DYNAMIC APPROACH TO EVALUATE THE IMPACT OF CONTEXTUAL VARIABLES IN AGRICULTURAL RESEARCH EFFICIENCY

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ABSTRACT

In this paper we measure technical efficiency for each of the Brazilian Agricultural Research Corporation research centers. We model DEA efficiency residuals as dependent on a set of contextual variables: improvement of administrative processes, quality of the reports on the impact of technologies generated by the research centers, intensity of partnerships and revenue generation. Intensity of partnerships and revenue generation are assumed to be endogenous to the production process. Estimation is based on generalized method of moments and dynamic panel data modeling. We conclude that there is a persistent inefficiency effect and statistically significant effects of lagged values of partnerships and revenue generation.

KEYWORDS. Contextual variables. Two-Stage Analysis. Dynamic panel data.

RESUMO

Neste artigo é medida a eficiência técnica de cada um dos centros de pesquisa da Empresa Brasileira de Pesquisa Agropecuária. Os resíduos da eficiência são modelados como dependentes de um conjunto de variáveis contextuais: melhoria de processos administrativos, qualidade dos relatórios sobre o impacto das tecnologias geradas pelos centros de pesquisa, intensidade de parcerias e geração de receita. As variáveis intensidade de parcerias e geração de receitas são assumidas como endógenas ao processo de produção. A estimação é baseada no método de momentos generalizados e em painel dinâmico de dados. Conclui-se que há um efeito de ineficiência persistente e efeitos estatisticamente significativos de valores defasados de parcerias e geração de receitas.

PALAVRAS-CHAVE. Covariáveis. Análise em dois estágios. Painel de dados dinâmico.

1. Introduction

The Brazilian Agricultural Research Corporation (Embrapa) monitors the production process of 37 of its 42 research centers since 1996, using a nonparametric Data Envelopment Analysis (DEA) production model. This model provides a measure of technical efficiency of production for each research center. For details see Souza et al. (1999, 2007, 2010, 2011).

The measure of technical efficiency proposed here assesses the performance of Embrapa's research centers using a single output and a three dimensional input vector. Inefficiency errors are stochastic and further assumed to be dependent on a set of contextual variables.

This article is concerned with the identification of contextual variables external or not to the production process, which may be affecting or causing efficiency. Typically these variables are in the control of the institution. The assessment of their effect is of managerial importance, since they may serve as a tuning device to improve management practices leading to efficient units. Here we are interested in studying the effects on technical efficiency of the improvement of administrative processes (PRO), impact of the technologies generated by the research centers (IMP), intensity of partnerships (PART) and revenue generation (REV).

The identification of causal factors of efficiency demands appropriate statistical modeling. The literature is rich in parametric and semi parametric statistical models to assess the significance of covariates in efficiency models. Typical semi parametric approaches can be seen in a DEA context in Simar and Wilson (2007) and Souza and Staub (2007). Recently, Souza (2006) and Souza et al. (2007) assessed the influence of covariates on the DEA efficiency measurements using analysis of variance, dynamic panel data, instrumental variables and maximum likelihood methods. The typical approach followed in those cases is based on a two-stage DEA. Efficiency measurements are computed in the first stage and then regressed on a set of covariates in the second stage. This approach has been criticized in the literature mainly by Simar and Wilson (2007, 2011).

Two problems arise in this context. Correlation among efficiency measurements in the first stage and endogeneity of the contextual variables which are typically involved in the production decisions. The first problem, given that contextual variables are indeed exogenous, does not seem to invalidate the approach even in the presence of heteroscedasticity. For a deterministic model, and assuming iid observations, Banker (1993) provides a motivation for the approach based on a univariate production function. Banker's results are extended for the non iid case by Souza and Staub (2007). Indeed there are cases where the correlation is not a problem at all. For example, in an Analysis of Variance model with a single positive response, the standard statistical analysis for treatment comparisons is obtained considering a DEA model with a unit input. In this instance the correlation is induced by the division of a response observation by its maximum. F and t tests are invariant under location and scale transformations. See Gomes et al. (2008) for additional details. Other references in which this assumption does not seem to be considered a problem are Coelli et al. (2005), Souza (2006), Souza et al. (2007, 2010, 2011), Ramalho et al. (2010, 2011), and Banker and Natarajan (2008, 2011). Here we test the validity of this assumption.

