w_1 \ln z & \ln z \\
\ln w_1 \ln g & \ln g \\
t \ln w_1 & t \\
0.5(\ln y)^2 & 0 \\
\ln y \ln z & 0 \\
\ln y \ln g & 0 \\
t \ln y & 0 \\
0.5(\ln z)^2 & 0 \\
\ln z \ln g & 0 \\
t \ln z & 0
\end{bmatrix}
\quad \text{and} \quad
\beta = \begin{bmatrix}
\alpha_0 \\
\alpha_1 \\
\beta \\
\phi \\
\delta \\
\gamma \\
\alpha_1^w \\
\alpha_1^y \\
\alpha_1^z \\
\alpha_1^g \\
\alpha_1^t \\
\beta^y \\
\beta^z \\
\beta^g \\
\beta^t \\
\phi^z \\
\phi^g \\
\phi^t
\end{bmatrix}.
$$

In general, the vector β represents expected values of the parameters of H regressors

in G equations. The randomness in the parameter vector is introduced as:

(8) $\quad \beta_{(ip)t} = \beta + \delta_{(ip)},$

where $\delta_{(ip)}$ is the random component of the parameter vector for farm (ip). Inserting

equation (8) into equation (7), the system can be written as:

(9) $\quad y_{(ip)t} = X_{(ip)t}\beta + \eta_{(ip)t}, \quad \eta_{(ip)t} = X_{(ip)t}\delta_{(ip)} + u_{(ip)t}.$

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Following Biørn, Lindquist, and Skjerpen (2003), independence is assumed among

$X_{(ip)t}$, $\delta_{(ip)}$, and $u_{(ip)t}$ while the distributional assumptions are $\delta_{(ip)} \sim \text{IIN}\left(\mathbf{0}_{H1}, \Sigma^{\delta}\right)$

and $u_{(ip)t} \sim \text{IIN}\left(\mathbf{0}_{G1}, \Sigma^{u}\right)$, where IIN stands for independently, identically, and

normally distributed. The covariance matrices for the two error components are given

as: $\Sigma^{\delta} = \begin{pmatrix} \sigma_{11}^{\delta} & \cdots & \sigma_{1H}^{\delta} \\ \vdots & \ddots & \vdots \\ \sigma_{H1}^{\delta} & \cdots & \sigma_{HH}^{\delta} \end{pmatrix}$ and $\Sigma^{u} = \begin{pmatrix} \sigma_{11}^{u} & \cdots & \sigma_{1G}^{u} \\ \vdots & \ddots & \vdots \\ \sigma_{G1}^{u} & \cdots & \sigma_{GG}^{u} \end{pmatrix}$.

The former matrix assumes full coefficient heterogeneity allowing a very flexible

specification. However, as noted by Biørn, Lindquist, and Skjerpen (2003), such a

specification may run into estimation problems and zero restrictions on the Σ^{δ} matrix

may be necessary. In our case, a random intercept model is estimated by restricting

Σ^{δ} to: $\Sigma^{\delta} = \begin{pmatrix} \sigma_{11}^{\delta} & \cdots & 0_{1H} \\ \vdots & \ddots & \vdots \\ 0_{H1} & \cdots & 0_{HH} \end{pmatrix}$.

Once the properties of each error component are established, properties of the

composite error term $\eta_{(ip)t}$ can be derived. As shown by Biørn, Lindquist, and

Skjerpen (2003), equation (9) can be re-written as:

$$(10) \quad y_{(ip)} = X_{(ip)}\beta + \eta_{(ip)}, \quad \eta_{(ip)} = X_{(ip)}\delta_{(ip)} + u_{(ip)},$$

where $y_{(ip)}$, $X_{(ip)}$, $\eta_{(ip)}$, and $u_{(ip)}$ are created by stacking the p observations for each

farm (ip). Biørn, Lindquist, and Skjerpen (2003) further show that $\eta_{(ip)} \mid X_{(ip)}$ are

independent and $\eta_{(ip)} \mid X_{(ip)} \sim \text{N}\left(\mathbf{0}_{Gp,1}, \Omega_{(ip)}\right)$. $\Omega_{(ip)}$ is a $Gp \times Gp$ covariance matrix

defined as:

$$(11) \quad \Omega_{(ip)} = X_{(ip)}\Sigma^{\delta}X'_{(ip)} + I_{p} \otimes \Sigma^{u},$$

where I_p is a $p \times p$ identity matrix. The log-likelihood functions that underlie the estimation of the cost system with unbalanced panel data are provided in Biørn, Lindquist, and Skjerpen (2003).

Data

We use unbalanced panel of 4,768 Norwegian dairy farms covering the period 1999–2007.[3] The dataset combines production data obtained from the dairy herd recording system and breeding data obtained from Geno.[4] According to TINE, 98% of the dairy cows in the country were included in the recording system in the year 2007. The production data contain information about quantities of inputs and outputs, unit values of variable inputs, farm level production quotas for milk, and financial support received from the state. Forage is largely produced on the farm, and the unit value is constructed from variable cost data of the inputs used in forage production.

The genetic data contain estimated breeding values (EBVs) of the ten traits targeted by the breeding program. The EBV is a statistical estimate of the unobservable true genetic merit of an animal. The estimate is based on observable characteristics (phenotypes) of the animal itself, its relatives, and herd mates as well as a priori information on the heritability and correlation of targeted traits. The EBV for each trait, in a dairy herd in any given year, is a weighted average of the EBV's of these traits for the sires of all cows on the farm during that year. The number of days that a cow is active in milk production, during the year, is used as the weight. Each EBV is expressed in the same unit of measurement as the trait itself. It has to be interpreted relative to the population mean, which is normalized to 100 with a standard deviation of 7.[5] Accordingly an EBV of more than 100 represents increasingly better animals while an EBV of less than 100 represents increasingly

worse animals relative to the performance of the population average. Using weights determined by the breeding organization, the EBV's for the ten traits are summarized by an aggregate breeding index, which represents overall genetic progress. Furthermore, three sub-indices for genetic progress in production, functional, and conformation traits are calculated. Table 1 shows the traits included in each sub-index.

We include four variable inputs: forage, concentrates, veterinary and insemination services, and other costs. The other costs category includes energy and maintenance costs for buildings, tractors, and other farm equipments. The prices for veterinary and insemination services and other costs categories were constructed as Laspeyres indices based on figures provided by the Norwegian Agricultural Economics Research Institute (2010). Quasi-fixed inputs are included in the model as total subsidies received by farms on per cow, per acre, and per management unit basis. We lack data on labor use and consequently forced to assume weak separability between non-labor and labor inputs.[6] As shown by Fuss (1977), this implies a two-stage optimization model where farms are assumed to choose the optimal mix of non-labor inputs first. Then, the aggregate of non-labor inputs is optimized with labor inputs. We include two outputs: milk and meat. Milk is measured as energy corrected milk (ECM) to partially account for milk quality differences.[7]

Table 2 provides the descriptive statistics of the data. Norwegian farms are small. The mean variable costs were about NOK 252,000.[8] The average output was about 122,000 liters of milk and 1.9 tons of meat. The economic support is substantial so the average farm received about NOK 159,000 in subsidies. We may also note that there are substantial differences in the herd quality. The breeding index for the best herd was about 17% higher than for the worst herd.

Estimation and Results

The cost system is estimated using the `xtmixed` module in STATA® version 11 (StataCorp 2009). The trend variable is normalized to be zero in year 2007 while all other variables are normalized by dividing each variable with its mean value in 2007 before taking logarithms. This normalization allows first-order parameters to be interpreted as cost elasticities at the point of normalization. Linear homogeneity in input prices is imposed by dividing all input prices with the price of the other costs category. Consequently, the share equation for the other costs category is dropped from the estimated system. Two versions of the system are estimated. First, the aggregate breeding index g is used to evaluate the cost effects of an overall genetic progress (Model-I). Second, the system is estimated by introducing the sub-indices for production g_1, functional g_2, and conformation g_3 traits to evaluate the contribution of each group of traits to the cost performance (Model-II). Parameter estimates and associated p-values are reported in table 3 for Model-I and in table 4 for Model-II.

The estimated variable cost function is nondecreasing with respect to each input price and output quantity at any reasonable level of significance. Furthermore, the cost function is non-increasing with respect to quasi-fixed inputs in both models at the 5% level of significance.

Characteristics of the Dairy Technology

The estimated parameter of the trend variable is positive and statistically different from zero at the 5% level of significance. This positive trend suggests technical regress for Norwegian dairy farms during the study period. Similar results are reported for Norwegian dairy farming by Løyland and Ringstad (2001) for the period 1972–1996 and by Kumbhakar et al. (2008) for the period 1976–2005. This apparent

regress may be explained by several factors as discussed in Kumbhakar et al. (2008).

First, they argue that the observed technical regress could be due to changes in the

regulations concerning input use, for example, the application of pesticides and

fertilizers. Second, for their specific case they argue that larger real increases in input

than output prices may lead to results that may look like technical regress. Third, they

argue that regulations promoting animal health and welfare may be one possible

explanation. However, as discussed below, policies promoting animal health and

welfare may not always be cost increasing, at least, when it comes to breeding.

Finally, Kumbhakar and Heshamti (1995) proposed additional factors that can be

responsible for apparent technical regress such as increased technical inefficiency,

lack of external competition, and restrictions on the transfer of farms between

generations. The latter two reasons may be valid for the institutional arrangement of

Norwegian dairy farming that involves active protection from foreign completion and

rigid dairy quota transfer policies that restricted quota mobility, although these

policies are becoming less restrictive over time.

Additional tests on the characteristics of the technology are conducted for

Model-I. As shown in table 5, Cobb-Douglas technology is rejected. We also tested

for optimality of the scale of operation for the average farm. Banker (1984)

introduced the concept of most productive scale size (MPSS), and he defined it as the

point where the average product is at its maximum. Banker (1984) also showed that at

the MPSS the technology will exhibit constant returns to scale (CRS). We use a Wald

test to test for CRS. We follow Panzar and Willig (1977) to construct a measure of

returns to scale (RTS) in a multi-output setting. Their proposed measure of aggregate

returns to scale for the multi-output case is given as $RTS = \left(\sum_k \partial \ln C / \partial \ln y_k \right)^{-1}$.

Table 5 shows that CRS is rejected at any reasonable level of significance, and the

scale of operation is suboptimal. Given that $\sum_{m=1}^{2} \beta_m < 1$, cost reductions can be

obtained by increasing the scale of operations. This result is as expected, given the

milk quota regime, and in line with the results of Løyland and Ringstad (2001) who

also found suboptimal scale of operation among Norwegian dairy farms.

The technical regress we found may affect all inputs and farm sizes identically

or differently and therefore Hicks and scale neutrality is tested for. As shown in table

5, technical regress has been neither Hicks nor scale neutral. In table 3, Hicks non-

neutrality of technical regress is exhibited as a positive effect on the cost shares of

forage as well as veterinary and insemination services and as a negative effect on the

cost share of concentrates. With respect to output size, the cost increasing effects of

technical regress get weaker as the milk and meat production increase, suggesting that

technical regress affected small scale operations more.

Genetic Progress and Production Cost

Table 3 shows that overall genetic progress has been cost saving. At the point of

normalization, an overall genetic progress of 1% resulted in a 0.53% decline in

variable costs. Like technical change, cost reductions through genetic progress are

scale dependent. As shown in table 5, the null hypothesis of scale independent cost

reductions from genetic progress is rejected at any reasonable level of significance.

The parameter estimates reported in table 3 show that cost reductions from genetic

progress get smaller as meat production increases while increasing milk production

has no statistically significant effect. Similarly, genetic progress has different effects

on factor cost shares. As shown by the interaction terms between the breeding index

and input prices in table 3, genetic progress increased the cost share of concentrates

while it had no effect on other inputs. Similar increases in concentrate intensity for

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high performing dairy cows has also been observed by, for example, Walsh et al. (2008), and these increases suggest that a high quality feed ration is required to maximize returns from high-performing dairy cows.

The results in table 4 show that progress in each group of traits have been cost reducing at the point of normalization. The reduction is statistically significant at the 1% level for functional traits, at the 10% level for production traits, while it is insignificant for conformation traits. A genetic progress of 1% in production and functional traits leads to a 0.14% and 0.29% reduction in variable costs, respectively. These reductions indicate that the breeding program has generated cost saving effects from genetic progress in functional traits without causing a cost increasing deterioration of production performance. Finally, the insignificant cost saving effects from genetic progress in conformation traits may be explained by the role of conformation traits in indirect selection of functional performance; i.e., successful direct selection for functional traits makes indirect selection less important in determining cost performance.

Cost Savings from Genetic Progress

We computed cost savings associated with genetic progress in aggregate and in the different traits by using the estimated parameters and equations (4), (5), and (6). Cost savings for genetic progress in confirmation traits was not significantly different from zero and hence we do not calculate any cost savings for this group of traits. Our point of normalization is 2007 so we use the 2007 values of the variables in our computations.

The results are summarized in table 6. The average predicted variable cost is NOK 318,466 in Model-I and NOK 318,644 in Model-II. The cost elasticity of overall

genetic progress reported in table 3 implies that the variable cost of producing the output level in 2007 would be reduced by NOK 3,436 for an overall genetic progress equivalent to one sample standard deviation from the normalization point. This corresponds to a cost reduction of 1.1% from the predicted cost at the same point. Similarly, the cost elasticities for genetic progress in different traits reported in table 4 imply that the comparable variable cost reductions in production and functional traits would be NOK 1,290 and NOK 1,952, which correspond 0.4% and 0.6% of the predicted cost, respectively.

Next the cumulative cost savings from genetic progress between 1999 and 2007 is estimated as a difference between the variable costs of producing the output at the point of normalization and producing the same level of output if genetic indices remained at their 1999 levels, ceteris paribus. The cumulative cost savings in variable costs is NOK 8,525. The corresponding cumulative cost savings for functional and production traits are NOK 3,153 and NOK 2,706, respectively.

Finally, perpetual farm level cost savings are computed. A real discount rate of 4% is used. This discount rate is within the recommended range of 3% to 5% (Bird and Mitchell 1980) for evaluation of animal breeding projects. The average annual genetic progress rates observed on the average farm are 0.63%, 0.73%, and 0.43% for the aggregate, functional, and production indices, respectively. The perpetual cost saving from aggregate genetic progress is NOK 26,620 for the average farm. This implies that the average farm reduced its variable cost of producing the output level in 2007 for eternity by 8.4% of the predicted variable cost in 2007, ceteris paribus. Corresponding perpetual cost savings for functional and production traits are NOK 8,289 and NOK 9,802.

According to TINE Group (2007), there were 16,310 farms in the dairy cooperative in 2007. Then the industry wide perpetual cost saving from genetic

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progress in functional traits is close to NOK 160 million. The corresponding savings from overall genetic progress is about NOK 434 million.

Conclusions

Selective breeding for production traits has contributed to significant increases in milk yield per cow across the world. However, high emphasis on production traits has resulted in diminished welfare and overall functionality of dairy cows. Recently, changes in the production environment and consumers' attitude towards animal welfare have increased the importance of cost efficient dairy cows that also have few health problems. Responding to such needs, breeding programs have begun to select for functional performance both directly and indirectly through correlated traits.

The breeding program for the Norwegian Red (NRF), begun selecting for health and fertility traits as early as the 1970s. Therefore, the Norwegian case provides a unique opportunity to evaluate the farm level consequences of shifts in breeding emphasis. Using farm level data, cost savings from genetic progress in three different groups of traits have been estimated. During 1999–2007, the average cumulative cost saving due to overall genetic progress was NOK 8,525. Breeding for functional and production traits resulted in cumulative cost savings of NOK 3,153 and NOK 2,706, respectively. The cost savings for genetic progress in confirmation traits was not significantly different from zero.

Furthermore, given that genetic progress is permanent, present value of the perpetual cost saving from genetic progress can be calculated. The perpetual cost saving from overall genetic progress is NOK 26,620 for the average farm and about NOK 434 million for the dairy industry. Correspondingly, the perpetual cost savings from genetic progress in functional traits is NOK 9,802 for the average farm and

about NOK 160 million for the dairy industry. These values indicate that the Norwegian Red breeding program has been quite successful in achieving cost-reducing genetic progress in functional traits.

Footnotes
[1] For example, selection for mastitis resistance has been done through somatic cell count data, which can be measured objectively, has a strong correlation with mastitis resistance, and has a heritability estimate that is two or three times higher (Boettcher 2005).

[2] Perpetuity is a stream of income that continues forever with a present value (PV) equal to $PV = A \times 1/r$ where A is the annual income and r is the discount rate.

[3] The data employed in this article are the property of TINE SA and cannot be made public due to contractual agreement and sensitive personal information about individual farmers.

[4] We filtered out extreme observations before estimation. The filtering involved removing observations that are ± 4 standard deviations from the mean of all variables. Less than 3% of farms and observations were dropped as a result.

[5] The population mean is a moving average of the EBV's of all examined sires that are born in the past three years.

[6] Assuming weak separability due data limitations is common in empirical analysis. Examples involving cost functions are Griffin and Gregory (1976); Schumacher and Marsh (2003); and Mulik and Koo (2011).

[7] Energy corrected milk (ECM) is computed according to different formulas depending on whether lactose percentage is recorded or not (TINE Group 2011). When lactose percentage is recorded, the formula is used is:

ECM = Amount of milk × (0.01 + (Fat % × 0.122) + (Protein % × 0.077) + (Lactose % × 0.053)).

When lactose percentage is not recorded, the formula used is:

ECM = Amount of milk × (0.25 + (Fat % × 0.122) + (Protein % × 0.077)).

