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Evaluating Technical Efficiency of Turkish Sugar Production in Pre and Post Privatization Periods

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Türk Şeker Üretiminin Özelleştirme Öncesi ve Sonrası Teknik Etkinliğinin Değerlendirilmesi

Abstract

The sugar production sector of Turkey has undergone a large-scale privatization in 2018. Since then, 10 out of 33 sugar factories have been privatized. The objective of this research is to investigate the effects of the privatization on the technical efficiency of the sugar factories. For this purpose, the data of 31 factories operating in different parts of the country are utilized. We evaluate the efficiency before and after privatization in two periods: pre-privatization (September 2017 - August 2018) and after-privatization (August 2018 - September 2019) using Data Envelopment Analysis, Malmquist Productivity Index and DEA by Sequential Exclusion of Alternatives methods. First, while results derived from all models reveal a technical efficiency decline among factories in general, the privatized factories stand out as the only subset that experience an increase in technical efficiency for the period analysed. Secondly, the benchmarks for the inefficient factories are identified in the short term and the long term using 'DEA by Sequential Exclusion of Alternatives' to assist improvement decisions. Finally, the research presents some methodological insights on the application of the 'DEA by Sequential Exclusion of Alternatives' approach by experimenting with changing parameters that have the potential to aid future applications.

Keywords : Sugar Production, Technical Efficiency, Data Envelopment Analysis, Privatization.

JEL Classification Codes : C14, D24, L33, L66.

Öz

2018 yılında Türk şeker sanayisi büyük ölçekli bir özelleştirmeyi tecrübe etmiştir. O yıl, 33 şeker fabrikasından 10 adeti özelleştirilmiştir. Bu araştırmanın amacı, bu özelleştirmelerin fabrikaların Teknik etkinliğine olan etkisini gözlemlemektir. Bu amaçla ülkenin çeşitli bölgelerinde yer alan 31 adet fabrikanın verisi kullanılmaktadır. Teknik etkinlik, Veri Zarflama Analizi (VZA), Malmquist Verimlilik Endeksi ile Alternatiflerin sıralı hariç tutulmasına dayalı VZA yöntemleri kullanılarak iki dönem için değerlendirilmektedir: özelleştirme öncesi (Eylül 2017 - Ağustos 2018) ve özelleştirme sonrası (Ağustos 2018 - Eylül 2019). Sonuçlar, öncelikle, analiz edilen dönemler arasında genel anlamda bir etkinlik düşüşüne işaret etmektedir. Bununla beraber, özelleşen fabrikalar etkinlikte artış gösteren tek alt küme olmaktadır. Araştırma, etkin olmayan fabrikalar için alternatiflerin sıralı hariç tutulmasına dayalı VZA kullanılarak elde edilen referans kümelerini de sunmaktadır. Çalışma ayrıca bu metodun gelecek uygulamalarına bir kavrayış sağlama amacına yönelik parametre değerlerinin değiştirilmesine dayanan testler de içermektedir.

Anahtar Sözcükler : Şeker Üretimi, Teknik Etkinlik, Veri Zarflama Analizi, Özelleştirme.

1. Introduction

Sugar is produced either from sugar cane or sugar beet in more than 100 countries in the world. While sugar cane constitutes 78% of the global sugar production, sugar beet corresponds to 22%. Following Russia, France, Germany, and the United States, Turkey is ranked as the fifth country in the world producing sugar from beets and the fourth country in Europe. The share of the country in the world's sugar beet production is about 7% (FO Licht, 2019). In the 2018/2019 marketing period, with the increase in quotas, 20.5 million metric tons (MMT) of sugar beet have been produced in the 335,000 hectares (ha) harvesting area (USDA, 2019).

Recently, the sugar production sector of Turkey has experienced large scale privatization. 10 out of 33 sugar factories have been privatized during 2018 and the plan is to resume privatization during 2020 (USDA, 2019). The privatization in Turkish sugar production is important since the factories play an eminent role in the economy of the provinces they are located. Such a large-scale privatization may have effect on the labor force through massive layoffs and on the producers & organizations take part in sugar production (Cicek & Sahin, 2018). In this research, the main objective is to investigate the effects of this mass privatization on the technical efficiency of the sugar factories. For this purpose, we utilize the data of 31 factories operating in different parts of the country and evaluate the efficiency before and after privatization in two periods. The first period covers pre-privatization (September 2017 - August 2018) and the second one covers post-privatization (August 2018 - September 2019).

The methodology of the research is mainly based on the Data Envelopment Analysis (DEA). DEA, proposed by Charnes et al. (1978), is a well-known linear programming-based methodology for efficiency evaluation, in which homogeneous Decision-Making Units (DMUs) producing multiple outputs through the use of multiple inputs are evaluated relative to a non-parametric efficient frontier. The method produces relative efficiency scores for the evaluated units between 0 and 1 as well as benchmark units for the inefficient units, which is valuable for decision-making for future advancements. Build upon DEA, the change of the scores from one period to another is usually measured with Malmquist Productivity Index (MPI) approach developed by Caves et al. (1982) and Färe et al. (1992). One of the major application areas of DEA and MPI is agricultural production (see Emrouznejad et al., 2008; Atıcı & Podinovski, 2012). It has been applied to evaluate efficiency in sugar production as well (see Section 2 for a brief review).

In theory, one of the main assumptions of the DEA method is the homogeneity of the evaluated units. However, derivations of the method to deal with potential heterogeneity of the units have been introduced in the literature. One of the methods that enable us to handle heterogeneity is DEA by Sequential Exclusion of Alternatives (DEA-SEA) proposed by Aleskerov & Petrushchenko (2013; 2015) and Abankina et al. (2016). The method relies on

adjustment of the efficient units to the barycentre of the production set so that the potential drawbacks of heterogeneity and outliers are undermined. Furthermore, since the frontier approaches the barycentre, it is possible to obtain more attainable targets for the inefficient units for the shorter terms. Since our data set consists of both public, private and privatized factories operating in different regions of the country and therefore, heterogeneity to some extent can be assumed, we also employ DEA-SEA methodology for both periods and observe the changes. The method is also applied since it has a potential to produce longer and shorter-term reference sets and these sets can provide insight for future decisions at factory level.

