Measuring the metafrontier efficiencies and technology gaps of dried apricot farms in different agro-ecological zones

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Abstract

Dried apricot (*Prunus armeniaca* L.), which is extensively produced in Malatya region, is one of the most exported crop in the Turkish agriculture. Malatya is not only in Turkey, but also is the most producer region of whole world. Apricot is cultivated in all zones of Malatya under varying agro-ecological conditions that reflect production technology. Due to the conditions, performance of the farms and output quantity also varies. Thus, the present research focused to the production efficiency (TE) and technological gaps (TGR) of the farms in the different agro-ecological zones of Malatya, which is six, using stochastic metafrontier approach. The measured average individual technical efficiency (TE), metafrontier (MFTE) and TGR varied between 50%-83%, 16%-33% and 20%-56%, respectively among the zones. The empirical results reveal that dried apricot farms in the six agro-ecological zones adopt heterogeneous production technologies due to differences in their production environments. Therefore, agricultural policies should be developed to reduce the technology gap between specific zones and the overall agricultural sector.

Key words: Dried apricot. Stochastic metafrontier. Metatechnology.

1. Introduction

Nearly 175 thousand tons of dried apricot have been produced annually in recent decades in the world and 145 thousand metric tons of this amount have been exported. Turkey which produces 60% of the world's dried apricot is also the dominant country in apricot export. Based on long term data, Turkey has been exporting an average of about 90 thousand tons of dried apricot yearly, which amounts to about 75% of export value of dried apricot in the whole world. Tajikistan, Uzbekistan and Kazakhstan follow Turkey with about 10, 6 and 4 thousand tons of export, respectively (INC, 2019; ITC, 2019). Substantial shares of dried apricots (90-95%) are exported especially to the USA and European countries, and about 85% of the world's dried apricots is produced in Malatya province of Turkey. The dried apricot exported from Malatya provides about 350 million dollars to Turkey and Malatya province (TSI, 2019).

Dried apricot production carries certain risks related to yield, price, ecology and farming practices in different agro-ecological zones in Malatya. To cope with the risks about the productivity and low income, farmers may sometimes overuse agricultural inputs, assuming that input overuse would ensure efficiency. However, non-optimal use of inputs cannot achieve desired productivity levels and could result in problems concerning quality of the products and the environment. These facts have led to a wide heterogeneity in the available production technology used by the farming households in different agro-ecological regions. It is important to note that the technical efficiency (TE) of farming households operating under different technologies is not comparable under the same production frontier. This is because households make choices among different sets of input-output combinations (O'Donnell et al., 2008). In the present study, efficiency analyses were carried out at the level of agro-ecological zones taking into account the effect of technology in the emergence of efficiency differences between the farms.

When analyzing the efficiencies of farms at the level of groups (country groups, regions, provinces, villages, acreages, etc.) and comparing their efficiencies, these groups are assumed to be homogeneous. Thus, efficiency levels of the decision-making units in one group could be compared in relation to the decision-making units in another group. However, Battese et al. (2004) indicated that in comparing the efficiency scores of groups, it is not appropriate to estimate only one efficiency score and that estimation-based efficiency scores of metatechnology ratio must be obtained for making comparisons. Thus, the technology use and gaps of farm groups could be determined, and reliable solutions and policy proposals could be developed. Efficiencies including the metatechnology ratio at the level of agro-ecological zones were estimated in the present study.

The main purpose of the present study was to measure the efficiencies of dried apricot-producing farms in Malatya province of Turkey, the world's leading dried apricot production region, based on agro-ecological zones using two-year data collected at farm level. Measuring the efficiency and technological gaps of agricultural farms at the level of agro-ecological zones with stochastic metafrontier method, the present study is the first in Turkey, and is expected to contribute to the scientific literature.

2. Literatures Review

There have been almost no scientific studies measuring the efficiencies of farms in establishing the macro- and micro-policies in the region where the research was carried out. Only two studies have been found on the efficiency of dried apricot farms, and in the first of these studies, Gündüz et al. (2010) measured the efficiency using the data from 102 farms in Darende district with the help of Data Envelopment Analysis (hereafter DEA). The study revealed that the local farms did not operate economically at 50% efficiency. In the other study, Gündüz et al. (2011) estimated the efficiencies of 97 farms engaged in dried apricot farming in the Central district of Malatya Province using DEA. This study found that as the size of the farms increased, so did their technical efficiency levels. Small farms had a 74% efficiency level, while the efficiency level of large farms was 91%. Thus, in two studies conducted in two different regions, considerable differences were observed among the efficiency levels of farms producing dried apricots. This finding indicates that it is necessary to determine the efficiency levels of each specific agro-ecological zone with studies targeting that specific zone.

Because the efficiency levels of farms using different input-output combinations but operating in different zones could vary, Battese et al. (2004) developed metafrontier analysis using metafrontier function outlined by Hayami and Ruttan (1971). In the present study, the efficiency scores of farms located in different agro-ecological sub-regions but producing dried apricots were investigated using stochastic metafrontier approach.

In recent years, the number of studies using the metafrontier function to perform and compare the efficiencies of farms operating in different zones has been increasing. O'Donnell et al. (2008) employed the model developed by Battese et al. (2004) to predict the efficiency and technological gap using five-year agricultural input and output data from 97 countries, and contributed to the development of the model. Kabir and Khan (2010) calculated cross-regional efficiency scores and technological gaps using the metafrontier approach for small farms producing biogas plants in Bangladesh. Collecting panel data from 46 dairy cow farms in Argentina, 47 in Chile and 70 in Uruguay, Moreira and Bravo-Ureta (2010) studied technological gaps and efficiencies using metafrontier approach. They found technical efficiencies of 72.8, 65.8 and 73.4% for Argentina, Chile and Uruguay, respectively. Villano et al. (2010) estimated that there were differences in efficiency among the farms growing different tree nuts in Iran and that technological gaps originated from the input use. Khanal et al. (2018) measured the technological gap and efficiencies of farmers in different agro-ecological zones in Nepal using the stochastic metafrontier method. However, to our best knowledge, there has been no study estimating the efficiency of agricultural farms in Turkey using this approach.

