Received: 17 August 2021 | Revised: 19 November 2021 | Accepted: 23 November 2021
DOI: 10.1002/mde.3514

RESEARCH ARTICLE

WILEY

Decomposition of efficiency in the global seed industry: A nonparametric approach

Richard D. Smart[1] | Amer Ait Sidhoum[1,2] | Johannes Sauer[1]

[1]Department of Agricultural Production and Resource Economics, Technische Universität München, Freising, Germany
[2]Economics and Society, Natural Resources Institute Finland (Luke), Helsinki, Finland

Correspondence
Amer Ait Sidhoum, Technische Universität München, Department of Agricultural Production and Resource Economics, Alte Akademie 14, 85354 Freising, Germany.
Email: amer.ait-sidhoum@luke.fi

We analyzed the efficiency levels of nine of the largest commercial seed-producing firms globally for the period 2008–2015 and assessed if there is a relationship between firm size and efficiency. We employed the nonparametric technique of data envelopment analysis (DEA) using an input-oriented model with balanced panel data. We accounted for the assumption of time invariance of the frontier by using the DEA windows analysis technique. Aggregate mean overall technical efficiency increased by 0.8%. We decomposed these results to pure technical efficiency and scale efficiency, and found no meaningful relationship between firm size (assets) and efficiency.

1 | INTRODUCTION

The seed industry is an integral component of the first link in the agri-food value chain, which also comprises, among others, the fertilizer and crop protection industries (FAO, 2019). The seed industry makes an important contribution to the sustainability of the global agri-food system and to food security. Within this food chain, the seed sector and food processing and large-scale distribution sector are the smallest and most important sectors (measured by sales), respectively (Bonny, 2017). Seeds that farmers acquire for planting generally fall into two broad categories, namely, commercial (produced by seed firms) and noncommercial seed (Federico, 2005). Seeds in the former category are two to three times more expensive because of a technology fee (Bonny, 2014) as they typically have superior genetic traits, which afford their users the potential for increased productivity. The latter category comprises seeds from the plant breeding efforts of farmers (i.e., farmers' seed systems), seeds saved from conventional seeds (farm-saved seeds), and seeds from public research (scarcely sold to farmers).

The global commercial seed industry comprises around 7500 firms ranging in size from very small enterprises (specialists in local, specific crops) to small and medium enterprises, to several large firms with origins in the chemical sector (exceptions are KWS and Limagrain) (Bonny, 2017). Firms develop seeds primarily by conventional plant breeding techniques, but some firms also employ technology intensive methods, specifically transgenesis, for developing genetically engineered (GE) (also known as transgenic or genetically modified) crops. The aforementioned comprise the formal seed sector, while the "informal seed sector comprises farmer-saved seeds … [and] seeds exchanged in local markets" (Bonny, 2014). Commercial seed firms are vertically integrated (Howard, 2009) "managing the entire production, distribution and marketing phases" (Fernandez-Cornejo & Spielman, 2002). Furthermore, the diversity of seed types and their pricing (dependent on both the crop and method of seed development) and firm profile (firm origin; offer of product mix: seeds and agrochemicals; and involvement in agricultural inputs) make the seed sector highly heterogeneous (Bonny, 2017).

In the 1990s, many developing economies, especially in South America and Africa, initiated structural reform programs to rectify macroeconomic imbalances that developed in the preceding two decades. Reducing the state's role in the agricultural sector was an important feature of these reforms. Consequently, these economies' seed sectors were opened to the private sector (Cromwell et al., 1992). For example, the privatization of the seed sector in Ghana took place in 1990 "because it [was] generally accepted that the private sector would be more efficient in the production and supply of seed relative to the public sector" (Konja et al., 2019). Since the 1980s, consolidation in the global seed sector increased through corporate activity (takeovers, mergers and acquisitions [M&As], cooperation agreements, and demergers), often also involving the crop protection (herbicides and pesticides) industry. The result is market concentration in this sector (Lianos et al., 2016; Mammana, 2014), which has, and continues to accord these few, large firms with perceived power and influence on global food production at the start of the agro-food chain (Bonny, 2014). The negative impacts of the increasing power of the agrochemical-seed industry include increased seed prices and the reduced ability of farmers to save seeds (Howard, 2015). In the late 1990s, patent applications in the plant biotechnology and seed industries—mainly by these few, large firms—increased exponentially (Pray et al., 2005). Bonny (2014) predicted that market concentration would continue and that the focus would sharpen "on the most profitable or widely cultivated crops." Her prediction is vindicated by the merger of Dow AgroSciences and DuPont Pioneer (Dow DuPont, 2017) and the takeover of Syngenta by ChemChina (Syngenta website, 2020) in 2017 and the acquisition of Monsanto by Bayer in 2018 (Bayer website, 2020).

The market concentration of the seed industry arose from "the dynamic interplay between business strategies, scientific breakthroughs, and government policies" (Schenkelaars et al. (2011) cited by Bonny (2017)). Fernandez-Cornejo and Spielman (2002) examined the effects of industry concentration on market power and costs in the US corn (maize or *Zea mays* L.) seed industry. They found that the overall effect of concentration for this industry appears to be economically beneficial (during their study period) and that a strong processing-cost-reducing effect overpowers the market power-enhancing effect of concentration.

Pray et al. (2005) point out that "concentration brings to the foreground the economic tradeoff between static efficiency and dynamic efficiency that is inherent in any [research and development] (R&D)-based industry. Static efficiency—the maximization of social welfare in the market (for agricultural biotechnology products such as seeds) at a specified point in time—occurs when the market structure is competitive and no firm has market power. However, the absence of market power prevents firms from recovering investments necessary to enter the market … M&As by larger firms have increased the concentration of patent ownership much more than R&D alone." Moreover, Brennan et al. (2005) report that the seed industry is highly concentrated. Mobility indices indicate that this concentration is persistent as the same few firms dominate the innovation market from year to year. Their concern is that the leading plant biotechnology firms have the potential to reduce the seed industry's level of R&D activity.

Disquiet expressed by a broad spectrum from society, ranging from farmers to nongovernmental organizations (NGOs) (see Shand, 2012), that market concentration in the seed sector devolve asymmetric power on these firms, thus giving them strong influence on the world's food production (Bonny, 2014), supports the need for further scientific inquiry to empirically validate these concerns. According to Bonny (2014), there is "a lack of precise appraisals and analyses" for the seed sector. In 2017, she states that an "analysis of the seed sector is a particularly difficult task given the extent of partial or biased analyses, as well as a lack of data on certain aspects … the economic data are heterogeneous and sometimes non-concordant." Additionally, she notes that representatives of seed companies involved in M&A activities justified their intentions by emphasizing that "their assets and activities were complementary, and how consolidation would lead to better efficiency and to an enhanced capacity for innovation, which in turn would benefit all stakeholders." Separately, KWS improved efficiency throughout its seed production cycle by introducing a data integration system to streamline its order, delivery, and logistics processes for better inventory management (Proagrica website, 2021). In the two preceding examples, and the notion of the private sector being more efficient than the public sector (see our earlier reference to Konja et al., 2019), no empirical evidence is presented to support how efficiency was, or would be, improved. This lack of evidence is a gap in the literature. However, we found two reports analyzing the efficiency of seed firms in China (Hu & Dou, 2015; Liu & Huang, 2010). To the best of our knowledge, the efficiency of non-Chinese seed firms has not been formally analyzed, and that generally, there is a dearth of scientific literature in this field.

Our research contributes to the small pool of formal knowledge by analyzing the efficiency levels of nine of the largest commercial seed-producing firms globally for the period 2008–2015 and assessing if there is a relationship between firm size and efficiency. Firms criticized for contributing to the concentration of the global seed market are included in our study. Thus, we add empirical evidence (efficiency scores) to (1) the debate about whether market concentration (e.g., through M&As) compromises firm efficiency and (2) whether managerial tactics like demergers or consolidating R&D activities impact firm efficiency positively.

We employ the nonparametric technique of data envelopment analysis (DEA) using an input-oriented model with balanced panel data spanning this period.[1] DEA windows analysis technique is used to account for the assumption of time invariance of the frontier. This method has been used to study the efficiency of, among others, the biotech industry (Kim et al., 2009), banks (Drake, 2001; Řepková, 2014; Sufian & Majid, 2007; Webb, 2003), hospitals (Jia & Yuan, 2017; Kazley & Ozcan, 2009), pharmaceutical firms (Al-Refaie et al., 2019), and environmental management (Zhou et al., 2020).

The paper is organized as follows. In Section 2, we cover the methodology that we employed and describe our data set. In Section 3, we present and discuss our empirical results. The paper ends with the concluding remarks section.

2 | TESTING FOR EFFICIENCY IN THE SEED SECTOR

2.1 | Methodology

2.1.1 | Data envelopment analysis

Fundamentally, efficiency is the ratio of inputs to outputs. Resources (inputs) are used by a firm in ways that minimize waste and maximize outputs for quality, cost, and production (Cooper et al., 2000). Two widely applied techniques for measuring efficiency are (1) the econometric approach (the parametric stochastic frontier analysis [SFA]) and (2) the mathematical programming approach (and the nonparametric DEA) (Berger & Humphrey, 1997). The important difference between the two approaches is the way in which each method treats the random noise (Fried et al., 2008). The calculation of efficiency in SFA is based on the choice of a particular functional form and on specific distributional assumptions of the statistical noise and the inefficiency term. Since empirical findings from a stochastic frontier are susceptible to parametric assumptions, modeling biases and incorrect inferences may arise.