If the contextual variables are endogenous we believe that this situation may invalidate the statistical analysis in a way similar to what happens with simultaneous equations models. In this case, it is appealing to consider instrumental variable estimation in the second stage. To lessen the problem of interference of the covariates on the production frontier, Daraio and Simar (2007) proposed a measure based on the conditional FDH to obtain insights on the effects of covariates. The correlation problem is not addressed. Souza et al. (2010) explore these ideas and conclude via generalized method of moments (GMM) that the set of contextual variables is statistically significant for the Embrapa application. Their analysis is dynamic and they pinpoint efficiency persistence in the process and marginal significance of processes improvements, revenue generation capacity and changes in administration.

The model we propose here to assess the statistical significance of contextual variables is dynamic, based on DEA and follows the assumptions of Arellano and Bover (1995) and Blundell and Bond (1998). It is a two-stage approach. Inefficiencies computed in the first stage are assumed to follow a dynamic panel data where some of the right-hand side variables are endogenous. Endogeneity is taken care by proper instrumentalization.

Our exposition proceeds as follows. In Section 2 we review the production model relative to which DEA production functions produce interesting asymptotic statistical results and present the statistical model used in this article. In Section 3 we review Embrapa's production process and the production variables used in the analysis including contextual variables. Section 4 is on statistical results. Finally Section 5 summarizes our findings.

2. Production Functions, Statistical Models and Contextual Variables

Consider a production process with n production units, the Decision Making Units (DMUs). Each DMU uses variable quantities of s inputs to produce a single output y. Denote by $Y=(y_1,\dots,y_n)$ the $1\times n$ output vector, and by $X=(x_1,\dots,x_n)$ the $s\times n$ input matrix. Notice that the element $y_r>0$ is the output of DMU r and $x_r\geq 0$, with at least one component strictly positive, is the $s\times 1$ vector of inputs used by DMU r to produce y_r.

Let K be compact and convex in the nonnegative orthant of R^s. The maximum output (frontier output) achievable from $x\in K$ is given by the production function $y=g(x)$. We assume $g(x)$ to be continuous and, additionally,

1. Monotonicity: If $x\geq w$ are points in K, then $g(x)\geq g(w)$.
2. Concavity: If x and w are points in K, then $g(tx+(1-t)w)\geq tg(x)+(1-t)g(w)$, for $t\in[0;1]$.
3. For each $j=1,\dots,n,\ g(x_j)\geq y_j$.

One can use the observations (x_j,y_j), with $x_j\in K$, and DEA to estimate $g(x)$ only in the set (1).

$$K^*=\left\{x\in K; x\geq\sum_{j=1}^{n}\lambda_j x_j, \text{for some } (\lambda_1,\dots,\lambda_n)\geq 0, \sum_{j=1}^{n}\lambda_j=1\right\} \quad (1)$$

For $x\in K^*$ the DEA production function is defined by (2).

$$g_n^*(x)=\sup_{\lambda_1,\dots,\lambda_n}\left\{\sum_j\lambda_j y_j; \sum_j\lambda_j x_j\leq x, \lambda_j\geq 0, \sum_{j=1}^{n}\lambda_j=1\right\} \quad (2)$$

This formulation imposes variable returns to scale. If the technology defined by $g(x)$ shows constant returns to scale only non negativity is imposed on the weights λ_j.

The subset K^* is convex and closed in K. For each r, $g_n^*(x_r)=\phi_r^* y_r$, where ϕ_r^* is the solution of the LP problem $max_{\phi,\lambda}\phi$ subject to $\sum_j\lambda_j y_j\geq\phi y_r$ and $\sum_j\lambda_j x_j\leq x_r$, $\lambda=(\lambda_1,\dots,\lambda_n)\geq 0$, $\sum_j\lambda_j=1$. The function $g_n^*(x)$ satisfies conditions 1-3 and has the property of minimum extrapolation, that is, $g(x)\geq g_n^*(x), x\in K^*$.

If one assumes that the production observations (x_j,y_j) satisfy the deterministic statistical model $y_j=g(x_j)-\varepsilon_j$, where the technical inefficiencies ε_j are nonnegative random variables with probability density functions $f_j(\varepsilon)$ concentrated on R^+, and the inputs x_j are a random sample drawn independently with density functions $h_j(x)$ with support set contained in K, one can show that if x_0 is a point in K^* interior to K, then $g_n^*(x_0)$ converges almost surely to $g(x_0)$.

Let M be a subset of the DMUs included in the sample that generates the n production observations. The asymptotic joint distribution of the technical inefficiencies $\varepsilon_{nj}^* = g_n^*(x_j) - y_j,\ j \in M$, coincides with the product distribution of the $\varepsilon_j,\ j \in M$. See Souza and Staub (2007), where one can see the extension of Banker (1993) results to not equally distributed inefficiencies.