3. Material and Method

3.1. Analytical methodology

In limited number of studies comparing the efficiency of farms in different groups such as countries, regions or in more microscales, different frontier functions were created and analyzed for each group (Moreira and Bravo-Ureta, 2010). For example, Gündüz (2011) examined dried apricot producers in two layers and performed separate efficiency analysis for each. However, the efficiencies of farms in different groups but using the same production technology could be studied under a general frontier function (Moreira and Bravo-Ureta, 2010). Measuring the efficiency by developing a production frontier is possible through using metafrontier function. The metafrontier function was developed by Hayami (1969) and Hayami and Ruttan (1971) and states that a single production function can be created by assuming that all farmers in different groups use the same technology. Later, Battese and Rao (2002) developed the concept of stochastic metafrontier to show that separate stochastic frontiers created to represent the efficiencies of different groups can be examined using a single frontier function in the form of an envelope. Battese et al. (2004) and O'Donnell et al. (2008) mentioned that stochastic metafrontier developed by Battese and Rao (2002) would not be able to provide metafrontier completely, and they further improved the model.

Battese et al. (2004) and O'Donnell et al. (2008) indicated that the exponential model of the stochastic frontier function (Cobb-Douglas or translog production function) to be estimated for N number of farms in j number of groups would be as follows:

$$Y_{it} = f(x_{1it}, x_{2it}, \ldots, x_{Kit}, \beta^j) e^{v_{it}^j - u_{it}^j} = e^{x_{it}^{'} \beta^j + v_{it}^j - u_{it}^j} \tag{1}$$

Y_{it} is the output obtained by the ith farm in the jth group in the tth period; x^{it} is the kth input used by the ith farm in the jth group in the tth period (k=1,2,...,K); v_{it}^j is a random error which has normal distribution with constant variance and zero mean; and u_{it}^j is non-negative independent random variable which reflects the technical inefficiency by using specific characteristics which belong to the ith farmer. Battese and Coelli (1995) developed the following model in explaining the changes in u_{it}^j, which reflect the technical inefficiency.

$$u_{it} = z_i \delta \tag{2}$$

In the formula, z_i represents variables that reflect specific characteristics affecting technical efficiency (education, age, experience and non-agricultural income) while δ shows parameters.

The input and output values for each farm in the jth zone can be used to obtain the maximum likelihood (ML) estimates of the unknown β parameters. It is then possible to calculate the technical efficiencies of each farm in the jth zone taking into account the zone's production frontier using the formula employed by Battese and Rao (2002) and given below:

$$TE_{it}^j = \frac{y_{it}}{e^{x_{it}^{'} \beta^j + v_{it}^j}} = e^{-u_{it}^j} \tag{3}$$

If $e^{-u_{it}^j}$ =1, then the farm is fully efficient. In the study, a separate production frontier was set for each agro-ecological zones (j=1,....6) using the Eq 2. This requires testing whether each farm uses the same technology depending on the specified production frontier. For this, likelihood ratio test (LR) can be used.

$$LR(\lambda) = 2[\ln\{L(H_A)\} - \ln\{L(H_0)\}] \tag{4}$$

$L(H_0)$ represents the log-likelihood function of the stochastic frontier estimated by pooling the data for all agro-ecological zones and $L(H_A)$ is the sum of the values of the log-likelihood ratios of individual agro-ecological zones. If the estimated λ value rejects the null hypothesis that the same technology is not used for each zone, then it means that the metafrontier estimate would be appropriate (Battese et al., 2004). Battese et al. (2004) mentioned that the production functions estimated for the farms in each zones would be stochastic while the metafrontier estimated through taking into account pooled farms would be deterministic. O'Donnell et al. (2008) mentioned that deterministic estimation of metafrontier would produce more reliable results. The frontier values obtained by deterministic metafrontier would be larger than or equal to the values estimated by the stochastic approach. Thus, the deterministic metafrontier model can be expressed as:

$$y_{it}^{*} = f(x_{1it}, x_{2it}, \ldots, x_{Kit}, \beta^{*}) \equiv e^{x_{it}^{'}\beta^{*}} \tag{5}$$

where y* and β* denote the outputs and unknown parameters of the deterministic metafrontier function, respectively. Thus, the following condition would always be satisfied between the parameters to be predicted for each agro-ecological zone and the parameters of the metafrontier function.

$$e^{x_{it}^{'}\beta^{*}} \geq e^{x_{it}^{'}\beta^{j}} \tag{6}$$

Since the metafrontier model is considered to be deterministic, the parameters of the model can be obtained in two ways (Battese et al. 2004): a) minimization of the sum of the absolute deviations of the distance between the metafrontier and the j[th] group frontier, and b) minimization of the sum of the squares of the deviations of the values on the metafrontier from those of the group specific stochastic frontiers at the observed input levels. Battese et al. (2004) stated that metafrontier parameters were better when estimated by minimization of the sum of absolute deviations. Therefore, to estimate the Metafrontier, the objective function for the minimization of the sum of absolute deviations is given below:

$$\underset{\beta^{*}}{Min} \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\ln f(x_{1it}, x_{2it}, \ldots, x_{Kit}, \beta^{*}) - \ln f(x_{1it}, x_{2it}, \ldots, x_{Kit}, \hat{\beta}^{j})\right] \tag{7}$$

$$s.to \quad \ln f(x_{1it}, x_{2it}, \ldots, x_{Kit}, \beta^{*}) \geq \ln f(x_{1it}, x_{2it}, \ldots, x_{Kit}, \hat{\beta}^{j})$$

The minimization problem is solved by pooling the data from all zones and with the help of linear programming. Similarly, Battese et al. (2004) used arithmetic averages of inputs to create the objective function of the minimization problem. Thus, the objective function is formed as follows:

$$\begin{aligned} &\underset{\beta^{*}}{Min}\ \bar{x}^{'}\beta^{*} \\ &s.to\ x_{it}^{'}\beta^{*} \geq x_{it}^{'}\beta^{j} \end{aligned} \tag{8}$$

Where $\bar{x}^{'}$ is the average of the x_{it} input over all farms in all periods. In the study, parameter estimates of metafrontier were solved using the Eq. 8. An analysis of the literature shows that the reliability of coefficients is controversial when a deterministic model is used in calculating the metafrontier parameters. While many studies in the literature showed that censored models are preferred at this stage, Simar and Wilson (2007) mentioned that parameters estimated deterministically using the bootstrap method were more reliable. In the present study, standard errors of deterministic metafrontier parameters were similarly estimated using the bootstrap method proposed by Simar and Wilson (2007). Bootstrapping was carried out with 1000 replications using STATA 14.0 software.