These corrections do not account for other quality attributes of fluid milk such as somatic cell count.

[8] 1 USD = 5.742 NOK on February 9, 2012. (Source: http://www.norges-bank.no/english/).

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Table 1: Breeding Traits and Their Weights in the Breeding Program, 1999–2007.

Trait	Weight	Characterization of trait
Production		
Milk	24	Combined index: protein, fat and milk yield
Meat	9	Carcass value of young bull
Functional		
Other diseases	3	Milk fever, ketosis and retained placenta
Stillbirths	1	Paternal and maternal
Calving difficulties	1	Maternal
Mastitis resistance	22	Frequency (treatments) of clinical mastitis first, second and third lactation
Fertility	15	Female fertility for heifers and first lactating cows
Temperament	4	Behavior of cows when milked recorded as: extra calm, normal or uneasy
Conformation		
Legs	6	Combined index: rear leg side view, rear leg rear view, foot angle and hoof quality
Udder	15	Combined index: fore teat placement, supernumerary teats, udder balance, teat attachment, fore and rear udder attachment, udder support and teat length

Note: Table 1 is adapted from Steine, Kristofersson, and Guttormsen (2008).

Table 2: Descriptive Statistics of Norwegian Dairy Farms, 1999–2007

Variable and symbol	Unit	Mean	SD	Min	Max
Variable costs[1]	NOK	252.32	108.43	22.09	924.37
Outputs[1]					
Milk, y_1	Liters	121.52	52.40	10.11	400.92
Meat, y_2	Kilograms	1.91	1.05	0.00	7.18
Inputs[1]					
Forage, x_1	Feed units	54.38	23.47	7.25	173.83
Concentrates, x_2	Feed units	36.17	16.82	0.15	125.67
Vet. and insemination, x_3	NOK	19.12	10.09	0.28	68.97
Other costs, x_4	NOK	100.51	61.22	0.00	431.69
Subsidy, z_1	NOK	158.62	42.54	20.39	372.15
Prices					
Forage, w_1	NOK/Feed unit	0.60	0.21	0.01	1.54
Concentrates, w_2	NOK/Feed unit	2.80	0.20	1.86	3.76
Vet. and insemination, w_3	Index	79.22	14.14	57.50	100.00
Other costs, w_4	Index	88.37	10.26	71.20	103.20
Breeding indices					
Aggregate breeding index, g	Index	99.12	2.08	90.84	106.57
Production, g_1	Index	98.18	2.87	86.85	109.35
Functional, g_2	Index	100.46	2.19	91.65	107.93
Conformation, g_3	Index	97.64	2.93	87.47	108.66
Trend, t	1=1999	5.19	2.61	1.00	9.00
Sample size, n	16,695				

[1] Variable costs are measured in 1,000.

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Table 3: Parameters of the Variable Cost Function: Aggregate Breeding Index (Model-I)[1]

Variable		$\ln w_1$	$\ln w_2$	$\ln w_3$	$\ln y_1$	$\ln y_2$	$\ln z$
Constant	12.671 (0.001)						
$\ln w_1$	0.144 (0.001)	0.092 (0.001)					
$\ln w_2$	0.395 (0.001)	−0.023 (0.001)	0.061 (0.001)				
$\ln w_3$	0.083 (0.001)	−0.008 (0.001)	−0.031 (0.001)	−0.059 (0.001)			
$\ln y_1$	0.803 (0.001)	0.005 (0.001)	0.051 (0.001)	−0.004 (0.001)	0.148 (0.001)		
$\ln y_2$	0.031 (0.001)	−0.002 (0.001)	−0.009 (0.001)	−0.001 (0.001)	−0.002 (0.556)	0.003 (0.001)	
$\ln z$	0.015 (0.094)	0.015 (0.001)	−0.010 (0.006)	0.001 (0.281)	−0.107 (0.001)	−0.005 (0.226)	0.147 (0.001)
$\ln g$	−0.531 (0.001)	−0.017 (0.437)	0.344 (0.001)	−0.004 (0.806)	0.186 (0.280)	0.165 (0.015)	−0.235 (0.400)
t	0.039 (0.001)	0.001 (0.001)	−0.005 (0.001)	0.003 (0.001)	−0.004 (0.004)	−0.001 (0.067)	−0.003 (0.175)

[1] *p*-values are printed in parentheses.

Table 4: Parameters of the Variable Cost Function: Disaggregate Breeding Indices (Model-II)[1]

Variable		$\ln w_1$	$\ln w_2$	$\ln w_3$	$\ln y_1$	$\ln y_2$	$\ln z$
Constant	12.672						
	(0.001)						
$\ln w_1$	0.144	0.092					
	(0.001)	(0.001)					
$\ln w_2$	0.395	−0.023	0.062				
	(0.001)	(0.001)	(0.001)				
$\ln w_3$	0.083	−0.008	−0.031	−0.059			
	(0.001)	(0.001)	(0.001)	(0.001)			
$\ln y_1$	0.802	0.005	0.051	−0.005	0.149		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
$\ln y_2$	0.032	−0.002	−0.010	−0.001	−0.002	0.003	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.377)	(0.001)	
$\ln z$	0.014	0.015	−0.011	0.001	−0.107	−0.005	0.145
	(0.135)	(0.001)	(0.005)	(0.280)	(0.001)	(0.255)	(0.001)
$\ln g_1$	−0.143	−0.010	0.086	−0.001	0.190	0.020	−0.143
	(0.074)	(0.410)	(0.007)	(0.885)	(0.055)	(0.606)	(0.376)
$\ln g_2$	−0.286	0.015	0.217	−0.005	0.077	0.027	0.099
	(0.005)	(0.332)	(0.001)	(0.691)	(0.542)	(0.560)	(0.638)
$\ln g_3$	−0.075	−0.029	0.028	0.004	−0.150	0.166	−0.200
	(0.415)	(0.046)	(0.454)	(0.686)	(0.177)	(0.001)	(0.274)
t	0.039	0.001	−0.005	0.003	−0.003	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.031)	(0.006)	(0.325)

[1] p-values are printed in parentheses.

Table 5:Properties of the Dairy Technology, Model-I

Restriction	Parametric restriction	Wald test statistic	p-value
Constant returns to scale	$H_0: \sum_{m=1}^{M} \beta_m = 1,$		
	$\sum_{m=1}^{M} \beta_{mn}^w = \sum_{m=1}^{M} \beta_{mm'}^y = \sum_{m=1}^{M} \beta_{mq}^z = \sum_{m=1}^{M} \beta_{mk}^g = \sum_{m=1}^{M} \beta_{tm}^t = 0$	2641.0	0.001
Cobb-Douglas technology	H_0: All interaction terms equal to zero	41,946.0	0.001
Technical change			
Hicks neutral	$H_0: \alpha_{1t}^t = \alpha_{2t}^t = \alpha_{3t}^t = 0$	178.8	0.001
Scale neutral	$H_0: \beta_{1t}^t = \beta_{2t}^t = 0$	18.2	0.001
Genetic progress			
Hicks neutral	$H_0: \alpha_1^g = \alpha_2^g = \alpha_3^g = 0$	41.2	0.001
Scale neutral	$H_0: \beta_1^g = \beta_2^g = 0$	10.5	0.005

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Table 6:Predicted Farm Level Cost Savings from Genetic Progress

Source	Cost savings (NOK)	% of costs in 2007
Genetic progress of 1 SD in:		
Aggregate breeding index	–3,435.7	1.08
Production traits	–1,290.2	0.40
Functional traits	–1,951.9	0.62
Cumulative, 1999–2007:		
Aggregate breeding index	–8,524.8	2.68
Production traits	–2,706.4	0.85
Functional traits	–3,152.7	0.99
Perpetual cost savings from:		
Aggregate breeding index	–26,620.3	8.36
Production traits	–8,288.6	2.60
Functional traits	–9,801.9	3.08

Note: All other variables are held constant at their mean values in 2007 in all computations. Moreover, cost savings from conformation traits are assumed to be zero since they are not significantly different from zero in Model-II.
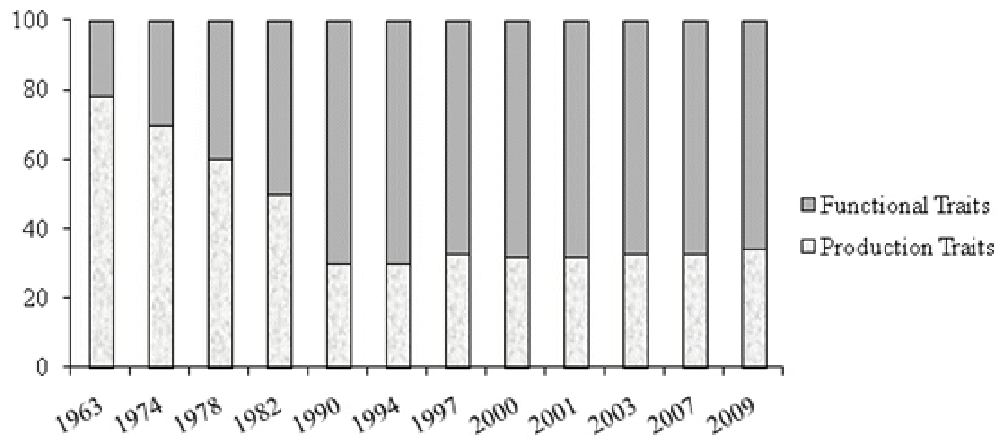
Fig. 1. Weights of groups of traits in the breeding goal, 1963–2009.
Source: Adapted from:
http://www.genoglobal.no/Home/Norwegian-Red-Characteristics/Norwegian-Red/

Paper III

The Effect of Dairy Quota on Milk Composition

Daniel Muluwork Atsbeha

Abstract

Under incentive schemes encouraging better milk composition, quota-restricted dairy farms may improve profitability by increasing proportions of high-value milk components (e.g., protein). A theoretical model of such quota-induced substitution effects is developed. Empirical results from Norwegian dairy farms show that quota-induced substitution effects are positive for protein and negative for fat. This implies that Norwegian dairy farms do not substitute towards high-value milk component as the quota regime gets restrictive. A combination of low financial incentives, high over production penalties, and cost complementarity between protein content and milk quantity are likely explanations of the result.

Key words: dairy quota, multiple component pricing, milk composition, profit function.

JEL Codes: D21, D22, Q12

Introduction

The demand for fluid milk has declined in many developed countries while that of processed dairy products has increased. These trends are confirmed by many studies, for example, Gould, Cox, and Perali (1990) and Gould (1996) for the U.S.; Cash, Wang, and Goddard (2005) for Canada, and Rickertsen and Gustavsen (2002) for Norway. Forecasts (e.g., Schmit and Kaiser 2006; European Communities 2006) also suggest that this trend is likely to continue. Simultaneously production capacity at the farm level has continued to expand. The expansion has been due to factors like scale adjustments and technological developments such as advances in breeding.

The resulting mismatch between demand and supply has led to two important developments. First, following the rise in the demand for processed dairy products, raw milk demand for industrial use has increased. Since the processing properties of milk depend on its hygienic quality and nutrient composition, multiple component pricing schemes have evolved. Second, despite the increase in demand for raw milk as an input, the overall demand for raw milk failed short of supply in many developed countries. In order to control excess supply, supply management policies that include administrative pricing, border controls, and quotas on milk supply are widely used.

The effect of marketing quota on a product on the supply of other products, which are jointly produced with the supply-restricted product, has been investigated in several studies (e.g., Moschini 1988; Fulginiti and Perrin 1993; Asche, Gordon, and Jensen 2007). However, in markets where product composition affects price, potential effects of quota on the composition of the restricted product itself is less explored for agricultural products. This article adds to the literature by investigating the effect of dairy quota on

milk composition when dairy processors pay component premiums. As discussed by Alston and James (2002), product quality related responses to quota restrictions can have implications for evaluating welfare effects of quotas. They argued that quota-induced quality improvements will reduce transfer efficiency of quota systems and reduce consumer losses.[1] Therefore, stricter quota restriction has to be imposed in order to achieve a targeted level of transfer efficiency if producers get around quota restrictions through quality adjustments (Alston and James 2002).

Dairy quotas are likely to affect milk composition in two ways. First, given premiums for better milk composition, dairy farms may seek to increase the level of valuable components, for example through feed ration adjustment, to minimize the effect of quota on their profits. Such quota-induced substitution of quantity by valuable attributes of a product is widely studied for nonagricultural products. For example, Aw and Roberts (1986) found evidence of quality upgrading in U.S. footwear imports that were subjected to import quotas. Similarly, Feenstra (1988) found that U.S. quotas on Japanese car imports led to substantial quality upgrading of imported cars from Japan. Furthermore, the possibility for quota-induced high-grading is also discussed in fisheries (e.g., Anderson 1991; Turner 1997; Kristofersson and Rickertsen 2009) though empirical support is limited due to low financial incentives and/or regulation against high-grading (Leal, De Alessi, and Baker 2005). Alston and James (2002) also argue that the high quality of tobacco in the U.S. relative to imported tobacco can partially be due to quality effects of marketing quotas governing its supply.

Second, even when dairy farms are not actively seeking to change the composition of milk, feed ration adjustment is the most practical way of responding to

quota changes in the short run. Milk composition is likely to respond for these feed adjustments (Jenkins and McGuire 2006).

In this article, a theoretical model about the supply of milk components by quota-restricted dairy farms is formulated. The model assumes that dairy farms are paid component premiums according to a minimum standard set by the processor itself. Comparative statics is used to motivate farm level empirical analysis about the effect of changing quota size on milk composition. Data from the Norwegian dairy farms, which have operated under milk quota regimes since the early 1980s, is used for the empirical analysis

The Evolution of Dairy Quota in Norway

Norway introduced a farm-level dairy quota system in 1983. Initial quota levels were determined by production levels in the previous three years. The policy was enforced through a two-price system where each farm received a low price for milk delivered outside its quota. The quota was non-transferable and redistribution of quota was only possible administratively through exemption rules. Following further declines in demand for dairy products, a quota buy-out scheme was introduced in 1991. Under this scheme, dairy farms were encouraged to exit production for certain period in exchange for financial rewards. However, the scheme was not very successful in reducing production and was abandoned in 1994.

After using yearly adjustments of farm level quotas until 1996, a new system that allowed market transfer of quotas was established. However, this new quota buy and sell scheme was based on state-determined quota prices, did not allow partial transfer of

quota, and the entire quota had to be sold to the state when a farm decides to sale its quota. Prospective buyers of quota could then purchase from the state only with very strict limits on geographical location and quantity that could be purchased. The resulting rigidities limited the mobility of quota. In 1997, the two-price system was replaced with a levy system that imposes penalty as high as the price per liter on surplus milk deliveries more than a certain percentage of the quota.

In 2003, some modifications were made to the buy and sell scheme. The state reduced the amount of quota farmers had to sell at administered prices to 70% of the total farm quota. The remaining 30% could be freely traded with other dairy farms operating within the same trading region. In 2008, the proportion of farm quota that could be sold in the free market increased to 50% but the geographic restrictions were not removed. Regional quota rental markets were also introduced in March 2009 for single farms (i.e., excluding consolidated farms) with annual quotas of up to 400,000 liters.

Although tradability of farm milk quotas has increased over time, rigidities in the quota market imply that the farm quota is still a key determinant of each farm's milk output. The farm level quota has in general increased over time for the average farm. This is partly due to farm consolidations encouraged by a subsidy scheme favoring joint operations over single family farms of the same size (Flaten 2002). More details on the evolution of the Norwegian dairy quota system are provided in Jervell and Borgen (2000) and OECD (2005).

Theoretical Model

Let b_i be the quantity of component i per liter of milk and b_i^e be the quantity of component i expected by the dairy processor per liter of milk. This quantity will be referred to as the processor's minimum. Let y be the farm's milk output and q be the farm's milk quota. Assume the dairy farms are specialized and operate in a dairy market where dairy processors control milk composition through component premiums. Furthermore, it is assumed that output is given by the quota (i.e., $y = q$).[2] Under this condition, the producer's price p per liter of milk is:

$$(1) \qquad p = p^w + \sum_{i=1}^{I} p_i \Delta b_i,$$

where p^w is an exogenously determined price of milk within the quota, Δb_i is the incremental component i per liter of milk, i.e., $\left(b_i - b_i^e \right)$, and p_i is the premium for a unit of incremental component i.

Consider a technology that transforms variable inputs x and services of quasi-fixed inputs z into milk output y of certain composition $\Delta b_i = \left(\Delta b_1, ..., \Delta b_I \right)$ at time period t. Therefore, when $\Delta b_i = 0, \forall i = 1, \cdots, I,$ the farm is producing milk with component levels equal to the processor's minimum. In this specification, the dairy farmer will decide on the quantity of inputs to produce the milk quota with certain composition relative to the processor's minimum. However, inputs are non-allocable in component production and inputs provided to influence one component may also affect the production of other components.[3] Therefore, it is unrealistic to assume perfect control

over milk composition. Therefore, appropriate representation of the component

production technology has to reflect imperfect control over milk composition.

As shown by Turner (1997), one implication of imperfect control is the violation

of free disposability of outputs.[4] Assuming two components (e.g., protein and fat) and a

fixed milk output, one such technology is presented in figure 1. The technology is similar

to the one described by Turner (1997) with one minor difference, which reflects even

more restriction on the extent milk composition can be controlled. That is, milk has to

retain its natural characteristics despite possibilities to change its composition. Therefore,

there are lower limits for both components and the level of each component cannot go

below these limits without a fundamental change to the natural characteristics of the milk.

