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Spatial Concentration of Milk Production in Norway: The Flow of Quotas

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Abstract

This paper sets up several random effects spatial autoregressive panel data models with nested Translog production function with non-constant and non-neutral technological change to explain the variation of milk quantity with given stocks of capital, labor (hired and family) and feed production area as other limited productive resource. The aim of the paper is to discover the spatial spillovers in Norwegian milk production as a result of changing quota systems by introducing a spatially lagged variable of milk output. The paper examines three distinctive 5-year balanced panel data sets to account for the evolving milk quota system, such as: no quota, restrictive quota and transferable quota system. The paper also derives joint and conditional Lagrange Multiplier (LM) tests for detecting spatial error correlation (ρ), serial correlation (ψ) and random individual effects (μ) in panel models as well as Moran's I test for testing spatial dependence on panel variables. The tests help to avoid misspecifications of the spatial models. The outcome of the **SAREM2SRRE** model verified our hypothesis of increasing quota flows within the counties, since the spatial spillover parameters (λ) showed increasing trend under the distinguished dataframes. As a conclusion, the quota system gave rise to positive structural changes because it increased the spatial interdependence and spatial relations between Norwegian dairy farmers.

1 Introduction

In this paper we make an attempt to combine econometric production analysis with novel static spatial panel models. In both economic theories many handy tests have been established in order to make legitimate decisions in applied studies and utilize the most stable and powerful model specifications. In production theory, a number of various production functions were derived to find the appropriate model which seeks to capture the fundamental features of the system being studied. The performance of an economy or a sector of an economy at any point in time will depend upon the decisions of the economic agents (e.g. farmers), taken in the context of the existing state of technology with a given stock of capital, labor, and other limited productive resources. We intend to find a generalized form of a production function specification which can be later employed in spatial panel models.

The inclusion of geographical space and the evolved spatial aspect in economic analysis has been one of the major events in economic literature which become extended in many ways in recent decades (Anselin, 1988, Elhorst, 2003, Elhorst et al., 2007, Kapoor et al., 2007). Spatial models deal with correlation across spatial units usually in a cross-sectional setting (Anselin, 1988), although spatial panel models become more and more popular recently because they can control for both heterogeneity and spatial correlation across observed units (Baltagi et al., 2003). Apart from a few exceptions, the standard panel techniques have their spatial counterparts, but in many applied papers the spatial consideration is missing due to the lack of precise spatial data.

In this analysis, the Norwegian dairy farm accountancy survey data was employed with spatial extension. Three individual medium sized balanced panel dataframes were constructed, each captured for five-year period blocks of no quota, restrictive quota and transferable quota systems; in the periods of 1974-1978, 1990-1994 and 2008-2012, respectively. As a result of balancing a number of observations were lost. The final dataframes consist 162, 348, and 196 dairy farms that operated in Norway consecutively over the examined five-year periods; thus in total each period contained 810, 1740 and 980 observations respectively ($N \times T$).

The use of panel data methods provides a powerful framework to control for spatio-temporal heterogeneity and dependence, as well as potential omitted variable bias, to model production variation over space and time. We test our dataframes on different production function specifications, also for spatial correlation on panel variables with an arbitrarily chosen proximity matrix which was constructed under the $k-nearest\ neighbor\ weights$ theory as we obtained point pattern location/spatial data. In all cases the 5 closest farms were considered as neighbors in the sparse matrix, regardless of the distance. The proximity matrices were built uniformly to obtain non-negative, standardized, symmetric matrices, where the diagonal elements were set to zero.

Apart from the potentially beneficial effect of the evolving quota systems in Norway in terms of productivity, we further investigate the effect of quotas with the focus on their spatial dependence and pose the hypothesis of the increasing spatial correlation of milk production is due to the spatially restrictive quota distribution in the second period, and later as a result of allowing market-based quota flows within the regions in the third period. As the strict quota regulation was imposed in 1983, the government allocated the quotas to eliminate overproduction according to setting out individual quota levels for farmers. These were based on the average milk production of the previous years with a prescribed 20% decrease. Later in 1996, with respect to the unfair quota allocation and to the strong lobby activities of dairy farmers, they forced a significant policy change to make quotas transferable within the regions. Theoretically, that would result quota transfer from less competitive farms or exiting farms to farms are having comparative advantages in their production technology or carrying on production on more fortunate location. In Norway the climate and the quality of the soil are considerably heterogenous, and in terms of agriculture it is not negligible, this is why we suppose that spatial correlation is increasing between farms within the region. Given the fact that we do not have data on the feasible quotas of the individuals, we substitute it with the produced milk quantity. Since quotas became crucial production factors, any output increase genuinely assumes earlier investment of buying quota.