Through the Eq. 8, which solves the parameter estimates of metafrontier, technical efficiency scores of metafrontier and technological gap ratios are also obtained. This is achieved by dissolving the Eq. 3 as follows:

$$y_{it} = e^{-U_{it}^{j}} \ x \ \frac{e^{x_{it}^{'}\beta^{j}}}{e^{x_{it}^{'}\beta}} \ x \ e^{x_{it}^{'}\beta + V_{it}^{j}} \tag{9}$$

The first term on the right side of the equation shows the technical efficiency of the kth farm in the jth zone given in Eq 1. The second term on the right side of the equation represents the technological gap ratio (metatechnology ratio). The difference between metafrontier technical efficiency (MFTE) and technical efficiency (TE_j) of the agro-ecological zones (distance to a certain frontier) is termed technological gap ratio (hereafter TGR) or metatechnology ratio (MTR) (Battese et al., 2004; O'Donnell et al., 2008). Thus, TGR is shown as follows:

$$TGR_{it}^{j} = \frac{e^{x_{it}^{'}\beta^{j}}}{e^{x_{it}^{'}\beta}} \tag{10}$$

The TGR takes a value between 0 and 1. TGRj compares the efficiencies of the farms in the jth group in relation to a potential production frontier (metafrontier).

If the latest term on the right side of Eq. 9 is moved to the left side of the equation, it would measure a technical efficiency as stated in Eq. 1, which is the technical efficiency of metafrontier (MFTE). Thus, MFTE is:

$$MFTE_{it} = TE_{it}^{j} \ x \ TGR_{it}^{j} \tag{11}$$

Efficiencies of dried apricot producing farms in different agro-ecological zones were determined using FRONTIER 4.1 software developed by Coelli (2007). Metafrontier efficiency parameters, on the other hand, were determined using SHAZAM econometric software codes which was developed by O'Donnell et al. (2008) and are given in the appendix.

In the present study, efficiency scores by agro-ecological zones were estimated using the maximum likelihood method and Cobb-Douglas function with discrete normal distribution recommended by Battese and Coelli (1995). Khanal et al (2018) suggested that Cobb-Douglass functional form provided more consistent results for different agro-ecological zones. Cobb-Douglas functional form has been widely used in efficiency analyses in agriculture (Battese, 1992; Mayen et al., 2010; Gunduz et al., 2011; Manjunatha et al., 2013; Mango et al., 2015; Balogun and Akinyemi, 2017; Khanal et al., 2018).

In this type of function, natural logarithms (Ln) of dependent and explanatory variables of the technical efficiency are used.

$$\ln Y_{it} = \beta_0 + \sum_{i=1}^{n} \beta_i \ln X_i + v_i - u_i \qquad (12)$$

Since the Cobb-Douglas production function is expressed as a fully logarithmic form, the coefficients of the model measure the income as well as the elasticity. The sums of β coefficients greater than 1 indicates increasing return to the scale, while those smaller than 1 indicates decreasing return and those equal to 1 indicates constant return (Kumbhakar and Lovell, 2000).

3.2. Research area and data

Malatya province (38.19° E; 38.21°N) located in eastern Turkey (Fig. 1), encompasses 1,241,200 ha area, and approximately 34% of this area is used for agricultural production. The selected research area is responsible for 100% of the total dried apricot production of Turkey.

In the study, six agro-ecological zones in Malatya region, whose borders were determined by Turkish Ministry of Agriculture and Forestry, were investigated as study area. The agro-ecological zones consist of different number of districts where apricot production is made. These zones were: The first zone: Dogansehir and Kuluncak districts; The second zone: Hekimhan district, The third zone: Central, Akcadag, Darende and Yesilyurt districts, The fourth zone: Battalgazi, Doganyol, Kale and Yazıhan districts; The fifth zone: Elbistan district, and The sixth zone: Baskil District.

Data of two consecutive years (2014/2015 and 2015/2016 production seasons) from 328 randomly selected dried apricot producing farms in different agro-ecological zones were used as the research material.

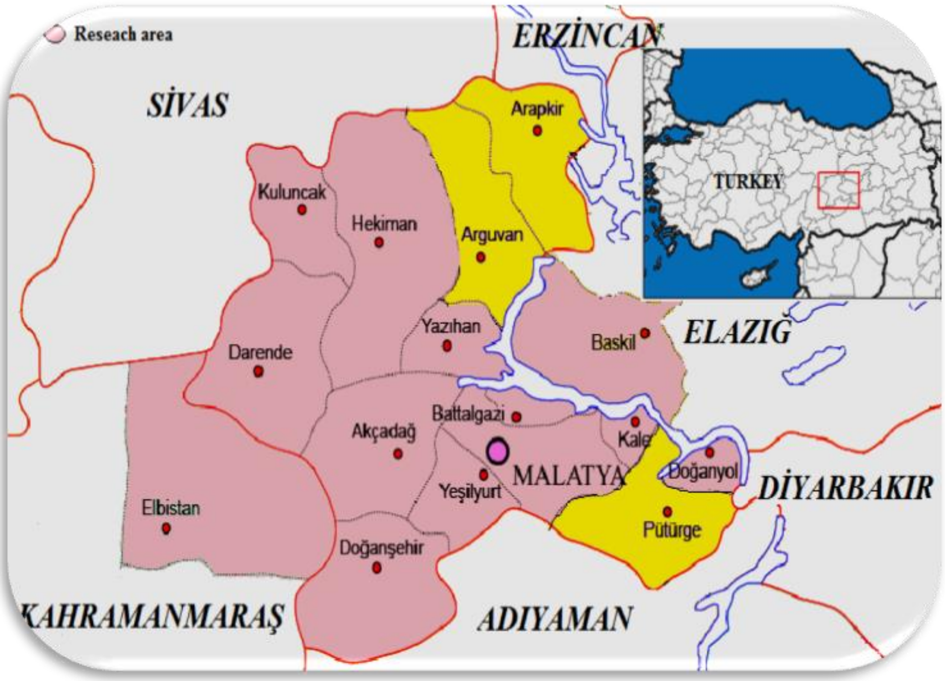

Figure 1: Research area

In determining the sample size, a two-stage sampling procedure was employed. In the first stage each agro-ecological zone was evaluated as target population and five villages that could represent each zone were selected using purposive sampling. In the second stage, the sample size in each agro-ecological zone was calculated by the random sampling method (Yamane, 1967).

$$n = \frac{N * s^2 * t^2}{(N-1) * d^2 + s^2 * t^2} \qquad (13)$$

Where n: sample size, N: Total number of farms in the i^{th} zone, s: standard deviation of apricot land of k^{th} farms, t: value at 95% confidence level, 1.96), d: precision (5%). As a result of the implementation of the formula, distribution of 328 farms sampled were as follows: 45 in the first zone, 50 in the second, 91 in the third, 71 in the fourth, 42 in the fifth and 29 in the sixth zone.