Then the intersection of the lower limits, shown by $b^{\min}$ in figure 1, defines the lowest

point in the set of feasible compositions rather than the origin as in Turner (1997).

Imperfect control is also reflected by the boundaries of the technology characterized by

fixed proportions, except on a certain region where substitution between components is

possible. In figure 1, this region of the boundary is given by the curve AD. As noted by

Turner (1997), violation of free disposability under imperfect control is reflected by the

fact that dairy farms cannot push the level of one component to its lowest limit without

pushing the other component to its lowest limit as well.

Given component premiums, milk quota, and production technology that exhibit

imperfect control over milk composition, the economic problem of the dairy farm can be

presented as a constrained profit maximization problem. Assuming premiums are paid for

protein and fat only, the variable profit function of the dairy farm is:

$$(2) \qquad \Pi^V \left(p, w; z, t \right) = py - C \left(w, y, \Delta b_i; z, t \right), \qquad\qquad i = 1, 2$$

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where p is as defined by equation (1), w is a vector of variable input prices, and

$C(w, y, \Delta b_i; z, t)$ is the variable cost function. The economic problem of the dairy farm is

then given as:

(3) $\quad \underset{y, \Delta b_i}{\operatorname{Max}} \Pi^V (p, w; z, t)$ $\qquad i = 1, 2,$

Subject to:

$(3a)$ $\quad y = q$

$(3b)$ $\quad \Theta_{ij}^{\min} \left(b_j - b_j^{\min} \right) \le b_i - b_i^{\min}$ $\qquad i, j = 1, 2,$

$(3c)$ $\quad b_i - b_i^{\min} \le \Theta_{ij}^{\max} \left(b_j - b_j^{\min} \right)$ $\qquad i, j = 1, 2,$

$(3d)$ $\quad b_i^{\min} \le b_i,$ $\qquad\qquad\qquad i = 1, 2,$

where $\Theta_{ij} = \dfrac{b_i - b_i^{\min}}{b_j - b_j^{\min}}$ measures the slope of a straight line from $b^{\min}$ to (b_i, b_j). $\Theta_{ij}^{\min}$ and

$\Theta_{ij}^{\max}$ are extreme values of Θ_{ij} and represent the boundaries of the production possibility

set characterized by fixed proportions. We can substitute equation (1) and $(3a)$ into

equation (2) to get $\Pi^V (p, w; z, t) = p^w q + \Pi^{VC} (p, w; z, t)$, where

$\Pi^{VC} (p, w; z, t) = q \sum_{i=1}^{I} p_i \Delta b_i - C(w, q, \Delta b_i; z, t)$ or a variable component profit function.

Since the farmer cannot choose p^w and q, the re-writing implies that the economic

problem of the dairy farm can be reduced to maximization of $\Pi^{VC} (p_i, w; q, z, t)$.

$\Pi^{VC} (p_i, w; q, z, t)$ is assumed to satisfy the properties of variable profit functions

except monotonicity with respect to q.[5] Accordingly, $\Pi^{VC} (p_i, w; q, z, t)$ is monotonic

with respect to p_i and w (nondecreasing in p_i and nonincreasing in w), convex and

positively linearly homogeneous with respect to p_i and w, and concave with respect to z.

Assuming that $(3d)$ is not binding for simplicity, only three cases remain to solve the maximization problem: where neither $(3b)$ nor $(3c)$ is binding and where either $(3b)$ or $(3c)$ is binding, in addition to $(3a)$. In the former case, the corresponding Lagrangian function of the economic problem is:

$$(4) \qquad L = p^w q + q \sum_{i=1}^{I} p_i \Delta b_i - C(w, q, \Delta b_i; z, t) - \lambda q$$

where λ is the Lagrangian multiplier that represents shadow value of milk quota.

As noted by Falvey (1979) and Lutz (2007) in the context of international trade, the quota-induced incentive to improve milk composition is related to the shadow value of quota, reflecting the profit loss due to quota. Improving milk composition allows dairy farms to minimize this loss. This can easily be seen by differentiating (4) as follows:

$$(5) \qquad \frac{\partial L}{\partial q} = \left(p^w - \lambda + \sum_{i=1}^{I} p_i \Delta b_i \right) - \frac{\partial C(w, q, \Delta b_i; z, t)}{\partial q} = 0.$$

However, adjusting milk composition also has cost implications. Therefore, the choice of incremental component levels will be based on what happens to variable component profit when incremental component per liter is changed. More formally, this choice can be represented by the first-order condition underlying maximization of variable component profit, or:[6]

$$(6) \qquad \frac{\partial L}{\partial \Delta b_i} = \frac{\partial \Pi^{VC}(p_i, w; q, z, t)}{\partial \Delta b_i} = p_i q - \frac{\partial C(w, q, \Delta b_i; z, t)}{\partial \Delta b_i} = 0;$$

i.e., the profit maximizing level of Δb_i occurs at the point where the marginal revenue from incremental component i equals the marginal cost of producing it.

Given that $\Pi^V(p,w;z,t) = p^w q + \Pi^{VC}(p,w;z,t)$, Hotelling's lemma can be used to derive incremental component supply equations for milk components, conditional factor demand equations for variable input use, and the shadow price equation for the quota from $\Pi^{VC}(p,w;z,t)$ as follows:[7]

(7a) $\quad \dfrac{\partial \Pi^{VC}(p_i,w;q,z,t)}{\partial p_i} = q\Delta b_i(p_i,w;q,z,t),$

(7b) $\quad \dfrac{\partial \Pi^{VC}(p_i,w;q,z,t)}{\partial w} = -x(p_i,w;q,z,t), \quad$ and

(7c) $\quad \dfrac{\partial \Pi^{VC}(p_i,w;q,z,t)}{\partial q} = \lambda(p,w;q,z,t) - p^w.$

Given incremental component supply functions, it can be shown that a change in quota will have scaling and substitution effects on incremental component supply. This can be obtained by differentiating (7a) with respect to q as:

(8) $\quad \dfrac{\partial q\Delta b_i(p_i,w;q,z,t)}{\partial q} = \Delta b_i(.) + q\dfrac{\partial \Delta b_i(.)}{\partial q}.$

The scaling effect is represented by the first term on the right hand side of (8). Given the definition of Δb_i, this term will be positive (negative) for producers of milk with component levels above (below) the processor's minimum. This suggests that the supply of incremental components will increase following an increase in quota and vice versa. The second right hand side term in (8) is the substitution effect. The sign of the substitution effect is however ambiguous. It depends on how milk quantity and its component levels are technically related as well as on what the dairy farmer chooses to do to influence this relationship. Figure 2 illustrates these two effects graphically.

Although the complex interaction between technical and economic factors makes it difficult to sign the substitution effect with certainty, useful insights can be drawn from

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comparative static. Differentiating (6) with respect to $q,$ as in Lau (1978) and Moschini (1988), results in:

$$(9) \quad \frac{\partial \Pi^{VC}(p_i, w; q, z, t)}{\partial \Delta b_i \partial q} = p_i - \left[\frac{\partial^2 C(.)}{\partial \Delta b_i \partial q} + \frac{\partial^2 C(.)}{\partial \Delta b_i^2} \frac{\partial \Delta b_i}{\partial q} \right] = 0$$

$$\frac{\partial \Delta b_i(.)}{\partial q} = \left(p_i - \frac{\partial^2 C(.)}{\partial \Delta b_i \partial q} \right) \left(\frac{\partial^2 C(.)}{\partial \Delta b_i^2} \right)^{-1}.$$

Assuming positively slopped supply curves for incremental components, the sign of (9) is determined by $\left(p_i - \dfrac{\partial^2 C(.)}{\partial \Delta b_i \partial q} \right),$ which is the difference between the changes in marginal revenue and marginal cost of incremental component in response to changing quota size.

If there are cost complementarities in the production of q and Δb_i $\left(\text{i.e.,} \ \dfrac{\partial^2 C(.)}{\partial \Delta b_i \partial q} \leq 0 \right),$ then the substitution effect will be unambiguously positive. This suggests that milk produced after the change in quota will contain more incremental component i per liter than before. On the contrary, when $\dfrac{\partial^2 C(.)}{\partial \Delta b_i \partial q} > 0,$ the sign of the substitution effect can go either way and can only be determined empirically.[8]

Empirical Approach

By estimating derived incremental component supply functions either separately or in a system framework, the response of component supply to milk quota changes can be obtained by equation (8). Then, the ambiguous substitution effect can be identified by re-writing (8) in elasticity form and re-arranging as follows:[9]

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$$(10) \quad \frac{\partial q \Delta b_i(.)}{\partial q} \cdot \frac{1}{\Delta b_i} = \left[\Delta b_i(.) + q \frac{\partial \Delta b_i(.)}{\partial q} \right] \cdot \frac{1}{\Delta b_i},$$

$$\varepsilon_q^{\Delta b_i} = \varepsilon_q^{q \Delta b_i} - 1,$$

where $\varepsilon_q^{\Delta b_i} = \frac{\partial \Delta b_i(.)}{\partial q} \frac{q}{\Delta b_i}$ measures the substitution effect discussed above and

$\varepsilon_q^{q \Delta b_i} = \frac{\partial q \Delta b_i(.)}{\partial q} \cdot \frac{1}{\Delta b_i}$ measures the overall response of incremental component supply to

quota change (i.e., the sum of scaling and substitution effects). $\varepsilon_q^{q \Delta b}$ is similar to the

elasticity of intensity of Diewert (1974) with two notable differences. First, the response

is with respect to a change in output restriction and not in a fixed input level as in

Diewert (1974). Second, the response variable is an attribute of a product and not the

quantity of another physically distinct product that is jointly produced with the restricted

product as in other applications of the measure (e.g., Asche, Gordon, and Jensen 2007).

Once the response of incremental component supply $\left(\text{i.e., } q \Delta b_i(.) \right)$ to a quota

change is known, the response of total component supply $\left(\text{i.e., } q b_i(.) \right)$ to the quota

change can also be obtained. Given that total component supply is equal to the sum of

minimum component supply $q b_i^e$ and incremental component supply or

$q b_i(.) = q b_i^e + q \Delta b_i(.),$ the response of total component supply to quota change is given

as:

$$(11) \quad \frac{\partial q b_i(.)}{\partial q} = b_i^e + \left(\Delta b_i(.) + q \frac{\partial \Delta b_i(.)}{\partial q} \right).$$

By multiplying both sides by $\frac{1}{b_i}$, equation (11) can be expressed in elasticity

form as follows:

$$(12) \quad \varepsilon_q^{qb_i} = \frac{b_i^e}{b_i} + \left(\frac{\Delta b_i(.)}{b_i} + \frac{\partial \Delta b_i(.)}{\partial q} \cdot \frac{q}{b_i} \right).$$

Furthermore, the expression in the parenthesis can be re-written as

$\frac{\Delta b_i(.)}{b_i} \left(1 + \frac{\partial \Delta b_i(.)}{\partial q} \cdot \frac{q}{\Delta b_i} \right)$ by multiplying it with $\Delta b_i / \Delta b_i$. Then using the result in

equation (10), the response of total component supply to a quota change can be re-written

as:

$$(13) \quad \varepsilon_q^{qb_i} = \frac{b_i^e}{b_i} + \frac{\Delta b_i(.)}{b_i} \varepsilon_q^{q\Delta b_i}.$$

This is a very intuitive result suggesting that the total effect of a 1% change in quota on

total component supply is the weighted sum of the response of the quota itself

$\left(\text{i.e., } \frac{\partial q}{\partial q} = 1 \right)$ and the response of incremental component supply $\left(\text{i.e., } \frac{\partial q \Delta b_i}{\partial q} = \varepsilon_q^{q\Delta b_i} \right)$ to

quota change. The weights are shares of minimum component supply per liter and

incremental component supply per liter relative to the total component level per liter.

Finally, technical progress can also affect the development of incremental

component per liter over time in addition to changes in quota. Assuming a trend variable t

is used to proxy technical progress, the relative contribution of technical progress to the

change in incremental components per liter over time can be derived. To obtain such a

measure, equation (7a) is differentiated with respect to t as follows:

$$(14) \quad \frac{\partial q \Delta b_i(.)}{\partial t} = \frac{\partial q}{\partial t} \Delta b_i(.) + \left(\frac{\partial \Delta b_i(.)}{\partial q} \frac{\partial q}{\partial t} + \frac{\partial \Delta b_i(.)}{\partial t} \right) q.$$

Multiplying both sides by $\frac{1}{q \Delta b_i}$, equation (14) can be re-written as:

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$$(15) \quad \frac{1}{q\Delta b_i}\frac{\partial q\Delta b_i(.)}{\partial t} = \frac{1}{q}\frac{\partial q}{\partial t} + \frac{1}{\Delta b_i}\frac{\partial \Delta b_i(.)}{\partial q}\frac{\partial q}{\partial t} + \frac{1}{\Delta b_i}\frac{\partial \Delta b_i(.)}{\partial t}.$$

Equation (15) implies a logarithmic differentiation of (7a) with respect to t and measures the relative change in the supply of incremental component i for an absolute change in t. Furthermore equation (15) decomposes incremental component supply growth into three sources shown by the three right-hand side terms. These are quota growth, effect of quota growth on incremental component per liter, and effect of technical progress, respectively. The empirical implementation of isolating the effect of technical progress from the other sources can be simplified by expressing the effect of technical progress as a residual and re-arranging the resulting expression as follows:

$$(16) \quad \frac{1}{\Delta b_i}\frac{\partial \Delta b_i(.)}{\partial t} = \left(\frac{1}{q\Delta b_i}\frac{\partial q\Delta b_i(.)}{\partial t} - \left(\frac{1}{q}\frac{\partial q}{\partial t} + \frac{1}{\Delta b_i}\frac{\partial \Delta b_i(.)}{\partial q}\frac{\partial q}{\partial t} \right) \right)$$
$$= \left(\frac{1}{q\Delta b_i}\frac{\partial q\Delta b_i(.)}{\partial t} - \frac{1}{q}\frac{\partial q}{\partial t}\left(1 + \varepsilon_q^{\Delta b_i} \right) \right),$$

i.e., the effect of technical progress on incremental component i per liter can be obtained by subtracting the growth rate of quota over time and its effect on incremental component i per liter from the growth rate of incremental component i over time. Dividing equation (16) by equation (15) provides the relative contribution of technical progress to incremental component supply growth over time.

Econometric Model

For empirical analysis of the above model, the variable component profit function is specified as a Symmetric Normalized Quadratic profit function (SNQ) (Diewert and Wales 1987; Kohli 1993). This functional form has some advantages compared to

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popular alternatives such as the translog. For example it allows negative profits and global imposition of curvature conditions without losing its flexibility (Kohli 1993). Furthermore, due to symmetric treatment of all netput prices, parameter estimates are independent of numeraire choice unlike, for example the Normalized Quadratic function.

For m netputs s_m ($m = 1,\ldots,6$, where 1 = incremental protein, 2 = incremental fat, 3 = forage, 4 = concentrates, 5 = veterinary and insemination services, 6 = other inputs like energy and maintenance costs) and a vector z_k containing milk quota ($k = 1$), a trend ($k = 2$), and quasi-fixed inputs ($k = 3$), the parameter specification for the SNQ is given as:[10]

$$(17) \quad \Pi_{ht}^{VC} = \sum_{m=1}^{6} \alpha_{mh} v_{mt} + \frac{1}{2} \left(\sum_{m=1}^{6} \omega_m v_{mt} \right)^{-1} \sum_{m=1}^{6} \sum_{n=1}^{6} \alpha_{mn} v_{mt} v_{nt} + \frac{1}{2} \left(\sum_{m=1}^{6} \omega_m v_{mt} \right) \sum_{k=1}^{3} \sum_{l=1}^{3} \beta_{kl} z_{kht} z_{lht} + \sum_{m=1}^{6} \sum_{k=1}^{3} \varphi_{mk} v_{mt} z_{kht},$$

where h and t are farm and time indicators, respectively, $v_{mt} = \left[p_{1t}, p_{2t}, w_{3t}, \cdots, w_{6t} \right]$ is a netput price vector, ω_m is the average share of netput m from the sum of total cost and total revenue; i.e., average of $\omega_{mht} = v_{mt} |s_{mht}| \Big/ \sum_{m=1}^{N} v_{mt} |s_{mht}|$. Therefore $\sum_{m} \omega_m = 1$.

Homogeneity of degree one in netput prices is imposed by $\left(\sum_{m=1}^{6} \omega_m v_{mt} \right)$ and identification of all α_{mn}s is made possible by imposing the restriction $\sum_{n=1}^{6} \alpha_{mn} v_n^* = 0$ for all $m \neq n$, where v_n^* is an arbitrary point of normalization (Diewert and Wales, 1987). For the empirical analysis in this article, the point of normalization is set at the sample mean of

netput prices (e.g., Bezlepkina, Oude Lansink, and Oskam 2005). In addition, symmetry is imposed by requiring $\alpha_{mn} = \alpha_{nm}$ for all m and n as well as $\beta_{kl} = \beta_{lk}$ for all k and l.

In addition to homogeneity and symmetry, the estimated variable component profit function is required to satisfy monotonicity and curvature properties. These theoretical properties are usually violated when flexible functional forms like the SNQ are employed (Diewert and Wales 1987; Kohli 1993; Sauer, Frohberg, and Hockman 2006). As noted by Sauer, Frohberg, and Hockman (2006), this is partly related to the tradeoff between theoretical consistency and flexibility. Additional reasons can be data problems such as aggregation and insufficient price variations, technological properties such as increasing returns to scale technology for which a profit maximizing netput mix does not exist or even wrong behavioral assumptions. In most cases, the reason responsible for violation of theoretical properties is not clear á priori. Therefore, the proposed solution in the case of violations is to impose the required properties either globally or locally. In some cases, global restrictions of theoretical consistency may compromise flexibility (e.g., translog) while in other cases (e.g., curvature constraints for the SNQ) restrictions can be imposed globally without affecting flexibility (Diewert and Wales 1987; Sauer, Frohberg, and Hockman 2006).