At this stage of the investigation we focus on general static panel models that include a spatial lag of milk production to address spatial correlation. In the error term we control for spatial autoregressive disturbances, which gives rise to two possible specifications (detailed in Section 2.2). The dynamic consideration is left for future work.

The paper is organized as follows: the next section discusses and reviews the specification of different production functions and the relevant static spatial panel models; Section 3 details the conducted tests and estimations; Section 4 delineates the results of the performed models and concludes.

2 Proposed estimation frameworks

As we know, all models are inevitably simplifications of reality and in research we seek to capture the fundamental features of the system being studied. The paper follows a two-step specification strategy; wherein the first step we identify the appropriate production function which will be nested in the second step. Therefore, in the fist part of this section we propose various production functions, while in the second part we specify the different approaches of spatial panel models.

2.1 Notes on production functions

As a point of departure, we investigate and compare the suitability of some parametric regression methods for analyzing production technologies and finding the optimal production function that we can utilize later in spatial panel models. The theoretical standpoint of regression analysis is to evaluate the effects of one or more explanatory variables on a single dependent variable. This is conducted by evaluating the conditional expectation of a dependent variable given the explanatory variables, which can be expressed as:

$$y_{it} = f(x_{it}) + \varepsilon_{it} \tag{2.1}$$

in a panel data setting.

In economic production analysis the association between output and input factors is detected by various specification techniques of the functional form. In general, economic output is not a (mathematical) function of input, because any given set of inputs can be used to produce a range of outputs. To satisfy the mathematical definition of a function, a production function is customarily assumed to specify the maximum output obtainable from a given set of inputs. The production function, therefore, describes a boundary or frontier representing the limit of output obtainable from each feasible combination of input (El-Shahat, 2015). In cross-section analysis, we assume that the same technology is available for all firms, because all observations refer to the same period of time. However, in panel data setting we allow to perform inter-temporal analysis and relax the strong assumption on the state of technology. When observations can originate from different time periods technology might change as an effect of innovation and R&D. Hence, it is an occasion to include the state of the available technology as an explanatory variable in order to conduct reasonable production analysis. In practice, often a time trend is used as a proxy to identify the gradually changing technology.

As a first parametric association of output and inputs were derived by Cobb and Douglas (1928)(CD). They explicitly used the concept of an algebraic production function which later became the most extensively performed functional form in applied work. In case of CD production function, usually a *linear* time trend is added to account for technological change:

$$lny = \alpha_0 + \sum_i \alpha_i lnx_i + \alpha_t t \tag{2.2}$$

where the coefficient of the linear time trend (α_t) can be interpreted as the rate of technological change per year. The *equation* (2.2) has been substantially modified to relax the assumption of unitary elasticity of substitution, which is assumed to be fixed and constant. In the early '70s Christensen et al. (1971) proposed a more flexible generalization of the Cobb-Douglas function, the Transcendental logarithmic production function (henceforth, Translog). The Translog production function represents, in fact, a class of flexible functional forms for the production functions, wherein the CD specification is nested. Thus, it has become an integral tool for analyzing comprehensively the production structure. The Translog function is conceptually simple and imposes no a priori restrictions on elasticities of substitutions and returns to scale. One of the main advantages of the respective production function is that, unlike in case of CD production function, it does not assume rigid premises such as: "perfect" or "smooth" substitution between production factors or perfect competition on the production factors market (J.Klacek et al., 2007). In applied work it has been utilized to examine input substitution, technical change, productivity growth and productive efficiency.

We build two specifications of the Translog function: one with the assumption of constant and neutral technological change, and another as relaxing this assumption with non-constant and non-neutral technological change. Therefore, in the second Translog specification we can account for increasing or decreasing rates of technological change. This can be done by extending *equation* (2.3) with a quadratic time trend and cross-product terms between time and input measures, as it is obtained in *equation* (2.4).

Translog production function with constant and neutral technological change:

$$lny = \alpha_0 + \sum_i \alpha_i lnx_i + \frac{1}{2}\sum_i \sum_j \alpha_{ij} lnx_i lnx_j + \alpha_t t \tag{2.3}$$

Translog production function with non-constant and and-neutral technological change:

$$lny = \alpha_0 + \sum_i \alpha_i lnx_i + \frac{1}{2}\sum_i \sum_j \alpha_{ij} lnx_i lnx_j + \alpha_t t + \sum_i \alpha_{ti} lnx_i + \frac{1}{2}\alpha_{tt} t^2 \tag{2.4}$$

The estimation of the production functions are detailed in Section 3, as well as the selection method by utilizing the Wald test.