The order of ideas above is used in Souza and Staub (2007) to analyze treatment effects and apparently assumed to be true in Banker and Natarajan (2008, 2011).

Although the deterministic model may be used as a motivation for two-stage regressions assuming, for example, that $\varepsilon_{nj}^* = \exp\left\{h\left(z_{nj}\right)\right\} w_{nj}$ is true, where w_{nj} is a positive random variable and $h(z)$ is a function of contextual variables z, this formulation does not handle the problems of persistent inefficiencies, endogeneity of some of the contextual variables and potential serial correlation. For this reason we prefer to use the statistical model (3), where z_{njt}^1 is a vector of strictly exogenous covariates, z_{njt}^2 are endogenous covariates, α's and β's are parameters to be estimated, the ν_j are the panel-level effects, the u_{njt} are independent of ν_j and iid over the whole sample with variance σ_u^2. See Stata (2011). The model is robust against first order serial correlation. In (3) t represents time, l represents the lags and all contextual variables are in log form and include lagged values.

$$\log\left(\varepsilon_{njt}\right) = \sum_{l=1}^{L} \alpha_l \log\left(\varepsilon_{njt-1}\right) + z_{njt}^1\beta_1 + z_{njt}^2\beta_2 + \nu_j + u_{njt},\ \ j = 1 \ldots n,\ t = 1 \ldots T_j \qquad (3)$$

3. Embrapa's Production Model

The following discussion mimics Souza et al. (2010).

Embrapa's research system currently comprises 42 research centers. Five of these units were recently created and are not formally included in the evaluation system. For this reason, our sample consists of 37 DMUs. Input and output variables have been defined from a set of performance indicators known to the company since 1991. The company uses routinely some of these indicators to monitor performance through annual work plans. With the active participation of the board of directors of Embrapa as well as the administration of each of its research units, 28 output and three input indicators were selected as representative of production actions in the company.

The output indicators were classified into four categories: Scientific production; Production of technical publications; Development of technologies, products, and processes; Diffusion of technologies and image. By scientific production we mean the publication of articles and book chapters aimed mainly to the academic world. We require that each item be specified with complete bibliographical reference. Specifically the category of scientific production includes the following items.

1. Scientific articles published in refereed journals and book chapters – domestic publications.
2. Scientific articles published in refereed journals and book chapters – foreign publications.
3. Articles and summaries published in proceedings of congresses and technical meetings.

The category of technical publications groups publications produced by research centers aiming, primarily, agricultural businesses and agricultural production. Specifically,

1. Technical circulars. Serial publications, written in technical language, listing recommendations and information based on experimental studies. The intended coverage may be the local, regional or national agriculture.
2. Research bulletins. Serial publications reporting research results.
3. Technical communiqués. Serial publications, succinct and written in technical language, intended to report recommendations and opinions of researchers in regard to matters of interest to the local, regional or national agriculture.
4. Periodicals (document series). Serial publication containing research reports, observations, technological information or other matters not classified in the previous categories. Examples are proceedings of technical meetings, reports of scientific expeditions, reports of research programs etc.
5. Technical recommendations/instructions. Publication written in simplified language aimed at extensionists and farmers in general, and containing technical recommendations in regard to agricultural production systems.
6. Ongoing research. Serial publication written in technical language and approaching aspects of a research problem, researches methodologies or research objectives. It may convey scientific information in objective and succinct form.

The category of development of technologies, products, and processes groups indicators related to the effort made by a research unit to make its production available to society in the form of a final product. We include here only new technologies, products and processes. These must be already tested at the client's level in the form of prototypes or through demonstration units or be already patented. Specifically,

1. Cultivars. Plants varieties, hybrids or clones.
2. Agricultural and livestock processes and practices.
3. Agricultural and livestock inputs. All raw materials, including stirps, that may be used or transformed to obtain agricultural and livestock products.
4. Agro-industrial processes. Operations carried out at commercial or industrial level envisaging economic optimization in the phases of harvest, post harvest and transformation and preservation of agricultural products.
5. Machinery (equipment). Machine or equipment developed by a research unit.
6. Scientific methodologies.
7. Software.
8. Monitoring, zoning (agro ecologic or socioeconomic) and mapping.

Finally, the category of diffusion of technologies and image encompasses production actions related with Embrapa's effort to make its products known to the public and to market its image. Here we consider the following indicators.