Approaches suggested by Lau (1978) as well as Diewert and Wales (1987) can be used to impose curvature on the SNQ. Both approaches involve replacing the relevant sub-Hessian matrix with different parameters. For example, convexity of the SNQ with respect to prices require the matrix $\mathbf{A} = \begin{vmatrix} \alpha_{11} & & & \\ \alpha_{12} & \alpha_{22} & & \\ \vdots & \vdots & \ddots & \\ \alpha_{m-1,1} & \alpha_{m-1,2} & \cdots & \alpha_{m-1,m-1} \end{vmatrix}$ be positive semi-

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definite. When this condition is not met, the approach suggested by Diewert and Wales (1987) based on a previous work by Wiley, Schmidt, and Bramble (1973) imposes convexity in netput prices by substituting $\mathbf{A}$ with the inner product of a lower triangular

matrix $\mathbf{D} = \begin{vmatrix} d_{11} & 0 & \cdots & 0 \\ d_{21} & d_{22} & \vdots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ d_{m-1,1} & d_{m-1,2} & \cdots & d_{m-1,m-1} \end{vmatrix}$ where $d_{mn} = 0$ for $\forall m < n$, and its transpose $\mathbf{D}'$.

For example, for a system of four netputs, this can be implemented as

$\mathbf{A} = \mathbf{D}\mathbf{D}' = \begin{vmatrix} d_{11}^2 & d_{21}d_{11} & d_{31}d_{11} \\ d_{21}d_{11} & d_{21}^2 + d_{22}^2 & d_{31}d_{21} + d_{32}d_{22} \\ d_{31}d_{11} & d_{31}d_{21} + d_{32}d_{22} & d_{31}^2 + d_{32}^2 + d_{33}^2 \end{vmatrix}$. The homogeneity restriction is used

to recover the last element of each row and column.

Concavity with respect to quasi-fixed inputs require the matrix

$\mathbf{B} = \begin{vmatrix} \beta_{11} & & & \\ \beta_{12} & \beta_{22} & & \\ \vdots & \vdots & \ddots & \\ \beta_{k,1} & \beta_{k,2} & \cdots & \beta_{k,k} \end{vmatrix}$ be negative semi-definite. When the estimated model violates

this condition, a procedure similar to the one used for convexity can be used to impose it (Diewert and Wales 1987).

Applying Hotelling's lemma to equation (17) provides incremental component supply and input demand equations that take the following form:

$$(18) \quad s_{mht} = \alpha_{mh} + \left(\sum_{m=1}^{6} \omega_m v_{mt} \right)^{-1} \sum_{n=1}^{6} \alpha_{mn} v_{nt} - \frac{1}{2} \omega_m \left(\sum_{m=1}^{6} \omega_m v_{mt} \right)^{-2} \sum_{m=1}^{6} \sum_{n=1}^{6} \alpha_{mn} v_{mt} v_{nt} +$$

$$\frac{1}{2} \omega_m \sum_{k=1}^{3} \sum_{l=1}^{3} \beta_{kl} z_{kht} z_{lht} + \sum_{l=1}^{3} \varphi_{ml} z_{lht}.$$

Note that equation (18) has a farm specific intercept to allow for unobservable farm heterogeneity for example in terms of managerial ability. Direct estimation of the fixed

effects is, however, avoided by applying the within transformation of model variables. This procedure has also been used in applied studies like Peerlings and Polman (2004) and Bezlepkina, Oude Lansink, and Oskam (2005).

Assuming optimizing behavior, a system of netput equations shown in (18) is estimated. The profit function is not included in the system because the fixed effects in the netput equations appear as slope coefficients and all other parameters of the profit function can be obtained by estimating the netput equations only. Furthermore, each equation in the system is expressed stochastically by appending additive error term to facilitate econometric estimation of its parameters. The error terms represent random deviations from the profit maximizing levels of netputs. Accordingly, stacking observations by equation, each netput equation can be expressed as:

$$(19) \qquad s_m = X_m \theta_m + u_m \qquad\qquad \text{for } m = 1, \cdots, 6,$$

where X_m is the design matrix of each equation, θ_m is a vector of parameters to be estimated, and u_m is a vector of additive error terms. The error terms are assumed to be normally distributed with a zero mean vector. Furthermore, it is assumed that

$$E[u_{mht}, u_{m'ht}] = \sigma_{mm'} \text{ for } m \neq m' \text{ and } E[u_{mht}, u_{m'h't'}] = 0 \text{ for all } m = m' \ h, \ h', \text{ and } t \neq t' \text{ in}$$

order to allow for contemporaneous correlation across equations.

Stacking the equations, the equation system can be written as:

$$(20) \qquad \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_6 \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_6 \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_6 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_6 \end{bmatrix} = s = X\theta + u.$$

Once the model is estimated, elasticity of intensity estimates can be calculated as:

$$(21) \quad \varepsilon_{z_l}^m = \left(\omega_m \sum_{l=1}^{K} \beta_{kl} z_{kht} + \varphi_{ml} \right) \frac{z_l}{s_m}.$$

The elasticity of intensity measures the response of netputs for a given change in the level of the respective fixed inputs or outputs. Given that trend is included in z, equation (21) also underlies computation of the technical change effect discussed above. Similarly, shadow price of milk quota can be obtained using:

$$(22) \quad \lambda_{ht} = p_t^w + \left(\sum_{m=1}^{N} \varphi_{mk} v_{mt} + \left(\sum_{m=1}^{N} \omega_m v_{mt} \right) \sum_{l=1}^{K} \beta_{kl} z_{lht} \right),$$

for $k = 1$. Both equation (21) and (22) can be computed either for each data point or at a point of interest such as the sample mean. In this article, all computations are made at the sample mean.

Data

The dataset used for estimation is obtained from the Norwegian dairy herd recording system owned and operated by TINE, the largest dairy cooperative in the country.[11] The raw dataset has a total of 11,222 observations from 3,415 Norwegian dairy farms covering the period 2004–2009. Extreme observations are filtered out before estimation.[12] In addition, due to the within transformation required for the fixed effect specifications only farms observed for two or more years are included. The final estimation sample has 10,503 observations where each farm is observed for 3.9 years on average.

The processor's minimum of protein and fat is set by TINE. Since 2003, it has been 3.2% for protein and 4% for fat. The component premiums have been stable at NOK 1.0 per liter for protein and NOK 0.15 per liter for fat, for each 1% increment above the processor's minimum during the 2004–2009 period.[13] The relatively higher valuation of

protein is caused by market conditions for dairy products that favor low fat products and cheese.

The incremental protein and fat levels are computed for each farm over the sample period. As a difference between observed milk composition and the processor's minimum, incremental protein and fat levels provide information on whether the dairy farm chose to change milk composition and the extent of such changes. In general, protein and fat content of milk has been improving over time. During the sample period, protein content was 0.14 percentage points and fat content was 0.08 percentage points above the processor's minimum on average.

Figure 3 is a running line smoothing of incremental protein and fat per liter against milk quota after controlling for trend and herd size. With technology and herd size kept constant, the figures show what will happen to milk composition as farms respond to changes in milk quota through other means such as feed manipulation. As milk quota increase, protein percentage of milk also increased while fat percentage decreased although with some fluctuations. This implies that farm level changes, for example through feed manipulation, in response to changing quota size can have component specific effects. An example of such a strategy is increasing concentrate-to-forage ratio. As shown in Jenkins and McGuire (2006), high concentrate-to-forage ratio is known to increase protein content and milk yield while it depresses fat content. Furthermore, figure 3 shows that substitution between components tends to level off after about 250,000 liters. This exemplifies the limited substitution possibility among components through short run measures such as feed manipulation.

In addition to incremental component quantities, the netput vector includes quantities of forage and concentrates in terms of feed units, which can account for feed

quality differences. Implicit quantity indices (i.e., value divided by a price index) for veterinary and insemination services as well as other costs are also included. The other costs category includes energy and maintenance costs for buildings, tractors, and other farm equipments. The prices for forage and concentrates are measured as unit values per feed unit. Forage is largely produced on the farm and forage prices are computed as unit variable costs from variable cost data in forage production. The prices for veterinary and insemination services as well as the other costs categories were constructed as Laspeyeres price indices (2009 = 100). These indices were constructed based on quantity and value data of these cost components for the dairy sector of the country as compiled by the Norwegian Agricultural Economics Research Institute (NILF).

Quasi-fixed inputs are measured as a composite input based on total subsidies received from the state either on per cow, per acre, and per management unit basis. Note however that this measure does not account for labor, which is a major cost component for dairy farms. Labor use data at the farm level is not also available for the sampled farms. Therefore, there was no choice but to assume weak separability of non-labor (NL) inputs from labor (L) inputs. In terms of a production function, weak separability in non-labor inputs implies that the production function F can be written as

$F(NL, L) = f(g(NL), L)$. In addition, the weak separability assumption implies that the marginal rate of technical substitution between any two non labor inputs is independent

of labor inputs or $\dfrac{\partial}{\partial L}\left(\dfrac{\partial F/\partial NL_i}{\partial F/\partial NL_j}\right) = 0$. Furthermore, as shown by Fuss (1977), weak

separability implies a two-stage optimization process where the optimal mix of non-labor

inputs is selected first. In a second stage the optimal quantity of labor is selected together with the aggregate quantity of non-labor inputs from the first stage.

Descriptive statistics of all variables included in the model is given in table 1. At the incremental component prices stated above and the average incremental component quantities, the average dairy farm increased its revenue by 4.2% through better milk composition as compared with the revenue associated with zero incremental components.

Estimation and Results

All variables are normalized by dividing with their mean values. As noted above, this means the sample mean is the point of normalization for the SNQ. Farm fixed effects are removed by a within transformation of all variables prior to estimation.[14] The system of netput equations is initially estimated using Zellner's Iterative Seemingly Unrelated Regressions (ITSUR) in STATA® version 11 (StataCorp 2009).[15] Then regularity conditions are checked for the estimated model. Monotonicity is checked for each data point using the signs of predicted netput quantities. The predicted netput quantities are positive for all outputs and negative for all inputs at every data point. This suggests that monotonicity is satisfied globally. Convexity with respect to netput prices and concavity with respect to fixed factors are checked using eigenvalue decompositions of the **A** and **B** matrices.[16] In our case, the eigenvalues of **A** are 0.144, 0.054, $-5.278 \times e\text{-}14$, -0.092 and the eignevalue of **B** is -0.37. These values suggest that convexity with respect to netput prices is violated while concavity with respect to quasi-fixed inputs is satisfied. Consequently, convexity with respect to netput prices is imposed as discussed above. The resulting model is nonlinear in parameters and therefore the Iterative Feasible

Generalized Nonlinear Least Squares (IFGNLS) estimator is used to obtain model parameters. The nlsur routine in STATA® version 11 (StataCorp 2009) is used for the estimation.[17]

The Effect of Quota Change

As shown in table 2, most parameter estimates of the model are statistically different from zero at the 5% level of significance. Direct interpretation of these coefficients is difficult and hence table 3 provides elasticity of intensities with respect to all fixed factors in the model. The elasticity of intensity is 1.220 for incremental protein and 0.405 for incremental fat. According to Equation (8), these figures imply substitution effects of 0.220 for protein and –0.595 for fat following a 1% change in quota size. Both estimates are statistically different from zero at the 5% level of significance. Therefore, an increase in production level due to additional quota will augment protein content while it decreases fat content. One explanation for the observed signs of substitution effects is the nature of cost complementarity between milk quantity and component percentages. The positive substitution effect for protein implies that cost of producing the marginal protein declines as more milk is produced. In other words, farm level responses to quota increases are likely to augment protein than fat content of the milk. For example, from elasticities of intensity with respect to feed quantities shown in table 3, one can see that increasing quota size results in relatively higher increase in concentrate than in forage use. This leads to higher concentrate-to-forage ratio, which is associated with increases in protein content and reduction of fat content (Jenkins and McGuire 2006).

On the other hand, the negative and statistically significant quadratic term for quota in the incremental component supply functions implies that cost complementarity between protein content and production level gets weaker as production increases. It also implies that increasing production due to more quota leads to increasingly bigger reductions in fat content. Combining the two results, it can be inferred that farm level adjustments following quota increase lead to rapidly declining fat content for increasingly smaller gains in protein content.

More importantly, if we take protein content as an indicator of high quality milk due to its value, then the sign of the substitution effect is opposite to what was found in similar studies discussed above; i.e., milk quality decreases as the quota regime gets more restrictive and vice versa. The unexpected sign of the substitution effect may be due to two factors. First, component premiums are too small to generate deliberate component manipulation for profit. Second, feed adjustments to augment protein make over production of the quota likely. Given the severe over production penalty, producing within quota can therefore be more important for Norwegian dairy farms than manipulating components for a relatively small increase in revenue.

Table 3 also shows response of variable input use for change in quota. The elasticities of intensity for all inputs are positive and significantly different from zero at the 5% level of significance. This implies that all inputs are complements to quota and their use will change in the same direction as the change in quota.

The Effect of Fixed Factors

In addition to quota, elasticities of intensity are also computed with respect to the trend variable and quasi-fixed inputs. Elasticities of intensity with respect to trend are shown in the second column of table 3. As discussed above, these values are computed through logarithmic differentiation and therefore can be interpreted as growth rates of the respective variables. The supply of incremental components has increased over time with incremental fat increasing the most. As discussed above, the growth over time in incremental component supply is partly due to the temporal growth in quota size and the consequent effect on milk composition while the rest is due to technical progress. The relative contribution of technical progress is isolated in equation (16) and 88.5%of the growth in incremental protein per liter and 98.1% of the growth in incremental fat per liter has been due to technical progress. This implies that technical progress is the major determinant of changes in component level per liter on Norwegian dairy farms. Furthermore, the positive temporal growth of fat content imply that the fat depressing effects of a high concentrate-to-forage ratio are more than compensated by technical progress. This can be due to successful breeding and the availability of tools like Tine OptiFor. Tine OptiFor is an internet-based tool available to dairy farmers since 2006. The tool can be used for feed formulation and optimization to an individual cow level based on up to date research results about feed, rumen function and digestibility.

The elasticities with respect to trend are negative for veterinary and insemination services as well as the other inputs category, suggesting the demand for these inputs have declined over time. According to the estimates, demand for veterinary and insemination services has declined by 14.5%. This decline may be due to several factors. First, the

Norwegian breeding program has emphasized health and fertility traits since early 1970s. Second, the establishment of National Cattle Health Services (NCHS) in 1995 is believed to have contributed to the decline in the incidence of animal diseases (Østerås et al. 2007). This service includes provision of periodic herd health reports for each farm to assist herd management. In line with this, Østerås et al. (2007) reported a more than 50% decline in the incidence of animal diseases in Norway for years after 2000 relative to the 1990s. In contrast, the demand for feed inputs has increased over time: by 6.5% for concentrates and by 2.3% for forage.

Elasticities of intensity with respect to quasi-fixed inputs are also reported in table 3. It can be seen that changes in quasi-fixed inputs has effects on all netputs except on incremental fat supply and the other inputs category. The effect on incremental protein supply is negative, suggesting that increasing the quantity of quasi-fixed inputs results in reductions in protein content of the milk. The largest effect with respect to inputs is on the demand for forage. Both these effects are intuitive considering the quasi-fixed inputs included in the composite measure. For instance, increasing the number of cows producing a given level of milk will require depressing yield per cow, for example by decreasing the concentrate-to-forage ratio. Reduced concentrate-to-forage ratio however will lead to a decline in protein content given the nature of cost complementarity in the dairy technology. Similarly, more land will facilitate additional supply of forage on the farm, which will reduce the concentrate-to-forage ratio with an associated reduction in protein content.

Shadow Price of Quota

Finally, the shadow price of the quota is computed and the result is shown in table 4. The shadow price of a quota is the difference between the observed milk price and the marginal cost of producing the milk quota. The latter can be understood as the price that would make the dairy farm supply the quota output in the absence of the quota. The difference between the observed and shadow prices of milk is then a measure of the rent associated with the quota, and it represents the lost profit per liter or the maximum amount a producer is willing to pay to have the farm quota increased by one liter. The quality-unadjusted average price of milk has been NOK 3.78 per liter, and the average incremental component premium has been NOK 0.15 per liter. These values suggest that an average quality-adjusted milk price would be NOK 3.93 per liter. The shadow price of milk or the marginal cost of producing the quota computed at mean has been NOK 1.6. Therefore, the quota rent per liter has been NOK 2.3, which is 59% of the average price. However, it has to be noted that this estimate of the quota rent does not include major cost components such as labor costs and is likely to get lower when such costs components are taken into account.

Conclusions

Empirical studies (e.g., Asche, Gordon, and Jensen 2007; Kumbhakar et al. 2008) show that exogenous restriction on the supply of a product generate transfer of resources towards unrestricted products that are jointly produced with restricted one. Such transfer of inputs occurs to minimize the effect of the restriction on profits. In markets where producers are paid for improved composition of a product while facing a quantity

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restriction on its supply, substitution towards high-value components may arise for the same reason. In addition to the profit motive, technical interdependence between quantity and composition can generate substitution effects from supply restrictions.