In order to determine the efficiencies and factors affecting them for the farms investigated in the study, variables in Table 1 were used in the models.

Table 1: Summarized descriptive statistics of the variables used in the frontier and maximum likelihood models

	Zone I	Zone II	Zone III	Zone IV	Zone V	Zone VI	Pooled
				2014 / 2015			
Yield (kg ha^{-1})	913.24 (1075.23)	678.40 (712.14)	906.99 (1082.30)	728.19 (398.08)	515.44 (218.51)	483.16 (599.37)	703.31 (836.55)
Apricot land (ha farm^{-1})	2.92 (2.27)	2.82 (1.98)	3.00 (3.19)	3.01 (3.62)	3.13 (2.66)	2.43 (2.68)	2.97 (3.01)
Labor (h ha^{-1})	196.47 (172.83)	200.86 (176.12)	170.22 (110.29)	207.07 (82.32)	143.34 (130.05)	177.70 (111.01)	185.50 (176.12)
Machinery (h ha^{-1})	63.86 (39.15)	205.48 (181.57)	65.37 (35.26)	60.84 (22.09)	57.09 (37.44)	76.33 (52.08)	67.48 (51.57)
Diesel (l ha^{-1})	52.34 (16.67)	92.18 (42.03)	59.00 (22.29)	53.75 (14.80)	51.73 (11.46)	50.64 (16.60)	55.62 (22.03)
Pesticide ($ ha^{-1})	315.09 (219.52)	291.68 (229.68)	322.27 (204.72)	325.97 (159.64)	228.66 (165.01)	294.49 (177.68)	299.33 (205.07)
NPK (kg ha^{-1})	107.32 (93.08)	107.77 (94.67)	190.66 (123.01)	175.70 (100.17)	187.91 (140.75)	143.25 (125.69)	158.35 (119.14)
				2015 / 2016			
Yield (kg ha^{-1})	1024.86 (1115.03)	1195.45 (1342.07)	761.70 (351.14)	1279.81 (833.29)	415.65 (596.54)	1929.13 (1102.52)	1147.12 (1112.47)
Apricot land (ha farm^{-1})	2.92 (2.27)	2.82 (1.98)	3.00 (3.19)	3.01 (3.62)	3.13 (2.66)	2.43 (2.68)	2.97 (3.01)
Labor (h ha^{-1})	420.91 (389.32)	424.63 (415.24)	384.42 (273.21)	425.62 (303.93)	158.61 (186.02)	382.27 (286.40)	404.63 (415.24)
Machinery (h ha^{-1})	69.91 (39.15)	75.28 (47.16)	139.40 (113.19)	69.10 (43.82)	47.69 (32.92)	78.25 (51.06)	75.28 (47.16)
Diesel (l ha^{-1})	78.35 (50.80)	77.35 (40.36)	56.60 (28.29)	50.38 (22.15)	52.88 (31.54)	48.44 (19.42)	61.09 (38.36)
Pesticide ($ ha^{-1})	313.93 (240.90)	263.56 (195.23)	281.88 (185.42)	280.44 (171.11)	139.88 (119.40)	251.30 (130.23)	264.76 (188.12)
NPK (kg ha^{-1})	89.19 (78.03)	139.86 (116.43)	165.18 (87.19)	152.82 (112.53)	149.12 (96.64)	173.69 (127.82)	145.33 (104.43)
				Farmer Specific Characteristics			
Age (year)	52.86 (12.23)	53.20 (10.51)	54.96 (13.64)	48.99 (12.87)	52.46 (9.68)	47.76 (10.00)	52.00 (11.49)
Education (year)	7.42 (3.11)	9.42 (3.30)	8.47 (4.14)	7.76 (3.38)	5.93 (1.93)	7.38 (3.48)	7.73 (3.22)
Non-farm income (Dummy. 1:yes)	0.52 (0.50)	0.31 (0.47)	0.36 (0.48)	0.49 (0.50)	0.36 (0.48)	0.38 (0.49)	0.36 (0.48)
Experience (year)	33.78 (13.18)	33.82 (12.45)	35.10 (13.92)	32.06 (13.00)	35.81 (10.33)	29.59 (10.84)	33.36 (12.26)

Notes: Standard deviations are shown in parentheses. ha, h, l and kg indicate hectare, hours, liter and kilogram, respectively.

The descriptive statistics of variables used in the frontier and maximum likelihood models were summarized by years in Table 1. The dependent variable (output) was dried apricot yield as kilograms per hectare. Input variables used in the apricot production per farm in the frontier production model were total apricot area (hectare), total labor use calculated as man-days labor unit (hours per hectare), total machinery use calculated as horse power (hours per hectare), diesel fuel use (liter per hectare), pesticide use ($ per hectare) and fertilizer use which was the amount of nitrogen, phosphorus and potassium active ingredients (NPK) (kg per hectare).

In the second stage of the empirical model, four farmer-specific variables were included to the model which contributed to the explanation of the inefficiencies. Farmer's age and education variables were included as number of years. Non-farm income sources were included as a dummy variable that took the value of 1 if the farmer had an income from non-farm activities. The farmer's experience variable was measured as number of years as a farmer, which was based on how many years s(he) produced dried apricot.

4. Results and Discussion

Descriptive statistics of farmers data provided for the consecutive years were summarized in Table 1 given above. Dried apricot output and input used per farm, except land, varied year by year and by different agro-ecological zones. Considering the pooled data, for instance, dried apricot output per farm, which was 703 kg/ha in the previous year, increased to 1147 kg/ha. Variations in output and inputs by different agro-ecological zones were showed in Table 1. Farmers in the second, fourth, fifth and sixth zone had low gamma score. It meant that reasons of the inefficiency of these farmers were not due to farm/farmer specific characteristics or variations in year by year, but was due to the random factors (frost, hail, etc.).

