Measuring efficiency of Nepal's dairy producing firms and its interregional gap

(Preliminary Study)

Mitsuhiko Kataoka
Graduate School of Business, Rikkyo University, Tokyo, Japan
mkataoka@rikkyo.ac.jp

Ram Bahadur Basnet
Graduate School of Business, Rikkyo University, Tokyo, Japan
16KN609N@rikkyo.ac.jp

ABSTRACT

The dairy sector in Nepal has a strong backward linkage in the rural household sector which improves the utilization of local resources and contributes to poverty reduction. Given its vital economic role, the government of Nepal has implemented several industrial policies to promote the output growth in the dairy sector for decades. In 1969, the first public dairy enterprise was established as a pilot plant and then the production spread across the country by increasing the dairy plants. At present, many non-public firms operate dairy productions.

We use the Data Envelopment Analysis (hereinafter referred to as DEA) to measure the relative efficiencies of Nepal's dairy firms in the operational performance. Given a statistical noise wrapped by the conventional DEA efficient frontier, we employs the bootstrapping procedure to estimate the bias-corrected efficiency score and then compare the mean efficiency scores by firm location, public ownership, and foreign management influences. We utilize the two output-oriented DEA models, by using the different selections of the input (physical assets, labour costs, and intermediate input values) and output variables (total sales and profits). Our data is sourced from the enterprise survey data in the year of 2012 from National Census of Manufacturing Establishments 2011-2012.

We found that the mean score values of the conventional overall technical and pure technical efficiency shows the statistically significant positive bias and are over-estimates of the true efficiency scores. We also found that the majority of the firms more seriously face the managerial performance efficiency of input-output operation than resource allocation inefficiency.

The paired t-test results for the bias-corrected mean efficiency score indicates that the firms with non-public ownership operate more efficiently in operation scale and firm with foreign management influences operate more efficiently in managerial performance; however, the firms located in the metropolitan districts do not operate more efficiently than those in the non-metropolitan districts.

Our decomposition analysis found that the interfirm gaps in managerial performance is larger than those in operation scale. Thus, technical supports for enhancement in managerial performance are more essential to improve efficiency than increase in for enlargement in operation scale. And the transfer technology from foreign firms may serve as possible solutions for firms' efficiency improvement.

Keywords: Bootstrap Data envelopment analysis, Efficiency measurement, Dairy sector, Nepal
JEL classification code: O12, O53

1. Introduction

The development in the dairy sector contributes to improve the long-term social welfare in agrarian economy as it generates the employment opportunities in the rural sector, particularly among landless laborers, small and marginal farmers, and women (Ramphul 2012). The dairy products, especially milk, is highly perishable and requires immediate processing, storage and preservation to move it form production area to demand centers. Therefore, the dairy production in the rural areas develops the intersectional economic linkage with the agriculture sector well as the rural-urban economic linkage, given the consumers in the urban locations (Doornbos and Gertsch 1994, Ohlan 2013). The increase in incomes and the employment opportunities of the rural household trough the development in the rural dairy sector can reduce the huge rural-urban labor migration.

Agriculture is a critical component of Nepalese economy covering more than 33% of GDP and about three fourth of the entire workforce (Central Bureau of Statistics, CBS 2014). Nepal's agriculture being subsistent in nature, crop yield is low and family labor is not fully employed (FAO 2010 pp. 55). Most of the rural farmers are involved in the milk production for their non-agricultural income sources. Given the economic and social importance of the dairy sectors, Government of Nepal (GoN) have been making efforts for its development. Dairy Development Corporation (DDC), a fully state owned corporation, was initiated in 1969 with the four main objectives: 1) to formulate the guaranteed market system to the milk producers to the rural farmers with fair price, 2) to supply pasteurized milk and milk products to urban consumers, 3) to develop organized milk collection system to meet increasing demand for pasteurized milk and milk products, and 4) to develop an organized marketing system for milk and milk products in urban areas (FAO 2010 pp. 3). GoN also implemented ten year dairy development plan from 1991and National Dairy Development Board (NDDB) was established as an apex level autonomous institution of dairy development in Nepal. The dairy development policy has been formulated in 2008 with the vision of commercial, qualitative and competitive development of dairy sector and contribute employment generation and poverty reduction.

During 1980s, GoN privatized more than half of the public enterprises; however, DDC is still owned by state and have been operating five milk processing plants around the nationwide. The private sector started getting involved in the dairy-processing sector from late 1970s and currently, there are 56 dairy processing sectors are in operation.[1] DDC and private dairy firms in channeling milk from the rural areas through different channels account for 40% and 60% market shares, respectively (FAO, 2010).

With the rapidly growing urbanization, increasing population, and household income, the demand for dairy product can be expected to increase more in the future. However, the market competency of Nepalese dairy processing sectors is low, given that the markets of the high value-added dairy products are dominated by the imported products. According to FAO (2010), the milk produced domestically by the formal sector accounted for only 10% in total domestic consumption in Nepal and NoG promotes import-substitution industrialization to reduce the huge trade deficits,

[1] This number is based on the CBS (2011) enterprise survey data that contains the firms with over 9 employees. FAO (2010) shows 250 dairy processing firms in nationwide, regardless of employment size.

by replacing foreign dairy imports with domestic production with the product diversification, quality improvement and efficient utilization of the local resources.

Geographically, Nepal is divided into three ecological regions: Mountain, Hill, and Terai (or Plain). The Mountain region, over 4,800 meters above sea, covers 35% of total land, but accounts for only about 8 percent of the total population as the transportation and communication facilities are very limited due to the extraordinarily harsh terrain. On the other hand, the Hill region which ranges in altitude from 610 meters to 4,800 meters is densely populated. This region covers nearly 45% of national land and 41% of total population and also includes a number of very fertile valleys such as the Kathmandu and Pokhara valleys. Terai region located in the southern part of the country is the most fertile part of the country, more developed the transportation and communication network facilities than the aforementioned two regions, and attracted newly emerging industries. This region covers nearly 23% of national land and 47% of total population. Administratively, the country consist of 7 provinces and 77 districts in 2019. The government classified that 16 districts in the Mountain region, 41 districts in the middle constitute Hill, and 20 districts in the south fall in the Terai Region.