Using data from dairy production in Norway the effect of quota changes on component supply is investigated. Empirical results show that the substitution effect of the dairy quota is positive for protein and negative for fat. This implies that the supply of protein declines while that of fat increase as the quota regime gets more restrictive. Given that protein is valued more than six times than fat in the Norwegian dairy market, the sign of substitution effects is unexpected. However, two factors are likely to explain the result. First component premiums may be too low to generate component manipulation for profit. Second, the dairy technology exhibits cost complementarity between protein content and milk quantity. This implies that a restrictive quota regime increases the cost of producing protein. Furthermore, severe over production penalty may discourage substitution towards protein if adjustments to augment protein content also increase milk output. One such adjustment is increasing concentrate-to forage ratio. However, component supply has improved over time. Technical progress is the major source of this improvement, accounting more than 88% of the growth, while quota growth and resulting substitution effects accounted the rest

Footnotes
[1] Transfer efficiency of a quota refers to "the ratio of farm income change to change in program expenditure, in the form of either consumer or taxpayer costs." (OECD 2005).

[2] It is possible that dairy farms may under- or overproduce their quota. However, deviations from quota are assumed to be the consequence of imperfect control over

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outputs and optimization errors. The average dairy farm has produced 99.9% of its quota and annual deviations never exceeded 2% of the quota during 2004–2009. This figure is for example equivalent to the allowed surplus production before over production penalties have to be paid. The system of charging penalties for milk deliveries beyond certain percentage of the farm quota started in 1997. The penalty can be as high as the per liter milk price (OECD 2005).

[3] For example, for the dominant dairy breed on Norwegian dairy farms, the genetic correlation between fat and protein percentages is 0.64. Therefore, cows selected for producing milk with high protein content also are likely to produce milk with high fat content.

[4] Free disposability of outputs implies that if a given combination of outputs is feasible, any other combination with smaller quantities of outputs is also feasible.

[5] Unlike other restricted variable profit maximization problems, where the quantity restriction affects only the production cost of unrestricted outputs (e.g., Moschini 1988), q appears both on the revenue and cost side of the restricted variable component profit function. Therefore, $\Pi^{rc}\left(p_i, w, q; z\right)$ is not necessarily nonincreasing with respect to q.

[6] When (3a) and (3b) are binding, the first-order conditions with respect to Δb_i and Δb_j become $p_i q - \lambda_2 = \dfrac{\partial C(.)}{\partial \Delta b_i}$ and $p_j q + \lambda_2 \Theta_{ij}^{\min} = \dfrac{\partial C(.)}{\partial \Delta b_j}$, where $\lambda_2 > 0$ is the Lagrange multiplier associated with (3b). Assuming $\dfrac{\partial C(.)}{\partial \Delta b_i} > 0$ and $\dfrac{\partial C(.)}{\partial \Delta b_j} > 0$ the optimal Δb_i will be lower and the optimal Δb_j will be higher than their respective optimal values when only (3a) is binding. The opposite is true when (3a) and (3c) are binding.

[7] Given that a constant value is subtracted from all observed component levels, the incremental component supply function can be interpreted as the component supply function as well.

[8] One source of cost complementarities in joint production is the existence of normal non-allocable inputs (an input is normal when the compensated output elasticity of the demand for that input is nonnegative) and cost competitiveness can occur when jointness in production arises due to the existence of allocable fixed factors (Moschini 1988).

[9] This expression is valid only when $\Delta b_i \neq 0$.

[10] s_{mht} is non-positive for inputs. However, unlike in other netput specifications, the netput vector can be negative for outputs in our case since Δb_i can be less than zero.

[11] The raw data contains sensitive farm level financial information and its use is subject to strict confidentiality agreements. The data can therefore not be made publicly available.

[12] Observations ±4 standard deviations from the mean are treated as extremes and less than 5% of the observations were excluded as a result.

[13] Due to this lack of temporal variation in prices, the response of output supply and factor demand equations to changes in component premium cannot be estimated.

[14] The within transformation is applied on the normalized variables. In general, the within transformation results in variables that do not vary over time being dropped out of the model. However, this is not always the case for the SNQ functional form due to nonlinearity in variables. For example in our case, component prices are constant over time. However all prices in equation (18) are normalized by a price index, which is constant across farms but varies across time. Therefore the normalized price variable will vary over time as well. Consequently, applying the within transformation on the

normalized variable will not remove the component prices as it would be the case if prices are specified as linear. However, after the within transformation the normalized component prices are simply the inverse of the price index scaled by the constant component prices themselves. When two or more variables that are constant over time are involved, as in our case, the variables will be perfectly correlated and create estimation problems. Furthermore, there is no interest in the coefficient of the price index. Therefore, after applying the within transformation on the normalized prices, the coefficients of all variables that did not vary across time before the within transformation are constrained to zero.

[15] Cross-equation restrictions were imposed using a restriction matrix as discussed in Henningsen and Hamann (2007) using the micEconSNQP package (Henningsen 2010) available for the statistical program R (R Development Core Team 2011).

[16] Note that $\mathbf{A}$ is 4×4 since component premiums are constant over time and hence excluded after the within transformation.

[17] The default starting value for nlsur (which is set to zero) failed to provide estimates for some parameters. Consequently, alternative starting values of 0.01 and 0.5 were used. The parameter estimates were stable to the different starting values.

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Table 1 - Descriptive Statistics, 2004–2009[1]

Variable	Units	Mean	Std. Dev.	Minimum	Maximum
Netput Prices					
Incremental protein, p_1	NOK / Liter [a]	100.00	0.00	100.00	100.00
Incremental fat, p_2	NOK / Liter [a]	15.00	0.00	15.00	15.00
Forage, w_1	NOK / FU	0.66	0.23	0.01	1.67
Concentrates, w_2	NOK / FU	2.87	0.30	1.64	4.34
Vet. & insemination, w_3	Index	85.31	8.80	72.20	100.00
Other Inputs, w_4	Index	92.70	7.43	80.90	104.80
Netput Quantities					
Incremental protein, q_1	Liters	191.86	163.31	-267.03	905.36
Incremental fat, q_2	Liters	99.06	212.44	-781.32	983.69
Forage, x_1	FU (in 100s)	-628.59.	278.94	-2,115.08	-89.84
Concentrates, x_2	FU (in 100s)	-437.20	207.94	-1,573.96	-68.42
Vet. & insemination, x_3	[b]	-286.72	136.60	-981.49	0.00
Other Inputs, x_4	[b]	-1,298.57	737.60	-4,910.38	0.00
Other Variables					
Quota, z_1	Liters (in 100s)	1,303.09	591.97	321.81	4,069.40
Trend, z_2	(2004 = 1)	3.34	1.55	1.00	6.00
Quasi-fixed inputs	NOK (in 100s)	1,736.06	503.35	233.01	3,903.71
Milk price [c]	NOK / Liter	3.78	0.55	2.10	5.90

FU stands for feed units.

[a] Note that these prices are per liter as opposed to per liter per 1% deviation from the processor's minimum as discussed above.

[b] Implicit quantity index i.e., value divided by the corresponding price index.

[c] Before adjustment for milk composition.

Table 2 – Parameters of the Restricted Profit Function

Parameter	Value	p-value	Parameter	Value	p-value
α_{33}	0.035	0.000	φ_{12}	0.379	0.000
α_{34}	−0.032	0.000	φ_{13}	−0.208	0.000
α_{35}	−0.007	0.397	φ_{21}	0.405	0.000
α_{36}	0.004	0.653	φ_{22}	0.729	0.000
α_{44}	0.269	0.000	φ_{23}	0.047	0.640
α_{45}	−0.100	0.000	φ_{31}	−0.449	0.000
α_{46}	−0.137	0.000	φ_{32}	0.034	0.000
α_{55}	0.049	0.010	φ_{33}	−0.153	0.000
α_{56}	0.058	0.000	φ_{41}	−0.554	0.000
α_{66}	−0.074	0.000	φ_{42}	0.108	0.000
β_{11}	−0.195	0.000	φ_{43}	0.035	0.343
β_{12}	−0.218	0.000	φ_{51}	−0.389	0.000
β_{13}	0.247	0.000	φ_{52}	0.179	0.000
β_{22}	−0.104	0.002	φ_{53}	−0.058	0.008
β_{23}	−0.136	0.000	φ_{61}	−0.107	0.002
β_{33}	−0.378	0.000	φ_{62}	0.184	0.000
φ_{11}	1.229	0.000	φ_{63}	0.067	0.129

Table 3 - Elasticity of Intensity With Respect to Milk Quota, Trend, and Subsidy at Mean [1]

Netputs	Milk Quota	Trend	Quasi-fixed inputs
Incremental protein, q_1	1.220	0.353	−0.223
	(0.001)	(0.001)	(0.001)
Incremental fat, q_2	0.405	0.727	0.046[a]
	(0.001)	(0.001)	(0.648)
Forage, x_1	0.470	0.023	0.186
	(0.001)	(0.001)	(0.001)
Concentrates, x_2	0.617	0.065	0.066
	(0.001)	(0.001)	(0.001)
Vet. & insemination services, x_3	0.402	−0.145	0.077
	(0.001)	(0.001)	(0.001)
Other inputs, x_4	0.167	−0.018	0.029[a]
	(0.001)	(0.044)	(0.329)

[1] p-values reported in parentheses; all elasticities are statistically different from zero at 1% level of significance except those indicated with [a].

Table 4 –Marginal Cost of Production and Shadow Price of Milk Quota at Mean[1]

Year	Milk Price (NOK / Liter)	Component Premium (NOK / Liter)	Marginal Cost (NOK)	Shadow Price of Quota (NOK / Liter)
2004	3.510	0.092	1.498	2.104
2005	3.570	0.131	1.514	2.187
2006	3.566	0.139	1.548	2.157
2007	3.826	0.179	1.585	2.420
2008	4.094	0.190	1.698	2.585
2009	4.394	0.176	1.856	2.714
Mean	3.777	0.150	1.597	2.329

[1]The milk price used in the shadow price computation includes subsidies for milk but it is not corrected for milk composition.
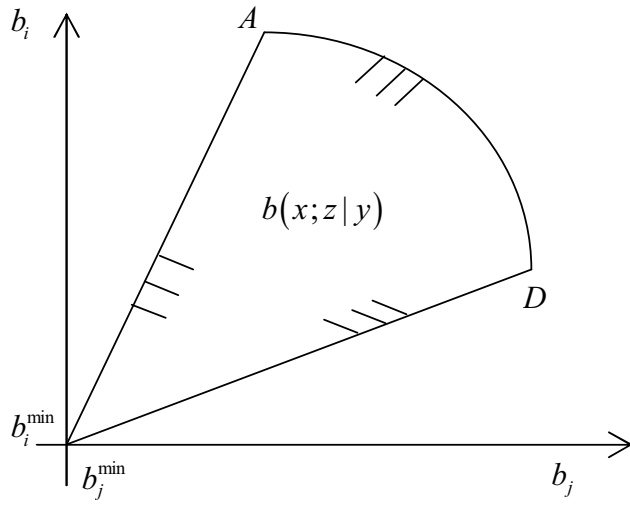
Figure 1. The production possibility set of component production.
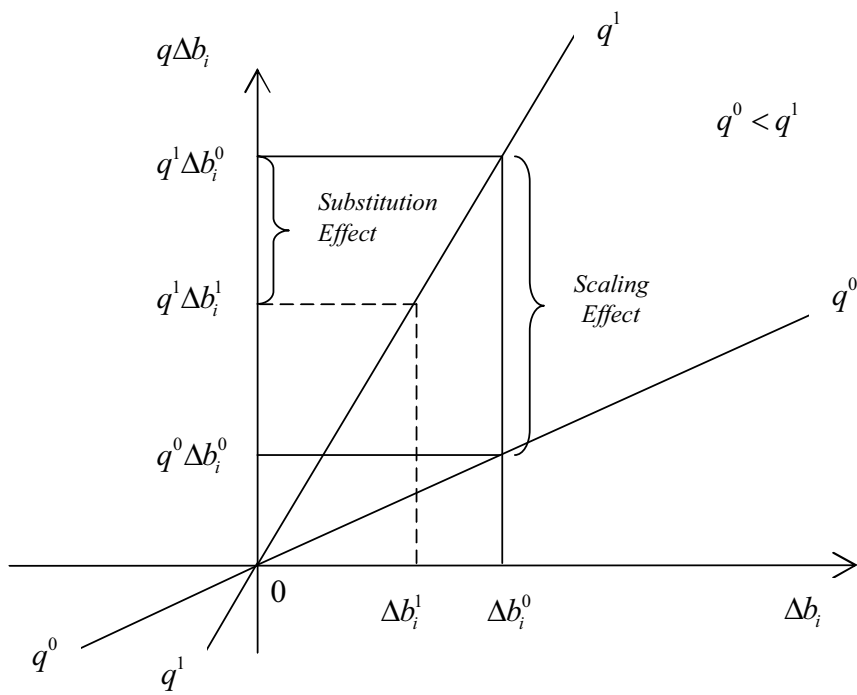
Figure 2. The effect of milk quota change on incremental milk components supply.
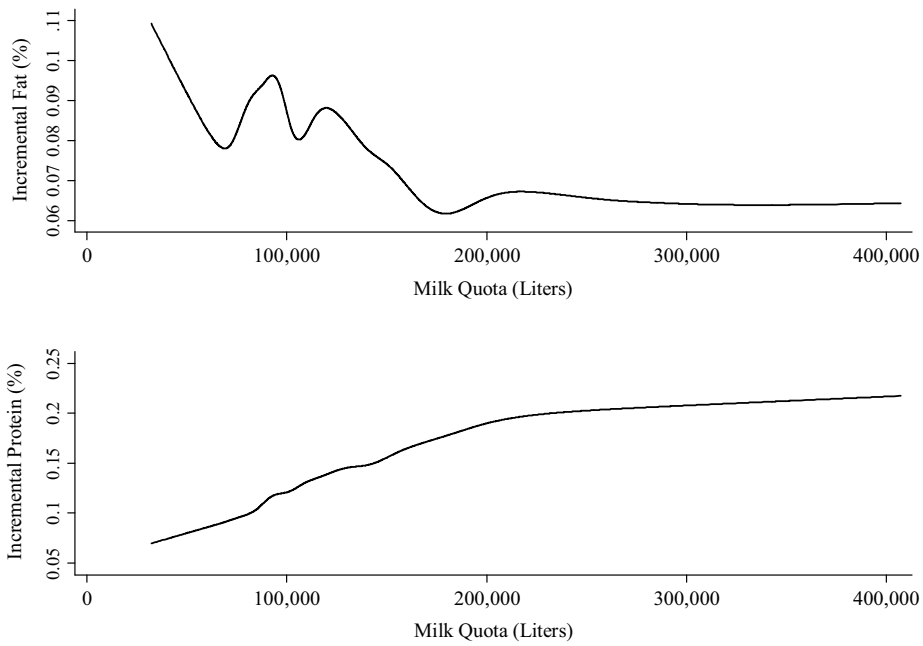
Figure 3 – Incremental components at different milk quota levels.
Note: The graphs are running line smoothing adjusted for herd size as well as trend. In addition 10 smoothing passes were used.

Paper IV

Milk Supply Response Under Two-Price Systems

Daniel Muluwork Atsbeha

Abstract

Borges and Thurman (1994) proposed a model of supply response under two-price systems used to enforce certain marketing quota programs. However, their estimation of yield densities depends on the common but unlikely assumption of yield per single input that is independent of other input choices. A generalization of their approach to a multiple input setting is presented. The model is applied to measure milk supply response in Icelandic dairy production. On average, estimated supply response to price changes in the quota milk market is more than 64% higher than comparable estimates from the single input approach.

Key words: dairy quota; milk yield; production risk; supply response; two-price system.

JEL Codes: D22, Q12, Q13

Introduction

Iceland introduced farm level marketing quotas (hereafter quotas) in 1980 to deal with excess milk production (Agnarsson 2007). The approach used to enforce the quota is a two-price system, which continues to this day. In two-price systems, raw milk receives a higher price if it is produced within quota. Milk produced outside quota receives the market price, which is usually a low price relative to the quota milk price. When milk yield is uncertain, planned production may exceed quota even when surplus milk prices are not profitable (Fraser 1986; 1995). In the words of Alston and Quilkey (1980), excess production under unprofitable surplus market conditions can be described as "insurance milk". This is because the excess production is to ensure against two potential losses associated with milk yield uncertainty. These are loss of revenue from forgone sales in the high-priced quota milk market when quota shortfalls occur and loss of unused quota in future allocations of production rights.

A more formal treatment of yield uncertainty in the relationship between planned production and quota was developed by Fraser (1986; 1995). For risk neutral producers with quotas, Fraser (1986) showed that yield uncertainty has ambiguous effect on planned production relative to quota. It was shown that the effect depends on the profit margin of sales in the preferred quota market and the degree of yield uncertainty. Babcock (1990) extended Fraser's analysis by allowing for risk averse behavior and showed that risk aversion tends to increase planned production when the risk of revenue loss from quota shortfalls is emphasized.

Building on Babcock's framework, Borges and Thurman (1994) evaluated the probability of planned production exceeding quota and the response of planned

production to price incentives under yield uncertainty. Using data from peanuts production in North Carolina, Borges and Thurman (1994) found that planned production was very likely to exceed quota with a probability range of 0.87 to 0.97. Consequently, the authors found that supply response to price changes in the quota peanuts market was very small. In particular, Borges and Thurman (1994) found that the relative supply response to a price change in the surplus peanuts market was at least thirty times higher than it is for an equivalent price change in the quota peanuts market.