Also, on average, farmers were 52 years old and had an approximately eight years of formal education and proportion of having non-farm income was low, and experience for apricot production was 33 years (Table 1).

Using the LR analysis, the study tested H_0 hypothesis, which stated that there was no difference between the frontiers of the groups and pooled frontier. Here the LR test was performed as follows:

$$LR(\lambda) = 2\left[\ln\{L(H_A)\} - \ln\{L(H_0)\}\right]$$

H_A: The sum of log likelihood function results of all groups, H_0: Result of the log likelihood function for pooling data.

$$LR(\lambda) = 2[-235.11 - (-401.72)] = 333.72$$

Thus, this result, which was statistically significant at 1% level, meant that there was technological variation among the agro-ecological zones. This finding indicated the necessity for estimating the metafrontier production efficiency. This process, which supports the Metafrontier decision, was also used by many researchers (Odchimar and Tan-Cruz, 2007; Ferdushi et al. 2011).

For the farms which were in different zones but used the same production technology, parameter estimates which were obtained by pooling data from all farms and which reflected the overall status, and metafrontier parameters that made up a new frontier that enveloped the zones were estimated and given in Table 2.

According to the results of the research, it was found that farms in the second and sixth zones had increasing return to the scale while farms in all other zones had decreasing returns. The return to the scale for pooled data was 0.83. This result could be interpreted in a way that a 1% increase in input increased the output of the farms by 0.17%.

Gamma (γ) values are close to 1 in the first and third zones, which indicated that the farms in these zones did not operate efficiently since they could not use the production methods well, while low gamma values in other zones showed that these farms did not have efficiency due to random factors (frost, hail, diseases or pests).

The statistical reliability of the maximum likelihood parameter estimation model for the effect of explanatory variables on dried apricot yields varied among the zones. The coefficients of the explanatory variables which were statistically significant were discussed.

It was found that of all variables used to explain dried apricot yield, apricot land variable was non-significant in the fourth and fifth zones, but significant in other zones and in pooled. Although statistically significant, the sign of the apricot land variable was estimated to be negative for the first zone, and this finding was not expected. Since the coefficients also represent the elasticity, a 1% increase in the land devoted to dried apricot farming increased the yield by 0.36% in the second zone, 0.001% in the third zone, 0.16% in the sixth and 0.17% in the pooled analysis, whereas a 1% increase in the first zone decreased the yields by 0.04%. While the apricot land variable had different effects in different zones covered in the present study, land variable was reported to result in yield increases in all zones studied in rice (Mariano et al. 2011) and pistachio production (Villano et al. 2010).

Table 2: Estimated parameters for the agro-ecological zone frontiers and the metafrontier

	Zone I	Zone II	Zone III	Zone IV	Zone V	Zone VI	Pooled	Meta frontier
Constant	4.942***	-0.819	4.837***	1.777***	2.106***	0.261	1.757***	3.449***
	(0.295)	(1.057)	(0.002)	(0.482)	(0.744)	(0.968)	(0.299)	(0.236)
Apricot land (ha farm^{-1})	-0.046**	0.363***	0.001*	0.022	0.045	0.157*	0.169***	0.208**
	(0.023)	(0.133)	(0.001)	(0.051)	(0.094)	(0.091)	(0.039)	(0.091)
Labor (h ha^{-1})	0.012	1.045***	0.000***	0.924***	0.534***	1.074***	0.569***	0.493***
	(0.027)	(0.127)	(0.000)	(0.077)	(0.120)	(0.111)	(0.035)	(0.017)
Machinery (h ha^{-1})	0.010	0.130*	-0.000*	-0.043	0.139**	-0.185*	-0.042**	0.019*
	(0.012)	(0.068)	(0.000)	(0.112)	(0.062)	(0.102)	(0.019)	(0.010)
Diesel (l ha^{-1})	0.020*	-0.051	-0.000	-0.207*	-0.106	0.327**	-0.041	0.182**
	(0.012)	(0.210)	(0.000)	(0.116)	(0.216)	(0.155)	(0.065)	(0.083)
Pesticide ($ ha^{-1})	-0.022**	0.139**	-0.000	0.081*	-0.002	-0.033	0.161***	-0.088***
	(0.010)	(0.060)	(0.000)	(0.045)	(0.079)	(0.158)	(0.041)	(0.016)
NPK (kg ha^{-1})	-0.020	-0.008	-0.000*	-0.082*	0.002	0.110**	0.009	-0.061***
	(0.026)	(0.079)	(0.000)	(0.049)	(0.079)	(0.053)	(0.029)	(0.009)
RTS	-0.046	1.618	0.001	0.695	0.612	1.450	0.825	
σ^2	0.517***	0.624***	0.763***	0.321***	0.465**	0.291***	6.588*	
γ	0.998***	0.459**	0.842***	0.461***	0.431*	0.295*	0.938***	
Log likelihood (Log L)	6.42	-99.05	66.45	-88.51	-69.53	-50.89	-401.72	
Likelihood ratio (LR) test	72.44	8.54	49.42	5.83	1.23	7.35	35.85***	

***, ** and * indicate significance at %1, %5 and %10 level, respectively.
RTS: Returns to scale,
Values in the parentheses were standard errors.
Note: The reason why some values seem to have 0 values is that up to three decimals are used in the table.

Effect of the labor variable, one of the most important inputs of intensive use in agriculture especially in apricot production, on apricot yield, was positive in all zones as expected. The labor variable was statistically significant in other zones except for the first zone. A 1% increase in labor use increased the yield by 1.05% in the second zone, 0.01% in the third, 0.93% in the fourth, 0.53% in the fifth, 1.07% in the sixth zone and 0.57% in the pooled analysis. Although the effect of labor on yield or output was generally positive in similar studies dealing with the efficiency analysis, there were also some studies reporting negative effects of labor. Villano et al. (2010) found positive effects of labor use in all zones. They observed that a 1% increase in the amount of labor use increased the yields by 0.14-0.23%. Similarly, Asravor et al. (2019) found that the labor had a positive impact on yield in rice production zones of Ghana, but Lakner et al. (2015) estimated that the labor had a negative impact in organic production carried out in Switzerland, Germany and Austria.

