https://doi.org/10.17221/172/2021-CJFS

Analysis of production and investment efficiency in the Mexican food industry: Application of two-stage DEA

Martin Flegl[1], Carlos Alberto Jiménez-Bandala[2], Isaac Sánchez-Juárez[3], Edgar Matus[4]*

[1]*Department of Industrial and Systems Engineering, School of Engineering and Sciences, Tecnologico de Monterrey, Mexico City, Mexico*
[2]*Tourism Management and Marketing Division, Universidad Autónoma del Estado de Quintana Roo, Cancún, Mexico*
[3]*Department of Social Sciences, Laboratory of Structural Problems of the Mexican Economy, Autonomous University of Juárez City, Ciudad Juárez, Mexico*
[4]*Business School, Universidad La Salle México, Mexico City, Mexico*

**Corresponding author: martin.flegl@tec.mx*

Citation: Flegl M., Jiménez-Bandala C.A., Sánchez-Juárez I., Matus E. (2022): Analysis of production and investment efficiency in the Mexican food industry: Application of two-stage DEA. Czech J. Food Sci., 40: 109–117.

Abstract: The food industry in Mexico is a precarious sector and lags behind other manufacturing industries, it is made up mainly of small and medium-sized enterprises. Its importance in the food assurance of the country requires strategic monitoring of the yield and efficiency variables that allow successful interventions to improve results. Commonly, the efficiency in the agriculture sector is evaluated as a one-stage data envelopment analysis (DEA) process using a specific set of variables. In this article, we applied a two-stage process to evaluate the efficiency in the Mexican food industry. The first stage evaluates the efficiency of the production, whereas the second stage evaluates the efficiency of investments in the sector. The process is demonstrated on a sample of 1 672 Mexican municipalities using data from 2014 and 2019 Census. The results indicate a growth in production efficiency with significant differences between regions. Moreover, the results also revealed very low investment efficiency in the whole food sector with a negative tendency.

Keywords: data envelopment analysis; agri-food sector; production efficiency; regional development; economic asymmetries; regional polarization

The food industry in Mexico represents 4.6% of the national economy (INEGI 2020). In the last trimester of 2020, the food industry generated 4.35 billion pesos in gross domestic product (GDP), representing a growth of 5.88% compared to the same period of the previous year. As Figure 1 shows, the food industry GDP has been constantly increasing during the last almost 20 years, reaching its highest value in 2019 with 16.9 billion pesos. In 2019, the whole industry included 433 370 economic units, employed 1.9 million workers, and the states with the biggest reported gross productions were Jalisco (2.25 billion pesos), Estado de México (1.92 billion pesos), and Guanajuato (1.43 billion pesos) (INEGI 2020).

The Mexican economy relies mainly on micro, small, and medium companies (MSMEs). In the food industry, there were 420 862 (97.11%) companies with 0–10 employees, 9 312 (2.15%) companies with 11–50 employees, 1 134 (0.26%) companies with 51–100 employees, and 2 062 (0.48%) companies with 101+ employees (INEGI 2020). In addition, the Mexican economy is one of the most unequal in the American continent. The north of the country represents a more developed industry, while the southern industries are more labour intensive with a lack of investments (Jiménez-Bandala 2018). This was confirmed by Becerril-Torres et al. (2011) who investigated the efficiency of the Mexican agricultural sector in 31 Mexican states, resulting