Given the significant policy concerns, our study employs the frontier analysis technique to access the relative input-output efficiency in the dairy firms in Nepal. The techniques can be divided into two groups: parametric (Stochastic Frontier Approach, Distribution-Free Approach, Thick Frontier Approach) and non-parametric (Data Envelopment Analysis, Free Disposal Hull) methods. The former group requires assuming the specific functional forms and distribution in inefficiency and error terms, and modifications for multiple input and output frontier estimation. The latter imposes less structure on the frontier, as it allows estimation of the multiple input and output frontier, and has no requirements for specific functional forms or distributional assumptions of error terms; however, it is deterministic in nature and highly sensitive to outliers (Coelli et al. 2005; Paradi et al. 2006, Bhattacharjee et al. 2009, Tang et al. 2014). This study employs the most widely used non-parametric DEA technique.

The conventional DEA method derives the piecewise-linear frontier assembled by the best-practice observed decision making units (DMUs), using inputs to produce outputs and implicitly assumes that all of the distance between an observed unit and the optimal frontier reflects inefficiency. However, the corresponding distance reflects both inefficiency and statistical noise as the observed input-output data could be subject to measurement error, or there could be noise in the data due to omitted input or output variables. We apply the homogeneous bootstrap (resampling) DEA method, introduced by Simar and Wilson (1998), to our study as it overcomes to a certain extent the shortcomings of the conventional DEA approach.

The, we compare the firm's efficiency scores by firm location, public ownership, and foreign influence in management. We also decompose the inequality in overall efficiency to inequality in managerial performance and operation scale to identify which factor is more important in overall efficiency gap.

2. Literature Review

There is a major public consensus that food and beverage manufacturing sector is the first step towards industrialization in the developing economies. It is driven by domestic demand and uses mainly local agricultural inputs, with low value added to input ratios. However, only a few studies have analyzed the sector-specific productivities and efficiencies in Nepale. Adhikari and

Bjornadal (2012) examined the level of inefficiency in Nepalese agriculture sector, using two measurement techniques, DEA and stochastic frontier analysis (hereinafter referred to as SFA) and found that the large proportion of farms operate far below the efficient frontier. Oczkowski and Sharma (2005) analyzed the efficiency of Nepalese manufacturing sector, using a Trans log stochastic production frontier and maximum likelihood econometric methods. They found that firm size, capital intensity, foreign participation, rate of protection, and proportion of export has been taken as determinants of firm's efficiency. Jha and Shrestha (2006) measured the DEA efficiency scores of hydropower plants in Nepal and Khanal and Bhatta (2003) studied efficiency of personnel loans in Nepalese commercial banks.

To the best of our knowledge, no study had examined dairy sector of Nepal although many studies analyzed the dairy sector in other countries. Doucouliagos et al (2000) analyzed the efficiency of Australian dairy processing sectors, using SFA. They used state-level panel data for six year periods and analyzed the change in efficiency over years, using single output (real turnover) and four inputs (labor, energy, milk, and capital stock). They found that the sector is reasonably technically efficient on the state-level average and that the states converged the productivity. Kelly et al (2013) computed the DEA-efficiency scores of Irish dairy farms, using 266 farm-level survey data. They revealed that producers shows the overall technical efficiency score 0.757, indicating that their potential outputs can achieve the substantial increase in output without significant increase in input through improved managerial performance and operation scale. Ramphul (2012) analyzed the efficiency and total factor productivity (TFP) of Haryana's dairy sector in India, by using input-oriented DEA-based Tornqvist index. He found the mean overall technical efficiency score of 0.59 indicating the possibility of reduction in input by 41% while maintaining the same level of output. Haryana's dairy processing sector has experienced positive growth in TFP during the 1980s but declined during 1990s and 2000s. Steenveld et al (2012) compared the DEA technical efficiency between farms, using an automatic milking system (AMS) and a conventional milking system (CMS) in Netherlands. They used capital, labor cows and land as inputs and total farm revenue as output and conclude that the AMS and CMS farms are not different in their input-output efficiency. Ohlan (2013) analyzed the efficiency scores and TFP growth in Indian dairy sector, using the similar approach to Ramphul (2012). He found the average technical efficiency scores of Indian dairy sector is 0.72 and TFP has grown at 2.4% per year. Barac et al (2013) analyzed the impact of capital investment on dairy processing sector using the macro data from Slovenia, Croatia and Serbia. Using ordinary least square method, they found positive association of capital investment and foreign ownership. Capital investment per employee significantly increases productivity measured by the earnings before interest, taxes, depreciation, and amortization (EBITDA) and personal cost. Slade et al (2016) studied the effect of different regulatory system on the efficiency of dairy farms, using the farm level data of Ontario and New York. They used the bootstrapped DEA and found technical efficiency was not different between two regions; however the significant differences in allocative and cost efficiencies which are higher in New York than Ontario. Yanjio et al (2017) studied the impact of dairy imports on domestic dairy processing sector in China. They used DEA-based Malmquist index to measure the change in TFP and efficiency over years and then use fixed effect model to analyze the impact of dairy imports on the efficiency variables. They found all these explanatory variables of dairy processing sector in China shows the improvement over time and the sector was developed gradually. The studies of Kannan et al (2010) and Barnes et al (2011) employ DEA technique to evaluate the input-output efficiency of the dairy farms. Reviewing the aforementioned previous studies, we found clear research gap of the empirical research and theoretical discussions in Nepalese dairy sector in spite of its significant policy concerns.

3. Methodology and Data

3.2. Data Envelopment Analysis (DEA)

DEA is a non-parametric linear programming method to assess the decision-making units' (DMUs') relative efficiency in using inputs to produce outputs.[2] DEA derives a surface called a "frontier," which follows the peak performers and envelops the remainder. The frontier connects all the DMUs with the best relative performance in the observed data and thus represents the estimated maximum possible production that a DMU can achieve for any level of input (Cooper et al. 2006).

The DEA model has two returns-to-scale (RTS) versions with assumptions leading to different frontiers, the CCR and BCC models.[3] The CCR and BCC models are based on the assumption of constant returns to scale (CRS) and variable returns to scale (VRS), respectively. In the CRS frontier, all DMUs operate at the optimal scale, whereas in the VRS frontier, all DMUs operate at the maximum level. Imperfect competition, government regulation, financial constraints, and other factors can cause DMUs to operate at non-optimal scales. At a given scale, managerial underperformance can cause DMUs to operate below their maximum level.