2.2 On Static Spatial Panel Models

In spatial analysis, we account for the presumable spatial correspondence between units and underpin Tobler's first law of geography: *"Everything is related to everything, but close things are more related than things that are far apart"*. Spatial models deal with correlation across spatial units usually in a cross-sectional setting (Anselin, 1988), although recently panel setting became more popular due to its more informative feature and its open-source implementation is attainable (Millo and Piras, 2012, Millo, 2014). Elhorst (2003) gathered up the advantage and the extended modeling possibilities of using panel data, that it contains more information, more variability, less collinearity among the variables, more degrees of freedom and hence the estimators are likely to be more efficient. In general, panel data reduce the effects of omitted variables bias by controlling for individual heterogeneity. The model designs, those are combining the spatial and panel frameworks, can control for both heterogeneity and spatial correlation (Baltagi et al., 2003). Millo

(2014) concludes the economic meaning of spatial panel specification, that it can accommodate spatial spillovers from the dependent variable (spatial lag) at neighboring locations, spatial diffusion of idiosyncratic shocks, individual heterogeneity and time-persistence of idiosyncratic shocks. In this subsection we delineate the most influential findings in the literature and discuss the two possible specifications of spatial error component, pending on the interaction assumption between the spatial autoregressive effect and the individual error components (**SEM**, **SEM2**).

At early stage, Anselin (1988) derived the first static spatial model, which combines the spatial lag of the dependent variable with the spatial autoregressive disturbance (**SAREM** that stands for 'spatial autoregressive and spatial error model') :

$$y = \lambda(I_T \otimes W_N)y + X\beta + u$$

$$u = (\iota_T \otimes I_N)\mu + \varepsilon \tag{2.5}$$

$$\varepsilon = \rho(I_T \otimes W_N)\varepsilon + e$$

where y is an $NT \times 1$ vector of observations on the dependent variable, X is a $NT \times k$ matrix of observations on the non-stochastic exogenous variables, I_T is an identity matrix of dimension T, W_N is the $N \times N$ spatial weight matrix of known constants whose diagonal elements are set to zero, and λ the corresponding spatial parameter that accounts for spatial spillovers. The disturbance vector u is a composite error term of the time-invariant individual specific effects μ, which is not spatially correlated, and of the spatially autocorrelated idiosyncratic errors ε where the spatial element is included by the same W_N matrix as used at the lagged outcome variable. The ρ in the error structure stands for the spatial autoregressive parameter, while e is the noise which is $e \sim IID(0, \sigma_e^2)$ distributed. In the set of *equation* (2.5), two models are nested: the spatial autoregressive model (**SAR**), when the spatial consideration only accounts for the lagged variable, and the spatial error model (**SEM**), when only the error includes the spatial aspect. As the interest of the paper is to calculate the true spatial lag coefficient λ, in each latter specification we stick together with the lagged outcome variable and make different assumptions on the error term.

As in the classical panel data literature, the individual effects μ can be treated as fixed or random. In a random effect specification the unobserved individual effects are assumed uncorrelated with the other explanatory variables in the model, and can therefore be safely treated as components of the error term (Wooldridge, 2002, Millo, 2014). In this case, $\mu \sim IID(0, \sigma_\mu^2)$ and the error term can be rewritten as: $\varepsilon = (I_T \otimes B_N^{-1})e$, where $B_N = (I_N - \rho W_N)$. As a consequence, when random error structure is assumed, the composite error term becomes $u = (\iota_T \otimes I_N)\mu + (I_T \otimes B_N^{-1})e$. Baltagi et al. (2003, 2007) derived several lagrange multiplier tests (LM) on this expression to explore the data and find the best model specification (details in Section 3).

Kapoor et al. (2007) (henceforth KKP), considered a different specification on the error term, where they assumed that spatial correlation can be applied on the whole structure of the composite error term u while assuming random effects, thus both the individual effects and the remainder error components will be spatially correlated. They removed the spatial association from the lagged variable and kept the focus on the error structure, where the first order spatial autoregressive process took the form of (**SEM2**):

$$u = \rho(I_T \otimes W_N)u + e \tag{2.6}$$

Baltagi et al. (2013) pointed out that the economic meaning of the two models is also different: in the first model (**SEM**) only the time-varying components diffuse spatially (*equation* (2.5)), while in the second the spatial spillovers also have a permanent component. As it was mentioned, the general KKP error specification does not include the spatial lag component of the dependent variable, although Mutl and Pfaffermayr (2011) derived the extension of the **SAR** part. That model is performed and labeled as **SAREM2RE**.