The contributions of the research are threefold. First of all, we investigate the effects of recent privatization on the sugar factories of Turkey comprehensively and reveal a technical efficiency increase after privatization from different angles. Secondly, the research also provides benchmarking information for the inefficient factories in the short term and the long term to assist enhancement decisions. Finally, we present methodological insights on the DEA-SEA approach in a first-time application of the method in agricultural sectors through experimenting with changing parameters that have the potential to aid future applications.

The current paper is organized as follows. Section 2 provides the related literature on efficiency measurement in sugar farming and production. In Section 3, we present the basics of the methods used in the research. Section 4 presents the findings of the empirical analysis together with the description of the data. Finally, Section 5 concludes with the implications of the findings.

2. Previous Research on Efficiency in Sugar Production

The top ten sugar-producing countries in the world (India, Brazil, Thailand, China, USA, Mexico, Russia, Pakistan, France, and Australia) supply almost 70% of global production in 2018-2019 (October-September season). In the literature, it is possible to find a wide range of research that efficiency measurement methods have been applied in both sugar farming and production of various countries including the leading ones. Table 1 presents a sample of the research that focuses on efficiency at two different levels as factory-level and farm-level. The majority of the research has been conducted in Asian countries such as India, Iran, Pakistan, Thailand, and China. There also exists research that focuses on the sugar production sectors of European countries such as the Netherlands, Hungary, Ireland, Denmark, Ukraine, and Turkey.

Applied methods can be considered in two categories as parametric and non-parametric approaches. Usually, a single modelling approach has been employed. On the non-parametric side, the research is dominant with Data Envelopment Analysis. On the parametric side, Stochastic Frontier Analysis is the dominant methodology. Studies employing both types also exist (Wu et al., 2003; Mulwa et al., 2009).

It is also observed the greater number of the research deals with multiple periods, hence, with panel data. In DEA research it is common to use Malmquist Productivity Index

(MPI) to observe the changes in efficiency over time (e.g. Raheman et al., 2009; Ye et al., 2016).

Table: 1
A Sample of Efficiency Research on Sugar Production

Study	Country	Period	Level	Method
<i>Ferrantino & Ferrier (1995)</i>	India	1980-1985	Factory-level	SFA
<i>Johnson et al. (1995)</i>	USA	1986-1992	Factory-level	SFA
<i>De Koeijer et al. (2002)</i>	Netherlands	1994-1997	Farm-level	DEA
<i>Wu et al. (2003)</i>	USA	not noted	Farm-level	NPM & TOBIT
<i>Fogarasi (2006)</i>	Hungary	2004-2005	Farm-level	DEA & MPI
<i>Murty et al. (2006)</i>	India	1996-1999	Factory-level	MPI
<i>Bogetoft et al. (2007)</i>	Denmark	2003	Farm-level	DEA
<i>Mulwa et al. (2009)</i>	Kenya	1980-2000	Factory-level	DEA & SFA
<i>Goncharuk (2009)</i>	Ukraine	2006	Factory-level	DEA
<i>Raheman et al. (2009)</i>	Pakistan	1998-2007	Factory-level	DEA & MPI
<i>Demirtas (2011)</i>	Turkey	2009-2010	Factory-level	DEA
<i>Kumar & Arora (2011)</i>	India	2003-2004	Factory-level	DEA
<i>Patilola et al. (2012)</i>	India	1992-2007	Factory-level	SFA
<i>Palcic & Reeves (2015)</i>	Ireland	1984-2000	Factory-level	TFP
<i>Ye et al. (2016)</i>	China	2004-2013	Farm-level	DEA & MPI
<i>Borjheipour et al. (2017)</i>	Iran	2002	Factory-level	DEA
<i>Murali & Prathap (2017)</i>	India	2011-2013	Farm-level (Cane)	SFA
<i>Ullah et al. (2019)</i>	Thailand	not noted	Farm-level (Cane)	DEA
<i>Duarte et al. (2019)</i>	Brazil	2010-2014	Factory-level	DEA

Abbreviations: DEA: Data Envelopment Analysis, SFA: Stochastic Frontier Analysis, MPI: Malmquist Productivity Index, NPM: Non-parametric Methods, TFP: Total Factor Productivity.

The privatization of the sugar production entities is of interest in various research. The impact of privatization on technical efficiency has been measured and discussed. For instance, Mulwa et al. (2009) analyse the change in efficiency before and after the privatization of the firms (in 1992) operating in the sugar industry in Kenya for the 1980-2000 period by using Data Envelopment Analysis and Stochastic Frontier Analysis approaches. Interestingly, no statistically significant difference is detected between the two periods. However, they reveal a decline in efficiency levels between the years 1992 and 1998 followed by an increase in the succeeding years. Palcic & Reeves (2015) study the financial and economic performance of Irish Sugar Company for 10 years before and after privatization. Although the company exhibited rapid growth and recovery in the pre-privatization period, it has been detected that privatization has no strong relationship with financial performance and productivity. The company's food division's performance has been greatly influenced by its exposure to market forces after privatization. However, surprisingly, there has been no improvement in overall performance in a highly competitive environment.

The privatization of Turkish sugar factories has been on the agenda for several years. In an earlier study than this current research Demirtas (2011) mentions the importance of investigating the Turkish Sugar Inc., which is one of the most important companies in Turkey and holding the 25 sugar factories in the year of the research. It is stated that the efficiency values calculated with the help of the DEA-based clustering approach can guide the decision-makers in the privatization process. However, privatization has not taken place until 2018.

3. Methodology

3.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a well-established non-parametric method aiming to identify relative efficiency of homogeneous Decision-Making Units (DMUs) producing multiple outputs through the use of multiple inputs. DEA has presented to the literature by the seminal research of Charnes et al. (1978). The efficiency of a DMU is measured relative to all other DMUs with the simple restriction that all DMUs lie on or below an efficient frontier (Seiford & Thrall, 1990).