Each DMU is assigned an efficiency score between zero and unity. If the score is equal to (below) one, we consider it as a sign of efficiency (inefficiency). The CCR and BCC models measure the scores for overall technical efficiency (*oe*) and pure technical efficiency (*pe*), respectively. The ratio of *oe* to *pe* is the scale efficiency (*se*) score, expressed as

$$\mathrm{oe} = \mathrm{pe} \times \mathrm{se} \tag{1}$$

The *pe* score helps assess the ability of a DMU to utilize a given resource, whereas the *se* score helps assess the optimality of the operation size (Tsolas 2013, Kataoka 2018).

A DMU is scale efficient if it operates at CRS. A DMU with an inappropriate DMU size (i.e., too large or too small) is regarded as scale inefficient and takes the form of either increasing returns to scale (IRS) or decreasing returns to scale (DRS). A DMU exhibiting IRS (DRS) operates at a suboptimal (supraoptimal) scale, due to its small (large) size of operation, in which case it may be essential to enhance its efficiency by increasing (decreasing) its operation scale. IRS (DRS) reflects economies (diseconomies) of scale, which implies that doubling all inputs should lead to more (less) than a doubling of output (Tsolas 2013).

DEA models have two orientations: input-oriented and output-oriented. The former minimizes DMUs' levels of inputs while keeping output unchanged, whereas the latter maximizes DMUs' outputs while keeping inputs unchanged.

We treat a district as a DMU and use output-oriented CCR and BCC models in order to

---

[2] We briefly outline DEA in this sub-section, while more detailed and technical discussions can be found in Coelli et al. (2005) and Cooper et al. (2006).

[3] The CCR and BCC models are named after the authors of Charnes et al. (1978) and Banker et al. (1984), respectively.

take into account given firm-specific endowments and the presence of economies / diseconomies of scale in Nepal's dairy sector.

Suppose that each district i ($i = 1, \ldots, n$) uses multiple types of the inputs to produce the multiple types of outputs, given the input–output data ($x_{i,}$, $y_{i,}$, $i = 1, \ldots, n$). Using the given dataset, we measure the pure efficiency $\hat{\theta}_k$ under the following the liner-programing model where the subscription k indicates the district under the evaluation.

$$Max_{\theta,z}\theta = \hat{\theta}_k \quad (2)$$

Subject to

$$\sum_{i=1}^{n} z_i \cdot x_i \leq x_k \quad (2a)$$

$$\sum_{i=1}^{n} z_i \cdot y_i \geq \theta \cdot y_k \quad (2b)$$

$$\sum_{i=1}^{n} z_i = 1 \quad (2c)$$

$$z_i \geq 0 \quad (2d)$$

where θ and z are model's decision variables. Removing the second-last constraint, we obtain the overall technical efficiency (oe) under CRS. The efficiency value $\hat{\theta}_k$ takes the positive value with the more or equal to the unity$\left(1 \leq \hat{\theta}_k\right)$, the firm with $\hat{\theta}_k = 1(> 1)$ is judged DEA efficient (inefficient). By our definition, the efficiency score indicates $\left(\hat{\theta}_k\right)^{-1}$ as the score ranges between 0 and 1.

3.2. Bootstrapping

As previously explained, the conventional DEA estimator is biased as the frontier is only defined relative to the best-practice observations in the finite sample. Although this procedure rules out the possibility that the 'true' frontier lies below the constructed frontier, it might be the case that it lies above if more efficient regions exist outside the sample data (Enflo and Hjertstrand 2009). The upward and downward biases are evident theoretically. By definition, the conventional efficiency score is upward (downed) biased when it shows the larger (smaller) score value than the "true" efficiency score values (Enflo and Hjertstrand 2009; Moradi-Motlagh et al. 2015, Defung et al. 2016). To tackle the aforementioned drawback, our study employs the homogeneous DEA bootstrapping procedure developed by Simar and Wilson (1998). The process can be summarized as following steps, referring to:

(1) For each district given the input–output data ($x_{i,}$, $y_{i,}$) ($i = 1, \ldots, n$), we measure the efficiency score $\hat{\theta}_k$ under the liner-programing model in Equation (2).
(2) The random sample of $\hat{\theta}_k$, given $\theta_{1b}^*, \ldots, \theta_{nb}^*$ $(k = 1, \ldots, n\,)$ with sample size n is generated, using Kernel density distribution. The subscription b and superscription * indicate the bootstrap replication and the bootstrap value.
(3) A pseudo-data set $(x_i, y_i^*)(i = 1, \ldots, n\,)$ is calculated to construct the reference bootstrap technology.
(4) The bootstrap estimate efficiency $\hat{\theta}_{kb}^*$ of $\hat{\theta}_k$ is calculated for each district k, using the pseudo-data set.
(5) Steps (2)−(4) are repeated interactively B times to generate a set of estimates $\left(\hat{\theta}_{kb}^*,\ b = 1, \ldots, B\right)$, where B is the total number of the bootstrap replication. In this study, B=2000.

3.3. Cheng and Li's (2006) inequality decomposition

After computing efficiency scores at the district level, we use Cheng and Li's (2006) inequality decomposition approach to identify the inequality decomposition of multiplicative components of *oe* in Equation (1).

Let μ_{oe}, μ_{pe}, and μ_{se} be the districts' mean efficiency scores [$\mu_{oe} = (1/n) \sum oe_i$] and its corresponding multiplicative elements [$\mu_{pe} = (1/n) \sum pe_i$, $\mu_{se} = (1/n) \sum se_i$]. Then the district's inequality in overall technical efficiency is measured by Theil's second measure as;

$$T(oe) = 1/n \sum_{i=1}^{n} \ln(\mu_{oe} / oe_i) \; [T(oe) \geq 0] \tag{3}$$

where T represents Theil's second measure (Theil 1967; Anand 1983).[4]