Machine use, which is one of the major inputs affecting dried apricot yield, was predicted to have negative effects in the third, fourth, sixth zones and in pooled while its effect in other zones was positive. This variable was statistically significant in all zones except for the first and fourth. A 1% increase in machine use increased dried apricot yields by 0.13% in the second zone and 0.14% in the fifth zone but decreased the yield by 0.01% in the third zone, 0.19% in the sixth zone and by 0.04% in pooled analysis. In their studies with data from many countries around the world, Rao et al. (2003) found that the impact of machine use on total agricultural output was positive in all zones except for only one. Mariano et al. (2011) estimated that use of machinery positively affected the yield in all regions of rice production. Their results conflicted with the positive effects of the machinery use estimated in only some of the production areas in the present study.

Fuel use had negative impact on dried apricot yields in all zones except for the first and sixth. The coefficients of the fuel use variable were significant in the first, fourth and sixth zones. A 1% increase in fuel use increased the dried apricot yields by 0.02% in the first zone and 0.33% in the sixth zone, while a 0.21% reduction was observed in the fourth zone. No studies were found using the amount of fuel as a variable that determines the efficiency, but it was revealed that in some studies the value of this variable was included in total expenditures variable. In a study conducted by Villano et al. (2010), effect of variable costs in peanut production was positive in all but one zone.

The coefficient of the pesticide use variable, which is one of the most basic inputs in apricot production, was statistically significant for the first, second, fourth zones and for the pooled analysis. This variable had a negative effect in all zones except for the second and fourth zones and in the pooled analysis. It was found that a 1% increase in pesticide expenditure decreased the dried apricot yields by 0.02% in the first zone while in the second zone it resulted in increases of 0.14% in the second zone, 0.08% in the fourth zone and 0.16% in the pooled. Mariano et al. (2011) included the amount of pesticide used in the model for rice production and found that it made about a 2% positive contribution to yield in each zone.

Fertilizer use had negative effects on apricot yields in all zones except for the fifth and sixth and in pooled. The coefficient of this variable was statistically significant for the third, fourth and sixth zones. The results showed that with a 1% increase in the amount of fertilizer used, dried apricot yields decreased by 0.001% in the third zone and 0.08% in the fourth zone while the same amount of increase in fertilizer use increased the apricot yield by 0.11% in the sixth zone. Odchimar and Tan-Cruz (2007) listed the fertilizer costs within the capital costs and found that this variable had a positive effect in all zones. Rao et al. (2003) included the fertilizer use variable directly in the model and predicted that effect of this variable was positive in all zones except for one. Similarly, Asravor et al. (2019) predicted that fertilizer use had positive effects in all zones.

The estimated results of the variables which affected the inefficiency of the farms calculated by maximum likelihood model are given in Table 3. As could be seen in the table, the effects of the inefficiency variables varied significantly among the zones. Variables had positive signs in some zones, and they improved the efficiency (i.e. they alleviated the inefficiency) whereas their signs were negative in some zones and thus they increased the inefficiency. The coefficients of statistically significant variables were discussed below.

Table 3: Maximum-likelihood estimates for parameters of the inefficiency effects model of the Cobb-Douglas production function by agro-ecological zones

	Zone I	Zone II	Zone III	Zone IV	Zone V	Zone VI	Pooled
Constant	0.20	-0.30	1.22*	-0.07	1.08	1.68***	-0.41*
	(0.69)	(1.16)	(0.71)	(1.09)	(1.20)	(0.37)	(0.25)
Age (years)	-0.06*	0.66	-0.27	-0.20	0.36	0.46***	0.47***
	(0.03)	(0.47)	(0.21)	(0.17)	(0.70)	(0.16)	(0.08)
Education (years)	0.02	-0.01	-0.01**	0.01**	0.01	0.01***	0.01***
	(0.03)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Non-farm income (dummy; 1:Yes)	-1.09**	-0.76***	-0.14	0.00	-0.53*	-0.39***	-0.04
	(0.51)	(0.27)	(0.10)	(0.17)	(0.43)	(0.08)	(0.06)
Experience (years)	0.03	-0.01*	-0.00	0.01***	0.00	-0.01***	0.00*
	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)

***, ** and * indicate significance at %1, %5 and %10 level, respectively.
Values in the parentheses are standard errors.
Note: The reason why some values seem to have 0 values is that up to three decimals are used in the table.

The age of the farmer variable affected the technical efficiency positively in three zones (i.e. negatively the inefficiency) and negatively in three zones (positively the inefficiency). It affected the efficiency positively in the first, third and fourth zones while its effect was negative in the second, fifth and sixth zones. Its impact on efficiency in pooled was negative. The age variable was statistically significant only in the first and sixth zones. It was found that as the age of the farmers increased in the first zone, they were more efficient, and their inefficiencies decreased. In the sixth zone, on the other hand, inefficiency increased along with the age. It could be stated that across the farms as the age increased inefficiencies would be greater, i.e. technical efficiency would be impaired. Mariano et al. (2011) and Jirgi (2013) similarly predicted that as the farmer's age increased, his/her efficiency would decrease, i.e. inefficiency would increase.

The impact of farmer's education status variable on apricot yields was negative in the second and third zones but positive in the other four zones and in the pooled analysis. Coefficient of the variable was statistically significant in the third, fourth and sixth zones and the pooled farms. There was a negative relationship between the education variable and technical inefficiency in the third zone as expected, which indicated that as the farmer's education level increased, his/her efficiency performance would be higher. In contrast, the results showed that efficiency performance of older farmers were impaired in the fourth and sixth zones, and the pooled farms. Jirgi (2013) and Khanal et al. (2018) included the education level in their efficiency models and found positive relationships between education level and efficiency as expected.

The non-farm income variable had positive impact on apricot yields (i.e. increased the efficiency) in the third and sixth zones. As expected, the technical efficiency level decreased in zones where this variable had a positive sign because as the likelihood of farms to obtain income from sources outside the agriculture increases, their agricultural performance is expected to decrease. The coefficient of the variable was statistically significant in the first, second, fifth and sixth zones. The findings with this variable were in line with the results estimated by Mariano et al. (2011) and Asravor et al. (2019).