The DEA framework allows for overcoming the limitation of SFA. In this study, we employ the nonparametric DEA method proposed by Charnes et al. (1978), which is known as the Charnes, Cooper, Rhodes (CCR) model. Essentially, the CCR model measures the efficiency of each decision-making unit (DMU), which is obtained as a maximum of a ratio of weighted outputs to weighted inputs. The CCR model has a precondition, namely, that there is no significant relationship between the scale of operations and efficiency. This precondition is met by assuming constant returns to scale (CRS). The CRS precondition is only reasonable when all DMUs are operating at an optimal scale (Řepková, 2014; Sufian & Majid, 2007). The model's outcome is overall technical efficiency (OTE), which indicates a DMU's ability to maximize output from a given set of inputs (Ma et al., 2002).

In reality, it is unlikely that all DMUs operate at optimal scale, that is, DMUs may face either economies or diseconomies of scale. In such a scenario where CRS is assumed, the OTE scores are tainted with scale efficiencies (SEs) (Sufian & Majid, 2007). This restriction is overcome in the Banker, Charnes, Cooper (BCC) model, which assumes variable returns to scale (VRS) (Banker et al., 1984). If a change in inputs results in a disproportional change in outputs, the DMU operates under VRS. The BCC model measures pure technical efficiency (PTE) by ignoring the impact of scale size, which is achieved by comparing DMUs of similar scale (Ma et al., 2002). According to Al-Refaie et al. (2019), PTE is an indication of how a DMU uses resources under exogenous (nondiscretionary resources or products; Bogetoft & Otto, 2011) environments: the higher the score, the greater the efficiency with which the DMU manages its resources. In short, PTE measures OTE without SE effects.

The DEA efficiency model of DMU_n can be computed from the following programming problem. Following Řepková (2014), let us consider N DMUs ($n = 1, 2, \dots, N$) observed in T ($t = 1, 2, \dots, T$) periods using r inputs to produce s outputs. Let DMU_n^t represent a DMU_n in period t with an r input dimensional vector $x = (x_n^{1t}, x_n^{2t}, \dots, x_n^{rt})'$ and an s dimensional output vector $y = (y_n^{1t}, y_n^{2t}, \dots, y_n^{st})'$. If a window starts at time k ($1 \le k \le T$) with window width w ($1 \le w \le t - k$), then the inputs metric is given by

$$x_{kw} = \left(x_1^k, x_2^k, \dots, x_N^k, x_1^{k+1}, x_2^{k+1}, \dots, x_N^{k+1}, x_1^{k+w}, x_2^{k+w}, \dots, x_N^{k+w}\right)',$$

and the outputs metric is given by

$$y_{kw} = \left(y_1^k, y_2^k, \dots, y_N^k, y_1^{k+1}, y_2^{k+1}, \dots, y_N^{k+1}, y_1^{k+w}, y_2^{k+w}, \dots, y_N^{k+w}\right)'.$$

The CCR model of the DEA window problem for DMU_t^k is given by solving the following linear program:

$$\min\ \theta,$$

subject to

$$\theta' X_t - \lambda' X_{kw} \ge 0,$$

$$\lambda' Y_{kw} - Y_t \ge 0,$$

$$\lambda_n \ge 0\ (n = 1, 2, \dots, N \times w).$$

where θ is a measure of efficiency and λ' is the vector of intensity variables representing the weight of each DMU in the efficient frontier. By adding the restriction: $\sum_{n=1}^{n} \lambda_n = 1$, the BCC model formulation can be obtained (Banker et al. (1984) cited by Řepková (2014)). The objective values of the CCR model and the BCC model are designated OTE and PTE, respectively.

The BCC model is shown as:

$$\min\ \theta,$$

subject to

$$\theta' X_t - \lambda' X_{kw} \ge 0,$$

$$\lambda' Y_{kw} - Y_t \ge 0,$$

$$\sum_{n=1}^{n} \lambda_n = 1,$$

$$\lambda_n \ge 0\ (n = 1, 2, \dots, N \times w).$$

The BCC model allows for the OTE score to be decomposed to PTE and SE scores as follows:

$$SE = \frac{OTE}{PTE}.$$

SE is a measure of how scale size affects efficiency (Al-Refaie et al., 2019). Furthermore, a difference between the OTE and PTE scores for a given DMU indicates scale inefficiency (Sufian, 2007).

2.1.2 | Window analysis

We used the DEA windows analysis method to allow for the assumption of time invariance of the frontier. Windows analysis repeats the DEA model in time segments, called windows, across the

TABLE 1 Width of each window

Window	Width (year)							
1	2008	2009	2010	2011				
2		2009	2010	2011	2012			
3			2010	2011	2012	2013		
4				2011	2012	2013	2014	
5					2012	2013	2014	2015

time continuum of a panel dataset that comprises both time series and cross-section samples (Table 1) (Al-Refaie et al., 2019). Windows analysis works on the principle of moving averages (Řepková, 2014). This method facilitates the capturing of temporal variations in efficiency, which is achieved by treating each DMU (firm) as a different entity in each time period (Sufian & Majid, 2007).

Our dataset has nine seed-producing firms, thus $n = 9$. The number of outputs is one and inputs is three. The period under investigation is 2008–2015, yielding eight annual periods, so let $P = 8$. We increased the number of observations by choosing a window width of 4 years, so let $w = 4$. Although there is no theoretical basis for determining the width of a window (Tulkens & Vanden Eeckaut, 1995), Asmild et al. (2004) remark about the following tradeoff. A window should be small enough to minimize the temporal unfairness comparison but large enough to have sufficient sample size. Four years proved to be the optimal window width for our relatively small sample size and study period spanning 8 years. In her study on the banking sector, Řepková (2014) makes a case for a window width of 3 years.

Each firm is placed in a window as if it was a different firm for each of the 4 years within that window. Thus, for Window 1 (W1): years 2008, 2009, 2010, and 2011. This assumption increases the number of firms to 36 ($= n \times w = 36$), and the analysis is performed on these 36 firms. W2 shifts the yearly period out by one to 2012 and simultaneously excludes the first year, 2008. Thus, W2 is 2009, 2010, 2011, and 2012. This pattern is repeated until the final window, W5, analyzes 2012–2015 (Table 1).

A model of seed production by a commercial seed firm is the outset for testing its efficiency. One such model is that a seed firm combines capital with scientific knowledge (born from its R&D efforts, intellectual property, and know-how), human resources (labor) (Pray et al., 2005), and marketing-advertising-sales effort to produce improved seed (i.e., with superior genetic traits).

Our model uses a single-output (seed sales) production technology. From the data we collected, the following inputs are used to compute the efficiency scores: capital (assets), variable costs (a combination of sales, marketing, and advertising costs; R&D expenditure; and cost-of-goods), and labor (headcount). Typically, seed firms produce improved seeds comprising a unique range of plant species. Thus, the single output, namely, seeds, is in effect heterogeneous in terms of plant species composition and method of genetic improvement (Bonny, 2017). In terms of the latter, GE seeds could be considered to be a second category of output—with conventionally bred seeds the first—due to their high costs of development (Kalaitzandonakes et al., 2007; Phillips McDougall, 2011b), the lengthy period it takes for them to overcome regulatory hurdles for commercialization (Smart et al., 2016), and their market protection from competition through their patents, which "protect a marketed product for about 15 to 20 years after … product development" (Zhou, 2015). For simplicity, our model assumes that all seeds, irrespective of plant species and method of development, are a single homogenous output. Thus, seed sales—our single "homogenous" output variable—overcomes the aggregate problem of dealing with what is essentially a heterogenous output (multiple seed types (plant species) with two possible development methods (conventional plant breeding or genetic engineering), each with a different unit price per sales region).

2.1.3 | Data

We derived the data for our output and inputs for the firms studied (Table 2) by scrutinizing the content of two sources: (1) publicly available corporate documents such as annual reports and financial reports[2] and (2) annual reports obtained from a data analysis firm called Phillips McDougall (Phillips McDougall, 2008, 2010, 2011a, 2012, 2013, 2014, 2015, 2016), which specializes in "providing detailed analysis of the agrochemical and seed industries" (Phillips McDougall website, 2016). Documents of this type are commonly used in empirical benchmarking studies to examine firms' performance (e.g., Li et al., 2015; Mooneeapen et al., 2021; Yuan & Wen, 2018). Of importance is that our data collection effort proved fruitless for sourcing annual productivity data (e.g., tons of seed produced, area used for producing seed, and tons of fertilizer used) either directly from firms or from annual financial statements, because some firms are not publicly listed. Our experience supports the claim by Bonny (2014) that accessible data on this sector are scarce. The data of our finite sample comprise a balanced panel of eight consecutive years, with nine firms, one output variable, and five input variables.