Substituting Equation (1) into Equation (3) and multiplying the quotient inside the natural logarithm by ($\mu_{pe}.\, \mu_{se} / \mu_{pe}.\, \mu_{se}$) yields,

$$T(oe) = (1/n) \sum_{i=1}^{n} ln\{(\mu_{pe} / pe_i).(\mu_{se} / se_i).[\mu_{oe}/(\mu_{pe}.\mu_{se})]\} \tag{4}$$

$$= \left(\frac{1}{n}\right) \sum_{i=1}^{n} \ln(\mu_{pe} / pe_i) + (1/n) \sum_{i=1}^{n} ln\,(\mu_{se} / se_i) + (1/n) \sum_{i=1}^{n} ln\; [\mu_{oe}/(\mu_{pe}.\mu_{se})]$$

where the first and second additive terms of the right hand side are strict Theil's second measures with non-negative values. We rewrite Equation (4) as

$$T(oe) = T(pe) + T(se) + \ln[\mu_{oe}/ (\mu_{pe}.\, \mu_{se})] \tag{5}$$

where $\mathrm{T}(pe) = \left(\frac{1}{n}\right) \sum_{i=1}^{n} \ln(\mu_{pe} / pe_i)$ and $\mathrm{T}(se) = \left(\frac{1}{n}\right) \sum_{i=1}^{n} \ln(\mu_{se} / se_i)$.Now, focusing on the non-Theil term in Equation (5), we express the covariance of pe_i and se_i ($cov\,(pe, se)$) as follows:

$$cov\,(pe, se) = \left(\frac{1}{n}\right) \sum_{i=1}^{n} (pe_i - \mu_{pe})(se_i - \mu_{se}) = \mu_{oe} - \mu_{pe}.\mu_{se} \tag{6}$$

Dividing both sides by ($\mu_{pe}\;.\;\mu_{se}$), we get

$$\mu_{oe}/(\mu_{pe}.\, \mu_{se}) = cov(pe, se)/(\mu_{pe}.\, \mu_{se}) + 1 \tag{7}$$

Substituting Equation (7) into Equation (5), we obtain

$$T(oe) = T(pe) + T(se) + ln[cov(pe, se)/(\mu_{pe}.\, \mu_{se}) + 1]$$

$$= T(pe) + T(se) + I\,(pe, se) \tag{8}$$

where I denotes the interaction term, which can be positive, negative or zero if the element variables are correlated positively, correlated negatively or not correlated.

[4] Theil's second measure, expressed by Equation (3), is also referred to as the mean logarithmic deviation measure (MLD) and is a specific form of General Entropy Class Inequality Measures.

3.4 Data

The data for this analysis is taken from the National Census of Manufacturing Establishments (NCME) 2011-12 (CBS 2012). It covers all the manufacturing establishments engaging 10 or more persons located within the geographic boundary of Nepal. Our analysis uses the 55 dairy processing firms after eliminating one missing observation (Sarlahi distrcit).

Figure 1 shows all 56 dairy firms by district. This figure shows the almost all firms are located in the Hill (31 firms) and Terai (23 firms) regions; only two firms in Mountains. The seven firms are concentrated in the metropolitan areas, districts of Kathmandu and Kaski districts. The latter district includes Pokhara valley, the second largest urban area after the capital city of Kathmandu.

We used two cases to calculate the firm's efficiency: Cases 1 and 2. Case 1 incorporates three input variables (labor cost, average capital value, intermediate goods values) and two output variables (total sales and profit) to examine the efficiency in the dairy processing operations. The three inputs are total labor costs including wages and fringe benefits, annual average value of the fixed assets, and total values of raw material purchased while two outputs are total sales values and net profits. The net profit is defined as the net sum of total product sale values, industrial and non-industrial services revenues, and industrial and non-industrial services expense. Case 2 does not incorporates net profits Descriptive statistics of the data employed in this study are presented in Table 1.

4. Empirical Results and discussions

4.1 Conventional DEA Efficiency scores

The summary of all 55 firms' conventional efficiency scores are presented in Table 2 (All firm's scores in Case 1 are shown at Appendix Table 1). In Case 1, we found only one firms are overall technical-efficient (*oe* = 1.0), and five firms are pure technical-efficient (*pe* = 1.0), and 1 firms are scale-efficient (*se* = 1.0). Majority of the dairy firms in Nepal operate below the efficient frontier. We have the pure-technical efficiency median score 0.191 and this indicates that the firms can improve their pure-technical efficiency by 80.9%, improving the managerial performance without changing any input. The scale efficiency score 0.937 indicates that the firms can improve scale-efficiency by 6.3%, adjusting their operation size. Case 2 also shows the similar results. The each score between Cases 1 and 2 is highly correlated as the correlation coefficients of each score between Cases 1 and 2 ranges between 0.981 and 0.997.

We categorize each frim by returns to scale (RTS) into the three groups: firm operating in increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS). A firm exhibiting IRS (DRS) operates at a suboptimal (supraoptimal) scale, due to its small (large) size of operation, in which case it is essential to enhance its efficiency by increasing (decreasing) its scale of operations. At Tables 2, over 80% (45 firms out of 55 firms) of total firms exhibits DRS, indicating that those operate at a suboptimal level due to its small operation size. On the other hand, the five firms exhibit IRS, indicating that those operate at a supraoptimal level due to its large size of operation. The four of five IRS firms are public firms. The majority of Nepal's dairy firm improves the efficiency by increasing operation size.

4.2. Bias-corrected DEA efficiency scores

Table 3 presents the conventional and the homogenous bootstrap DEA mean efficiency scores and the 95% confidence intervals of sample. The bias-corrected scores, the lower and upper bound scores are denoted as BC, BL and BU, respectively. Any bias in the conventional DEA efficiencies is reflected in the difference between the conventional scores and the bootstrap DEA efficiency scores.

All our conventional estimates, except scale efficiency in Case 1, exceed the mean bootstrap bias-corrected efficiency scores, thus indicating a positive bias. And the conventional scores, except scale efficiency in both cases, are above the bootstrap upper bounds, and outside the confidence interval. This result implies that those conventional mean scores are over-estimates of the true efficiency scores, and that the bias is statistically significant. Although the five and two firms show the conventional pure technical and scale efficiency scores within the interval, respectively, majority of the conventional inefficiencies which we observe in Nepal's dairy processing firm underplay the true picture. Hereafter, we use the bias-corrected efficiency scores for the further analysis.

Using paired t-test, we found that the bias-corrected scale efficiency show the higher mean value than the bias-corrected pure technical efficiency at the statistically significance. Additionally, the 48 firms hold the lower pure technical efficiency score than the scale efficiency score. These indicates that the majority of the firms face the managerial performance efficiency of input-output operation more seriously than resource allocation inefficiency.

Table 4 shows the mean efficiency scores by firm's location, public ownership, and foreign management influences. The table also shows the results of the two-sample t-test as p-value. Firm's location indicates whether a firm locates at the metropolitan districts, Kathmandu and Kaski districts, or not. Public ownership indicates whether a firm is owned by public organization or not. Foreign management influences indicates whether a firm is owned by foreign capital or hires non-Nepali workers at the management level. Case 1's results are only shown.