The farmer's agricultural experience affected the inefficiency negatively in the second, third and sixth zones and positively in other zones. The coefficient of the variable was statistically significant for the second, fourth and sixth zones and in the pooled analysis. The coefficient of this variable was negative in the second and sixth zones as expected, which indicated that the farmers' performance increased along with their experience in agriculture. In the fourth zone and in the pooled analysis, the variable had negative sign, which meant that the experience had negative impact on the efficiency of farmers. However, since the value of coefficients with negative sign were quite close to zero, it could be stated that their impact on performance would be minimal. Jirgi (2013) had results similar to what we obtained in the second and sixth zones about the effect of experience on performance, whereas Mariano et al. (2011) and Khanal et al. (2018) concluded that the experience improved the farmer's performance.

In the study, the statistical significance of metafrontier parameters calculated by Eq. 8 was estimated using bootstrap, and it was found that all parameters were statistically reliable. Based on the metafrontier function, variables of land devoted to apricot farming, labor, machine and diesel fuel use had positive effects on yield, while pesticide and fertilizer use had negative impacts. Similarly, in estimations made by many researchers such as Battese et al. (2019), Asravor et al. (2019) and Khanal et al. (2018), who made the greatest contribution to the development of the stochastic metafrontier method, all metafrontier coefficients determined by bootstrap were statistically significant.

As explained in Methods section, with the estimation of metafrontier parameters, metafrontier efficiency (MFTE*) and technological gap (TGR or MTR) were also estimated. Results of these estimations are given in Table 4. The stochastic efficiency scores (TE^J) for the zones are also given in the same table.

Table 4: Summary statistics of TE^J, TGR (MTR) and $MFTE^*$ estimates by agro-ecological zones

	TE^J				TGR (MTR)				$MFTE^*$			
	Mean	St Dev	Min	Max	Mean	St Dev	Min	Max	Mean	St Dev	Min	Max
Zone I	**0.501**	0.295	0.042	0 .996	**0.486**	0.178	0.157	0.956	**0.221**	0.139	0.026	0.625
Zone II	**0.605**	0.188	0.054	0.896	**0.386**	0.171	0.121	1.000	**0.234**	0.132	0.018	0.708
Zone III	**0.592**	0.222	0.066	0.989	**0.556**	0.183	0.219	1.000	**0.321**	0.147	0.031	0.670
Zone IV	**0.834**	0.102	0.478	0.966	**0.405**	0.144	0.189	0.997	**0.334**	0.113	0.128	0.743
Zone V	**0.785**	0.097	0.528	0.934	**0.204**	0.046	0.133	0.449	**0.161**	0.048	0.101	0.402
Zone VI	**0.678**	0.203	0.105	0.953	**0.438**	0.233	0.100	1.000	**0.319**	0.226	0.032	0.871
Pooled	**0.621**	**0.161**	**0.107**	**0.880**	**0.434**	**0.198**	**0.100**	**1.000**	**0.308**	**0.150**	**0.018**	**0.871**

TE^J: Technical efficiency with respect to the group frontier; TGR (MTR): Technology gap ratio (Metatechnology ratio); $MFTE^*$: Technical efficiency with respect to the metafrontier.

The mean efficiency scores (TE^J) determined by the frontier within the agro-ecological zones ranged from 0.50 to 0.86, which was 0.62 in the pooled analysis. Based on the results from pooled dataset, it could be stated that the farms would be efficient if they reduced their input use by 38%.

The fourth zone with the highest level of efficiency compared to its zonal frontier (0.83) was the zone with the highest efficiency in relation to the metafrontier (0.33). In the third zone which had the highest technological gap (0.56), zonal efficiency level was 0.59, where the technical efficiency level dropped to 0.32 according to the metafrontier. The efficiency score of the farmers in the fifth zone with the lowest technological gap was 0.79 compared to their regional frontier and 0.16 compared to the metafrontier.

Technological gap ratios ranged from 0.20 (20%) to 0.56 (56%) on average. The lowest metatechnological gap was in the fifth agro-ecological zone, and the highest was in the third zone. These results showed that the farmers in the first zone produced only 49% of the maximum output that they could produce with the existing inputs, while the farmers in the second zone produced 39%, ones in the third zone 56%, ones in the fourth zone 41%, ones in the fifth zone 20% and ones in the sixth zone 44%.

The estimation that the metafrontier efficiency levels of farms were smaller than the zonal efficiency levels is a finding observed in all studies. The metafrontier efficiency levels were below the group efficiency levels for farms using different technologies (Battese et al. 2004), for rice farmers in Mindanao (Odchimar and Tan-Cruz 2007), for various types of tree nut farmers in Iran (Villano et al. 2010), for rice production in different agro-ecological zones in the Philippines (Mariano et al. 2011), for grain, pulse and oilseed farmers in Nepal (Khanal et al. 2018) and for the Ghanaian rice farmers (Asravor et al. 2019).

Based on these results, it could be stated that the efficiency levels of dried apricot farmers in a zone differed considerably compared to the farmers in other zones. It was also revealed that these farmers had a technology which allowed a production level far from the existing production potential.

Table 5 was organized to illustrate the TGR (MTR), TE^J and MFTE* levels of dried apricot producing farms in different agro-ecological zones. As can be seen from the table, the TGR (MTR), TE^J and MFTE* of farms in all zones were mostly below 0.5, indicating that input use performance was considerably low. There were also conflicting results among the efficiencies of the farms in relation to their zonal frontier and efficiencies in relation to metafrontier. In the third zone which had the highest level of efficiency in relation to its zonal frontier, the proportion of farms with an efficiency level greater than 70% was 43%, while 95% of farms in this zone had efficiency levels of less than 50% in relation to metafrontier. Similar results were also observed in other zones.