Table 2 provides summary statistics for 2015, the final year in our dataset, for the output (Y) and inputs (X) considered in this study. In the production frontier specification, output is represented by gross seed sales measured in USD, which is about 25,130M USD for the whole sample. Five input variables are used, namely, (1) assets (we used equity and noncurrent liabilities as a proxy for fixed assets), (2) cost-of-goods, (3) R&D expenditure, (4) sales-marketing-advertising costs (all the aforementioned are measured in USD), and (5) staff compliment (measured as headcount). For simplicity, we

TABLE 2 The expanded dataset of our sample for 2015 the final year in our study

Firm	Gross seed sales (USD M)	Assets (USD '000 M)	Cost-of-goods (USD M)	R&D (USD M)	Sales-marketing-advertising (USD M)	Staff (headcount)
Monsanto	10,021	21,920	3957	1482	2144	22,400
DuPont Pioneer	6787	41,166	3381	783	1469	12,300
Syngenta	2828	18,977	1386	640	588	4500
Dow	1453	68,026	668	285	304	700
Bayer	1417	80,473	508	551	165	2100
KWS	1179	1517	542	209	292	4816
DLF	617	328	425	32	131	816
Takii	429	1153	237	34	108	750
Sakata	399	851	197	43	120	1998
Sample total	25,130	234,411	11,301	4059	5321	50,380

TABLE 3 Top 11 firms globally ranked by seed and trait sales for 2008 and 2015 (nominal USD) and acquisitions made and events approved in the United States (2008–2015)

		Seed sales				
Rank	Firm	2008 (USD M)[a]	2015 (USD M)[b]	Increase 2008–2015 (%)	Firms acquired 2008–2015[d]	Events approved in the United States 2008–2015[e]
1	Monsanto	6632	10,021	51.10	13	14
2	DuPont Pioneer	3992	6787	70.02	11	7
3	Syngenta	2442	2838	16.22	19	6
4	Vilmorin[c]	1495	1518	1.54	NA	NA
5	Dow	470	1453	209.15	15	5
6	Bayer	662	1417	114.05	13	4
7	KWS	880	1179	33.98	8	1
8	AgReliant Genetics[c]	344	630	83.14	NA	NA
9	DLF	442	617	39.59	2	0
10	Takii	400	429	7.25	1	0
11	Sakata	304	399	31.25	4	0

[a]*Source*: Phillips McDougall (2008).
[b]*Source*: Phillips McDougall (2016).
[c]Excluded from our study due to insufficient data.
[d]Refer to Table S1.
[e]Refer to Table S3.

reduced the number of input variables from five to three by combining the input cost variables (2, 3, and 4 above). In summary, our single output (gross seed sales) is a function of the following three inputs: assets, variables costs (cost-of-goods, R&D, sales-marketing-advertising), and staff compliment.

"The total size of the seed market is not well known due to the difficulty of assessing the value of seeds saved by farmers and the total value of the commercial seed market. The latter was approximately 48.5 billion USD in 2015" (Bonny, 2017). Thus, our sample covers about half of the estimated global seed market in terms of sales for the final year in our sample (Table 2).

Each variable's total is reported for each firm's financial year.[3] For most firms, the financial and calendar years are asynchronous. As this feature remains constant in the panel, we avoided statistical manipulations to adjust asynchronous temporal data to align with the calendar- rather than financial year. An anomaly of the dataset for the firm Bayer is that its headcount remained unchanged for all years reported, which we consider unrealistic especially as it acquired 13 firms, inclusive of their personnel, during our study period (Table 3).

All firms grew inorganically through corporate activity, which contributed to the concentration of the global seed market. The total number of acquisitions made across all firms was 86. Syngenta (19) and Takii (one) made the most and fewest acquisitions, respectively (Table 3). The most and least active years for corporate activity were jointly 2008 and 2013 (15 acquisitions each) and 2015 (four acquisitions), respectively. Noteworthy, is that GE crop-producing firms made the most acquisitions (in descending order: Syngenta [19], Dow [15], Bayer [13], Monsanto [13], and DuPont Pioneer [11]; Table S1). These firms expanded their seed production and distribution bases and developed their technology platforms. This business strategy was followed because the GE seed market was in a growth phase, while the commercial seed market was considered mature (Phillips McDougall, 2016).

During our study period, Monsanto had the highest seed sales (nominal USD). Dow had the greatest growth in sales of around 209% and Vilmorin (excluded from our analysis together with AgRelaint Genetics because of incomplete data) the lowest growth of less than 2%. GE seed sales represented about 22.5% and 32% of global commercial seed sales in 2008 and 2012, respectively (Bonny, 2014). The sale of GE seeds contributes appreciably to the gross seed sales of firms producing these seeds (Phillips McDougall, 2016). Of the total number of GE crops approved for sale in the United States (i.e., petitions of events[4] granted nonregulatory status) during our study period, 37 were approved (extensions were granted to five events that were previously approved) by firms in our study. Monsanto was the leader in event approvals (14), and the year with the most event approvals was 2013 with eight (Table 3).

3 | EMPIRICAL RESULTS AND DISCUSSION

The body of scientific literature is lean on studies reporting on the economic efficiency of commercial seed-producing firms. This study provides new information on the efficiency of nine of the largest of these firms worldwide. The DEA model is applied in five 4-year windows for the period 2008–2015. The results are reported for the general trend in OTE for each window followed by decomposing them into PTE and SE. Trends in efficiency are described and discussed.

3.1 | Overall technical efficiency

We used the CCR model to compute the OTE scores for each firm. The OTE score indicates a seed firm's ability to maximize seed sales from the defined set of inputs (see Section 2.1) under conditions of CRS.

The trend for the temporal mean aggregate OTE score is convex shaped. Efficiency increased steadily from 93.5% in W1 to peak at 95.6% in W3, followed by a small decrease to W4 with a slightly steeper descent to W5 (94.3%). Overall, there was a slight increase in mean efficiency (W5 > W1) of 0.8% (Figure 1; note that the y axis is rescaled to the mean efficiency range 93% to 96%). This observation reflects the overall trend of managerial ability to maximize seed sales from inputs.

The following firms contributed most to the upward trend (W1–W3) in efficiency: Dow, Sakata, and Takii. The latter two contributed most to the subsequent downward trend, possibly as a result of declining sales revenue coupled with unfavorable exchange rates (Phillips McDougall, 2016). The overall change in the mean aggregate

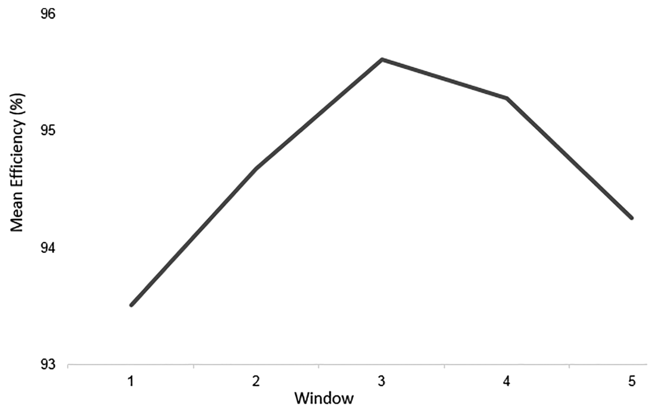


FIGURE 1 Mean aggregate OTE score (%) for all firms for Windows 1–5

OTE is positive but minuscule. Of the nine firms analyzed, a meager increase and decrease (less than ±2%) in OTE is displayed by two and six firms, respectively. This result indicates a relatively stable temporal OTE. The exception is Dow with an overall positive change in efficiency of 7.75% (Table 4). Dow's five GE crops that were approved in the United States and its phenomenal growth in seed sales (209%) (Table 3) contributed to this improvement in efficiency.

Table 5 reports the means and variances across all windows and the greatest differences by window and by year of OTE. The relative stability of each firm's performance is evident from these results, especially their low variances. DLF Trifolium is the strongest, most consistent performer (highest mean OTE score, lowest overall variance) with Sakata the weakest, most inconsistent performer (lowest mean OTE score, greatest overall variance). DLF Trifolium's stability is reinforced by two of its greatest difference scores (within a window and across the entire period) being the lowest (GDW = GDY = 2.97%). DLF Trifolium's performance was probably the result of its management having executed prudent decisions that resulted in consistent growth in seed sales, while simultaneously having managed inputs carefully. For example, following the acquisition of the Advanta grass seed business from Vilmorin in 2007, it reduced its excess research capability by divesting ASP Research in Oregon, United States. In 2010, it established a subsidiary in Moscow to grow its forage grass business there. In 2015, it expanded into Ireland by forming a joint venture with the local firm Seedtech (Phillips McDougall, 2016).

Dow had the lowest score for the greatest difference in the same year but a different window. Monsanto and KWS were both strong, consistent performers with remarkably similar results, but Monsanto performed better within a window and across the entire period. Monsanto's strategy of regularly bringing new GE crops to this growing market segment (2009 and 2010 are the only exceptions: see Table S3) probably contributed to its consistent performance. The bulk of KWS's seed sales (>80%) was from corn (e.g., sales in Brazil rose by 25.6% in 2015) and sugar beet (Phillips McDougall, 2016). KWS's strategy of maintaining this strong but narrow focus probably contributed to its consistently strong performance.