https://doi.org/10.17221/172/2021-CJFS

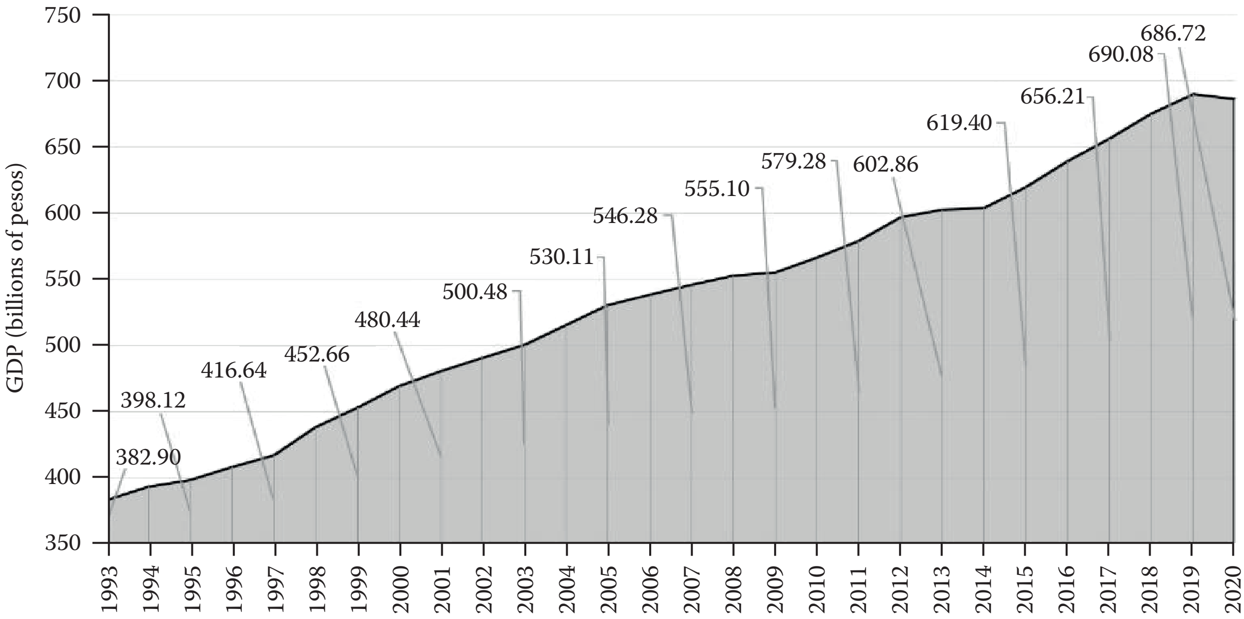

Figure 1. Evolution of the GDP in billions of pesos in the food industry in Mexico (constant 2013 prices)

Source: Own elaboration based on data from INEGI (2020)

in a high level of efficiency in the northern states compared to the rest of the country.

In terms of technology and innovation, the food sector is one of the most lagging in the manufacture and is considered precarious due to its low orientation to the external markets, low qualification of workers and processes more intensive in labour than in capital (Carbajal Suárez and de Jesús Almonte 2017; Isiordia-Lachica et al. 2020). One of the biggest problems that the sector presents is the low level of productivity and resource efficiency, compared to the rest of the manufacturing industry, resulting in a low impact on the national economic growth. Ayvar Campos et al. (2018) studied the efficiency of Mexican agriculture in the context of the Asia-Pacific Economic Cooperation (APEC) region. The authors affirmed that Mexican agriculture needs technological improvements to enhance its production and lower pollution emissions, which was also observed by Hoang and Alauddin (2012). In this case, Ibrahim et al. (2019) linked the efficiency problem in the production to low renewable energy consumption, extensive use of agricultural land, and high food imports.

For this reason, it is important to monitor production variables and investment efficiency in this sector. Therefore, the objective of the article is to analyse the production efficiency in the food industry with an application of data envelopment analysis (DEA).

MATERIAL AND METHODS

Data envelopment analysis (DEA): Two-stage network. DEA evaluates decision-making units (*DMUs*) regarding their multiple inputs and multiple outputs (Cooper et al. 2011). Each *DMU* has different m inputs to produce s different outputs. The Charnes-Cooper-Rhodes (CCR) model (Charnes et al. 1978) can be used if the model assumes constant returns to scale. The CCR input-oriented model for DMU_0 is formulated as follows:

$$e = \max \sum_{r=1}^{s} u_r y_{r0}$$

subjected to: (1)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$v_i \geq \varepsilon,\ i = 1, 2, \ldots, m;\ u_r \geq \varepsilon,\ r = 1, 2, \ldots, s$$

where: x_{ij} – quantity of the input i of the DMU_j; y_{rj} – amount of the output r of the DMU_j; u_r, v_i – weights of the inputs and outputs i = 1, 2, ..., m, j = 1, 2, ..., n, r = 1, 2, ..., s; ε – non-Archimedean element.

https://doi.org/10.17221/172/2021-CJFS

DMU is 100% efficient if $e = 1$, i.e. whereas *DMU* is inefficient if $e < 1$.