1. Field days. Research units organize these events. The objective is the diffusion of knowledge, technologies, and innovations. The target public is primarily composed of farmers, extensionists, organized associations of farmers (cooperatives), and undergraduate students. The field day must involve at least 40 persons and last at least 4 hours.
2. Organization of congresses and seminars. Only events with at least 3 days of duration time are considered.
3. Seminar presentations (conferences and talks). Presentation of a scientific or technical theme within or outside the research unit. Only talks and conferences with a registered attendance of at least 20 persons and duration time of at least one hour are considered.
4. Participation in expositions and fairs. Participation is considered only in the following cases: (a) With the construction of a stand with the purpose of showing

the center's research activities by audiovisuals and distributing publications uniquely related to the event's theme; (b) Co-sponsorship of the event.

5. Courses. Courses offered by a research center. Internal registration is required specifying the course load and content. The course load should be at least 8 hours. Disciplines offered as part of university courses are not considered.
6. Trainees. Concession of college level training programs to technicians and students. Each trainee must be involved in training activities for at least 80 hours to be counted in this item.
7. Fellowship holders. Orientation of students (the fellowship holders). The fellowship duration should be at least six months and the workload at least 240 hours.
8. Folders. Only folders inspired by research results are considered. Re-impressions of the same folder and institutional folders are not counted.
9. Videos. Videos should address research results of use for Embrapa's clients. The item includes only videos of products, services and processes with a minimum duration time of 12 minutes.
10. Demonstration units. Events organized to demonstrate research results – technologies, products, and processes, already in the form of a final product, in general with the co-participation of a private or government agent of technical assistance.
11. Observation units. Events organized to validate research results, in space and time, in commercial scale, before the object of research has reached its final form. Observations units are organized in cooperation with producers, cooperatives, and other agencies of research or private institutions. The events may be organized within or outside the research unit.

The input side of Embrapa's production process is composed of three factors:

1. Personnel costs. Salaries plus labor duties.
2. Operational costs. Expenses with consumption materials, travels and services, less income from production projects.
3. Capital. Measured by depreciation.

As indicators (inputs and outputs) of the process we consider a system of dimensionless relative indices. These are all quantity indexes. The idea, from the output point of view, is to define a combined measure of output as a weighted average of the relative indicators (indices). The relative indices are computed for each production variable and for each research unit within a year dividing the observed production quantity by the mean per research unit. Only research units that can potentially exercise the production activity related to the production variable in question are included in the computation of the mean. We see that, within a given year, the base of our system of production indices is defined by the set of means per unit defined by the production variables. In case of inputs the means use all 37 cases.

The input indices are indicated by x_i^o, i = 1, 2, 3. These quantities represent relative indices of personnel, operational expenditures, and capital expenditures, respectively.

Output measures per category are defined as follows. The output component y_i, i = 1, 2, 3, 4, of each production category is a weighted average of the relative indices composing the category. If o is the DMU (research unit) being evaluated then $y_i^o = \sum_{j=1}^{k_i} a_{ji}^o y_{ji}^o;\ 0 \le a_{ji}^o;\ \sum_{j=1}^{k_i} a_{ji}^o = 1$, where $a_{ji}^o,\ j = 1, \ldots, k_i$ is the weight system for DMU o in the category of production i, k_i is the number of production indicators comprising i and y_{ji}^o is the relative index of production j. The weights, in principle, are supposed to be user defined and should reflect the administration's perception of the relative importance of each variable to each DMU. Defining weights is a hard and questionable task. In our application in Embrapa we followed an approach based on the law of categorical judgment of Thurstone. See Torgerson (1958) and Kotz and Johnson (1989). The model is competitive with the AHP method of Saaty (1994) and is well suited when several judges are involved in the evaluation process. Basically we sent out about 500 questionnaires to researchers and administrators and asked them to rank in importance – scale from 1 to 5 – each production category and each production variable within the corresponding production category. A set of weights was determined under the assumption that the psychological continuum of the responses projects onto a lognormal distribution.

The efficiency models implicitly assume that the production units are comparable. This is not strictly the case in Embrapa. To make them comparable it is necessary an effort to define an output measure adjusted for differences in operation and perceptions. At the level of the partial production categories we induced this measure allowing a distinct set of weights for each production unit. In principle one could go ahead and use multiple outputs. This would minimize the effort of defining weights. The problem with such approach is that there is a kind of dimensionality curse in efficiency models. As the number of factors (inputs and outputs) increases, the ability to discriminate between units decreases. As Seiford and Thrall (1990) put it, given enough factors, all (or most) of the DMUs are rated efficient. This is not a flaw of the methodology, but rather a direct result of the dimensionality of the input/output space relative to the number of units. Thus the set of production variables monitored by Embrapa comprises an output y and a three dimensional input vector $\left(x^1,\ x^2,\ x^3\right)$. For the period 2002-2009 we have balanced information on the vector $\left(x^1,\ x^2,\ x^3,\ y\right)$ for all 37 Embrapa's research centers.