TABLE 4 Mean OTE scores for each firm in each window and overall difference

Firm	Mean efficiency (%) Window 1	Window 2	Window 3	Window 4	Window 5	Difference W1–W5 (%)
Bayer	90.03	89.79	90.25	90.34	89.96	−0.08
DLF Trifolium	99.77	99.30	99.63	98.89	99.06	−0.71
Dow	91.42	97.10	98.88	99.73	99.10	7.75
DuPont Pioneer	95.72	96.07	96.83	97.32	95.67	−0.05
KWS	98.74	97.99	98.54	98.81	97.81	−0.95
Monsanto	99.10	98.69	98.76	98.08	97.93	−1.19
Sakata	87.20	91.33	91.09	88.43	85.80	−1.64
Syngenta	84.83	85.19	87.32	87.85	86.32	1.73
Takii	94.78	96.71	99.26	98.12	96.67	1.96

TABLE 5 Mean, variance, and difference statistics (highest mean first) for OTE for all firms

Firm	Overall mean (%)	Overall variance (%)	GDW[a] (%)	GDY[b] (%)	TGD[c] (%)	Performance rating
DLF Trifolium	99.33	0.01	2.97	2.97	2.97	α[d]
Monsanto	98.51	0.02	3.00	2.67	3.00	α
KWS	98.38	0.02	5.54	2.26	5.54	α
Bayer	90.07	0.03	5.30	2.24	5.45	α
DuPont Pioneer	96.32	0.08	8.85	2.25	8.85	Ω[e]
Takii	97.11	0.10	9.15	2.73	9.15	Ω
Syngenta	86.30	0.14	12.94	4.09	12.94	Ω
Dow	97.25	0.30	24.06	0.62	24.06	Π[f]
Sakata	88.77	0.35	15.41	3.19	17.95	Π

[a]GDW: greatest difference within a window.
[b]GDY: greatest difference in the same year, but different window.
[c]TGD: total difference for the entire period.
[d]α: strong, consistent performers.
[e]Ω: average, inconsistent performers.
[f]Π: weak, inconsistent performers.

DuPont Pioneer's average, inconsistent performance might be ascribed in part to its high level of corporate activity (Tables 3, S1, and S2) and the associated managerial challenges of incorporating new businesses into the mother company (Bogetoft & Wang, 2005). Seed sales declined in 2015 due to declining maize and soybean seed volumes and prices in North and Latin America. Efforts to improve efficiency included the following. In 2008, it implemented a strategy "to improve and develop business agreements with independent seed companies separate from the Pioneer brand" to improve its access to markets. In 2014, it launched its precision agriculture service and entered into research and information-sharing agreements. Farmers are able to use these services to make financially driven decisions (Phillips McDougall, 2016) and presumably purchase "appropriate" seeds and matching agrochemicals from the company.

Although Bayer has the seventh lowest OTE score, it was the fourth best performer (Table 5). The acquisition of Stoneville in mid-2007 (the year before the start of our study period) made a significant contribution to sales growth in 2008 and 2009. Bayer's slight drop in performance from W4 to W5 was probably due to a 3.3% decline in seed sales (in USD terms) in 2015 "… due in part to a significant fall in global sales of cotton seed and sales of seed in Europe where currency conversion affected growth in dollar terms." Also playing a role in this decline in seed sales might have been Bayer's divestment in 2013 of its hybrid maize seed business in India (Phillips McDougall, 2016).

Takii is primarily involved in producing seeds of vegetables and flowers, which is largely "a consumer end-use driven market." Japan represents approximately two thirds of Takii's market, followed by Europe and the United States (approximately 11% each). To improve its market presence in Europe, Takii made acquisitions in 2007 and 2008 there. However, its average, inconsistent performance (Table 5) was mainly impacted by unfavorable currency effects (Yen vs. USD) (Phillips McDougall, 2016).

Despite Syngenta ranking third in terms of seed sales (Table 3), it was an average, inconsistent performer with the lowest overall mean OTE (Table 5) that was consistently below 88% (Table 4). Syngenta made the most acquisitions (Table 3), which were temporarily evenly distributed across windows (Table S2). Thus, it is possible that the managerial challenges associated with incorporating these new firms into Syngenta's corporate structure and business culture kept its OTE from improving (Bogetoft & Wang, 2005). Syngenta's relative inefficiency might also have been impacted by its lawn and garden products being excluded from its seed business from 2011, and that its key seed brands, despite being consolidated within its overall organization, operated relatively autonomously (Phillips McDougall, 2016). A possible downside of this autonomy is the loss of potential synergies arising from operating cooperatively.

Table 5 shows that Sakata was the weakest, most inconsistent performer with the second lowest overall mean OTE score. This performance might be ascribed to the following three factors: (1) Sakata made two divestments in 2009; (2) during the 2005 fiscal year (ending in May), it restructured the company's organization to make it more cost efficient; and (3) unfavorable currency fluctuations (Yen vs. USD) (Phillips McDougall, 2016).

In summary, the aggregate mean OTE (a measure of managerial ability) increased marginally by 0.8%. OTE displayed a convex-shaped trend that peaked in W3 at 95.6%. Dow, Sakata, and Takii contributed most to its upward trend with the latter two contributing most to its subsequent decline. The three strongest, most consistent performers were DLF Trifolium, Monsanto, and KWS, and the three weakest, most inconsistent performers were Syngenta, Dow, and Sakata. As it is likely that one or more of these firms operated under either economies or diseconomies of scale (the CCR model presuppose CRS, which is only justifiable when all firms are operating at optimal scale), the results for OTE are tainted with SEs (Sufian & Majid, 2007). The next section relaxes the CCR assumption of firms operating under CRS by analyzing VRS efficiency—also known as PTE.

3.2 | Pure technical efficiency

In this section, we analyze PTE using the BCC model, which assumes VRS. PTE measures OTE without SE effects (see Section 2.1). In theory, when one moves along the frontier from smaller to larger inputs in a VRS model, returns to scale display the following trend: increase, remain constant, and decrease. In economic terms, the equivalent trend is true for average product. The input level at which CRS is achieved is the most productive scale size and is where all firms would like to operate (Bogetoft & Otto, 2011). Increasing returns to scale (IRS) and decreasing returns to scale (DRS) are achieved before and after this input level, respectively. When a firm operates under either IRS or DRS, expanding or contracting its operations (i.e., scale size), respectively, are prudent management considerations.

Figure 2 (note that its *y* axis is rescaled to start at an efficiency score of 80%) displays the results of the relationship between PTE and scale (in terms of assets) for all firms across all windows. Four clusters are apparent: (1) with efficiency scores ranging from >94.5% to 100% with relatively low capital (≤USD 1454M); (2) with efficiency scores fluctuating in the range 80.8% to 100% with moderately low capital (a narrow band: USD 14,584M to USD 20,769M); (3) with efficiency ratings in the range >91% to 100% with medium capital

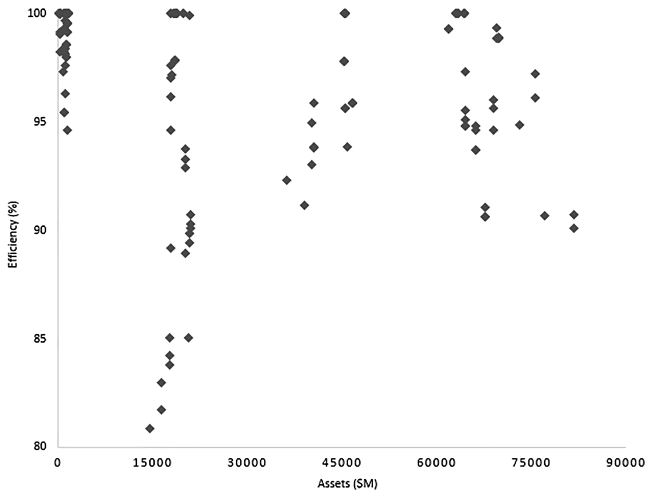


FIGURE 2 PTE versus assets of firms for all years and all windows

(USD 36,209M to USD 46,694M); and (4) firms that have efficiency scores in the range >90% to 100% with relatively high capital (USD 61,872M to USD 81,637M).