The mean differences in all bias-corrected efficiency scores between firms at the metropolitan and non-metropolitan districts are not statistically significant. The mean differences in overall and scale efficiency between public and non-public firms are statistically significant. The mean differences in overall and pure technical efficiency between foreign and non-foreign firms are statistically significant. Those indicates the non-public firms shows the higher scale efficiency and firms with foreign influences shows the higher pure technical efficiency; however, the metropolitan location of the firm does not matters the efficiency. Figures 3 and 4 are the choropleth maps, showing pure technical and scale efficiency, shaded in four classes according to the quartile classification. We could not find any specific clusters in pure technical efficiency.

4.3 Interfirm inequality decomposition in overall technical efficiency:

We explore the extent to which the efficiency factor contributes of *pe* and *se* to interfirm inequality in overall technical efficiency, using additive inequality decomposition of Theil's second measure in Equation (8). We calculated the interfirm inequality in bias-corrected overall technical efficiency in Case 1 and Case 2, $T(oe)$, are 0.178 and 0. 178, respectively. Additively decomposing, we found that the interfirm inequality in the pure technical efficiency, $T(pe)$, is the major decomposition factor contributing to the interfirm inequality in overall technical efficiency in both operations [$T(pe)$ = 0.234, $T(pe)$ = 0.238]. This indicates that the interfirm efficiency gaps in the managerial performance influences more on overall interfirm efficiency gap than interfirm efficiency gaps in the operation scale. To reduce the interfirm efficiency gap in the dairy sector, the assistances for the managerial technique and production technology plays the more significant role.

Besides, we found the high negative value of *I(pe, oe)*, -0.135 and -0.148, respectively. This indicates that the more efficient firms in the managerial performance tends to less efficient resource allocation.

5. Conclusion

We measure the relative input-output efficiency in Nepal's dairy processing firms, using DEA method. We found the huge inefficiency in the managerial performance to increase the firm's total sales and profits, keeping all the inputs constant, on average. The 80% of total firms operates inefficiently below the optimal scale due to its small size of operation and can improve its efficiency by increasing its operation scale. On the contrary, only five firms operates beyond optimal scale due to its large size of operation and those are mostly public firms.

As the conventional DEA efficient frontier can be warped by statistical noise, our study employs the bootstrapping approach to estimate the bias-corrected score. We found that the mean score values of the conventional overall technical and pure technical efficiency shows the statistically significant positive bias and are over-estimates of the true efficiency scores. We also found that the majority of the firms more seriously face the managerial performance efficiency of input-output operation than resource allocation inefficiency.

The paired t-test results for the bias-corrected mean efficiency score indicates that the firms with non-public ownership operate more efficiently in operation scale and firm with foreign management influences operate more efficiently in managerial performance; however, the metropolitan location of the firm does not matters the efficiency. Our decomposition analysis found that the interfirm gaps in managerial performance is larger than those in operation scale. Thus, technical supports for enhancement in managerial performance are more essential to improve efficiency than increase in for enlargement in operation scale. And the transfer technology from foreign firms may serve as possible solutions for firms' efficiency improvement.

Our work has several potential empirical extensions. First, other non-parametric efficiency analysis approach, such as stochastic frontier analysis, can be the next scope in this research subject. Second, the influencing factors to the operation performance efficiency is another extension. The third, the application to other sectors would be a great policy interest.

References

Adhikari, C. B., and Bjorndal, T. (2012). Analyses of technical efficiency using SDF and DEA models: Evidence from Nepalese agriculture. *Applied Economics, 44*(25), 3297-3308. doi:10.1080/00036846.2011.572856

Anand, S. (1983) *Inequality and poverty in Malaysia: Measurement and decomposition*. Oxford University Press, New York.

Barać, Ž. A., and Muminović, S. (2013). The impact of capital investments on dairy processing industry features: evidence from Slovenia, Croatia and Serbia. Mljekarstvo / Dairy, 63(3), 140-149.

Barnes, A. P., Rutherford, K. M. D., Langford, F. M., and Haskell, M. J. (2011). The effect of lameness prevalence on technical efficiency at the dairy farm level: An adjusted data envelopment analysis approach. *Journal of Dairy Science, 94*(11), 5449-5457.

Bhattacharjee, A.; de Castro, E.; Jensen-Butler, C. (2009) Regional variation in productivity: A study of the Danish economy. Journal of Productivity Analysis 31(3), 195–212.

Central Bureau of Statistics (2012) National Census of Manufacturing Establishments-2011/12, Survey data

Central Bureau of Statistics (2014) *Development of Manufacturing Industries in Nepal (Current State and Future Challenges)*

Central Bureau of Statistics (2016) *Statistical Yearbook of Nepal 2015*

Cheng, Y., and Li, S. (2006). Income Inequality and Efficiency: A Decomposition Approach and Applications to China. Economics Letters, 91 (1), 8-14.

Coelli TJ, Prasada R, Battese GE (2005) An introduction to efficiency and productivity analysis 2nd edition. Kluwer Academic Publishers, Boston.

Doucouliagos, H., and Hone, P. (2000). The efficiency of the Australian dairy processing industry. *Australian Journal of Agricultural and Resource Economics, 44*(3), 423.

Enflo, K. and P. Hjertstrand (2009). "Relative Sources of European Regional Productivity Convergence: A Bootstrap Frontier Approach." Regional Studies 43(5): 643-659.

Food Agricultural Organization (2010) *Dairy Sector Study of Nepal*

Jha, D. K., and Shrestha, R. (2006). Measuring efficiency of hydropower plants in Nepal using data envelopment analysis. *IEEE Transactions on Power Systems, 21*(4), 1502-1511.

Kapelko, M., Lansink, A. O., and Stefanou, S. E. (2017). Input-Specific Dynamic Productivity Change: Measurement and Application to European Dairy Manufacturing Firms. Journal of Agricultural Economics, 68(2), 579-599.

Kannan, E., and Birthal, P. S. (2010). Effect of trade liberalization on the efficiency of Indian dairy industry. *Journal of International and Area Studies, 17*(1), 1-15.

Kataoka, M. (2017). Inequality convergence in inefficiency and interprovincial income inequality in Indonesia for 1990-2010. *Asia-Pacific Journal of Regional Science*.