Let us consider n decision-making units. We assume that each decision-making unit j for $j = 1, 2, \dots, n$ uses m different inputs. x_{ij} . For $i = 1, 2, \dots, m$ and produces s different outputs. y_{rj} . For $r = 1, 2, \dots, s$. Let ϕ represent the efficiency score for unit o . Variables λ_j are introduced corresponding to each decision-making unit ($j = 1, 2, \dots, n$) to form a Production Possibility Set (PPS) consisting of observed units, their convex combinations, scaled units (because Constant Returns-to-Scale (CRS) is assumed) and outperformed units. The units on the boundary (frontier) of the PPS are defined as efficient and attains the efficiency score of 100%, where the efficiency scores for others are measured relative to the frontier. The linear programming formulation to calculate the efficiency score of unit o is given below:

$$\begin{aligned}
 & \text{Max } \phi \\
 & \text{s. t.} \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{io} \quad i = 1, 2, \dots, m \\
 & \sum_{j=1}^n \lambda_j y_{rj} \geq \phi y_{ro} \quad r = 1, 2, \dots, s \\
 & \lambda_j \geq 0 \quad j = 1, 2, \dots, n
 \end{aligned} \tag{1}$$

3.2. Malmquist Productivity Index (MPI)

DEA models provide efficiency measurement at a point in time (Let $D_o^t(x^t, y^t) = \phi$). Malmquist Productivity Index (MPI) approach (Caves et al., 1982; Färe et al., 1992) is developed and widely used to observe the changes in productivity during a period. In order to measure the change from one period to another MPI is calculated for each unit. MPI consists of two components as *Efficiency Change (EC)* and *Frontier Shift (FS)*. Efficiency Change component refers to the ratio of efficiency score in period $t + 1$ to the efficiency score in period t . This measure itself is not enough to identify the change in productivity from one period to another because these scores are relative to different frontiers. Therefore, it is essential to measure the change in the frontier from one period to another. This is the second component of the MPI known as Frontier Shift. The calculation of *EC* and *FS* components for a unit is given below:

$$EC = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{2}$$

$$FS = \left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \right) * \left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right) \right]^{1/2} \quad (3)$$

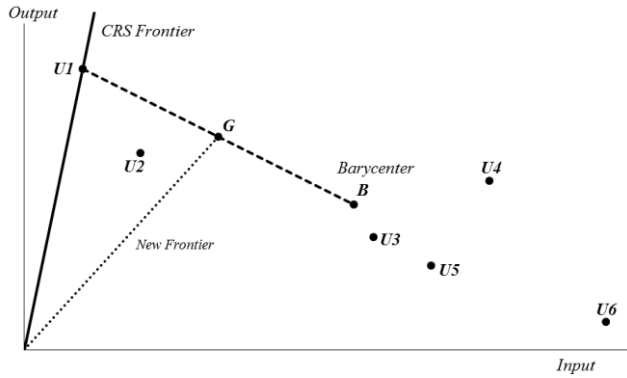
Once, both components are calculated relying on the linear programs, MPI of a unit is calculated as given below (given as $M_o(x^{t+1}, y^{t+1}, x^t, y^t)$ to represent the change from period t to $t + 1$).

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \right) \left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \right) \right]^{1/2} \quad (4)$$

3.3. DEA by Sequential Exclusion of Alternatives

Since the introduction of the original DEA approach, various theoretical and methodological improvements have been carried out. As one of the recent developments, Aleskerov & Petrushchenko (2013; 2015) propose, Cinar (2013) and Abankina et al. (2016) apply a new DEA methodology that enables assessment of the efficiency by adjusting the frontier by taking heterogeneity of the units into account. In highly heterogeneous data sets, many inefficient units have to be benchmarked against some exceptional ones which are very rare in the sample. One can assert that it is not fair and not practical when obtaining the reference sets. To overcome this issue, Aleskerov & Petrushchenko (2013; 2015) propose to adjust the efficiency frontier towards the barycentre of the units. To achieve this, the method is based on the sequential exclusion of alternatives with DEA iterations; therefore, it is referred as *DEA by Sequential Exclusion of Alternatives (DEA-SEA)* method. The approach can be illustrated via a graphical representation given in Figure 1 (Aleskerov & Petrushchenko, 2013; 2015; Cinar, 2013; Abankina et al., 2016).

Figure: 1
Graphical Interpretation of DEA-SEA Method



In Figure 1, a set of decision-making units (DMUs), $U1$ to $U6$ are given. According to the standard DEA (CRS) model, a vast majority of inefficient DMUs ($U3$, $U4$, $U5$, and $U6$) are located very far from the efficient frontier formed by unit $U1$ which can be seen as an outlier in the sample. In other words, $U1$ exhibits an exceptional efficiency via standard DEA calculation that when the other units are benchmarked against $U1$, their scores are

partially undervalued. From this point of view, the DEA-SEA approach asserts that the inefficient units can be evaluated less strictly than the case of the standard DEA model. For this aim, the method proposes the following steps:

- Firstly, the barycentre of all units (point B in Figure 1) is calculated in the usual geometrical or analytical sense. It means that the point B has i -th input (output) equal to the average of all the i -th input (output) in the whole sample (Abankina et al., 2016).
- As a second step, a new frontier is constructed via generating an imaginary unit G lying on the segment $BU1$ and by moving the frontier towards point G . The location of the unit G is identified by some extent to heterogeneity through μ and it is defined as:

$$G = \mu B + (1 - \mu)U1 \quad (5)$$

- Here, the index μ stands for the degree of adjustment for heterogeneity. It is between 0 and 1. The higher μ the nearer G to the barycentre B .
- As the next step, using DEA methodology the units $U3$, $U4$, $U5$ and $U6$ are benchmarked against the new efficient unit G instead of the older one ($U1$).
- Finally, since $U1$ and $U2$ remain unevaluated, to compute their efficiency scores the same algorithm is repeated excluding the previously evaluated inefficient units ($U3$, $U4$, $U5$, and $U6$) and calculating a new barycentre for the remaining units. The iteration stops when all units are taken into account.