Embrapa's production system is being monitored since 1996. Measures of efficiency and productivity are calculated and used for several managerial objectives. One of the most important is the negotiation of production goals with the individual research units. A proper management of the production system as a whole requires the identification of good practices and the implementation of actions with a view to improve overall performance and reduce variability in efficiency among research units. Parallel to this endeavor is the identification of non-production variables that may affect positively or negatively the system. It is of managerial interest to detect controllable attributes causing the observed best practices.

We use the information for the period 2002 to 2009 to analyze the effect of contextual variables on Embrapa's production model following the procedures laid out in the previous section. In this context we consider a vector of four covariates, corresponding to processes improvements (PRO), impact of technologies (IMP), intensity of partnerships (PART) and revenue generation (REV). These are considered continuous scores. IMPs are scores computed by Embrapa's administration reflecting perceptions regarding the quality of the reports on the impact of the technologies developed by the research centers – it's about form and contents of the reports, not about the importance of the technologies under concern. PRO is a value intended to measure the successful implementation of changes on some administrative processes. These processes are selected by the local research center. REV is a ratio of external to government funding. PART is a weighted average of external and internal partnerships, in which the weights are defined by the administration. Variables PART and REV are assumed to be endogenous to the production process.

We are aware that the use of ratios in DEA may pose convexity problems in the original scale of the production variables as emphasized in Hollingsworth and Smith (2003) and Emrouznejad and Amin (2009). Our choice was not to solve the problem via a new programming problem (Emrouznejad and Amin, 2009) but to impose the VRS assumption and interpret the DEA solution in the proper scale, as suggested in Hollingsworth and Smith (2003). In this regard, by using nonparametric methods, we have rejected the CRS assumption consistently in all years considered in our analysis (2002-2009).

4. Statistical Results

To test for random samples within years we used the run test of Swed and Eisenhart (1943). The null hypothesis of a random sample was not rejected for any point in time for the log of the inefficiency residuals excluding the efficient units. For purposes of illustration Table 1 (in the next page) presents the data base used in our work for 2009. For 2009 the p-value of the run test is 0.71.

Table 2 shows the estimation results. We used Stata 12 software in our analyses.

Table 2. Results of GMM estimation.

	Coefficient	Robust Standard Error	z	P>|z|	95% Confidence Interval]	
Residual						
lag(Residual)	0.1890	0.1064	1.78	0.076	-0.0194	0.3975
PRO						
--.	-0.0255	0.0701	-0.36	0.716	-0.1629	0.1118
lag(PRO)	0.0619	0.1176	0.53	0.599	-0.16869	0.2924
IMP						
--.	0.2799	0.3219	0.87	0.385	-0.3510	0.9108
lag(IMP)	-0.3053	0.2909	-1.05	0.294	-0.8755	0.2650
PART						
--.	-0.0757	0.1294	-0.58	0.559	-0.3293	0.1779
lag(PART)	-0.2499	0.06217	-4.02	0.000	-0.3718	-0.1281
REV						
--.	0.0080	0.1199	0.07	0.947	-0.22688	0.2429
lag(REV)	-0.1718	0.0542	-3.17	0.002	-0.2781	-0.0655
year	0.0130	0.0593	0.22	0.826	-0.1033	0.1293
constant	0.7624	1.1602	0.66	0.511	-1.5116	3.0363

The specification test of Arellano-Bond for zero autocorrelation in first-differenced errors is not significant (p-value 0.73) and does not indicate misspecification of the model. As one can notice in Table 2 we found a marginal persistent inefficiency effect and significant lag effects of PART and REV in the direction of efficiency improvement. IMP and PRO were not significant statistically.

5. Summary and Conclusions

We fit a dynamic non parametric (DEA) model for production data generated by Embrapa research centers for 2002-2009. A single combined output with a three dimensional input vector were used to model production. Residuals from DEA projections were computed under the assumption of variable returns to scale.