However, Borges and Thurman (1994), as well as Babcock (1990), used a single input (i.e., acreage) to compute yield.[1] The underlying assumption of this approach, hereafter the single input approach, is that yield per single input is unaffected by other input levels (Babcock 1990). However, agricultural production involves multiple inputs more often than not and yield levels from any single input are very likely to be affected by the level of other inputs. The exclusion of these other inputs is then a form of omitted variable problem that can result in biased single input yield indicators such as yield per acre. Since the measurement of probabilities and relative marginal supply response depend on empirically estimated yield densities, the bias in yield indicators is likely to affect these measures as well. With the increasing availability of detailed farm management data, a better alternative is then to compute yield levels in such a manner that the contribution of other inputs is accounted for.

Furthermore, although the pioneering work of Alston and Quilkey (1980) is based on dairy production, empirical studies about the effects of two-price systems, surplus markets, and yield uncertainty on supply behavior of dairy farms are unavailable. However, production control through milk quotas is pervasive (e.g., in Canada, EU, Norway, Iceland, and California in the US). Furthermore, dairy production can also be

affected by yield uncertainty arising from different sources. For example, in relatively small diary enterprises as in Iceland, significant portion of feed inputs are produced on the farm. Although the extent may vary, this implies that the same type of weather related risks that are mentioned in crop production can also be sources of yield uncertainty in dairy production. In the Icelandic case, this may even be more so since agricultural production takes place under difficult weather conditions characterized by long winters and short summers with unstable and low temperature. The adverse weather can also have implications for animal health since dairy cows have to be kept indoors for extended periods of time (Johannesson 2010). Random occurrences of dairy cow diseases such as mastitis also imply a second source of yield uncertainty as well as price uncertainty under pricing schemes that consider nutrient composition and hygienic quality of milk deliveries. Other sources of milk yield uncertainty are death of cows, wrong detection of heat time for artificial insemination, and also optimization errors.

This article has four objectives. First the Borges and Thurman (1994) model based on the single input approach is generalized into a multiple input setting. The generalized approach is referred to as the aggregate input approach since yield is computed per aggregate input than any single input. Aggregation over multiple inputs is achieved based on weights obtained from a parametric production frontier. In addition to facilitating aggregation of inputs, estimating a parametric frontier has two additional benefits in the context of yield density estimation. First, it facilitates data pooling, and hence reliable estimation of yield density parameters. This is possible through farm- and time-specific technical efficiency scores that can be used to correct observed output levels for technical efficiency differences across farms and time. Second, the underlying assumption of the single input approach is readily testable under a parametric yield frontier. Therefore, the

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appropriateness of the single input approach versus the aggregate input approach can be statistically tested.

Using the aggregate input approach, a second objective is to evaluate the probability of production exceeding quota on Icelandic dairy farms, for example due to precautionary motives generated by yield uncertainty.

Third, the relative marginal supply response to price changes in the quota and surplus milk markets is investigated. This will be useful for instance to evaluate the supply effects of price changes in the quota market, which are usually set administratively. The approaches used to achieve the last two objectives are the same as in Borges and Thurman (1994) except that yield is computed per aggregate input rather than a single input.

Finally, results from the single and aggregate input approaches are compared.

Model

The theoretical model of Borges and Thurman (1994) allows for the opportunity to carryover unused quota to subsequent production seasons, which was possible for the market they analyzed.[2] However, the Icelandic dairy quota system provides no opportunity to carryover unused milk quota. Therefore, the model used in this article is a simplified version of the theoretical model in Borges and Thurman (1994). In the remaining of this section, the Borges and Thurman (1994) model based on an aggregate input is presented first. Then construction of an aggregate input based on weights from a production frontier follows.

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Probability of Surplus Production and Relative Marginal Supply Response

Let y be milk yield per unit of an aggregate input x and Y be the total milk produced by a dairy farm, which is constrained by farm level quota q.[3] Then q/x is the yield per unit of an aggregate input that will meet the quota exactly or the yield requirement. Yield is assumed to be random and $f(y)$ is its probability density function. Consequently, $Y = x \cdot y$ and the economic problem of the farm reduces to the choice of aggregate input quantity. In this setting, observed levels of the aggregate input provide information about the unobservable planned production given yield densities. This allows evaluation of planned production relative to quota. For example, if the yield requirement is smaller than the expected yield, then we can infer that the dairy farm must have planned to exceed its quota.

Under risk neutrality, no price uncertainty, and no carryover of unused quota, the economic problem of the dairy farm can be presented as expected profit maximization problem as (Borges and Thurman 1994):

(1)
$$E\left(\Pi\right) = \int_{0}^{q/x} \left[p_q xy \right] f\left(y\right) dy +$$
$$\int_{q/x}^{\infty} \left[p_q q + p_a^o \left(xy - q\right) \right] f\left(y\right) dy - C\left(x\right),$$

where p_q is the price in the quota milk market, p_a is the price in the surplus milk market, and $C\left(x\right)$ is the cost of employing x. That is expected profit is the excess of a weighted sum of revenues over production cost. The probability that milk yield will be within or above quota is used as weight. Therefore, as in Borges and Thurman (1994),

$\phi = \int\limits_{q/x}^{\infty} f(y)\,dy$ is used as an estimate of the probability that planned production may

exceed farm quota.

The first order condition of the problem is:

$$(2) \qquad p_q \int\limits_{0}^{q/x} yf(y)\,dy + p_a \int\limits_{q/x}^{\infty} yf(y)\,dy = C'(x);$$

i.e., the farmer will adjust aggregate input quantity until marginal benefit of a certain

amount is equal to the associated marginal cost. As in Borges and Thurman (1994),

totally differentiating (2) provides a comparative statics result that can be used to

determine the relative importance of price changes in the two markets. Accordingly:

$$(3) \qquad dp_q \left[\int\limits_{0}^{q/x} yf(y)\,dy \right] + dp_a \left[\int\limits_{q/x}^{\infty} yf(y)\,dy \right] = \left[\mathrm{MC}' - p_q \frac{\partial \kappa}{\partial x} - p_a \frac{\partial \omega}{\partial x} \right] dx,$$

where $\kappa = \int\limits_{0}^{q/x} yf(y)\,dy$, $\omega = \int\limits_{q/x}^{\infty} yf(y)\,dy$ and $\mathrm{MC}' = \dfrac{\partial^2 C(x)}{\partial x^2}$. Then the effect of a price

change on quantity of the aggregate input or the marginal supply response can be

recovered from (3) as follows:

$$(4a) \qquad \frac{\partial x}{\partial p_q} = \frac{\displaystyle\int\limits_{0}^{q/x} yf(y)\,dy}{\left[\mathrm{MC}' - p_q \dfrac{\partial \kappa}{\partial x} - p_a \dfrac{\partial \omega}{\partial x} \right]},$$

$$(4b) \qquad \frac{\partial x}{\partial p_a} = \frac{\displaystyle\int\limits_{q/x}^{\infty} yf(y)\,dy}{\left[\mathrm{MC}' - p_q \dfrac{\partial \kappa}{\partial x} - p_a \dfrac{\partial \omega}{\partial x} \right]}.$$

By combining these partial responses, Borges and Thurman (1994) constructed a measure of relative marginal supply response. Accordingly, combining (4a) and (4b) the relative marginal supply response for price changes in the two milk markets would be:

$$(5a) \quad \Theta_q = \frac{\partial x / \partial p_q}{\partial x / \partial p_q + \partial x / \partial p_a} = \frac{\int_0^{q/x} y f(y) \, dy}{\int_0^{\infty} y f(y) \, dy}, \qquad 0 \le \Theta_q \le 1,$$

$$(5b) \quad \Theta_a = 1 - \Theta_q.$$

Θ_q measures the relative marginal supply response to a price change in the quota milk market relative to an equivalent price change in the quota and surplus milk markets. Therefore, Θ_q implies increasing importance of price changes in the quota milk market as it gets closer to unity and vice versa.

As noted by Borges and Thurman (1994), $\lim_{q/x \to 0} \Theta_q = 0$ and $\lim_{q/x \to \infty} \Theta_q = 1$. That is for a given quota size, the relative importance of a price change in the quota milk market for supply response declines as q/x decreases. This is intuitive since declining q/x implies higher probability to exceed quota. On the contrary, as q/x approach infinity, the price in the quota milk market becomes the price at the margin and its relative importance for supply response increase.

Constructing Aggregate Input

As the name implies, the aggregate input is a weighted aggregation of inputs. In this section construction of weights required to compute the aggregate is presented. Given that yield levels imply a technical relationship between an input and output, an obvious

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candidate to generate aggregation weights is a production frontier. The production

frontier is a mathematical relationship representing the best available technique of

transforming inputs into outputs. In order to obtain an econometric estimate of the

production frontier, a mathematical relation between inputs and outputs is specified in a

translog form, which provides a second order approximation to any unknown function

(Christensen, Jorgenson, and Lau 1973); i.e.,:

$$(6) \quad \ln Y_{it}\left(x_{jit};t\right) = \alpha_0 + \sum_{j=1}^{n} \alpha_j \ln x_{jit} + \rho t + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \alpha_{jk} \ln x_{jit} \ln x_{kit} +$$

$$\sum_{j=1}^{n} \alpha_{jt} t \ln x_{jit} + \frac{1}{2} \rho_{tt} t^2 + \varepsilon_{it}.$$

x_{jit}'s are the j inputs used to produce milk, t is a time trend introduced to capture the

effect of technical change, and ε_{it} is a composite error term containing a random noise

component, v_{it}, and a non-negative time-varying technical inefficiency component, u_{it},

or $\varepsilon_{it} = v_{it} - u_{it}$. The farm- and time-specific technical efficiency (TE_{it}) scores for each

farm are given as $TE_{it} = \exp\left(-u_{it}\right)$. Following Battesse and Coelli (1992), the temporal

pattern of technical inefficiency is specified as $u_{it} = \exp\left\{-\eta\left(t-T\right)\right\} \cdot u_i$, where η is a

decay parameter and T is the terminal period in the data. When $\eta > 0$ technical efficiency

increases over time while it decreases when $\eta < 0$. Furthermore, technical inefficiency is

assumed to follow a truncated normal distribution i.e., $u_i \sim N\left(\mu, \sigma_u^2\right)$, which also nests

the commonly used half-normal distribution or $u_i \sim N\left(0, \sigma_u^2\right)$. A nested hypothesis

testing can therefore be used to choose the distributional assumption that fits the data

best. The random noise term v_{it} is symmetrical, and normally distributed or

$v_{it} \sim N\left(0, \sigma_v^2\right)$. In addition the two error terms are assumed to be independently and identically distributed as well as orthogonal to each other and the independent variables of the model.

Given the parameters of the production frontier, the aggregate input is constructed as:

$$(7) \qquad x_{it} = \sum_{j=1}^{n} \left(\delta_{jit} / \delta_{it}\right) \cdot x_{jit},$$

where $\delta_{jit} = \dfrac{\partial \ln Y_{it}}{\partial \ln x_{jit}}$ and $\delta_{it} = \sum_{j=1}^{n} \delta_{jit}$. Under constant returns to scale or $\delta_{it} = \sum_{j=1}^{n} \delta_{jit} = 1$, the weights can be understood as the share of each input from the total output. This is

because $\dfrac{\partial Y_{it}}{\partial x_{jit}} = \dfrac{\delta_{jit} \cdot Y_{it}}{x_{jit}}$. Furthermore, when markets are competitive, inputs are paid their marginal product, and profits are maximum, it can be shown that (Kim 1992):

$$(8) \qquad \frac{\delta_{jit}}{\delta_{it}} = \frac{\ln Y_{it} / \ln x_{jit}}{\sum_{j=1}^{n} \ln Y_{it} / \ln x_{jit}} = \frac{w_{jt} x_{jit}}{C_{it}},$$

where w is input price and C is minimum cost of production. Therefore, the aggregate input can also be described as a cost share weighted aggregate input. Given duality relationships between the cost function and input distance function (Färe and Primont 1995), equivalent expression can also be derived from the input distance function.

The validity of the single input approach, instead of the aggregate input approach outlined above, can be tested using parametric restrictions on a yield frontier. To illustrate say the yield frontier is given as:

(9) $\quad \ln \tilde{y}_{it} = \beta_0 + \sum_{j=1}^{J-1} \beta_j \ln \tilde{x}_{jit} + \rho t + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \alpha_{jk} \ln \tilde{x}_{jit} \ln \tilde{x}_{kit} +$

$$\sum_{j=1}^{n} \alpha_{jt} t \ln \tilde{x}_{jit} + \frac{1}{2} \rho_{tt} t^2 + \varpi_{it},$$

where $\tilde{y}_{it} = \dfrac{Y_{it}}{x_{Jit}}$ and $\tilde{x}_{it} = \dfrac{x_{jit}}{x_{Jit}}$, and x_J is the input selected for computing yield per single

input. ϖ_{it} is a composite error term with similar properties as ε_{it} in equation (6). The

underlying assumption of the single input approach is that yield per single input is

independent of other input levels. This implies the parametric restriction

$\dfrac{\partial \ln y_{it}}{\partial \ln x_{jit}} = 0$ for $\forall j \neq J$ on equation (9). Rejection of this restriction on equation (9)

implies that the assumption is invalid and the single input approach is inappropriate for

the data in hand.

Empirical Strategy

Under the methodology specified, milk yield density has to be estimated. However, two

problems arise in estimating yield densities. First, ideally farm level yield densities

should be estimated (Ker and Coble 2003). However, a common problem is that yield

observations per farm are usually quite few to provide reliable estimates of farm level

yield densities (Goodwin and Ker 2002). Therefore, data pooling under certain

assumptions such as equal yield variance and yield data from some aggregate levels such

as counties are commonly used to ensure sufficient observations for yield density

estimations (Borges and Thurman 1994; Ker and Coble 2003). Number of observations

per farm is also few for the data used in this article and some form of data pooling is

unavoidable.

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In this article, we start by assuming that the yield density is identical for all farms. However, two issues must be addressed before this assumption can be justified. First technical efficiency, and hence expected yield, can vary across farms in a given year and over time. Second, even if it is common to assume common technology for all farms in a given year, expected yield and yield variance can change across time due to technical change.[4] Using farm- and time-specific technical efficiency scores from equation (6), the first issue can easily be addressed. This is achieved by correcting observed output levels for technical inefficiency as $Y_{it}^* = Y_{it} / \exp(-u_{it})$, where Y_{it}^* is the output level that would have been observed if farms are technically efficient or $TE = \exp(-u_{it}) = 1$. Given that inferences are to be made about planned production, computing yield based on Y^* rather than Y is logical since no rational farm will choose input levels planning to be technically inefficient.

The approach used by Borges and Thurman (1994) to control efficiency differences across counties can be used to address the second issue with respect to technical change. Their approach was to subtract county average yields from each observation and add back the average of the least productive county. The resulting data was used to estimate the yield density function of the least productive county. The yield density functions for the other counties are then obtained by scaling the density function of the least productive county with the difference of each county's average yield from the average yield of the least productive county. The underlying assumption of this approach is that the shape and variance of yield densities are identical across counties.

By assuming technical change affects expected yield only while keeping the shape and variance of yield densities intact, the same approach can be used to address the effect

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of technical change as well. In particular, annual average yields are subtracted from each observation and yield level of the least productive year is added back. This will allow pooling of observations across years as well and the pooled data is used to estimate the yield density function of the least productive year. Yield density functions of the other years are then obtained by scaling the estimated yield density of the least productive year. However, one can question the validity of the underlying assumption about effects of technical change on the yield density since new technology may not be neutral with respect to scale and shape of yield density. For example, Traxler et al. (1995) found that new wheat varieties released before 1971 increased yield variance while varieties released after 1971 decreased yield variance. This implies that in addition to the expected value, technical change may affect the scale of yield densities as well. To deal with this problem, statistical tests can be used to check if the assumption of homogeneous variance across years is valid for a given data. When the assumption is rejected, annual yield density functions have to be estimated using each year's data.

A second problem about estimating yield densities relates to choice of parametric form for the yield density function.[5] Several parametric probability density functions have been proposed for modeling crop yield densities. Some examples are the Beta, the Gamma, the Weibull, the Normal and the Log-normal (Ramirez, McDonald, and Carpio 2010). With observation of negative skewness in crop yield densities, probability density functions that can accommodate non-symmetry like the Beta distribution are used the most (Goodwin and Ker 2002). However, estimation of yield densities for dairy production is not as common as it is for crop production. For example in the US, this is partly due to the fact that insurance schemes, where yield densities can be used to model risk, were limited to crop production only. Insurance schemes for livestock production

were made available only since the Agricultural Risk Protection Act in 2000 (Belasco et al. 2009).

With the lack of previous literature to guide choice of parametric form for milk yield densities, statistical tests such as non-normality tests and visual inspection of data, for example through Cullen and Frey plots, can be used. A better alternative to avoid specification error is to use a flexible form such as the Johnson distribution system (Johnson 1949; Johnson, Kotz, and Balakrishnan 1994). The Johnson distribution system is a system of four distributions that can accommodate any finite and feasible combination of the first four moments. Consequently, it is flexible enough to approximate a wide range of distributions, including those that are commonly used for modeling crop yield data. The distributions forming the Johnson family are identified by a set of normalizing transformations proposed by Johnson (1949). In particular, given a continuous random variable with unknown density function (e.g., yield per unit of aggregate input in this case), Johnson (1949) proposed a set of normalizing transformations with the general form (Johnson 1949):

$$(9) \qquad Z = \gamma + \delta \cdot g(u),$$

to obtain a unit normal distributed variable Z. γ and $\delta > 0$ are shape parameters while

$u = \dfrac{y - \xi}{\lambda}$, where ξ and $\lambda > 0$ are location and scale parameters, respectively. $g(u)$ is

the transformation function that assumes different forms to define the distributions in the Johnson family. These forms are (Johnson 1949; Johnson, Kotz, and Balakrishnan 1994),

$$(7) \quad g(u) = \begin{cases} \ln(u), & \text{for the } S_L \text{ (the Log-normal) family,} \\ \ln\left[u + \sqrt{u^2 + 1}\right], & \text{for the } S_U \text{ (unbounded) family,} \\ \ln\left[\dfrac{u}{(1-u)}\right], & \text{for the } S_B \text{ (bounded) family, and} \\ u, & \text{for the } S_N \text{ (normal) family.} \end{cases}$$

Plotting the theoretically possible combinations of skewness and kurtosis for the Log-normal (S_N) distribution divides the skewness-kurtosis plane into two. The S_B covers all the theoretically possible skewness-kurtosis combinations on the one side of the Log-normal line including commonly used distributions for modeling crop yield data like the Beta and Gamma distributions. On the other hand, the S_U covers all the theoretically possible skewness-kurtosis combinations on the rest of the plane (Johnson, Kotz, and Balakrishnan 1994).