Note that the efficient units in the data do not change through these steps, only the scores for the inefficient ones are adjusted by shifting the frontier towards G which depends on μ . Also, the convexity assumption of standard DEA is not violated in any of the iterations. The main implication of DEA-SEA methodology is to obtain more optimistic scores for the inefficient units that may be more realistic for the short-term. It weakens the potential drawbacks of the outliers, therefore heterogeneity in the data. Additionally, in the case of multiple efficient units on the frontier, the reference sets for the inefficient units may change via the shift of the frontier towards G . This is potentially insightful for setting short term benchmarks, which is also explored in the scope of the empirical application of the current research.

4. Empirical Application

4.1. DEA & MPI Results

The data consists of performance indicators of 31 sugar factories operating in Turkey with available data¹ covering two periods (2017-2018 and 2018-2019). According to the sugar legislation of Turkey, one period corresponds to the dates between 1st of September of

¹ Note that 33 sugar factories are operating in Turkey. Two factories (one public and one privatized) are excluded due to a lack of available data.

the given year to 31st of August of the succeeding year². Of those 31 factories, the majority were public entities (23 out of 31) in the 2017-2018 period. The sector has experienced large scale privatization (corresponding to 9 factories in our data set) in 2018, which results in 14 public, 17 private factories operating in the 2018-2019 period. For measuring the relative efficiency of the factories, we identify three input factors and one output factor presented in Table 2. Sugar production amount is the single output. On the input side, the raw material (sugar beet processed). These factors are common in sugar production efficiency measurement and used in all research presented in Table 1. The number of workers is included in line with the previous literature evaluating the effects of privatization in sugar production (see Mulwa et al., 2009; Demirtas, 2011; Palcic & Reeves, 2015). We also have operating days as an input factor since the factories differ in their time of operations during the analysis period.

Table: 2
Input and Output Factors

	Factor	Measure
Input 1	Operating Days	Day
Input 2	# of Workers	Number
Input 3	Sugar Beet Processed	Tons
Output	Sugar Production	Tons

As a first step to the analysis, CRS-DEA model -as given in (1)- is employed to 31 factories in the data set for both periods. The results can be evaluated in two subsets as public and private factories. Table 3 provides the main characteristics of the data set in terms of ownership together with the efficient factories in both periods. At the end of the first period, 9 factories have been privatized, therefore counted as private factories in the following period.

Table: 3
Data Set & Efficient Factories

	2017-2018	2018-2019
# of Public Factories	23	14
# of Private Factories	8	17*
Total # of Efficient Factories	5	6
Efficient Public Factories	Public 14	Public 14
Efficient Private Factories	Private 2, Private 3, Private 4, Private 7	Private 2, Private 3, Private 4, Private 5, Private 7

* 9 public factories are privatized between two periods.

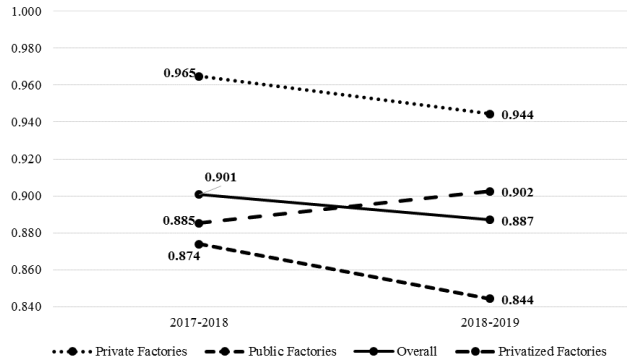
Efficient factories do not substantially change from one period to another. The ones that are efficient in period 1 are also found to be efficient in period 2 with an additional efficient unit (*Private 5*). As observed in Table 3, the majority of the efficient units consist of private factories. One efficient factory is *Public 14* which is a public entity during both periods. None of the privatized factories are found to be efficient in both periods. The CRS DEA efficiency scores for the individual factories are given in the first columns of Tables A.1 and A.2 of the Appendix for 2017-2018 and 2018-2019 periods, respectively. The

² <<https://www.mevzuat.gov.tr/MevzuatMetin/1.5.4634.pdf>>, 23.03.2020.

factories *Public 1* to *Public 9* in the 2017-2018 period represent the privatized factories, therefore labelled as *Private 9* to *Private 17* in the 2018-2019 period.

Figure 2 presents the change of average efficiency scores for three main subsets of the units, namely as *private factories*, *public factories*, and *privatized factories* together with the overall change. Interestingly, the only subset of the factories that experience an increase in the average efficiency is the privatized ones. Both public and private factories exhibit a decline in average efficiency scores resulting in a decline overall.

Figure: 2
Average Efficiency Scores



As discussed in Section 3.2, the change in efficiency scores represents only one dimension of the change since the shift of the frontier from one period to another should also be accounted for. Therefore, as a next step, we calculate the Malmquist Productivity Index (MPI) for each unit to observe the change between two periods as given in (2), (3) and (4). Table 4 presents the geometric mean values of MPI and its two components (Efficiency Change - *EC* and Frontier Shift - *FS*) for three subsets of the factories.

Table: 4
Malmquist Productivity Index (MPI) Results

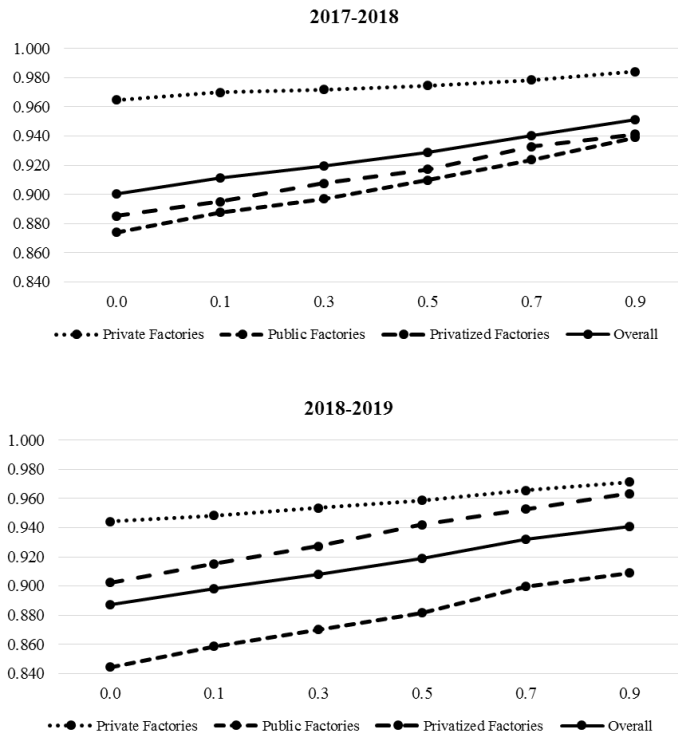
	Efficiency Change (EC)	Frontier Shift (FS)	MPI
Public Factories	0.964	1.039	1.001
Private Factories	0.976	1.029	1.004
Privatized Factories	1.024	0.981	1.005
Overall	0.984	1.019	1.003