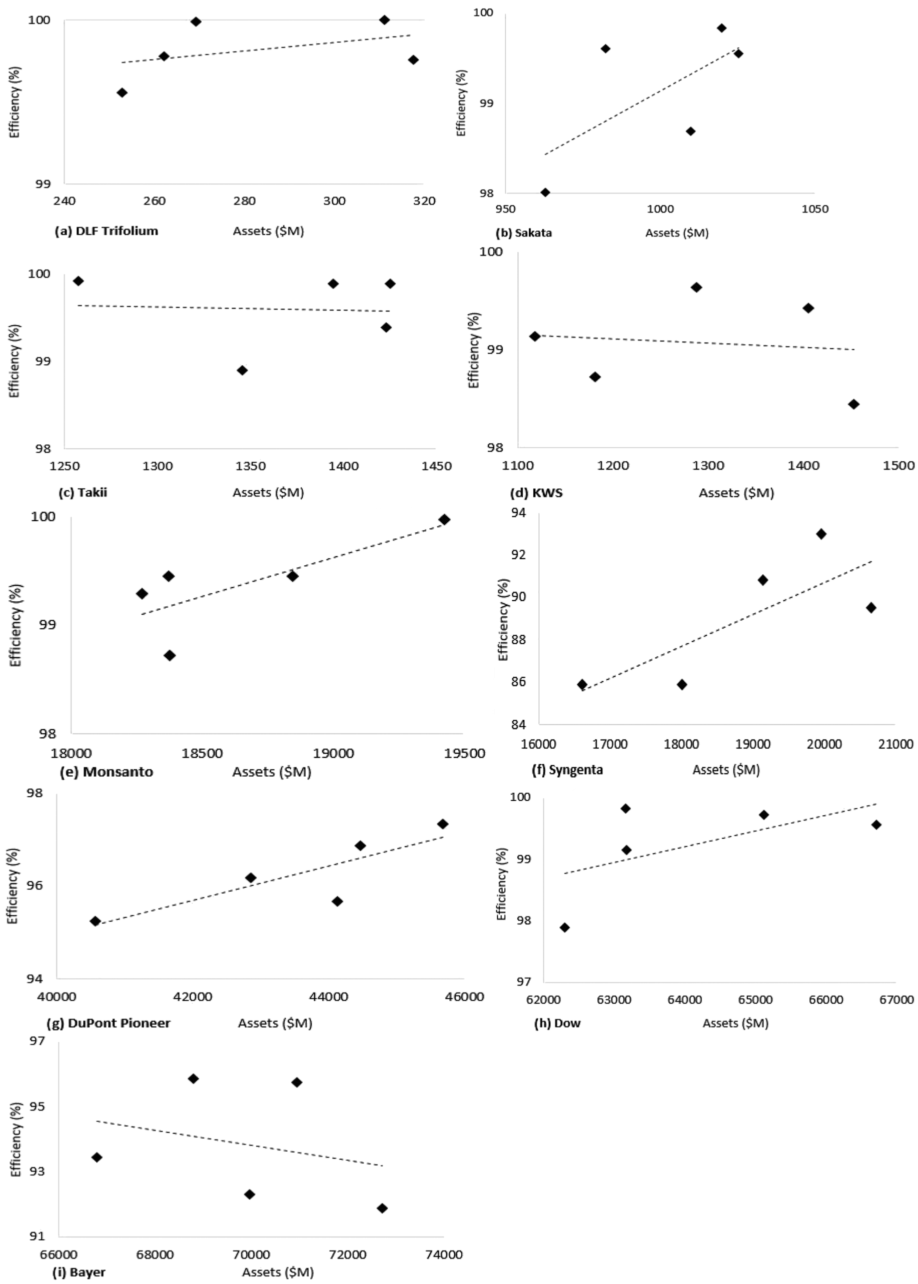
Therefore, within each cluster, firms differ in their ability to convert inputs into the output under the assumption of VRS.

As there is no clear relationship between PTE and asset size (Figure 2), we examined each firm's behavior. Due to the large range in the asset values across firms, we rescaled the axes of each firm's graph to reveal any trends and to assess if the firm operates under IRS, CRS, or DRS (Figure 3).

DuPont Pioneer, Monsanto, and Syngenta show an overall positive relationship between PTE and asset size, with Sakata's relationship weakly positive (Figure 3b,e,f,g). Thus, it appears that these firms operated under IRS, and in terms of PTE, their management could have considered expanding operations. DuPont Pioneer expanded by making acquisitions every year except 2008 and 2014 (Table S1). In mid-2008, DuPont Pioneer opened new seed research centers in Hungary and Italy. The following year, it invested in information technology firms that develop and market proprietary crop management software and online marketing and procurement; and it expanded seed production sites and facilities in Asia. In 2012, it opened a soybean seed production facility in Missouri, United States. Other noteworthy expansions in production included ones in Austria and the Philippines in 2011 and in Ukraine in 2013. In 2013, it expanded its operations in Africa by acquiring Pannar Seed in South Africa, which operated in eight other African countries. During our study period, it expanded its office space and seed mixing and packaging facilities in Denmark (Phillips McDougall, 2016).

DLF Trifolium operated at or close to CRS (Figure 3a and Table 6). It made two acquisitions, one each in 2012 and 2013—the second least number of acquisitions made by the firms in this study (Tables 2 and S1). The size of these acquisitions is unknown; however, it appears that this expansion strategy contributed to achieving its optimal size. Takii's PTE score of 99.9% corresponds to its lowest

FIGURE 3 PTE versus assets for each firm (rescaled *x* and *y* axes; linear trend line included)



asset value and implies CRS. Its next PTE score was marginally lower by about 1%, after which it returned to a level that effectively represents CRS (Figure 3c), which might reveal the effect of the merger between Takii Europe and K Sahin Zaden of the Netherlands (Phillips McDougall, 2016).

The relationship between PTE and asset size for Sakata (Figure 3b) and Bayer (Figure 3i) has a sawtooth trend. It is important to note that Figure 3 does not display a temporal trend. When we inspect the overall temporal trend in PTE (slightly negative) in Table 6 for these firms, Sakata's scores from W1 to W3 were fairly constant at just below 100% (implying CRS), after which they declined marginally thereby implying DRS. Bayer's PTE scores from W1 to W3 were approximately 96% after which they declined to around 92%. Bayer's slightly negative temporal trend in PTE implies that from W4 onwards it operated under DRS.

In terms of PTE, Sakata's divestments in 2009 from Frisa Planter in Denmark and its UK ornamentals subsidiary are questionable as it was operating close to CRS at that time. It made acquisitions in 2008 and 2009, which appear to have had a tiny positive impact on PTE. However, its acquisition in 2013 (Table S1), the size of which is unknown, is arguable as it was operating under DRS. From 2008 to 2010, Bayer made one acquisition. During the remaining 5-year period, it made 12 acquisitions (Table S1). The acquisitions might have formed part of a long-term business strategy. For example, each year during this study Bayer expanded its R&D capacities across the globe, which included acquiring firms specializing in R&D

TABLE 6 Mean OTE, PTE, and SE scores for all firms for Windows 1–5

Firm	Window 1			Window 2			Window 3			Window 4			Window 5		
	OTE (%)	PTE (%)	SE (%)	OTE (%)	PTE (%)	SE (%)	OTE (%)	PTE (%)	SE (%)	OTE (%)	PTE (%)	SE (%)	OTE (%)	PTE (%)	SE (%)
Bayer	90.0	95.4	94.4	89.8	95.9	93.7	90.2	93.5	96.6	90.3	92.3	97.9	90.0	91.9	97.9
DLF Trifolium	99.8	99.8	100.0	99.3	99.6	99.7	99.6	100.0	99.6	98.9	100.0	98.9	99.1	99.8	99.3
Dow	91.4	97.9	93.2	97.1	99.6	97.5	98.9	99.7	99.2	99.7	99.8	99.9	99.1	99.1	100.0
DuPont Pioneer	95.7	95.8	99.9	96.1	96.2	99.9	96.8	96.9	100.0	97.3	97.3	100.0	95.7	95.7	100.0
KWS	98.7	99.1	99.6	98.0	98.7	99.3	98.5	99.6	98.9	98.8	99.4	99.4	97.8	98.4	99.4
Monsanto	99.1	99.3	99.8	98.7	98.7	100.0	98.8	99.5	99.3	98.1	99.5	98.6	97.9	100.0	98.0
Sakata	87.2	99.6	87.6	91.3	99.6	91.7	91.1	99.8	91.2	88.4	98.7	89.5	85.8	98.0	87.5
Syngenta	84.8	85.9	98.8	85.2	85.9	99.1	87.3	90.8	96.2	87.9	93.0	94.5	86.3	89.5	96.5
Takii	94.8	99.9	94.9	96.7	99.9	96.8	99.3	99.9	99.4	98.1	99.4	98.7	96.7	98.9	97.7

(see Phillips McDougall, 2016). The economic impacts of these investments were probably delayed due to lengthy periods for developing and commercializing new seeds, especially GE seeds (Smart et al., 2016). However, from a PTE perspective, these acquisitions—all contributing to firm size—were theoretically unjustified.

Dow's initial sharply positive relationship between PTE and size (IRS) coincided with the period when it made most of its acquisitions (13 of 15 acquisitions from 2008 to 2012; Table S1). This trend peaked at an asset level of USD 63,154M (99.82%) where the firm effectively achieved and maintained CRS as its PTE scores remained above 99.9% (Figure 3h). Monsanto is an interesting case as it had a positive trend in PTE versus assets size, which peaked at 100%, thus indicating that up to this point, it theoretically operated under IRS (Figure 3e). Monsanto's acquisition strategy (acquisitions were made in all but 2 years; Table S1) was therefore legitimate from a PTE perspective. The relationship between PTE and asset size for Syngenta increased to peak at approximately 93% (asset level of USD 19,947M) after which it declined (Figure 3h). The overall trend, however, was positive thus indicating IRS, which supported its expansion strategy (it made 19 acquisitions; Tables 2 and S1). The *y* axis's exaggerated scale in Figure 3d (KWS) reflects the following trend for PTE versus asset size: a slight decrease from a PTE score of over 99%, an increase that peaked at 99.6% in W3 where it remained stable, and a slight decrease to 98.4% (Table 5). Therefore, KWS did not reach the efficient frontier. KWS made eight acquisitions, six of which were made during 2011–2012 when its PTE score peaked. This expansion strategy is supported by theory as it is likely that the firm was operating under IRS.

To sum up, we used the BCC model to measure PTE. No clear relationship between PTE and asset size is evident (Figure 2). In measuring PTE, the BCC model ignores the impact of scale size by comparing firms of similar scale (Ma et al., 2002). The firms in our sample span a wide range in terms of size, which may be problematic. Nevertheless, the results of this model reflect that the strong corporate activity (i.e., expansion via acquisitions) of most firms, except Bayer, was probably theoretically justified with Dow, DuPont Pioneer, Syngenta, and Monsanto being the best examples (Monsanto ended with a PTE score of 100% in W5; Figure 3e and Table 6). Takii and DLF Trifolium effectively operated under CRS as their PTE scores were consistently above 99%, except in W5 for Takii (98.9%). Next, we complete the decomposition of the OTE scores by analyzing the SE scores.