Kelly, E., Shalloo, L., Geary, U., Kinsella, A., Thorne, F., and Wallace, M. (2013). An analysis of the factors associated with technical and scale efficiency of Irish dairy farms. International *Journal of Agricultural Management* 2(3), 149-159.

Khanal, S., and Bhatta, B. (2017). Evaluating efficiency of personnel in Nepalese commercial banks. *International Advances in Economic Research, 23*(4), 379-394.

Moradi-Motlagh, A., et al. (2015). "Rising efficiency and cost saving in Australian banks: a bootstrap approach." Applied Economics Letters 22(3): 189-194.

National Dairy Development Board (2017) *Milk marketing strategy study in Nepal*

Ohlan, R. (2013). Efficiency and total factor productivity growth in Indian dairy sector. *Quarterly Journal of International Agriculture, 52*(1), 51-77.

Oczkowski and Sharma, (2005). Determinants of efficiency in least developed countries: Further evidence from Nepalese manufacturing firms. *Journal of Development Studies, 41(4)*

Ramphul. (2012). Productivity and efficiency analysis of Haryana's dairy industry. *Productivity, 53*(1), 42-50.

Scippacercola, S., and Sepe, E. (2016). Critical comparison of the main methods for the technical efficiency. *Electronic Journal of Applied Statistical Analysis, 9*(4), 760-780.

Shrestha, R. B., Huang, W., Gautam, S., and Johnson, T. G. (2016). Efficiency of small scale vegetable farms: Policy implications for the rural poverty reduction in Nepal. *Agricultural Economics / Zemedelska Ekonomika, 62*(4), 181-195.

Paradi, J.C, Vela S., Yang Z. (2006) Assessing Bank and Bank Branch Performance in Handbook on Data Envelopment Analysis 2nd eddtion 349-400

Simar, L. and P. W. Wilson (1998). "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models." Management Science 44(1): 49-61.

Simar, L.; Wilson, P.W. (1999) Estimating and bootstrapping Malmquist indices1. European Journal of Operation Research. 115(3), 459-471.

Singh, S., Coelli, T., and Fleming, E. (2001). Performance of dairy plants in the cooperative and private sectors in India. *Annals of Public and Cooperative Economics, 72*(4), 453.

Slade, P., and Hailu, G. (2016). Efficiency and regulation: A comparison of dairy farms in Ontario and New York State. *Journal of Productivity Analysis, 45*(1), 103-115.

Steeneveld, W., Tauer, L. W., Hogeveen, H., and Lansink, A. G. J. M. O. (2012). Comparing technical efficiency of farms with an automatic milking system and a conventional milking system. *Journal* of Dairy Science, 95(12), 7391-7398.

Tang R et al. (2014) The efficiency of provincial governments in China from 2001 to 2010: measurement and analysis. Journal of Public Affairs 14, 142-153

Theil H. (1967) *Economics and information theory*. Amsterdam: North-Holland.

Yanjiao, W., Jing, Z., and Yanan, C. (2017). Analysis on the Impact of Dairy Imports on Domestic Dairy Processing Industry, -From the Perspective of Productivity. *Revista De La Facultad De Ingenieria*, 32(10), 211-219.

Table 1 Descriptive statistics of input/output data (n=55, Unit: thousand NRS)

Variable	Case 1	Case 2	min	p25	p50	p75	max	mean	cv	skewness
Labor cost	Input	Input	208	886	1,350	3,802	94,461	5,663	2.593	4.704
Capital value	Input	Input	207	4,026	8,728	32,183	327,606	34,447	1.926	3.042
Intermediate goods	Input	Input	61	5,070	14,517	43,247	1,265,717	75,527	2.557	4.691
Total sales	Output	Output	86	7,962	20,668	75,370	2,093,678	116,345	2.661	5.058
Profit	Output		252	7,733	20,101	73,033	1,867,690	109,367	2.565	4.835

Table 2 Descriptive statistics of input-output efficiency score (n=55, Efficient DMU, if score =1)

Case 1												
variable	min	p25	p50	p75	max	mean	cv	skewness	Efficient DMU	IRS	CRS	DRS
oe	0.107	0.136	0.160	0.246	1.000	0.230	0.794	2.831	1			
pe	0.107	0.146	0.191	0.439	1.000	0.336	0.834	1.425	5			
se	0.160	0.849	0.937	0.996	1.000	0.824	0.315	-1.511	1	45	1	9
Case 2												
oe	0.098	0.135	0.156	0.232	1.000	0.223	0.817	2.957	1			
pe	0.098	0.144	0.191	0.433	1.000	0.333	0.844	1.438	5			
se	0.137	0.849	0.937	0.996	1.000	0.819	0.329	-1.525	1	45	1	9

Table 3 Homogeneous Bootstrap DEA efficiency scores and sample confidence intervals

Case 1	Conventional	BC	LB	UB
oe	0.230	0.171	0.085	0.217
pe	0.336	0.235	0.103	0.310
se	0.824	0.832	0.816	0.909
Case 2	Conventional	BC	LB	UB
oe	0.223	0.164	0.079	0.210
pe	0.333	0.234	0.104	0.309
se	0.819	0.816	0.807	0.828

Table 4 Mean efficiency score by group: Metro, Public, and Foreign (Case 1)

	Metro (n=14) vs Non-Metro (41)			Public (n=5) vs Non-public (n=50)			Foreign (n=2) vs Non-Foreign (n=53)		
	Metro	Non-Metro	p-value	Public	Non-public	p-value	Foreign	Non-Foreign	p-value
oe	0.167	0.183	0.324	0.118	0.176	0.004	0.629	0.154	0.075
pe	0.220	0.280	0.141	0.349	0.224	0.113	0.543	0.223	0.020
se	0.851	0.778	0.204	0.479	0.868	0.041	1.150	0.820	0.102

Note:
The parentheses shows the number of sample firms.
Metro: If firms lie in Kathmandu and Kaski districts Metro=1, Otherwise, Metro =0.
Public: If firms are owned by public organization, Public =1. Otherwise, Public=0.
Foreign: If firms employ the non-Nepali management and administrative workers, Foreign =1. Otherwise, Foreign=0.
The results of Case 2 are omitted as those are similar to those in Case 1.