Besides the number of mentioned advantages of panel data, there is a disadvantage which can be originated from the panel setting, namely the serial correlation. In many applied papers authors disregard it especially when they investigate in short panels. We aim to account for possible serial correlation, given the fact that proper remedies have already been established (Baltagi et al., 2007, Millo, 2014), although only a few applied papers have been acknowledged. Baltagi et al. (2007)

addressed this issue by considering the original Anselin model in *equation* (2.5) and specified the model errors as the sum of an individual, time-invariant component and an idiosyncratic one which is spatially autocorrelated and has serial correlation in the remainder v:

$$u = (\iota_T \otimes \mu) + \varepsilon$$

$$\varepsilon = \rho(I_T \otimes W_N)\varepsilon + v \tag{2.7}$$

$$v_t = \psi v_{t-1} + e_t.$$

This model stands for serial correlation in the remainder of the error term v, together with spatial correlation and random effects assuming **SEM**-type error structure; this model is labeled as **SAREMSRRE**. Millo (2014) proposed the KKP counterpart of serially correlated reminder error structure:

$$u = (\iota_T \otimes \mu) + \varepsilon$$

$$u = \rho(I_T \otimes W)u + v \tag{2.8}$$

$$v_t = \psi v_{t-1} + e_t$$

with a spatially lagged dependent variable, it is labeled as **SAREM2SRRE**.

There is a number of other interaction structure of the error term, for example a joint modeling of spatial and serial correlation, but these only focus on different assumptions on the error structure and disregard the spatial lag. In this paper we motivate the spatial autoregressive parameter λ, therefore other interesting implementations of the error term will be omitted.

3 Estimations and Tests

In the estimation we utilize multiple balanced panel datasets. Each data frame was derived from the Norwegian farm accountancy data, which is a sample unbalanced panel data with ca. 21000 observations in the period of 1972-2013. It is a long panel data which was constructed with the same methodology in every year. The participation in the sample was voluntary but the data record was strictly representative. In the data generating process we detected some human mistakes in the datasets (negative quantities) therefore the data were cleaned by excluding the effect of these observations. We utilized quantity measures in labor (age corrected labor hours), capital in depreciated monetary units, and area (in hectares) as explanatory variables. Milk quantity was measured in liters as outcome (dependent) variable. As it was mentioned, we often introduced a time trend variable for sequential years to account for technological change. The estimated variables were performed in a logarithmic mean-scaled form in order to observe immediately the true parameters of the Translog specification besides other practical considerations[1]. Also the time trend was mean-adjusted but not linearized, indicating that the time trend variable was zero at the sample mean.

In the first step of the estimation we were looking for the most flexible and meaningful production function form. In the previous section we detailed three production functions in *equation* (2.2) (2.3) and (2.4). As the CD specification is nested in the Translog forms, we can apply the Wald test to check whether the CD production function is rejected in favor of the Translog production function. As a result of a significant Wald test, under every specification (on the individual error term: fixed or random) the CD production function was rejected, in general, in favor of the Translog function with constant and neutral technological change. We also derived the Wald-test between the Translog specifications and found that the Translog production function with constant and neutral technological change was rejected in all data frames in favor of the Translog production function with non-constant and non-neutral technological change. We can conclude that the fit of

[1] In the Translog production function the first order coefficients are calculated by the first partial derivatives of the outcome variable: $\frac{\delta y}{\delta X_1}$, or $\frac{\delta y}{\delta X_2}$ etc. From the nature of the Translog functional form it follows (if there are two objects): $\frac{\delta y}{\delta X_1} = \beta_1 + \beta_{12} X_2$. However, if the variables are performed in a logarithmic mean-scaled form the outcome of X_2 become zero, therefore β_1 become the true coefficient, which, in economic terms, is equivalent with the output elasticities at the sample mean.

Translog production function with non-constant and non-neutral technological change was found significantly better than the fit of the other specification with constant and neutral technological change in all dataframes, therefore in the spatial estimation we utilized the most flexible Translog function.