3.3 | Scale efficiency

SE is the ratio of CRS efficiency (OTE) to VRS efficiency (PTE), which cannot exceed unity. SE measures how the scale size affects efficiency (Al-Refaie et al., 2019). A difference between the OTE and PTE scores for a given firm indicates scale inefficiency (Sufian, 2007). At a ratio of unity, firms theoretically operate at their optimal scale size, which is the level where the CRS and VRS technologies coincide.

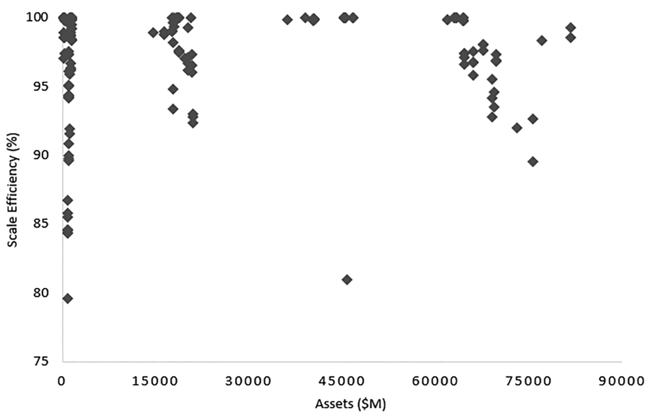


FIGURE 4 Scale efficiency for all firms for all years and all windows

The larger the SE score, the closer a firm is to operating at optimal scale (Bogetoft & Otto, 2011). The results of the CCR model (with CRS) are lower than those of the BCR model (with VRS): see the columns for OTE and PTE scores for each window in Table 6. As noted by Řepková (2014), this outcome is the consequence of the BCC model decomposing the efficiency of firms into PTE and SE.

SE is reported for all asset sizes up to a maximum of approximately USD 81,700M. If we ignore the reported 'outlier' SE score of 80.9% for an asset level of USD 45,747M (Dow is the firm), the most scale efficient cluster is bound by the asset range of USD 36,209M to USD 46,694M. SE exhibits a downward trend for assets greater than approximately USD 64,000M—an asset level up to which SE appears to be possible. Aside from this observation, no clear-cut relationship between SE and size is evident (Figure 4; note that its *y* axis is rescaled to start at an efficiency score of 75%). As with the preceding

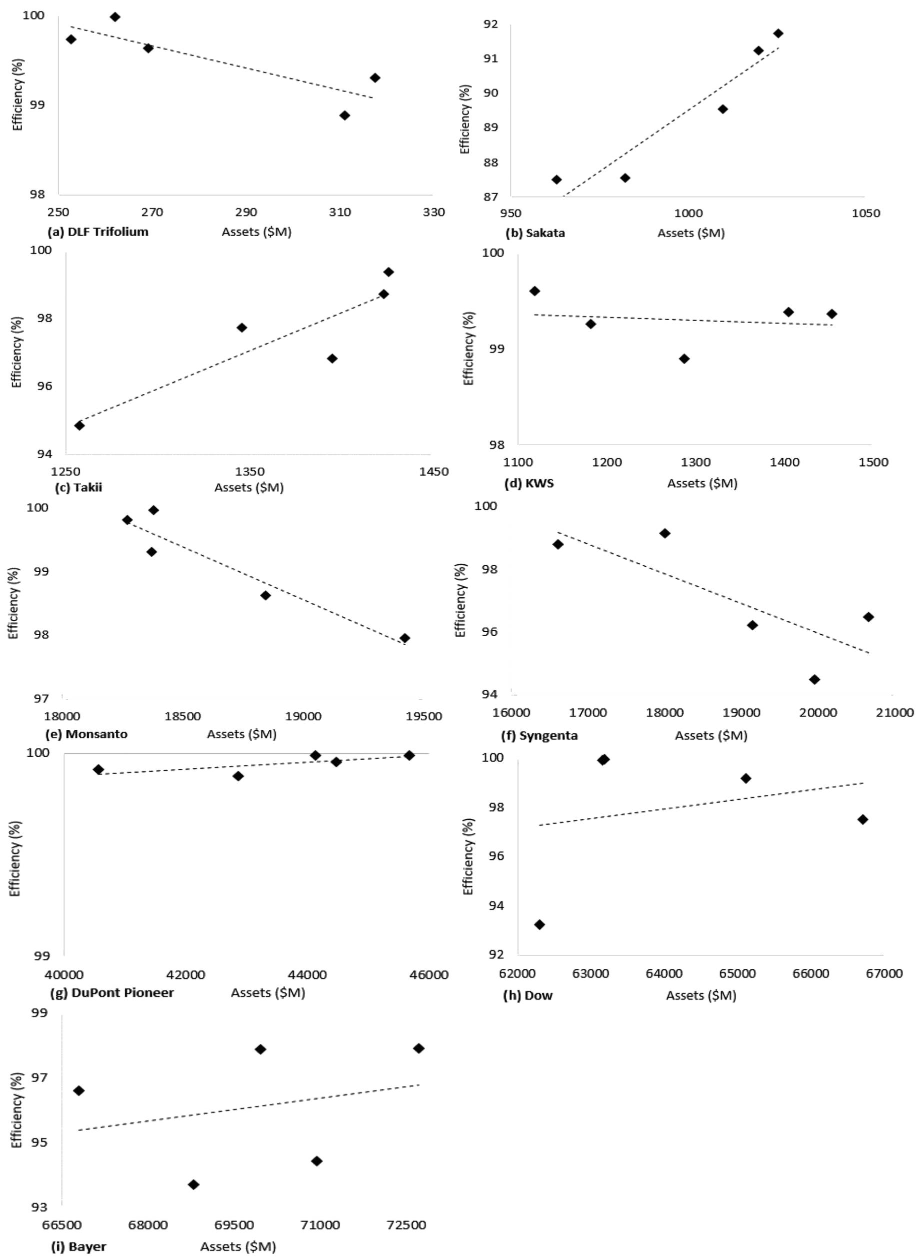


FIGURE 5 SE versus size (assets) for each firm (rescaled *x* and *y* axes; linear trend line)

subsection, we use Figure 5 to display each firm's results individually in panels (the *x* and *y* axes of each firm's graph were rescaled to reveal any trends, and a linear trend line is displayed).

DLF Trifolium achieved SE at an asset level of USD 262M (Figure 5a) in W1 (Table 6). Scale inefficiency resulted at asset levels on either side of this value. Sakata and Takii show an upward trend in SE (Figure 5b,c) but remained scale inefficient.

KWS's SE scores range between 98.9% and 99.6% (Figure 5d and Table 6). It, therefore, operated under slight scale inefficiency. Monsanto effectively operated in terms of SE at an asset level of about USD 18,340M, after which it was scale inefficient (Figure 5e).

Syngenta was always scale inefficient (Figure 5f). Despite Syngenta nearly reaching SE in W2 (99.1%), a minute difference between its OTE and PTE scores existed then, but both scores were below 86% (Table 6). Syngenta's relatively poor OTE and PTE scores are likely to be linked to challenges associated with its high corporate activity, corporate structure, and management ability to efficiently convert inputs to output. Although DuPont Pioneer was effectively scale efficient (Figure 5g), there was room for modicum improvement in both its managerial efficiency (OTE) and PTE scores (Table 6). Dow reached SE at an asset level of approximately USD 63,160M. On both sides of this asset level, Dow was scale inefficient (Figure 5h). From W2 to W5, Dow's PTE scores exceeded 99%. Therefore, managerial ability (OTE) was the main contributing factor to it being scale inefficient. A possible cause for managerial inefficiency could have been troubles associated with integrating the 15 firms it acquired during the study period (Tables 3 and S1). In all windows, Bayer was scale inefficient. Its best SE score of 97.9% corresponds to its highest asset level of approximately USD 72,700M (Figure 5i). Bayer's highest PTE of 95.9% means that it never achieved the efficient frontier (Table 6). Thus, Bayer needed to improve both its managerial ability (OTE) and PTE scores in all windows. For it to have achieved SE, these efficiency scores would have had to be equal in the same window.

4 | CONCLUSION

In this study, we used DEA to analyze the efficiency levels of nine of the largest commercial seed-producing firms globally for the period 2008–2015 and assessed if there was a relationship between firm size and efficiency score, specifically PTE and SE. We used the DEA windows analysis method to allow for the assumption of time invariance of the frontier. An input-oriented model (three inputs with one output) is used to represent the technology of a balanced panel data set. First, we analyzed OTE, which indicates a firm's ability to maximize seed sales from a defined set of inputs under conditions of CRS. Second, we relaxed the CRS assumption by analyzing efficiency under VRS or PTE, which reveals if firms are operating under IRS, CRS, or DRS and whether an expansion or a contraction in operation was justified. Third, we decomposed the OTE scores by analyzing SE, which indicates how scale size affects efficiency. SE is achieved when a firm's OTE and PTE scores converge.