In many cases, the single-stage process described in Equation 1 may not be suitable to describe production processes that can be divided into several sub-processes. In this case, some products are outputs of a sub-process on the one hand, and the inputs of another sub-process on the other hand. In this article, we consider a two-stage process as shown in Figure 2. Considering the notions presented by Kao and Hwang (2008), we assume that each DMU_j ($j = 1, 2, \ldots, n$) has m inputs x_{ij} ($i = 1, 2, \ldots, m$) to the first stage, and D outputs z_{dj} ($d = 1, 2, \ldots, D$) from that stage. Then, these D outputs become the inputs to the second stage and are referred to as intermediate measures. The outputs from the second stage are y_{rj} ($r = 1, 2, \ldots, s$). In this case, the intermediate measures are the only inputs to the second stage of the process and there are no additional independent inputs to the second stage.

Data. The analysis includes economic indicators related to the Mexican food industry from the 2014 and 2019 Economic Censuses carried out by the National Institute of Statistics and Geography in Mexico (INEGI 2014, 2019). The 2014 Economic Census refers to data from 2013 and the 2019 Economic Census refers to data from 2018. In the food industry, we included the information related to the following subsectors: agriculture-related services; preparation of animal feed; grinding grains and seeds and obtaining oils and fat; manufacture of sugars, chocolates, sweets and alike; preservation of fruits, vegetables and prepared foods; manufacture of dairy products; cattle slaughter, packing and processing of meat from cattle, poultry and other edible animals; preparation and packaging of fish and shellfish; preparation of bakery products and tortillas; other food industries; and branches grouped by the principle of confidentiality.

This information is linked to the Mexican municipalities as it is not possible to identify companies due

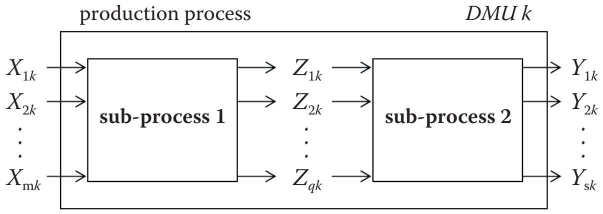

Figure 2. Two-stage process with inputs *X*, outputs *Y*, and intermediate products *Z*

DMU – decision-making unit

Source: Kao and Hwang (2008)

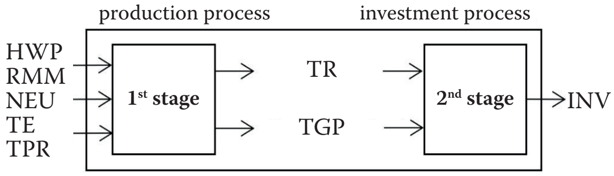

Figure 3. Structure of the two-stage DEA model

DEA – data envelopment analysis; HWP – hours worked by the personnel (thousands of hours); RMM – raw materials and materials (millions of pesos); NEU – number of economic units; TE – total expenditures (millions of pesos); TPR – total personnel remunerations (millions of pesos); TR – total revenues (millions of pesos); TGP – total gross production (millions of pesos); INV – total investments into the production (millions pesos)

Source: Own elaboration

to the confidentiality of the Economic Censuses. Further, to be able to compare the productivity between 2013 and 2018, we only included municipalities that appear in both Economic Censuses. In the end, the analysis includes 1 672 out of 2 446 (67.91%) municipalities in Mexico. These 1 672 municipalities include information from 164 558 economic units in 2013 and 189 590 economic units in 2018.