Table 5: Frequency distribution of TGR (MTR), TE^J and $MFTE^*$ by agro-ecological zones

		Efficiency Level				Total
		0.9-1.0	0.7-0.9	0.5-0.7	Below 0.5	
Zone I	TGR	0 (0.00)	4 (8.00)	17 (34.00)	29 (58.00)	50 (100.00)
	TE	5 (10.00)	11 (22.00)	7 (14.00)	27 (54.00)	50 (100.00)
	MFTE	0 (0.00)	0 (0.00)	2 (4.00)	48 (96.00)	50 (100.00)
Zone II	TGR	0 (0.00)	2 (4.44)	6 (13.33)	37 (82.22)	45 (100.00)
	TE	0 (0.00)	15 (33.33)	18 (40.00)	12 (26.67)	45 (100.00)
	MFTE	0 (0.00)	0 (0.00)	1 (2.22)	44 (97.78)	45 (100.00)
Zone III	TGR	1 (1.10)	9 (9.89)	49 (53.85)	32 (35.16)	91 (100.00)
	TE	3 (3.30)	36 (39.56)	18 (19.78)	34 (37.36)	91 (100.00)
	MFTE	0 (0.00)	0 (0.00)	5 (5.49)	86 (94.51)	91 (100.00)
Zone IV	TGR	0 (0.00)	2 (2.82)	9 (12.68)	60 (84.51)	71 (100.00)
	TE	5 (7.04)	63 (88.73)	3 (4.22)	0 (0.00)	71 (100.00)
	MFTE	0 (0.00)	0 (0.00)	4 (5.63)	67 (94.37)	71 (100.00)
Zone V	TGR	0 (0.00)	0 (0.00)	0 (0.00)	42 (100.00)	42 (100.00)
	TE	1 (2.38)	36 (85.71)	5 (11.90)	0 (0.00)	42 (100.00)
	MFTE	0 (0.00)	0 (0.00)	0 (0.00)	42 (100.00)	42 (100.00)
Zone VI	TGR	0 (0.00)	1 (3.45)	6 (20.69)	22 (75.86)	29 (100.00)
	TE	1 (3.45)	14 (48.28)	11 (37.93)	3 (10.34)	29 (100.00)
	MFTE	0 (0.00)	0 (0.00)	2 (6.90)	27 (93.10)	29 (100.00)

5. Conclusions

The objective of the present research was to compare technical efficiency for dried apricot farms in the six different agro-ecological zones in Malatya region of Turkey using a stochastic meta-frontier approach. Malatya is the production center of the world with the highest production amount (about 60% of the world's dried apricot production). The data of the research were obtained by questionnaires conducted in 328 randomly selected farms. Employment of farm level panel data collected for two consecutive years from the selected sample farms and performing the analyses on this data make this study quite. The inputs parameters which included apricot land, labor, machinery, diesel, fertilizer and pesticides cost had commonly significant effects on the output in different zones. It was also revealed in the present study that the farm specific variables such as age, education, non-agricultural income and experience had various effects on farm level efficiencies.

The results of the research showed that technical efficiency scores, technology gap ratios and metafrontier scores were different for the six agro-ecological zones. However, the differences were not large between the zones. On the average, the technical efficiency derived from the regional frontier was 62% for the pooled data. Technical efficiency from the metafrontier was 31%, and the technological gap ratio was 43%. This finding was not shown in the previous studies dealing with the efficiency of dried apricot farms in the region.

The production techniques were found to have exhibited decreasing returns to scale in the agro-ecological zones except for the second and sixth zones. This result suggested that the farms in the different zones had a fairly similar production technologies. In addition, these results showed that similar policy recommendations could be developed at the level of all agro-ecological zones producing dried apricot. Furthermore, the metafrontier results indicated that policies should be developed and extended to farmers for using appropriate production technology to reduce the technology gap between agro-ecological zones and for the agricultural sector as a whole.

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8. Appendix

```
* The file parm.txt contains estimated parameters of group frontiers (by column)
* The file sfa#.txt contains n# data observations for group #
* Sections 1 and 3 are problem-specific.
* 1. SET NUMBERS OF PARAMETERS ETC.
gen1 nparms = 7
gen1 ngroups = 6
gen1 n1 = 100
gen1 n2 = 90
gen1 n3 = 182
gen1 n4 = 142
gen1 n5 = 84
gen1 n6 = 58
* 2. READ THE ESTIMATED PARAMETERS OF THE GROUP FRONTIERS
smpl 1 nparms
read (parm.txt) parm / rows = nparms cols = ngroups
do # = 1,ngroups
  dim b# nparms
  copy parm b# / fcols=#;# tcols = 1;1
endo
* 3. READ THE DATA AND CONSTRUCT DATA MATRICES AND VECTORS
gen1 j2 = n1+1
gen1 j3 = n1+n2+1
gen1 j4 = n1+n2+n3+1
gen1 j5 = n1+n2+n3+n4+1
gen1 j6 = n1+n2+n3+n4+n5+1
gen1 k2 = n1+n2
gen1 k3 = n1+n2+n3
gen1 k4 = n1+n2+n3+n4
gen1 k5 = n1+n2+n3+n4+n5
gen1 n  = n1+n2+n3+n4+n5+n6
smpl 1 n
genr one=1
read (sfa1.txt) group t ly lx1-lx6
smpl j2 k2
```

```
read (sfa2.txt) group t ly lx1-lx6
smpl j3 k3
read (sfa3.txt) group t ly lx1-lx6
smpl j4 k4
read (sfa4.txt) group t ly lx1-lx6
smpl j5 k5
read (sfa5.txt) group t ly lx1-lx6
smpl j6 n
read (sfa6.txt) group t ly lx1-lx6
smpl 1 n
matrix x = one|lx1|lx2|lx3|lx4|lx5|lx6
dim x1 n1 nparms x2 n2 nparms x3 n3 nparms x4 n4 nparms x5 n5 nparms x6 n6 nparms
copy x x1 / frows=1;n1  trows=1;n1
copy x x2 / frows=j2;k2 trows=1;n2
copy x x3 / frows=j3;k3 trows=1;n3
copy x x4 / frows=j4;k4 trows=1;n4
copy x x5 / frows=j5;k5 trows=1;n5
copy x x6 / frows=j6;n  trows=1;n6
do # = 1,ngroups
  matrix yhat# = x#*b#
endo
matrix b = -(yhat1'|yhat2'|yhat3'|yhat4'|yhat5'|yhat6')'
* 4. OBTAIN AND PRINT PARAMETERS OF THE METAFRONTIER
stat x / means = xbar
matrix c = ((-xbar')|xbar')'
matrix A = (-x)|x
?lp c A b / iter = 5000 primal = bstar
dim beta1 nparms beta2 nparms
gen1 p1 = nparms+1
gen1 p2 = nparms*2
copy bstar beta1 / frows=1;nparms trows=1;nparms
copy bstar beta2 / frows=p1;p2 trows=1;nparms
matrix beta = beta1-beta2
print beta
* 5. OBTAIN AND PRINT TECHNOLOGY GAP RATIOS
do # = 1,ngroups
  matrix xbeta# = x#*beta
  matrix tgr# = exp(yhat#)/exp(xbeta#)
  stat tgr#
  print tgr#
endo
stop
```