We proceeded to investigate the effects of contextual variables ‘processes improvements’, ‘quality of the impact report on the generated technologies’, ‘intensity of partnerships’, and ‘revenue generation’ in the DEA residuals after projections. Using a dynamic panel accounting for serial correlation and endogeneity we found a marginal persistent inefficiency effect and significant lag effects for PART and REV in the direction of efficiency improvement. IMP and PRO were not significant statistically.

The message here is that Embrapa’s administration should not insist on the form of impact reports and on minor local changes as causing performance.

6. Acknowledgment

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Table 1. Production data and contextual variables. Inputs are X1, X2, X3. Output is Y. Contextual variables are processes improvement (PRO), impact (IMP), partnerships (PART) and revenue (REV). Year = 2009.

	X1	X2	X3	Y	PRO	IMP	PART	REV
DMU1	1.9491	2.3100	2.7117	1.5779	71.38	1.42	3.45	71.30
DMU2	0.9475	0.7801	0.6516	0.8873	45.88	4.27	3.64	36.50
DMU3	0.6054	0.6833	0.7612	1.5432	88.38	3.53	5.65	61.20
DMU4	1.3058	1.1456	1.1190	0.5541	72.79	4.20	7.65	17.70
DMU5	1.0482	1.1079	1.1601	1.3029	88.88	2.86	3.09	21.00
DMU6	0.6746	0.8532	0.6409	0.7294	58.50	3.86	8.15	21.40
DMU7	0.4377	0.5439	1.0545	1.8501	58.42	2.22	3.81	142.60
DMU8	1.0210	0.7785	0.7123	1.0453	80.68	4.61	3.91	44.40
DMU9	0.9175	0.9185	1.8102	0.7664	80.92	3.94	4.09	95.10
DMU10	1.3485	0.9039	1.5332	0.7837	95.13	4.10	4.15	262.70
DMU11	0.9720	1.0944	1.0455	0.7466	85.88	3.75	5.17	51.50
DMU12	1.0433	0.7983	1.0437	1.0598	57.75	4.10	6.17	7.30
DMU13	1.0481	1.0375	0.7269	1.2256	70.04	4.91	4.42	29.30
DMU14	1.4299	1.4462	1.4492	1.0583	81.88	4.07	7.40	74.80
DMU15	0.9104	0.7062	0.7744	1.0922	73.63	3.32	2.51	56.40
DMU16	0.8805	0.8380	0.9973	0.6600	79.48	4.54	3.18	76.30
DMU17	1.3737	1.7809	1.5852	1.1443	47.43	4.72	5.43	195.40
DMU18	1.0264	0.9054	0.9540	0.9172	76.50	4.47	5.75	72.90
DMU19	0.5765	0.5647	0.6141	1.8501	92.25	4.96	4.55	21.00
DMU20	0.6892	0.9250	1.0699	0.7055	76.38	4.02	6.10	31.30
DMU21	1.2903	1.1155	0.8306	0.5272	73.38	3.91	6.44	14.70
DMU22	1.7702	1.7286	1.5338	0.5682	85.38	4.22	5.16	56.70
DMU23	1.6006	1.7150	1.8198	1.1389	84.08	3.16	7.46	91.00
DMU24	0.7749	1.1940	0.6730	0.6848	85.40	3.84	6.87	19.10
DMU25	0.5078	0.4727	0.2901	0.4944	73.00	1.41	13.71	16.70
DMU26	0.7037	0.5547	0.4159	1.1163	.	3.10	15.39	34.00
DMU27	0.6122	0.5341	0.6379	1.4728	50.17	3.73	12.89	15.90
DMU28	1.1706	1.0919	0.8334	0.5575	2.50	1.77	7.03	95.10
DMU29	0.6368	0.7740	0.5731	0.6497	73.88	4.51	16.09	24.40
DMU30	0.7758	0.5738	0.6142	0.8509	86.54	4.85	4.90	9.70
DMU31	1.0206	0.9173	0.6094	1.2273	95.50	2.71	9.53	21.50
DMU32	1.3446	1.3243	1.1444	0.6782	65.14	4.32	5.70	49.60
DMU33	2.3904	2.1439	1.5218	0.8324	83.13	4.32	7.11	40.30
DMU34	0.6753	0.6457	0.7747	0.9863	83.80	4.35	5.55	61.50
DMU35	0.4118	0.4548	0.5033	1.5013	18.88	4.67	11.4	21.60
DMU36	0.7590	0.8277	1.0633	1.8501	90.25	3.04	4.45	46.70
DMU37	0.3500	0.8103	0.7465	0.7627	.	4.26	2.42	121.80

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