Our results show that (1) the mean temporal OTE increased by a mere 0.8%—an unremarkable reflection on managerial ability to improve on maximizing seed sales from inputs. The less than 1% overall change in mean OTE, however, reflects stability in managerial ability in this sector. Dow was the exception with an overall increase in OTE of 7.75%, which, for the firms in our dataset, implies that its strategies were the most successful for improving OTE. (2) There is no clear relationship between PTE and asset size. On a firm level, DuPont Pioneer, Syngenta, Monsanto, and Dow operated under IRS with the latter two reaching CRS—the most productive scale size. DLF Trifolium and Takii operated at or close to CRS. Sakata and Bayer displayed an inconsistent sawtooth-shaped trend in PTE versus size. Thus, they operated under both IRS and DRS. (3) No conspicuous overall relationship between SE and asset size is apparent. DuPont Pioneer was scale efficient in three consecutive windows, while DLF Trifolium, Dow, and Monsanto achieved this outcome in one (but not the same) window. All other firms were consistently scale inefficient with Sakata having the lowest SE scores (87.5% to 91.7%).

Our OTE results reveal that under conditions of CRS, seed firms consistently operated at a relatively high level of efficiency. Consolidation in this sector continued unabated during our study period, which Bonny (2014), inter alia, view critically. In terms of efficiency, and relevance from a policy perspective, our PTE analysis reveals that the corporate activity (M&As) of most firms was theoretically justified (Dow, DuPont Pioneer, Syngenta, and Monsanto were the best examples) but that Bayer's was not. However, the impact of market concentration on competition and innovation, for example, lay beyond the scope of our inquiry.

To summarize, we found that managerial ability as measured by OTE was at a consistently high level (>93.5%) and stable, with Dow the only firm where a meaningful, positive improvement was shown. All firms expanded through acquisitions, and in terms of PTE only, Bayer is the only firm whose expansion strategy we question. SE appears to be difficult to achieve consistently as it depends on OTE and PTE converging. DuPont Pioneer achieved SE in three windows. No obvious relationship between efficiency, specifically PTE and SE, and firm size was evident from our analyses.

Our study could be strengthened in four areas. First, our analysis of OTE scores—a measure of managerial ability, is bound by the assumption of CRS. This assumption is unrealistic as these results are likely to be tainted with SEs (Sufian & Majid, 2007). All the firms in our study expanded inorganically. In most cases, this growth was via M&As. Information on transaction sizes was unavailable. Therefore, we were unable to quantify the impact of this corporate activity on their growth. Also, growth of this sort does not necessarily translate into a proportional short-term improvement in firm performance (efficiency). Incorporating a new firm into an existing corporate structure and culture can present challenges that hinder a firm's OTE scores from improving (Bogetoft & Wang, 2005). Second, in measuring PTE, the BCC model ignores the impact of scale size by comparing firms of similar scale (Ma et al., 2002). The firms included in our sample span a wide range in terms of size (assets), which might be problematic. Third, as Kazley and Ozcan (2009) point out, "since

DEA relies on relative measurement, peer groupings are essential for homogenous comparison.". In terms of a generic output, all firms produced seed. However, on closer inspection, and as remarked by Bonny (2017), this solitary output is heterogeneous: firms neither produced the same kinds of seeds (e.g., some firms focus on horticultural crops, others on forage and grain crops) nor competed in the same geographical markets (e.g., Japan is the largest market for Sakata and Takii). Another source of heterogeneity is the use of biotechnology; not all firms in our sample produced GE seeds. We argue (also see Section 2.1) that GE seeds could be considered a second category of output. Some seed-producing firms also develop and produce agrochemicals, which are a complimentary output to seeds, and may impact firm efficiency. Fourth, our empirical analysis is limited by the availability of data, which neither allowed us to investigate the causes underlying the efficiency performance of the largest seed producers globally nor to include all 11 of these firms (Vilmorin and AgReliant Genetics, the fourth and eighth largest firm, respectively [Table 3], were excluded) in our analysis.

Future studies may aim to understand (1) the causes underlying the efficiency performance of the world's largest seed producers, which can be done by using bootstrapping techniques such as those proposed by Simar and Wilson (2007), and (2) the impact of market concentration on competition and innovation. We emphasize that the evidence reported in this study concerns only the firms' technical performance within the limits of our dataset and does not account for other aspects of firm performance. In particular, current changes in the business model have involved a fundamental shift in the measurement of firm performance that has moved beyond technical indicators to adopt environmental and social indicators. Hence, a future avenue for research is to study the corporate social responsibility performance of the global seed industry along the lines of Chambers and Serra (2018) or Puggioni and Stefanou (2019).

CONFLICT OF INTEREST

There are no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author.

ORCID

Amer Ait Sidhoum https://orcid.org/0000-0001-7089-6242

ENDNOTES

[1] An input-oriented model is used as the firms have little control over their outputs, but they have better possibilities to reduce their input use.

[2] See, for example, https://www.annualreports.com/HostedData/AnnualReportArchive/b/OTC_BAYZF_2008.pdf.

[3] The financial data reported were in USD (firms operating in other currencies had their financial data converted to USD by Phillips McDougall). As most economic behavior is assumed to be influenced by real rather than nominal variables (Wooldridge, 2013), we deflated these data from nominal- to real values as follows. The Organisation for Economic Co-operation and Development's (OECD's) producer price indices were used (OECD website, 2016). We used the country index for each firm's head office. The exception was Japan as it was not listed on the OECD's database. Here, we used the Bank of Japan's data (Bank of Japan website, 2016). This index was set to unity as the base value for 2008 by dividing all indices by the 2008 index value. The new indices were used to deflate all the variables (except headcount) by dividing each year's data by its index value.

$$newindex_t = (oldindex_t / oldindex_{newbase}).$$

The deflating exercise is the only adjustment that we made to our data.

[4] In the US's regulatory terminology, each genetic transformation (i.e., a GE crop) is called an event (Animal and Plant Health Inspection Service, 2020).

REFERENCES

Al-Refaie, A., Wu, C., & Sawalheh, M. (2019). DEA window analysis for assessing efficiency of blistering process in a pharmaceutical industry. *Neural Computing and Applications*, *31*, 3703–3717. https://doi.org/10.1007/s00521-017-3303-2

Animal and Plant Health Inspection Service. (2020). Movement of certain genetically engineered organisms. *Federal Register*, *85*(96), 29790–29838.

Asmild, M., Paradi, J. C., Aggarwall, V., & Schaffnit, C. (2004). Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *Journal of Productivity Analysis*, *21*(1), 67–89. https://doi.org/10.1023/B:PROD.0000012453.91326.ec

Bank of Japan website, 2016. Summary table of price indexes (updated every month). https://www.boj.or.jp/en/statistics/pub/pim/pimsummary.pdf

Banker, R. D., Charnes, A., & Cooper, W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Bayer website, 2020. Home. This is Bayer. History 2010-2018. https://www.bayer.com/en/history/2010-2018

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–121. https://doi.org/10.1016/S0377-2217(96)00342-6

Bogetoft, P., & Otto, L. (2011). *Benchmarking with DEA, SFA, and R* (p. 351). Springer. https://doi.org/10.1007/978-1-4419-7961-2

Bogetoft, P., & Wang, D. (2005). Estimating the potential gains from mergers. *Journal of Productivity Analysis*, *23*, 145–171. https://doi.org/10.1007/s11123-005-1326-7

Bonny, S. (2014). Taking stock of the genetically modified seed sector worldwide: Market, stakeholders, and prices. *Food Security*, *6*(4), 525–540. https://doi.org/10.1007/s12571-014-0357-1

Bonny, S. (2017). Corporate concentration and technological change in the global seed industry. *Sustainability*, *9*(9), 1632. https://doi.org/10.3390/su9091632

Brennan, M., Pray, C., Naseem, A., & Oehmke, J. F. (2005). An innovation market approach to analyzing impacts of mergers and acquisitions in the plant biotechnology industry. *AgBioforum*, *8*(2&3), 89–99.

Chambers, R. G., & Serra, T. (2018). The social dimension of firm performance: a data envelopment approach. *Empirical Economics*, *54*, 189–206.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Cooper, W. W., Seiford, L. M., & Tone, K. (2000). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software* (p. 318). Kluwer Academic Publishers.

Cromwell, E., Friis-Hansen, E., Tucker, M., 1992. The seed sector in developing countries: A framework for performing analysis. Overseas Development Institute, London, England. Working Paper 65. https://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/6969.pdf

Dow DuPont, 2017. Unlocking value creating three world-leading companies. 2017 Annual Report. https://www.annualreports.com/HostedData/AnnualReportArchive/t/NYSE_DOW_2017.PDF

Drake, L. (2001). Efficiency and productivity change in UK banking. *Applied Financial Economics*, *11*(5), 557–571. https://doi.org/10.1080/096031001752236825

FAO, 2019. Analysis on sales and profitability within the seed sector: Independent Report by IHS Markit (Phillips McDougall) for the Co-chairs of the Ad-hoc Openended Working Group to Enhance the Functioning of the Multilateral System of FAO's International Treaty on Plant Genetic Resources for Food and Agriculture. http://www.fao.org/3/ca6929en/ca6929en.pdf

Federico, G. (2005). *Feeding the world. An economic history of agriculture, 1800–2000* (p. 388). Princeton University Press.