The *EC* column of Table 4 reflects what is observed also in Figure 2. The privatized factories subset is the only one that experiences an increase in the *EC* component. The *MPI* scores reflect 0.1%, 0.4% and 0.5% productivity increase for the public, private and privatized factories, respectively. The increase is due to the *FS* component for public and private units, whereas, for the privatized factories, the level of *EC* component is the main reason behind the productivity increase. Overall, an increase in productivity by 0.3% is observed in the sugar production sector and this increase is mainly due to the *FS* component.

4.2. Application of DEA-SEA Method

Data Envelopment Analysis by Sequential Exclusion of Alternatives (DEA-SEA) methodology, as explained in Section 3, relies on adjusting the efficient frontier to the barycentre of the units so that the effects of heterogeneity in the data set are undermined. Also, by adjusting the frontier closer to the inefficient units, the method reduces the effects of any potential outliers. Furthermore, since the frontier approaches the barycentre, it is possible to obtain more attainable targets for the inefficient units for the shorter terms. In this part, we present the findings of DEA-SEA modelling to our sugar factory data set since heterogeneity to some extent can be assumed due to the fact that both public, private and privatized factories operating in different regions of the country are evaluated in the same set.

Figure: 3
Average Efficiency Scores w.r.t Changing μ



In DEA-SEA, the extent that the frontier is shifted towards the barycentre is controlled by parameter μ which is between 0 and 1, where $\mu = 0$ stands for the standard CRS DEA case. Increasing the value of μ represents shifting the units on the initial frontier closer to the barycentre of the units, in other words, obtaining an adjusted frontier. In order

to observe the effects of changing μ , we calculate efficiency scores of the factories at different μ levels as 0.1, 0.3, 0.5, 0.7 and 0.9. The efficiency scores at the factory-level are presented in Tables A.1 and A.2 of the Appendix for 2017-2018 and 2018-2019 periods, respectively. Figure 3 reveals the change in average efficiency scores of the subsets for both periods. As expected, the average efficiency scores are increasing with respect to changing μ . For both periods, the private factories attain higher levels of efficiency followed by the privatized factory and public factory subsets no matter the μ value is. Note that the efficient units do not change with the changing μ ; however, the scores of the inefficient ones are adjusted.

In order to observe the effects of changing μ on the efficiency scores, we also calculate the correlation coefficients between the scores at different levels of μ . Table 5 presents the correlation coefficients for both periods' scores. This is to show that as indicated by the original work of Aleskerov & Petrushchenko (2013), DEA-SEA modelling results in mild changes regarding the scores that means there is no significant shift from the nature of DEA modelling. However, the interpretation is quite insightful in terms of setting targets and reference sets as we discuss below and in the following section.

Table: 5
Correlations between Efficiency Scores at Different Levels of μ

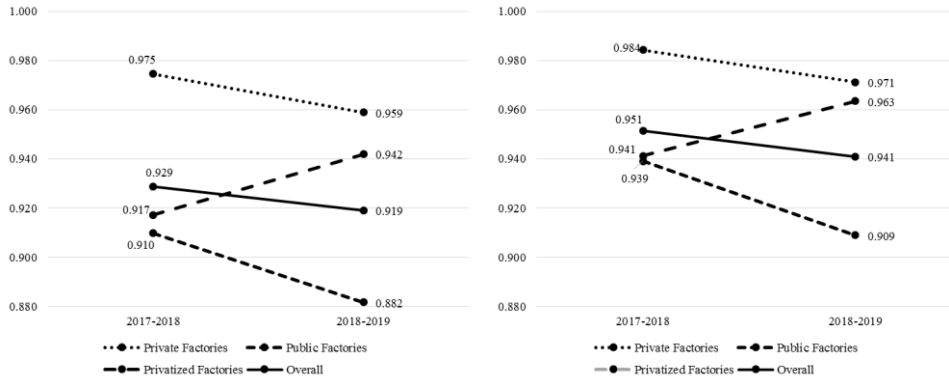
2017-2018							2018-2019						
μ	0.0	0.1	0.3	0.5	0.7	0.9	μ	0.0	0.1	0.3	0.5	0.7	0.9
0.0	1.000						0.0	1.000					
0.1	0.995	1.000					0.1	0.996	1.000				
0.3	0.989	0.996	1.000				0.3	0.991	0.998	1.000			
0.5	0.977	0.984	0.990	1.000			0.5	0.980	0.988	0.995	1.000		
0.7	0.963	0.975	0.986	0.991	1.000		0.7	0.964	0.974	0.984	0.990	1.000	
0.9	0.935	0.949	0.958	0.967	0.984	1.000	0.9	0.951	0.965	0.975	0.981	0.986	1.000

Here, we would like to refer the efficiency scores with respect to changing μ as the ranges of pessimistic to optimistic; alternatively, long to short term score for each factory. When the frontier approaches to the barycentre, it also approaches to the inefficient units resulting in a higher efficiency score, which may represent a more optimistic measurement. This optimistic measure, in a way, provides the improvement potential in the short term if the CRS frontier is assumed to the most pessimistic case. Let us illustrate the case for a specific unit. The factory Private 1 has an efficiency score of 86.5% in the standard CRS model for 2018-2019 period (see the first row of Table A.2 in the Appendix), which means that relatively it is possible to produce 1.156 times higher output (sugar) than its current level with the same input use. This refers to a 15.6% increase in the output. If this target is seen as too unrealistic for this factory, then it is possible to set more medium-term or short-term targets by adjusting the frontier with μ . The efficiency score at $\mu = 0.5$ is 90.5%, which corresponds to a 10.4% increase in production. If we move further, at $\mu = 0.9$, the score is 94.8%, which refers to only a 5.4% increase. Therefore, the unit can set its path for progress ending up on the frontier in the longer term.