For conducting valid and justified model-building procedure, first we need to explore the data by employing some important tests. To mention a few in the literature, Moran (1948), Anselin and Bera (1998), Baltagi et al. (2003, 2007) derived the most important tests to help researchers in the decision making procedure of spatial modeling. Moran (1948) in his pioneering work tested spatial dependence on cross sectional data which was later extended on panel setting to test spatial correlation on panel variables. The crucial element in spatial econometrics is the construction of the proximity matrix. Up to now, there is no commonly agreed practice in the literature (Getis and Aldstadt, 2004, Corrado and Fingleton, 2012, Gibbons and Overman, 2012, Gerkman and Ahlgren, 2014) on how to determine the most appropriate consideration of neighboring relations. Researchers mostly arbitrarily choose between specifications that they intuitively recognize the best solution. We follow the practice with a short affix, namely that we tested our variables on multiple sets of *k-closest neighbors* with changing *k=5, 8, 10.* According to the Moran's I statistic on panel variables, we found the *k=5* the most stable specification, therefore later in the estimation we applied this in a standardized matrix structure.

Baltagi et al. (2003) derived several Lagrange Multiplier (LM) tests for panel data regression models with spatial error correlation. Joint and conditional tests were built to test for random effects and spatial autocorrelation in the error term. The joint LM test simultaneously tests for the existence of spatial error correlation as well as random regional effects, while the conditional tests implicitly assume the existence either the random regional effect or spatial error correlation in the error term. These tests were important to perform, because ignoring spatial correlation and heterogeneity due to the random region effects will result inefficient estimates and misleading inference. All the three tests, the joint and the two conditional tests, were found statistically significant at 5% level, thus we found evidence for the presence of spatial correlation and random effect structure in the error term. Baltagi et al. (2007) addressed the issue of testing serial correlation in spatial panel models and extended their earlier work of the year 2003. We tested our datasets with their one-dimensional conditional test for no serial correlation allowing the presence of both spatial error correlation and random effects and in each panel data setting we had to reject the null hypothesis.

By concluding the findings of the performed tests, we need to find a model specification which allows for the coexistence of random effects and serial correlation together with the spatial correlation in the error term. Since random effects were detected, **OLS** would results inefficient estimates, so we need to find an other method.

Following the literature, generally there are two methods on estimating spatial models. One is by using maximum likelihood method (**ML**) (first proposed by Anselin (1988)) and the other one, more recently, is the generalized method of moments (**GMM**) (Conley, 1999, Kelejian and Prucha, 1999). Anselin (1988) advocates the spatial econometric model estimation by **ML**, who outlines the general procedure for a model with spatial lag, spatial errors and possibly nonshperical residuals. All of our models were calculated with ML method, including the spatially lagged dependent variable, while assuming different error structures (**none, SEM, SEM2**); thus we estimate five random effect models with a spatially lagged autoregressive parameter:

1) **SARRE**: no assumptions on the error term, therefore no spatial error correlation was considered.

2) **SAREMRE**: Anselin's and Baltagi's assumption on the error term as described in *equation* (2.5).

3) **SAREM2RE**: KKP's assumption on the error term as described in *equation* (2.6).

4) **SAREMSRRE**: Anselin's and Baltagi's assumption on the error term, also controlling for serial correlation as described in *equation* (2.7).

5) **SAREM2SRRE**: KKP's assumption on the error term, also controlling for serial correlation as described in *equation* (2.8).

We consider the **SAREM2SRRE** the true specification since it captures all the detected spatial correlations and spatial heterogeneities, and controls for serial correlation that we detected with the LM tests. In economic terms, this specification can accommodate spatial spillovers from the outcome variable at neighboring locations (**SAR**), spatial diffusion of idiosyncratic shocks (**SEM**) together with individual heterogeneity (**RE**) and accounts for time persistence of idiosyncratic shocks (serial correlation, **SR**).

4 Results and Conclusion

We derive five spatial panel models with different assumptions on the error structure on each panel periods. Results can be obtained in Table 1. The Translog production function with non-constant and non-neutral technological change formula is employed in all cases. The aim of the study is to model the spatial association of milk production in Norway, thus all models are based on the **SAR** structure. As the composite error component u was extensively tested under the Translog framework, therefore we suggest the **SAREM2SRRE** model which controls for all the weaknesses of the datasets that we justified.