Structure of the model. The selection of the variables (inputs and outputs) for the DEA models in the agricultural analysis depends on the objective of each study. For the input part, models include expenses of the production process (Atici and Podinovski 2015; Duman et al. 2017), contracted personnel (Kuo et al. 2014; Mardani and Salarpour 2015), working hours (Toma et al. 2015; Duman et al. 2017), machinery and materials (Mardani and Salarpour 2015), or the use of fertilisers in the production (Moreno-Moreno et al. 2018). So, the input variables can be categorised as personnel, material, and finance. For the output part, models include the incomes from the production (Kuo et al. 2014; Duman et al. 2017), level of production (Mardani and Salarpour 2015; Toma et al. 2015) or produced emissions (Moreno-Moreno et al. 2018).

Several authors applied a two-stage DEA process (Raheli et al. 2017; Marcikić-Horvat et al. 2019), but the second stage uses regression analysis to examine the effect of several factors on the efficiency. In this article, we use a two-stage DEA process to evaluate both the efficiency of the production and the efficiency of the investments in the sector at the same time rather than focusing on the factors' influence. The input part of the first stage of the model summarises the resources of each municipality in the production process – personnel: hours worked by the personnel in thousands of hours (HWP);

https://doi.org/10.17221/172/2021-CJFS

Table 1. Descriptive statistics of the used variables

Statistics	HWP (thousands of hours)	RMM (millions of pesos)	NEU	TE	TPR	TR	TGP	INV
				(millions of pesos)				
2013								
Max.	65 838.85	18 561.31	2 598.00	28 633.10	2 495.73	49 052.49	48 829.73	1 123.53
Min.	3.79	0.01	3.00	0.02	0.00	0.06	0.06	269.84
Mean	1 270.15	279.08	98.42	408.25	31.38	593.31	579.35	9.21
SD	3 974.76	1 284.36	209.32	1 849.05	140.83	2 805.09	2 747.69	54.33
2018								
Max.	70 066.09	29 399.33	2 843.00	45 550.62	4 478.13	58 790.20	56 328.04	1 491.12
Min.	4.30	0.01	3.00	0.07	0.00	0.12	0.12	0.00
Mean	1 432.66	387.81	113.39	542.47	40.41	762.04	735.06	11.69
SD	4 628.79	2 032.63	233.86	2 801.74	223.23	4 026.39	3 841.12	76.61

SD – standard deviation; HWP – hours worked by the personnel; RMM – raw materials and materials; NEU – number of economic units; TE – total expenditures; TPR – total personnel remunerations; TR – total revenues; TGP – total gross production; INV – total investments into the production

material: raw materials and materials in millions of pesos (RMM) and number of economic units (NEU); finance: total expenditures in millions of pesos (TE) and total personnel remunerations in millions of pesos (TPR).

The outputs of the first stage of the model and, consequently the inputs to the second stage, include: total revenues in million pesos (TR), evaluating the economic results in monetary terms, and total gross production in million pesos (TGP), evaluating the economic results in terms of volume. The output of the second stage of the model is related to total investments into the production (INV) in million pesos.

Figure 3 presents the model structure and Table 1 summarises the descriptive statistics of the variables.

We used the CCR output-oriented model as, first, the intention is to analyse the efficiency of the production of each municipality related to their resources and the efficiency of the investments based on their level of production and, second, we do not consider competition between the municipalities as different subsectors of the food industry are analysed. We used MaxDEA 7 Ultra software for all the calculations.

RESULTS AND DISCUSSION

Economic Census 2014. In the 1st stage, which evaluates the efficiency of each municipality with respect to the production measured by the total revenues and gross production, the average efficiency of the Mexican municipalities was 0.306 with a standard deviation (SD) of 0.148. In more detail, 11 municipalities (0.66% of the analysed sample) reached the efficiency of 1.0, resulting in very low efficiency of the food industry in 2013. As Figure 4 illustrates, we cannot identify a region with very high efficiency.