We also observe how average efficiency scores change from period 1 to period 2 at different levels of μ . Figure 4 presents the change in average efficiency scores for $\mu = 0.5$

and $\mu = 0.9$, which are referred to as medium- and short-term performance metrics. The same pattern with the standard DEA model is observed for both μ values (see Figure 2). Again, the only subset of the factories that experience an increase in the average efficiency is the privatized ones. Both public and private factories exhibit a decline in average efficiency scores resulting in a decline overall.

Figure: 4
Average Efficiency Scores for $\mu = 0.5$ and $\mu = 0.9$



4.3. Reference Sets

One of the main outputs of Data Envelopment Analysis (DEA) is the reference set information for the inefficient units to benchmark themselves in order to improve performance. The reference set of a unit consists of the closest units on the efficient frontier. These units are detected through the optimal λ values in the DEA model³. In this part, we present how the reference sets for the inefficient factories respond to the changing μ parameter. Tables A.3 and A.4 of the Appendix present the reference sets for the inefficient factories for periods 1 and 2, respectively (period 1 stands for 2017-2018 and period 2 stands for 2018-2019 as noted in section 4.1). The bold values in Tables A.3 and A.4 represent the units that attain the highest weight (λ).

As noted, increasing the value of μ represents shifting the units on the initial frontier (CRS frontier) closer to the barycentre of the units. It is observed that the reference units change for the majority of the units when the frontier (i.e. efficient units) shifts to the direction of the barycentre. As in interpreting the scores, these changing benchmarks can be seen as medium- and short-term references for the units. For instance, the factory *Private 1* has {*Private 2*, *Private 7*, *Public 14*} as its reference set in period 1 (see Table A.3 of the Appendix), in which *Public 14* as its main reference according to the CRS modelling. The reference set changes to {*Private 7*, *Public 14*} when $\mu = 0.1$ and changes to {*Private 2*} after $\mu = 0.3$. This implies that in the medium and short terms, *Private 1* can benchmark

³ See Model (1) in Section 3.

itself to *Private 2*, whereas in the long term, it should also consider *Private 7* and *Public 14* as its references. Another observation from Tables A.3 and A.4 is that there is a tendency to a less number of reference units with increasing μ . This can be interpreted as a more focused direction for short-term planning, whereas the number of benchmarking options is increasing for the long-term.

The change in the reference sets can also be observed when the counts of efficient units being in the reference sets are analysed. The numbers are presented in Table 6. As presented earlier, in our sugar factory data set, there are 5 efficient units in period 1 and 6 efficient units in period 2 that serve as the reference units for the inefficient ones (see Table 3). Only one public factory is found to be efficient, namely as *Public 14*. This factory is a reference to the majority of the factories with respect to the CRS frontier for both periods. When μ starts to change *Private 2* and *Private 4* become more predominant as a reference in periods 1 and 2, respectively. In general, the sets shift from the public (namely from *Public 14*) to private references.

Table: 6
Efficient Units as Main References to Others (#)

	2017-2018						2018-2019					
	CRS	0.1	0.3	0.5	0.7	0.9	CRS	0.1	0.3	0.5	0.7	0.9
Private 2	6	4	22	22	20	17	1	1	4	7	5	3
Private 3	0	0	1	1	4	7	0	0	0	1	2	4
Private 4	1	1	1	1	1	1	0	0	13	16	17	17
Private 5	0	0	0	0	0	0	0	0	0	0	0	0
Private 7	1	5	0	0	0	0	10	10	7	0	0	0
Public 14	18	16	2	2	1	1	14	14	1	1	1	1

5. Discussion and Conclusion

In this research, we explore the effects of the large-scale privatization in the sugar production sector of Turkey, which was mainly held during 2018, on the technical efficiency of the factories. For this aim, first of all, we evaluate the efficiencies of 31 factories for pre-privatization (Sept. 2017 - Aug. 2018) and after-privatization (Aug. 2018 - Sept. 2019) periods using Data Envelopment Analysis (DEA) and Malmquist Productivity Index (MPI).

DEA findings reveal that before and after privatization, the majority of the efficient units consists of private factories, only one public factory is efficient. None of the privatized factories are found to be efficient in both periods however, this is the only subset that experiences an increase between periods in the average efficiency. Both public and private factories exhibit a decline in average efficiency scores resulting in a decline overall. On the other hand, the Malmquist Productivity Index (MPI) scores reflect a slight productivity increase for all three subsets of factories (0.3%). This means that although average efficiency declines from one period to another, there is a technological improvement resulting in the frontier shift. It can be said that an increase in productivity is observed in the Turkish sugar production sector and this increase is mainly due to the frontier shift component of the MPI.

Moreover, since our data set consists of three subsets of the units, namely as private, public and privatized factories and they operate in different parts of the country; it is possible

to assume heterogeneity in the sample to some extent. Therefore, when measuring the efficiencies, we also employ one novel extension of the classical Data Envelopment Analysis (DEA) methodology, namely as DEA by Sequential Exclusion of Alternatives (DEA-SEA), which evaluates efficiency by constructing new frontiers taking into account heterogeneity at different levels. The main motivation behind applying DEA-SEA is to obtain adjusted efficiency scores and the reference sets for the factories by tuning the coefficient of heterogeneity (μ) with different values ranging between 0 and 1. The higher the μ , the closer the efficient frontier to the barycentre of the units. Therefore, by experimenting with different levels of this parameter, we obtain shorter-term improvement potentials if the standard DEA frontier is assumed to be the longest-term target. Besides, we provide some methodological insights about the DEA-SEA methodology. In order to observe the effects of changing μ , we calculate efficiency scores of the factories at different μ levels as 0.1, 0.3, 0.5, 0.7 and 0.9, where $\mu = 0$ stands for the standard CRS DEA case.