The reason we provide the results of the other four model specifications is twofold:

1) Spatial panel data econometrics is rather a novel but quickly growing research field, thus this paper intends to contribute by increasing the number of applications where multiple model specifications were conducted;

2) if we compare the coefficients and the spillover parameters from each outcome variable of the models in Table 1, we can see, that the differences are quite conspicuous (especially the λ) what indicates possible bias in the results. This bias is originated from some misspecification of the models and reveals the importance of exploring the data and so, the structure of the model has to address the occurrent drawbacks of the data.

Millo (2014) points out that a multi-parameter optimization of a relatively complex likelihood can have reliability issues, like all numerical procedures. The main issues concentrate on the Anselin or Baltagi type error structure (**SEM**, *equation* (2.5)) with occasional fails due to the $B^\top B$ matrix becoming computationally singular. He also notices (during his extensive trials) that the frequency of such problems increases with bigger examples, where the degree of sparseness of W typically grows. This is the reason of the failures in the second and fourth models[2]. The

[2]Reminder: The second pariod panel block is more than twice as big as the first one.

alternative KKP specifications (in *equation* (2.6)) are free from this problem.

As discussed in Section 2.2, the spatial error random effects models rise two possible specifications, pending on the interaction between spatial autoregressive effect and the individual error components. Due to the computational issues in the singular matrix errors we generalized the structure of the errors further, from now under KKP, assumptions[3]. The test for serial correlation was significant, so in this model specification we introduced serial correlation with the parameter ψ in the reminder errors. As the tests confirmed: $\lambda \neq 0$, $\rho \neq 0$, $\mu \neq 0$, $\psi \neq 0$, thus we consider the **SAREM2SRRE** the true specification. The parameters of the explanatory variables are significant, and the relation of hired labor look valid due to the reason that the Norwegian farm structure rarely affords to hire human labor force. The coefficients or the explanatory variables can be interpreted as any other log-linearized association because of the means-scaled feature of the data.

The estimated spatial autoregressive parameters of the lagged dependent variable (λ) show an increasing order in the true model. This proves the hypothesis that the implementation of output quota will indicate rising spatial concentration, hence higher level spatial dependence between dairy farmers in Norway.

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[3]Reminder: KKP assumptions, when the random effects are spatially correlated together with the idiosyncratic error.

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	Models	Intercept	Hrdlabor	Famlb	Cap	Area	mYear	lambda	phi	rho
First Period	**SARRE**	0.0468*	0.036***	0.0742*	0.1563***	0.4395***	-0.0053	0.16554***	4.9955	-
	SAREMRE	0.0461*	0.0354***	0.0676*	0.1506***	0.4342***	-0.0067	0.2387***	5.0908***	-0.1832*
	SAREM2RE	0.0472**	0.0364***	0.0731*	0.1538***	0.4301***	-0.0069	0.2283***	5.0830***	-0.1071
	SAREMSRRE	0.0403*	0.0304***	0.0885**	0.1599***	0.4088***	-0.0079	0.2376***	3.3561***	-0.1523
	SAREM2SRRE	0.0412*	0.0307***	0.0921**	0.1634***	0.4113***	-0.0078	**0.2174*** **	3.2393***	-0.0761
Second Period	**SARRE**	-0.221	0.0323***	0.1110***	0.1204***	0.1974***	-0.0163***	0.1779***	12.0127***	-
	SAREMRE	-	-	-	-	-	-	-	-	-
	SAREM2RE	-0.0113	0.0327***	0.1104***	0.1126***	0.1862***	-0.1342***	0.3675***	12.2261***	-0.2856**
	SAREMSRRE	-	-	-	-	-	-	-	-	-
	SAREM2SRRE	-0.0107	0.0312***	0.1106***	0.1127***	0.2036***	-0.0143***	**0.3941*** **	10.8593***	-0.3204***
Third Period	**SARRE**	-0.0678**	0.0332**	0.1167***	0.1339***	0.2186***	0.0234***	0.0272	8.9558***	-
	SAREMRE	-	-	-	-	-	-	-	-	-
	SAREM2RE	-0.0494**	0.0316**	0.1214***	0.1301***	0.2081***	0.0179***	0.1769	9.1706***	-0.2636
	SAREMSRRE	-0.1168***	0.0352***	0.1062***	0.1517***	0.1995***	0.0423***	0.5680***	0	0.4358***
	SAREM2SRRE	-0.1114***	0.0344***	0.1042***	0.1437***	0.2048***	0.0386***	**0.4802** **	7.4612***	0.3753***

Table 1: Parameter estimates for all specifications on the Translog production function under differentiated quota systems. Regressors are logged, except the year dummy mYear. *p<0.1, **p<0.05, ***p<0.01