The particular distribution that fits the data best can be selected based on the estimated skewness and kurtosis coefficients of the data, as suggested by Hill, Hill, and Holder (1976). However, such moment matching estimators are criticized, for example due to sensitivity of the third and fourth moment estimates to outliers (Slifker and Shapiro 1980). However, other estimators also exist such as the quantile-based estimator suggested by Wheeler (1980), where the best distribution is selected based on quantiles rather than the first four moments.[6]

Data

Production data from 324 Icelandic dairy farms covering the period 1998–2006 is used for estimation.[7] Extreme values were filtered before estimation.[8] Iceland is identified as one of the countries with very high support for agricultural producers. During 2004–2006

the producer support estimate (PSE) was 66% of the aggregate farm receipts, more than twice of the OECD average. Transfers for individual agricultural commodities (or Single commodity transfers, SCTs) constituted 94% of the PSE during the same period with milk being one of the most supported agricultural commodities (OECD 2007). The excess production problem that follows farm support programs were also encountered in the 1970s and the need for production control measures was becoming more apparent by the end of the decade (Agnarsson 2007). The first attempt to control production occurred in 1980 with the introduction of farm level marketing quotas, which were not tradable. However, the third milk agreement (1992–1997) between The Farmers' Association of Iceland and the Ministry of Agriculture allowed the free exchange of dairy quota with the exception of leasing (Bjarnadottir and Kristofersson 2008). This has resulted in the restructuring of the dairy sector towards few but larger dairy farms. Bjarnadottir and Kristofersson (2008) found that the number of dairy farms has been significantly reduced in the decade since 1995 while milk output of the average farm has doubled.

The quota entitles dairy producers the right to receive direct payments from the government and higher prices for all milk delivered within quota according to its composition and hygienic quality. Surplus milk can be sold in a surplus milk market where prices are determined by market forces still based on milk quality. The quota system also imposes the requirement that dairy farms fill their quota every two years or risk losing it. However, it is also possible to get permission not to use the quota for a certain period (Agnarsson 2007). The surplus production by the average Icelandic farm is small amounting to 3.8% of the average quota size. To give an idea of how systematic surplus production is as opposed to optimization error, a Norwegian case can be used. In Norway a two-price system used to operate until 1997 and replaced by a levy system

thereafter. Under this system farmers will pay penalties for surplus production. To allow for optimization errors, however, a farm can deliver milk up to 102% of its allocated quota. If the same allowance is used for Icelandic dairy farms, one can easily see that surplus production by choice may not be significantly high for the average Icelandic dairy farm. However, as shown in table 1, there is a significant variation across farms and over time in terms of surplus production. For the 83.4% of farms that have exceeded their quota in one year or the other, the average surplus production is 11.4% of the corresponding quota size during 1998–2006.

The translog production function for milk was specified with six inputs and a trend variable. The inputs are concentrates, capital, veterinary services, land, number of cows, and labor. The first three are all measured in monetary units that are deflated to 1998 prices. Consumer price index for agricultural products is used for deflating cost data since a price index for agricultural inputs was unavailable. Land is measured in hectares, and number of cows is measured in cow years, which is a weighted aggregate of number of cows on a farm. The number of days in a year a cow has been active in milk production is used as weight. Therefore, potential measurement error from the inclusion of non-lactating cows is avoided. Labor use is measured as labor months per year. A descriptive statistic of these inputs is provided in table 1. The use of all inputs except for labor has increased over time. The largest increase is for capital and concentrates, the application of which has increased by 15.6% and 6.5% per year, respectively. Quota size of the average farm has also increased by 5.6% per year as well as number of cows, which has increased relatively slowly by 1.7% per year. These changes in input use imply the significant structural adjustment that took place in the Icelandic dairy sector since 1992.

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Results

The maximum likelihood routine xtfrontier of STATA® version 11 (StataCorp 2009) is used to estimate the production frontier. All variables were normalized by their geometric mean before estimation. Therefore, parameters of the first order variables can be interpreted as output elasticities with respect to the respective variables at the geometric mean.

The estimated value for the truncation point for the inefficiency distribution (i.e., μ) was not statistically different from zero at any conventional level of significance. Hence the model is re-estimated under the assumption of half-normally distributed technical inefficiency term. Resulting parameter estimates are provided in table 2. The average technical efficiency score for Icelandic dairy farms is 85.3%. Furthermore, table 2 shows that all input elasticities are positive and statistically significant at the 5% level of significance, implying that the estimated production frontier is monotonic with respect to inputs at the geometric mean. However, as shown by Berndt and Christensen (1973), the translog functional form does not satisfy monotonicity and curvature properties globally nor can it be constrained to do so without losing its second order flexibility (Sauer, Frohberg, and Hockmann. 2006). Accordingly, for all data points where monotonicity is violated, the output elasticities are replaced with zeros prior to the construction of aggregation weights.[9]

The aggregate input is then constructed based on farm- and time-specific weights as in equation (7). The average aggregate input level is 481 units with a standard deviation of 222.4. Yield per unit of the aggregate input is 386.3 liters with a standard deviation of 52.1 and the average yield requirement is 321.1 liters with a standard

deviation of 130.1 liters. With respect to yield per cow data, the average number of cows is 31.8 with standard deviation of 12.6. Yield per cow is 5,328 liters with a standard deviation of 1,073.2 liters. The average yield requirement is 4,455 liters with a standard deviation of 1,162.1 liters.

The parameter of the trend variable is positive and significant at 5%. This implies that there had been technical progress on Icelandic dairy farms. This is as expected since milk yield per cow has increased by 32% between 1990–2007 (The Farmers Association of Iceland 2009). Several changes in Icelandic dairy sector can explain this. For example, feed quality has shown substantial improvement due to better feed storage and processing facilitated by the introduction of round bales in the late 1980s. Furthermore, widespread cultivation of better quality forage (e.g., Timothy grass), increased local production of concentrates due to better barely cultivars suitable for the agro-climatic conditions of Iceland, mechanization of feeding, and introduction of automated milk parlors may have contributed for the technical progress over time. Adjustment towards optimal scale of production facilitated by the quota trade reform in 1992 is also another important source of yield increase on Icelandic dairy farms.

Before yield densities are estimated, the assumption of homogeneous variance across years needs to be tested to check if data pooling across years is justified. This can be done using Levene's test, which is robust for deviations from normality unlike other tests such as Bartlett's test. Under the null hypothesis of homogeneous yield variance across years, the test statistic follows the F distribution. The calculated value of the test statistic based on yield per aggregate input data and yield per cow data are 3.46 (d.f. = (8, 1,113); p-value = 0.001) and 1.18 (d.f. = (8, 1,113); p-value = 0.309), respectively. Therefore the assumption of homogeneous yield variance across years is only valid for

the yield per cow data. As a result, yield density functions are estimated from each year's data when yield per aggregate input is used. For the yield per cow data, yield density functions are obtained based on pooled data according to the procedure outlined above.

The quantile-based estimator of Wheeler (1980) is used for estimation of yield densities. For the yield per aggregate input data the Johnson S_U is selected as the best fit functional form for the years 1998, 2003, and 2005 and the Johnson S_B for the year 2002. For all other years, the Log normal distribution is selected as the best fit. The parameters of these distributions are given in table 3. The Cullen and Frey plot for the yield per cow data is provided in figure 1. The plot, suggests the Johnson S_U distribution as the best fit for the pooled data. Similarly, the quantile-based estimator selects the Johnson S_U as the best fit functional form for the data. The parameters of this distribution are also reported in table 3.[10]

Using the empirical yield density functions for each year, the probability that planned production may exceed quota is computed under the aggregate input approach. As shown in table 4, the probability that the average Icelandic dairy farm will over produce its quota is 0.655. This figure has largely remained constant over time picking in 2004 and reaching its lowest point in 2005. Both these years are likely points for the extremes of the probability since 2004 was the year when prices in surplus market started to increase and become closely comparable to prices in the quota milk market. However, 2004 was also a year of relatively low precipitation during the study period that might have affected forage yield. This will then have an adverse effect on production in the subsequent year or 2005, dampening surplus production despite high prices in the surplus milk market.

Next the relative marginal supply response to price changes in the quota milk market is computed as in equation (5) and reported in table 4. Results show that the average supply response to a price change in the quota milk market is 0.265. This implies that the relative marginal supply response to a 1 ISK increase in milk price within the quota milk market is less than a third of the response to an equivalent and simultaneous price change in both markets. Therefore prices in the surplus milk market are the most important prices determining surplus milk production of Icelandic dairy farms.

Finally, the above computations were also made based on the single input approach and results are reported in table 4. The average probability that an Icelandic dairy farm will exceed its quota is 0.809. This is a significantly large figure compared to what was obtained under the single input approach. As a result, the responsiveness to price changes in the quota market is also smaller in this approach. In particular, under the single input approach Θ_q is 0.161, which is only 60.8% of the comparable estimate above. However, the single input approach results reported in this article are close to the results reported by Borges and Thurman (1994). The authors found that the probability that peanut producing counties will exceed their quota ranges between 0.868 to 0.977 while their estimate of Θ_q under the assumption that producers attach no value to carryovers range from 0.016 to 0.101. It can therefore be concluded that the single input approach has a tendency of providing higher probabilities of surplus production and consequently smaller estimates of supply response. This is more likely due to the failure of the single input approach to capture adjustments in other inputs that take place on the farm in response to price changes in the two markets.

As discussed above, the appropriateness of the single input approach can be tested using a Wald type test based on parameters of a yield frontier function. The null hypothesis for this test is that yield per cow is independent of all other inputs used in production. Alternatively, the null hypothesis can also be stated as the single input approach based on yield per cow is appropriate. A yield per cow frontier function is estimated for this purpose. This frontier has the same inputs and functional form as the production frontier except that all inputs and output are expressed on per cow basis. The Wald test statistic follows the Chi-square distribution and at the geometric mean the calculated value of the test statistic is $\chi^2 = 128.7$ with a p-value of 0.001. Therefore, the null hypothesis is rejected and the single input approach is invalid for the data in hand.

Conclusions

Borges and Thurman (1994) constructed a model of relative marginal supply response in a two-market set up based on a previous model proposed by Babcock (1990). Their approach can also be used to measure the probability of planned production exceeding quota. However, yield levels were computed based on a single input based on the unlikely assumption that other input levels have no effect. In this article a generalization of their approach to a multiple input setting is presented by constructing an aggregate input for yield computations. The aggregation is achieved using weights derived from a production function. Unlike a single input approach, the new approach has the advantage of allowing for changes in the whole production environment and the implication of these changes on yield levels. Furthermore, it allows statistical testing to choose the appropriate approach in a given setting.

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Based on the aggregate input approach, a similar analysis as in Borges and Thurman (1994) is conducted for dairy farms. Marketing quotas are pervasive in the dairy sectors of the developed world. Furthermore, one way milk marketing quotas are enforced is through two-price systems that allow surplus production though at lower prices. Yield uncertainty can also strengthen incentives for surplus production as dairy farms seek to avoid losses due to quota shortfalls and loss of unused quota in future quota allocations.

Data from Icelandic dairy farms for the period 1998–2006 is used for empirical analysis. Results show that the probability of planned production exceeding quota on the average Icelandic dairy farm is 0.655, indicating that the average Icelandic dairy farm plans to over produce its quota. Consequently, relative marginal supply response to price a price change in the surplus milk market is found to be almost three times as high as the response for equivalent price change in the quota milk market. Therefore, if significant surplus production is to occur in Icelandic dairy farms, prices in the surplus milk market have to be increased significantly from their normal levels.

Comparison of the above estimates with estimates from the single input approach of Borges and Thurman (1994) revealed that the latter tends to provide higher estimates of the probability of surplus production and consequently smaller relative supply response estimates to price changes in the quota market. This was likely due to the failure of the single input approach to consider adjustments that farmers will make in all inputs while responding to price changes.

Therefore, the aggregate input approach is likely to produce estimates closer to actual behavior than the single input approach when the assumption underlying the latter is invalid and detailed data on input use exist. However, when detailed data on input use

are missing, the single input approach is the only alternative. In this case interpretations of results must be cautious since estimated likelihoods for surplus production and relative supply response to price changes in the quota market can be higher and smaller, respectively.

Footnotes

[1] Note that Borges and Thurman (1994) used county-level data on peanut production in which case detailed information about the level of all inputs used in production may not be available. In such cases, the single input approach may be the only alternative. Results in this article can then highlight potential biases from these estimates that can be used to qualify interpretations of results from the single input approach.

[2] A limitation of their approach is that it did not consider quota markets, although the authors stated the existence of sale and rental markets for peanut quotas. The same limitation applies here since quota sale markets exist in Iceland. Hennessy and Wei (2000) provided theoretical results taking quota markets into account. However, to the best of our knowledge, an empirical implementation of their framework is yet to appear in the literature.

[3] All variables are farm and time specific unless stated otherwise.

[4] Borges and Thurman (1994) allowed for technical efficiency difference across counties. However, they did not allow for technical efficiency differences over time and for effects of technical change.

[5] An alternative to parametric formulations is to estimate the yield functions semi-parametrically or nonparametrically (e.g., see Ker and Goodwin 2000; Ker and Coble 2003).

[6] The computer program for this estimator is available under the 'SuppDists' package (Wheeler 2009) under the statistical program R (R Development Core Team 2011).

[7] The dataset also includes observations for the year 1997. However, milk production levels do not appear to be measured for the year and hence are equated with farm level quotas. Given the objective of the research, this year is therefore excluded.

[8] Observations that are ± 4 standard deviations were removed as outliers. Less than 1% of the observations were dropped.

[9] For the estimation sample, the percentage of negative output elasticities range between 0.4% for concentrates and 27.3% for veterinary services.

[10] The Cullen and Frey plots were generated using the 'fitdistrplus' package (Delignette-Muller et al. 2010) under the statistical package R (R Development Core Team 2011).

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Table 1 –Descriptive Statistic, 1998–2006

Variable	Units	Mean	Std. Dev.	Minimum	Maximum
Milk	Liters	145,816.2	67,861.5	29,249.0	520,137.0
Concentrates	1,000 ISK	1,208.5	692.9	41.5	5795.9
Capital	1,000 ISK	2,757.6	1,879.1	292.6	17,182.3
Veterinary services	1,000 ISK	218.4	151.1	2.8	998.7
Land	Hectares	46.9	18.1	13.0	138.0
Number of cows	Cow-years	31.8	12.6	4.9	115.7
Labor	Months/ year	24.4	8.4	10.0	74.0
Trend	1998=1	5.1	2.7	1.0	9.0
Milk quota	Liters	141,836.4	66,456.5	30,657.0	562,263.0
Over production	% of quota	3.8	16.3	−72.4	216.4

Note: 1 USD = ISK 124 on February 25, 2012. http://www.sedlabanki.is

Table 2 – Parameters of the Milk Production Function in Iceland, 1998–2006[1]

Variables		Concentrates	Capital	Vet. Ser.	Land	No. of cows	Labor	Trend
Constant	0.164*** (0.000)							
Concentrates	0.234*** (0.000)	0.087*** (0.000)						
Capital	0.074*** (0.000)	−0.069*** (0.000)	0.097 (0.208)					
Vet. services	0.023*** (0.000)	0.027* (0.012)	0.004** (0.019)	0.003 (0.204)				
Land	0.075** (0.044)	−0.087 (0.170)	0.022 (0.851)	−0.079 (0.820)	−0.006 (0.140)			
Number of cows	0.558*** (0.000)	−0.135** (0.026)	−0.049 (0.591)	0.022*** (0.005)	0.069 (0.941)	0.333 (0.758)		
Labor	0.103*** (0.000)	0.005*** (0.002)	−0.041 (0.354)	0.026 (0.525)	0.032 (0.328)	−0.133*** (0.000)	0.109* (0.064)	
Trend	0.025*** (0.000)	0.007 (0.887)	−0.010 (0.356)	−0.006 (0.353)	−0.003 (0.549)	0.021* (0.085)	0.008 (0.175)	−0.009 (0.426)

σ^2_ϵ = 0.067

ψ^a = 0.791

Average Technical Efficiency Score 85.4%

[1] Note: Significance codes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level; p-values in parenthesis.

a $\psi = \dfrac{\sigma^2_u}{\sigma^2_v + \sigma^2_u}$

Table 3. Parameter Estimates of Empirical Yield Distributions for Icelandic Dairy Farms, 1998–2006