The findings of the DEA-SEA method are evaluated from two perspectives: efficiency scores and reference sets. Regarding the efficiency scores, we calculate five different scores for each factory at different levels of μ . Mainly, we observe the private factories attain higher levels of efficiency followed by privatized and public factory subsets no matter the μ value is. The correlations between the scores at different levels of the μ values are found to be quite high, which reflects that changing μ does not cause a significant shift from the nature of DEA modelling. It means the scores are consistent. We propose to consider the efficiency scores for $\mu = 0.5$ and $\mu = 0.9$ as to the medium- and short-term performance metrics. In addition, we compare the scores for different μ for two periods. The same pattern with the standard DEA model is observed for all μ values as the only subset of the factories that experience an increase in the average efficiency is the privatized ones. Both public and private factories exhibit a decline in average efficiency scores resulting in a decline overall.

On the other hand, one of the main outputs of DEA is the reference set information for the inefficient units to benchmark themselves in order to improve performance. The main implication of DEA-SEA methodology is to obtain more optimistic scores for the inefficient units that may be more realistic for the short-term. It weakens the potential drawbacks of the outliers, therefore heterogeneity in the data. By this approach, one can find the benchmarks for the inefficient factories in both the short and the long terms and aid their future improvement decisions more realistically than using only the classical DEA model. We adopt this characteristic to our data set. This is the first time use of DEA-SEA for setting up shorter-term references. Another observation is that the sets are dominated by private factories rather than the single efficient public factory when μ increases.

The findings of the current research imply that the recent privatization in the sugar production in Turkey has a reflection on the technical efficiency levels of the factories operating in the sector. The average efficiency in the sector declines, there exists a technological improvement and the privatized factories seem to be improving their performance among the others. We also identified the factor level efficiency scores, which can aid any potential future privatizations. Furthermore, the reference sets identified might

be a piece of useful information for sugar factories to evaluate their improvement potential. Last but not least, we would like to note that privatization is a complex issue and its effects should be evaluated in different dimensions. Although the current research implies a positive effect for the privatized factories, one should also consider the socio-economic effects to assess any large-scale privatizations. In our case, the factories play a very important role in the provinces' economy and have important effects on the labor force. Therefore, technical efficiency is only one of the multiple dimensions to consider while evaluating the success of any privatization policy.

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Appendix

Table: A.1.
Efficiency Scores (2017-2018)

	Factory	CRS	0.1	0.3	0.5	0.7	0.9
1	Private 1	0.888	0.901	0.911	0.924	0.941	0.965
2	Private 2	1.000	1.000	1.000	1.000	1.000	1.000
3	Private 3	1.000	1.000	1.000	1.000	1.000	1.000
4	Private 4	1.000	1.000	1.000	1.000	1.000	1.000
5	Private 5	0.997	0.998	0.999	0.999	0.998	0.998
6	Private 6	0.985	0.999	0.993	0.991	0.991	0.988
7	Private 7	1.000	1.000	1.000	1.000	1.000	1.000
8	Private 8	0.849	0.861	0.871	0.883	0.899	0.923
9	Public 1	0.944	0.962	0.994	0.958	0.996	0.981
10	Public 2	0.865	0.873	0.882	0.894	0.910	0.941
11	Public 3	0.909	0.913	0.944	0.987	0.988	0.963
12	Public 4	0.839	0.847	0.856	0.868	0.884	0.907
13	Public 5	0.657	0.668	0.675	0.684	0.697	0.715
14	Public 6	0.982	0.996	0.990	0.989	1.000	0.998
15	Public 7	0.951	0.957	0.967	0.991	0.981	0.971
16	Public 8	0.918	0.932	0.943	0.955	0.973	0.999
17	Public 9	0.901	0.907	0.917	0.929	0.966	0.996
18	Public 10	0.926	0.955	0.966	0.979	0.997	0.993
19	Public 11	0.846	0.863	0.873	0.885	0.901	0.925
20	Public 12	0.894	0.902	0.911	0.924	0.941	0.967
21	Public 13	0.874	0.900	0.911	0.923	0.940	0.965
22	Public 14	1.000	1.000	1.000	1.000	1.000	1.000
23	Public 15	0.889	0.894	0.903	0.931	0.921	0.953
24	Public 16	0.885	0.892	0.901	0.917	0.943	0.941
25	Public 17	0.885	0.890	0.899	0.917	0.946	0.969
26	Public 18	0.911	0.946	0.958	0.971	0.988	0.994
27	Public 19	0.872	0.885	0.895	0.907	0.923	0.948
28	Public 20	0.820	0.833	0.842	0.853	0.869	0.892
29	Public 21	0.604	0.610	0.617	0.625	0.636	0.653
30	Public 22	0.868	0.886	0.896	0.908	0.925	0.949
31	Public 23	0.961	0.974	0.985	0.998	1.000	0.997

Note: Public 1-9 are privatized in the following year.

Table: A.2.
Efficiency Scores (2018-2019)