Figure 1 Number of Firms by District (56 firms in total)

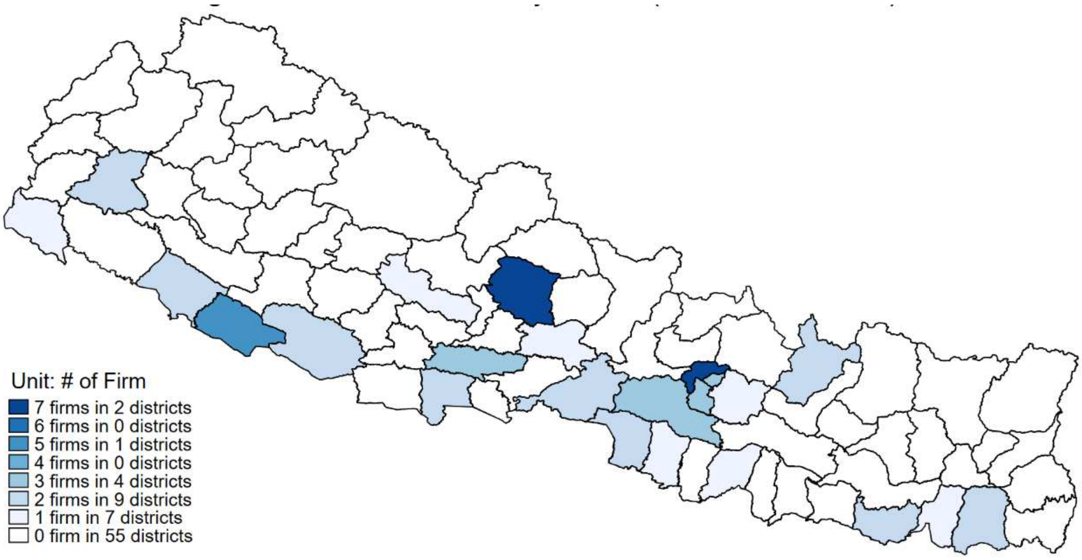


Figure 2 Pure technical efficiency by District (55 firms in total)

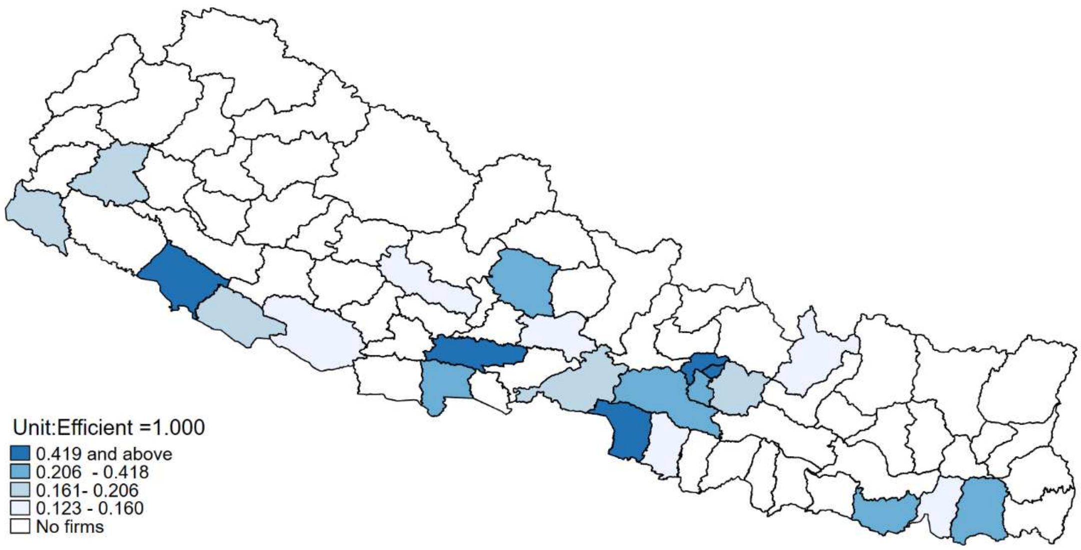
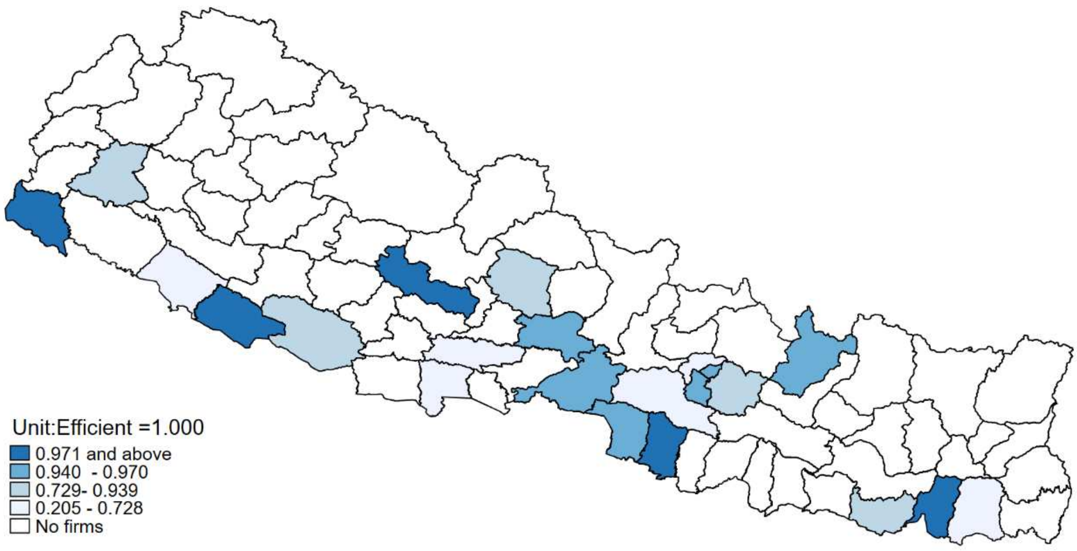
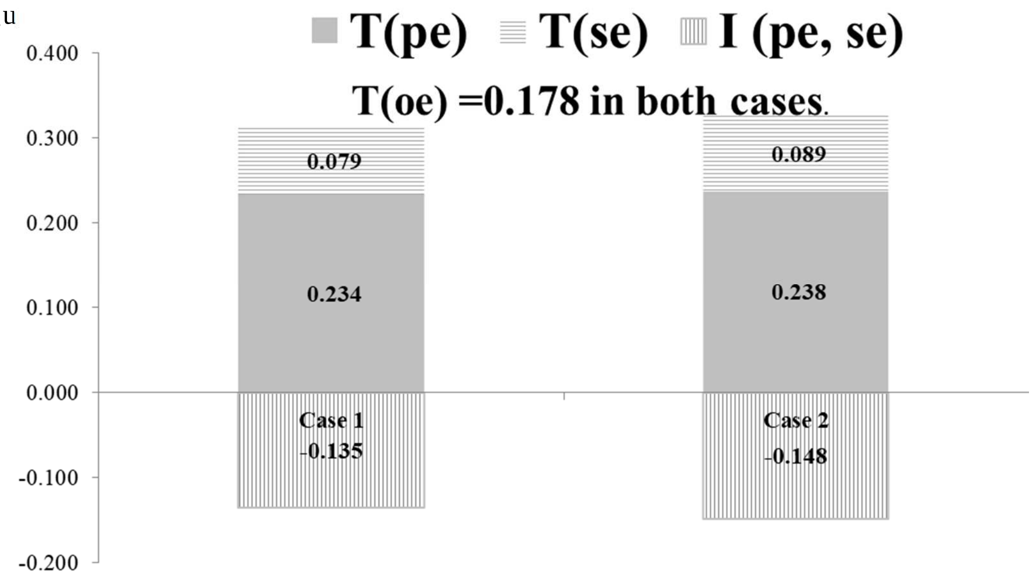