Year	Type	γ	δ	ξ	λ
Aggregate input approach					
1998	S_U	−1.2	1.5	222.2	119.6
1999	S_L	0.0	2.5	58.3	318.3
2000	S_L	0.0	4.1	−116.4	516.0
2001	S_L	0.0	3.3	−61.0	480.4
2002	S_B	2.0	1.4	139.8	1,474.7
2003	S_U	−0.5	1.1	376.7	106.5
2004	S_L	0.0	2.2	91.1	212.0
2005	S_U	−1.0	1.2	219.8	88.6
2006	S_L	0.0	2.8	32.6	283.0
Single input approach					
Pooled	S_U	−0.04	1.3	5,729.5	735.6

Table 4. Average Probabilities of Exceeding Quota and Relative Marginal Milk Supply Response to Price Changes in the Quota Milk Market of Iceland, 1998–2006

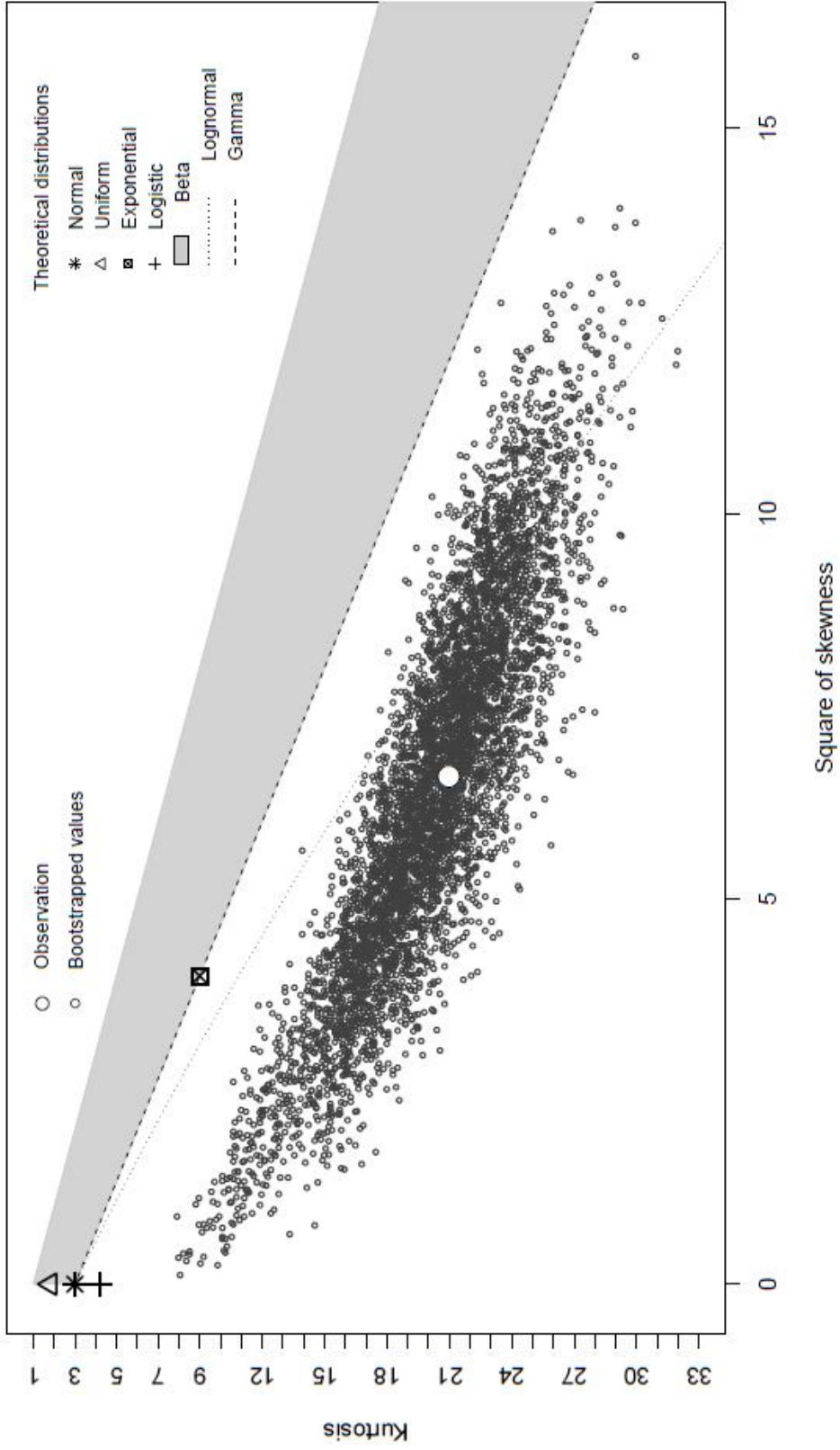| Year	Aggregate input approach		Single input approach	
	ϕ	Θ_q	ϕ	Θ_q
1998	0.642	0.266	0.803	0.167
1999	0.666	0.256	0.822	0.149
2000	0.660	0.260	0.787	0.182
2001	0.656	0.260	0.791	0.181
2002	0.660	0.252	0.830	0.144
2003	0.657	0.267	0.827	0.149
2004	0.686	0.249	0.861	0.118
2005	0.622	0.282	0.772	0.194
2006	0.642	0.283	0.792	0.202
Mean	0.655	0.265	0.809	0.161

Figure 1. The Cullen and Frey plot of observed and bootstrapped (5,000 repetitions) skewness and kurtosis coefficients of milk yield per cow data from Iceland, 1998–2006.

APPENDIX

The Decomposition of the Malmquist Productivity Index

Given the Malmquist productivity index (Caves, Christensen and Diewert 1982) in Equation (3), straightforward decompositions can be made to extract the contribution of different factors to productivity change. For example, by multiplying Equation(3) by one

or $\left(\dfrac{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^{t+1},a^{t+1}\right)}{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^{t+1},a^{t+1}\right)} \dfrac{D_I\left(\mathbf{x}^{t},\mathbf{y}^{t};g^{t},a^{t}\right)}{D_I\left(\mathbf{x}^{t},\mathbf{y}^{t};g^{t},a^{t}\right)} \right)$ 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:

$$M_I^{CCD}\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) = \frac{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^{t+1},a^{t+1}\right)}{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^t,a^t\right)} \times$$

$$\left[\frac{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^t,a^t\right)}{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^{t+1},a^{t+1}\right)} \times \frac{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^t,a^t\right)}{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^{t+1},a^{t+1}\right)} \right]^{0.5}$$

$$= \Delta TE\left(\mathbf{x},\mathbf{y}\right) \times \Delta T\left(\mathbf{x},\mathbf{y}\right).$$

Given that technical efficiency (*TE*) is defined as $TE = \dfrac{1}{D_I\left(\mathbf{x},\mathbf{y};g,a\right)}$, the first ratio in the above decomposition measures the change in productivity due to change in technical efficiency. In each of the two ratios in the square brackets, the input-output bundles are identical while *g* and *a* are from subsequent periods. Therefore, these ratios measure the change in the input requirement set caused by changes in technology between the two periods. In other words, the contribution of technical change to productivity growth is being measured.

In a similar manner the technical change component can be decomposed further. Again by multiplying with one or $\left(\dfrac{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^{t+1},a^t\right)}{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^{t+1},a^t\right)} \dfrac{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^t,a^{t+1}\right)}{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^t,a^{t+1}\right)} \right)$ and

rearranging, we get the component measuring the contribution of genetic-based technical change ΔG and the component measuring the contribution of non-genetic-based technical change ΔA as:

$$
\begin{aligned}
\Delta T(\mathbf{x},\mathbf{y}) = {} & \left[\frac{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^t,a^t\right)}{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^{t+1},a^t\right)} \times \frac{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^t,a^{t+1}\right)}{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^{t+1},a^{t+1}\right)} \right]^{0.5} \times \\
& \left[\frac{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^{t+1},a^t\right)}{D_I\left(\mathbf{x}^t,\mathbf{y}^t;g^{t+1},a^{t+1}\right)} \times \frac{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^t,a^t\right)}{D_I\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1};g^t,a^{t+1}\right)} \right]^{0.5} \\
= {} & \Delta G(\mathbf{x},\mathbf{y}) \times \Delta A(\mathbf{x},\mathbf{y}).
\end{aligned}
$$

In the distance function ratios within the first square brackets all arguments of the distance function are identical in each ratio corresponding to each period except the genetic component g. Similarly, in the distance function ratios within the second square bracket the distance function ratios for each period differ only by the non-genetic component a. Therefore, the distance function ratios in the first square bracket will reflect the change in the input requirement set caused by genetic-based technical change that follows breeding. On the other hand, the distance function ratios in the second square bracket will reflect the change in the input requirement set of producing a given output due to other forms of technical change unrelated to breeding. Other decompositions of the technical change indices, for example into magnitude and bias indices (Färe et al. 1997), are also possible.

The Effect of Output quality Change on Productivity Growth

Figure 1A illustrates the effect of unaccounted quality change on productivity growth measurement using the Malmquist index given by equation (3). The figure shows two isoquants, $Isoq(y^0; q^0)$ and $Isoq(y^1; q^1)$ representing period 0 and period 1, respectively. Let the quantity of milk remain constant in both periods $(i.e., y^0 = y^1)$ while milk quality improves $(i.e., q^0 < q^1)$. Since there are resource costs associated with improving milk quality at a constant technology, $Isoq(y^1; q^1)$ must lie to the right of and above $Isoq(y^0; q^0)$. If a producer operates at point B in period 0 and at point C in period 1, the producer will be technically efficient in both periods. Nevertheless, according to equation (3), the productivity change from period 0 to period 1 is

$$M_I^{CCD}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}\right) = \left(\frac{OC}{OB}\frac{OB}{OB} \times \frac{OC}{OC}\frac{OC}{OB}\right)^{0.5} = \frac{OC}{OB} > 1.$$ This implies that the milk

quality improvement will be measured as a productivity decline.

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Table A1. Parameter Estimates of the Unrestricted Input Distance Function, 1997–2006

Vars.	Const.	$\ln g$	$\ln x_1$	$\ln x_2$	$\ln x_3$	$\ln x_4$	$\ln x_5$	$\ln y_1$	$\ln y_2$	t
Const.	-0.263 (0.001)									
$\ln g$	0.164 (0.540)	11.695 (0.336)								
$\ln x_1$	0.116 (0.001)	0.489 (0.312)	0.070 (0.001)							
$\ln x_2$	0.039 (0.001)	-0.159 (0.695)	-0.015 (0.392)	0.016 (0.491)						
$\ln x_3$	0.097 (0.001)	-0.226 (0.683)	-0.024 (0.331)	0.029 (0.223)	0.097 (0.056)					
$\ln x_4$	0.588 (0.001)	0.343 (0.670)	-0.015 (0.644)	0.009 (0.781)	-0.204 (0.001)	0.453 (0.001)				
$\ln x_5$	0.031 (0.001)	-0.455 (0.082)	-0.015 (0.220)	0.015 (0.204)	0.023 (0.173)	-0.053 (0.016)	0.001 (0.939)			
$\ln y_1$	-0.634 (0.001)	0.488 (0.327)	-0.009 (0.669)	-0.026 (0.242)	-0.051 (0.165)	-0.030 (0.515)	0.083 (0.001)	-0.094 (0.031)		
$\ln y_2$	-0.018 (0.001)	0.033 (0.690)	0.005 (0.168)	-0.006 (0.062)	-0.009 (0.041)	0.007 (0.243)	0.000 (0.993)	0.013 (0.001)	-0.005 (0.001)	
t	0.009 (0.007)	0.071 (0.491)	0.002 (0.630)	0.000 (0.912)	0.011 (0.067)	-0.015 (0.064)	-0.005 (0.116)	0.010 (0.075)	-0.001 (0.358)	-0.007 (0.001)
z	-0.001 (0.001)									

μ	0.285 (0.001)	$\gamma = \dfrac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$	0.691
η	-0.022 (0.008)	Log Lik.	1,224.6
		AIC	-2,323.1
		BIC	-2,021.2

Note: p-values reported in parentheses.

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Table A2. Parameter Estimates of the Restricted Input Distance Function Without Quality Adjustment, 1997–2006

Vars.	$\ln x_1$	$\ln x_2$	$\ln x_3$	$\ln x_4$	$\ln x_5$	$\ln y_1$	$\ln y_2$	t
Const.	-0.255 (0.001)							
$\ln g$	0.128 (0.582)							
$\ln x_1$	0.098 (0.001)	0.043 (0.016)						
$\ln x_2$	0.042 (0.001)	0.001 (0.931)	0.046 (0.023)					
$\ln x_3$	0.126 (0.001)	-0.03 (0.238)	0.066 (0.001)	0.156 (0.003)				
$\ln x_4$	0.569 (0.001)	-0.049 (0.138)	-0.059 (0.025)	-0.22 (0.001)	0.511 (0.001)			
$\ln x_5$	0.024 (0.001)	0.003 (0.823)	-0.026 (0.005)	-0.001 (0.97)	-0.039 (0.087)	-0.004 (0.713)		
$\ln y_1$	-0.579 (0.001)	0.026 (0.226)	0.014 (0.453)	-0.048 (0.169)	0.003 (0.939)	0.113 (0.001)	-0.219 (0.001)	
$\ln y_2$	-0.014 (0.001)	0.005 (0.158)	-0.002 (0.462)	-0.012 (0.014)	0.006 (0.319)	0.004 (0.059)	-0.004 (0.244)	-0.004 (0.001)
t	0.002 (0.567)							-0.007 (0.001)
z	-0.001 (0.003)							
μ	0.303 (0.001)	$\gamma = \dfrac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$	0.709		AIC	-2,162.0		
η	-0.037 (0.001)	Log Lik.	1,125.0		BIC	-1,936.1		

Note: p-values reported in parentheses.

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Table A3. Technical Efficiency and Productivity Growth of Icelandic Dairy Farms Without Quality Adjustment, 1997–2006

Year	Technical Efficiency	Efficiency Change	Technical Change		Scale Effect	Productivity Growth
			Genetic-based	Nongenetic-based		
1997	78.4					
1998	77.8	-0.94	0.07	2.18	3.02	4.34
1999	76.7	-0.98	0.11	1.52	1.31	1.96
2000	77.0	-0.99	0.09	0.87	0.85	0.82
2001	76.8	-0.98	0.03	0.21	2.05	1.32
2002	75.7	-1.03	-0.01	-0.44	2.78	1.30
2003	75.2	-1.09	0.01	-1.10	1.15	-1.02
2004	74.6	-1.09	0.10	-1.76	-0.01	-2.75
2005	74.4	-1.10	0.15	-2.41	0.98	-2.37
2006	73.2	-1.14	0.12	-3.07	3.48	-0.60
Average	75.9	-1.04	0.09	-0.47	1.69	0.27
Cumulative		-9.32	0.68	-3.99	15.62	2.99

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$$\left(y^0 = y^1\right)$$
$$\left(q^0 < q^1\right)$$

$Isoq\left(y^1; q^1\right)$
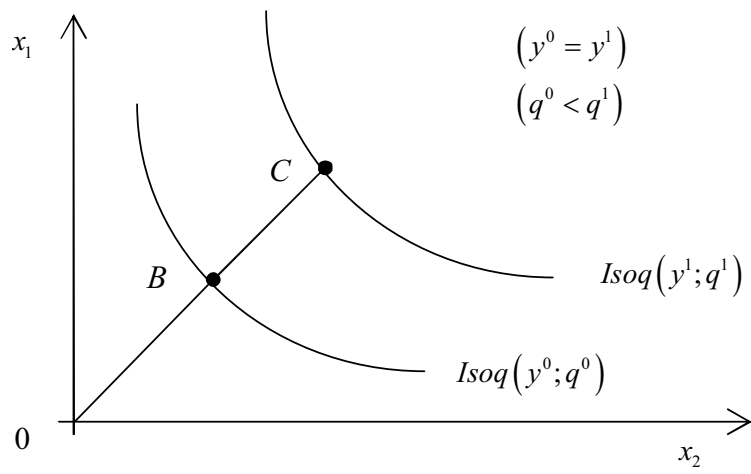
$Isoq\left(y^0; q^0\right)$

Figure 1A. The effect of output quality change on isoquants

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This dissertation compiles four articles investigating the effects of breeding and marketing quota in dairy production. Farm level panel datasets from Norway and Iceland were used for the analysis. In the first article, the main objective was to measure the contribution of animal breeding to productivity growth on Icelandic dairy farms. An extended decomposition of the Malmquist productivity index was proposed for the task. Average productivity growth during 1997–2006 was 1.6%. Scale effects contributed the most followed by breeding, which contributed about 19% of the growth. The second article investigated the effects of broad breeding goals on production cost of dairy farms in Norway. A cost system allowing for unobserved heterogeneity was used to derive cost effects of genetic progress. Results show that genetic progress in welfare-improving traits such as health and fertility led to a 1% cumulative cost saving during 1999–2007. This corresponds to a perpetual industry-wide cost saving of NOK 160 million. The effect of Norwegian marketing quotas on milk quality, as measured by milk composition, was the objective of the third article. A theoretical model of substitution effects between milk quantity, as determined by each farm's quota, and milk components was developed and empirically estimated. The substitution effect was positive for protein and negative for fat. Given the value of components, this suggests low milk quality as quota regimes get restrictive. The fourth article investigated supply response among Icelandic dairy farms under yield uncertainty and two-price system. An existing model of supply response that assumes single input in production was generalized to a multiple input setting. Results show milk supply response to a price change in quota milk market is only a third of the supply response to equivalent and simultaneous price change in quota and surplus milk markets. Finally, statistical testing preferred results from the generalized model.

Professor Kyrre Rickertsen, Associate Professor Dadi Kristofersson and Professor Rodolfo Nayga Jr. supervised the dissertation.