Factory	CRS	0.1	0.3	0.5	0.7	0.9
Private 1	0.865	0.875	0.890	0.905	0.922	0.948
Private 2	1.000	1.000	1.000	1.000	1.000	1.000
Private 3	1.000	1.000	1.000	1.000	1.000	1.000
Private 4	1.000	1.000	1.000	1.000	1.000	1.000
Private 5	1.000	1.000	1.000	1.000	1.000	1.000
Private 6	0.933	0.945	0.960	0.976	0.995	0.990
Private 7	1.000	1.000	1.000	1.000	1.000	1.000
Private 8	0.757	0.768	0.778	0.790	0.807	0.831
Private 9	0.870	0.878	0.893	0.909	0.926	0.946
Private 10	0.909	0.924	0.938	0.952	0.971	0.980
Private 11	0.887	0.893	0.916	0.962	0.950	0.939
Private 12	0.829	0.837	0.852	0.866	0.883	0.911
Private 13	0.833	0.857	0.869	0.882	0.901	0.928
Private 14	0.968	0.989	0.995	0.993	0.993	0.999
Private 15	0.988	0.997	0.996	0.994	0.993	0.991
Private 16	0.907	0.925	0.937	0.952	0.972	0.981
Private 17	0.929	0.937	0.951	0.966	0.985	0.994
Public 10	0.938	0.967	0.980	0.996	0.989	0.992
Public 11	0.784	0.798	0.810	0.822	0.839	0.864
Public 12	0.821	0.831	0.844	0.859	0.875	0.900
Public 13	0.837	0.863	0.875	0.889	0.908	0.935
Public 14	1.000	1.000	1.000	1.000	1.000	1.000
Public 15	0.887	0.894	0.908	0.921	0.972	0.937
Public 16	0.814	0.820	0.833	0.846	0.876	0.881
Public 17	0.854	0.860	0.873	0.890	0.921	0.910
Public 18	0.940	0.976	0.989	0.987	0.998	0.997
Public 19	0.828	0.842	0.854	0.868	0.885	0.911
Public 20	0.829	0.845	0.857	0.870	0.888	0.915
Public 21	0.570	0.576	0.585	0.594	0.606	0.624
Public 22	0.782	0.798	0.809	0.822	0.840	0.865
Public 23	0.935	0.949	0.963	0.979	0.998	0.995

Table: A.3.
Reference Sets (2017-2018)

	0 (CRS)	0.1	0.3	0.5	0.7	0.9
Private 1	Private 2, Private 7, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Private 5	Private 2, Private 3, Private 4	Private 3, Private 4	Private 3, Private 4	Private 3, Private 4	Private 3, Private 4	
Private 6	Private 2, Public 14	Private 7, Public 14				
Private 8	Private 7, Public 14		Private 2	Private 2	Private 2	Private 2
Public 1	Private 2 , Private 3		Private 3		Private 3	
Public 2	Private 2, Public 14		Private 2	Private 2	Private 2	Private 2, Private 3
Public 3	Private 2 , Public 14			Private 3	Private 3	Private 2, Private 3
Public 4	Private 2, Public 14		Private 2	Private 2	Private 2	Private 2
Public 5	Private 2, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Public 6	Private 2 , Public 14	Private 7, Public 14			Private 2	Private 2
Public 7	Private 2 , Public 14	Private 2 , Private 7	Private 2	Private 2 , Private 3	Private 2 , Private 3	Private 2 , Private 3
Public 8	Private 2, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Public 9	Private 2 , Public 14	Private 2, Private 7	Private 2	Private 2	Private 2, Private 3	Private 3
Public 10	Private 7, Public 14	Public 14	Private 2	Private 2	Private 2	Private 2
Public 11	Private 2, Private 7, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Public 12	Private 2, Public 14	Private 2, Private 7	Private 2	Private 2	Private 2	Private 2 , Private 3
Public 13	Private 2, Public 14	Public 14	Private 2	Private 2	Private 2	Private 2
Public 15	Private 2 , Public 14	Private 2 , Private 7	Private 2	Private 2 , Private 3	Private 2 , Private 3	Private 3
Public 16	Private 2, Private 7 , Public 14	Private 2, Private 7	Private 2	Private 2 , Private 3	Private 2 , Private 3	Private 2, Private 3
Public 17	Private 2 , Private 7, Public 14	Private 2, Private 7	Private 2	Private 2 , Private 3	Private 2, Private 3	Private 3
Public 18	Public 14		Private 2	Private 2	Private 2	Private 2
Public 19	Private 2, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Public 20	Private 2, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Public 21	Private 2, Public 14	Private 2, Private 7	Private 2	Private 2	Private 2	Private 2
Public 22	Private 2, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2
Public 23	Private 2, Public 14	Private 7, Public 14	Private 2	Private 2	Private 2	Private 2

Notes: The blank cells mean that the reference set does not change from one μ to another (left to the right). Bold ones represent main reference (highest λ)

Table: A.4.
Reference Sets (2018-2019)

	0 (CRS)	0.1	0.3	0.5	0.7	0.9
Private 1	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 2, Private 4
Private 6	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 4
Private 8	Private 4, Private 7, Public 14	Private 7, Public 14	Private 4	Private 4	Private 4	Private 4
Private 9	Private 7, Public 14		Private 2, Private 7	Private 2, Private 4	Private 2, Private 4	Private 2, Private 3
Private 10	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 4
Private 11	Private 2, Private 7		Private 2, Private 3	Private 2, Private 3	Private 2, Private 3	Private 2, Private 3
Private 12	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 2, Private 3
Private 13	Private 7, Public 14		Private 4	Private 4	Private 4	Private 4
Private 14	Private 7, Public 14		Private 4	Private 4	Private 4	Private 4
Private 15	Private 7, Public 14					
Private 16	Private 7, Public 14		Private 4, Private 7	Private 4	Private 4	Private 4
Private 17	Private 4, Private 7, Public 14	Private 4, Private 7	Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 4
Public 10	Private 4, Private 7, Public 14	Public 14	Private 4	Private 4	Private 4	Private 4
Public 11	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 4	Private 4
Public 12	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 2, Private 4
Public 13	Private 7, Public 14	Public 14	Private 4	Private 4	Private 4	Private 4
Public 15	Private 2, Private 7		Private 2, Private 7	Private 2, Private 4	Private 2, Private 3	Private 2, Private 3
Public 16	Private 2, Private 4, Private 7			Private 2, Private 3, Private 4	Private 2, Private 3, Private 4	Private 2, Private 3
Public 17	Private 2, Private 4, Private 7			Private 2, Private 3, Private 4	Private 2, Private 3, Private 4	Private 2, Private 3
Public 18	Public 14		Private 4	Private 4	Private 4	Private 4
Public 19	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 4
Public 20	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 4	Private 4
Public 21	Private 4, Private 7, Public 14	Private 7, Public 14	Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 4
Public 22	Private 7, Public 14		Private 4	Private 4	Private 4	Private 4
Public 23	Private 7, Public 14		Private 4, Private 7	Private 2, Private 4	Private 2, Private 4	Private 4

Notes: The blank cells mean that the reference set does not change from one μ to another (left to the right). Bold ones represent the main reference (highest λ).