Figure 4 Scale efficiency by District (55 firms in total)



Figu


T(pe)
T(se)
I (pe, se)
T(oe) =0.178 in both cases.
0.400
0.300
0.200
0.100
0.000
-0.100
-0.200
0.079
0.234
Case 1
-0.135
0.089
0.238
Case 2
-0.148

Appendix Table 1 Conventional Efficiency score by Firm, Case 1 (55 firms in total)

Seq	District	Region	Yes	public	foreign	oe	pe	se	rts
1	Morang	Terai	No	Yes	No	0.178	0.691	0.257	drs
2	Morang	Terai	No	No	No	0.138	0.147	0.937	irs
3	Sunsari	Terai	No	No	No	0.134	0.135	0.999	irs
4	Saptari	Terai	No	No	No	0.133	0.139	0.960	irs
5	Saptari	Terai	No	No	No	0.302	0.331	0.913	irs
6	Dolakha	Mountain	No	No	No	0.152	0.152	0.997	irs
7	Dolakha	Mountain	No	No	No	0.135	0.147	0.921	irs
8	Kavre	Hill	No	No	No	0.156	0.176	0.886	drs
9	Lalitpur	Hill	Yes	No	No	0.246	0.247	0.995	irs
10	Lalitpur	Hill	Yes	No	No	0.127	0.127	0.999	irs
11	Lalitpur	Hill	Yes	No	Yes	0.679	0.738	0.919	drs
12	Bhaktapur	Hill	Yes	No	No	1.000	1.000	1.000	crs
13	Bhaktapur	Hill	Yes	No	No	0.140	0.144	0.969	irs
14	Bhaktapur	Hill	Yes	No	No	0.197	0.228	0.864	irs
15	Kathmandu	Hill	Yes	No	No	0.107	0.107	1.000	irs
16	Kathmandu	Hill	Yes	No	No	0.167	0.175	0.955	irs
17	Kathmandu	Hill	Yes	Yes	No	0.160	1.000	0.160	drs
18	Kathmandu	Hill	Yes	No	No	0.324	0.439	0.738	irs
19	Kathmandu	Hill	Yes	No	No	0.370	0.370	0.999	irs
20	Kathmandu	Hill	Yes	No	No	0.411	0.449	0.915	irs
21	Kathmandu	Hill	Yes	No	No	0.274	0.815	0.336	drs
22	Makwanpur	Hill	No	No	No	0.144	0.258	0.559	drs
23	Makwanpur	Hill	No	No	No	0.232	0.233	0.996	irs
24	Makwanpur	Hill	No	Yes	No	0.132	0.455	0.290	drs
25	Bara	Terai	No	No	No	0.122	0.125	0.984	irs
26	Parsa	Terai	No	No	Yes	0.936	1.000	0.936	irs
27	Parsa	Terai	No	No	No	0.291	0.298	0.976	irs
28	Chitawan	Terai	No	No	No	0.124	0.124	0.999	irs
29	Chitawan	Terai	No	No	No	0.204	0.226	0.901	irs
30	Tanahu	Hill	No	No	No	0.153	0.161	0.951	irs
31	Kaski	Hill	Yes	No	No	0.152	0.158	0.964	irs
32	Kaski	Hill	Yes	No	No	0.358	0.365	0.978	irs
33	Kaski	Hill	Yes	No	No	0.137	0.144	0.953	irs
34	Kaski	Hill	Yes	No	No	0.174	0.191	0.915	irs
35	Kaski	Hill	Yes	No	No	0.157	0.496	0.316	drs
36	Kaski	Hill	Yes	No	No	0.560	0.628	0.892	irs
37	Kaski	Hill	Yes	No	No	0.140	0.179	0.784	irs
38	Baglung	Hill	No	No	No	0.124	0.124	0.999	irs
39	Palpa	Hill	No	No	No	0.148	0.319	0.463	irs
40	Palpa	Hill	No	No	No	0.167	0.181	0.924	irs
41	Palpa	Hill	No	No	No	0.402	1.000	0.402	irs
42	Rupandehi	Terai	No	No	No	0.121	0.127	0.954	irs
43	Rupandehi	Terai	No	Yes	No	0.161	0.340	0.472	drs
44	Dang	Terai	No	No	No	0.125	0.146	0.858	irs
45	Dang	Terai	No	No	No	0.153	0.153	0.996	irs
46	Banke	Terai	No	No	No	0.136	0.136	0.998	irs
47	Banke	Terai	No	Yes	No	0.173	0.173	1.000	irs
48	Banke	Terai	No	No	No	0.128	0.128	0.997	irs
49	Banke	Terai	No	No	No	0.294	0.325	0.903	irs
50	Banke	Terai	No	No	No	0.125	0.125	0.998	irs
51	Bardiya	Terai	No	No	No	0.217	0.879	0.247	irs
52	Bardiya	Terai	No	No	No	0.163	1.000	0.163	irs
53	Doti	Hill	No	No	No	0.173	0.204	0.849	irs
54	Doti	Hill	No	No	No	0.148	0.149	0.992	irs
55	Kanchanpur	Terai	No	No	No	0.164	0.164	0.999	irs