Fernandez-Cornejo, J., Spielman, D., 2002. Concentration, market power, and cost efficiency in the corn seed industry. 2002 Annual Meeting of the American Agricultural Economics Association, Long Beach, CA. https://ideas.repec.org/p/ags/aaea02/19877.html

Fried, H. O., Lovell, C. A. K., & Schmidt, S. S. (2008). *The measurement of productive efficiency and productivity growth* (p. 656). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195183528.001.0001

Howard, P. H. (2009). Visualizing consolidation in the global seed industry: 1996–2008. *Sustainability*, *1*, 1266–1287. https://doi.org/10.3390/su1041266

Howard, P. H. (2015). Intellectual property and consolidation in the seed industry. *Crop Science.*, *55*, 248–2495. https://doi.org/10.2135/cropsci2014.09.0669

Hu, H., & Dou, X. (2015). Studies on economic benefits evaluation of seed industry based on DEA model—A case study of Zhangye corn seed industry. *Journal of Agricultural Science and Technology*, *17*(6), 150–157. http://en.cnki.com.cn/Article_en/CJFDTotal-NKDB201506029.htm

Jia, T., & Yuan, H. (2017). The application of DEA (Data Envelopment Analysis) window analysis in the assessment of influence on operational efficiencies after the establishment of branched hospitals. *Health Services Research*, *17*(265), 1–8. https://doi.org/10.1186/s12913-017-2203-6

Kalaitzandonakes, N., Alston, J. M., & Bradford, K. J. (2007). Compliance costs for regulatory approval of new biotech crops. *Nature Biotechnology*, *25*(5), 509–511. https://doi.org/10.1038/nbt0507-509

Kazley, A. S., & Ozcan, Y. A. (2009). Electronic medical record use and efficiency: A DEA and windows analysis of hospitals. *Socio-Economic Planning Sciences*, *43*, 209–216. https://doi.org/10.1016/j.seps.2008.10.001

Kim, M.-R., Harris, T. R., & Vusovic, S. (2009). Efficiency analysis of the US biotechnology industry: Clustering enhances productivity. *AgBioforum*, *12*(3–4), 422–436.

Konja, D. T., Mabe, F. N., & Oteng-Frimpong, R. (2019). Profitability and profit efficiency of certified groundnut seed and conventional groundnut production in Northern Ghana: A comparative analysis. *Cogent Economics & Finance*, *7*(1), 1631525. https://doi.org/10.1080/23322039.2019.1631525

Li, J. H., Lin, L., Chen, D. P., & Ma, L. Y. (2015). An empirical study of servitization paradox in China. *The Journal of High Technology Management Research*, *26*(1), 66–76. https://doi.org/10.1016/j.hitech.2015.04.007

Lianos, I., Katalevsky, D., Ivanov, A., 2016. The global seed market, competition law and intellectual property rights: Untying the Gordian knot. Centre for Law, Economics and Society. Research Paper Series: 2/2016. UCL, London. https://www.ucl.ac.uk/cles/research-paper-series/research-papers/cles-2-2016

Liu, S., & Huang, Y. (2010). Comparative research into distribution efficiency of 9 seed listed companies: 2004-2008—Based on DEA method. *Systems Engineering*, *5*, 64–68. http://en.cnki.com.cn/Article_en/CJFDTotal-GCXT201005015.htm

Ma, J., Evan, D. G., Fuller, R. J., & Stewart, D. F. (2002). Technical efficiency and productivity change of China's iron and steel industry. *International Journal of Production Economics*, *76*(3), 293–312. https://doi.org/10.1016/S0925-5273(01)00195-5

Mammana, I., 2014. Concentration of market power in the EU seed market. Study Commissioned by the Greens/EFA Group in the European Parliament. http://greens-efa-service.eu/concentration_of_market_power_in_EU_see_market/files/assets/common/downloads/publication.pdf

Mooneeapen, O., Abhayawansa, S., Ramdhony, D., & Atchia, Z. (2021). New insights into the nexus between board characteristics and intellectual capital disclosure: The case of the emerging economy of Mauritius. *Journal of Accounting in Emerging Economies*. ahead-of-print. https://doi.org/10.1108/JAEE-12-2020-0322

OECD website, 2016. OECD.Stat. Welcome to OECD.Stat. http://stats.oecd.org/

Phillips McDougall, 2008. Phillips McDougall—AgriService seed service. The leading seed companies 2008 market situation (Pathhead, UK).

Phillips McDougall, 2010. Phillips McDougall—AgriService seed service. The leading seed companies 2009 market situation (Pathhead, UK).

Phillips McDougall, 2011a. Phillips McDougall—AgriService seed service. The leading seed companies 2010 market situation (Pathhead, UK).

Phillips McDougall, 2011b. The cost and time involved in the discovery, development and authorisation of a new plant biotechnology derived trait. A Consultancy Study for Crop Life International. https://croplife.org/wp-content/uploads/2014/04/Getting-a-Biotech-Crop-to-Market-Phillips-McDougall-Study.pdf

Phillips McDougall, 2012. Phillips McDougall – AgriService Seed Service. The Leading Seed Companies 2011 Market situation (Pathhead, UK).

Phillips McDougall, 2013. Phillips McDougall—AgriService seed service. The leading seed companies 2012 market situation (Pathhead, UK).

Phillips McDougall, 2014. Phillips McDougall—AgriService seed service. The leading seed companies 2013 market situation (Pathhead, UK).

Phillips McDougall, 2015. Phillips McDougall—AgriService Seed Service. The leading seed companies 2014 market situation (Pathhead, UK).

Phillips McDougall, 2016. Phillips McDougall—AgriService seed service. The leading seed companies 2015 market situation (Pathhead, UK).

Phillips McDougall website, 2016. Home. Welcome to PhillipsMcDougall. https://www.phillipsmcdougall.com/home.asp

Pray, C., Oehmke, J. F., & Naseem, A. (2005). Innovation and dynamic efficiency in plant biotechnology: An introduction to the researchable issues. *AgBioforum*, *8*(2&3), 52–63.

Proagrica website, 2021. KWS achieves greater efficiency throughout its seed production cycle. https://proagrica.com/customer_stories/kws-achieves-greater-efficiency-throughout-its-seed-production-cycle/

Puggioni, D., & Stefanou, S. E. (2019). The value of being socially responsible: A primal-dual approach. *European Journal of Operational Research*, *276*(3), 1090–1103. https://doi.org/10.1016/j.ejor.2019.01.065

Řepková, I. (2014). Efficiency of the Czech banking sector employing the DEA window analysis approach. *Procedia Economics and Finance*, *12*, 587–596. https://doi.org/10.1016/S2212-5671(14)00383-9

Schenkelaars, P., de Vriend, H., Kalaitzandonakes, N., Magnier, A., Miller, D., 2011. Drivers of consolidation in the seed industry and its consequences for innovation. COGEM Report. Commission on Genetic Modification. Bilthoven, The Netherlands. http://www.gruenevernunft.de/meldung/drivers-consolidation-seed-industry-and-its-consequences-innovation

Shand, H., 2012. The Big Six: A profile of Corproate power in seed, agrochemicals & biotech. The Heritage Farm Companion pp. 10–15. https://www.seedsavers.org/site/pdf/HeritageFarmCompanion_BigSix.pdf

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Smart, R. D., Blum, M., & Wesseler, J. (2016). Trends in genetically engineered crops' approval times in the United States and the European Union. *Journal of Agricultural Economics*, *67*(3), 1–17. https://doi.org/10.1111/1477-9552.12171

Sufian, F. (2007). Trends in the efficiency of Singapore's commercial banking groups: A non-stochastic frontier DEA window analysis approach. *International Journal of Productivity and Performance Management*, *56*(2), 99–136. https://doi.org/10.1108/17410400710722626

Sufian, F., & Majid, M. A. (2007). X-efficiency and share prices in the Singaporean banking sector: A DEA windows analysis approach. *Investment Management and Financial Innovations*, *4*(1), 73–90.

Syngenta website, 2020. Home. Company. Media. Syngenta news. Syngenta shareholders accept ChemChina offer. https://www.syngenta.com/company/media/syngenta-news/year/2017/syngenta-shareholders-accept-chemchina-offer

Tulkens, H., & Vanden Eeckaut, P. (1995). Non-parametric efficiency, progress and regress measures for panel data: Methodological aspects. *European Journal of Operational Research*, *80*(3), 474–499. https://doi.org/10.1016/0377-2217(94)00132-V

Webb, R. (2003). Levels of efficiency in UK retail banks: A DEA window analysis. *International Journal of the Economics of Business*, *10*(3), 305–322. https://doi.org/10.1080/1357151032000126256

Wooldridge, J. M. (2013). *Introductory econometrics: A modern approach* (5th ed.) (p. 881). Cengage Learning.

Yuan, R., & Wen, W. (2018). Managerial foreign experience and corporate innovation. *Journal of Corporate Finance*, *48*, 752–770. https://doi.org/10.1016/j.jcorpfin.2017.12.015

Zhou, W., 2015. The patent landscape of genetically modified organisms. Blog, Special Edition on GMOs. Harvard University. http://sitn.hms.harvard.edu/flash/2015/the-patent-landscape-of-genetically-modified-organisms/

Zhou, Z., Chen, Y., Song, P., & Ding, T. (2020). China's urban air quality evaluation with streaming data: A DEA window analysis. *Science of the Total Environment*, *727*, 138213. https://doi.org/10.1016/j.scitotenv.2020.138213

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Smart, R. D., Ait Sidhoum, A., & Sauer, J. (2022). Decomposition of efficiency in the global seed industry: A nonparametric approach. *Managerial and Decision Economics*, *43*(6), 2133–2147. https://doi.org/10.1002/mde.3514