To understand more the results, we divide the municipalities according to their geographical dependence: Northwest (Baja California, Baja California Sur, Chihuahua, Durango, Sinaloa, and Sonora), Northeast (Coahuila, Nuevo León, and Tamaulipas), West (Colima, Jalisco, Michoacán, and Nayarit), East (Hidalgo, Puebla, Tlaxcala, and Veracruz), Centre North (Aguascalientes, Guanajuato, Querétaro, San Luis Potosí, and Zacatecas), Centre South (Ciudad de México, Estado de México, and Morelos), Southeast (Chiapas, Guerrero, and Oaxaca), and Southwest (Campeche, Quintana Roo, Tabasco, and Yucatán). Table 2 indicates that the highest average efficiency in the 1st stage of the process in 2013 is reported in the Centre South region (0.334) with the third lowest SD (0.131), followed by the Southwest region (0.319, SD 0.122) and the Northwest region (0.313, SD 0.150). On the other hand, the lowest efficiency is reported in the Southeast region with 0.286 and SD 0.175, which is the highest SD in all the country. Applying the Games-Howell nonparametric test, as there are significant differences regarding the number of municipalities between the regions and the variances are different (Levene's test P < 0.001), we can observe statistically significant difference between the Central South and Southeast (0.048, P = 0.011) regions.

In the 2nd stage (Figure 5), which evaluates municipalities' efficiency to transform the production and in-

https://doi.org/10.17221/172/2021-CJFS

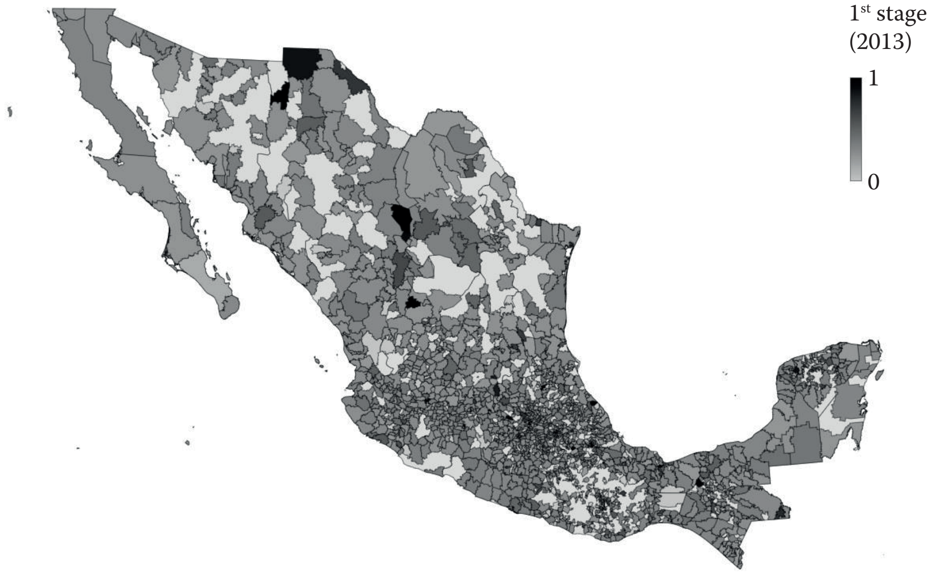

Figure 4. Efficiency in the Mexican food industry by municipalities in 2013 1st stage

Source: Own elaboration using GeoNames, Microsoft tool

comes into investments in the production process, the average efficiency is very low of 0.026 and only two municipalities (Chumatlán in Veracruz and General Simón Bolívar in Durango) reported an efficiency of 1.0. Both Chumatlán and General Simón Bolívar are very small municipalities with a level of their variables close to the minimum values (Table 1). Chumatlán reported 0.06 RMM, 0.16 TE, 0.28 TR, and 0.29 TGP. However, its ratio of investments to income is 80.63% (INV/TR) and to gross production is 80.35% (INV/TGP). Similarly, General Simón Bolívar reported 0.86 RMM, 1.21 TE, 2.36 TR, and 2.35 TGP, with INV/TR of 6.58% and INV/TGP of 6.60%. In this case, the high efficiency may be linked to the low level of efficiency in the 1st stage (0.397). The third highest efficient municipality is Tamuín in San Luis Potosí with an efficiency of 0.939, which can be considered as an average-size municipality with 137.03 RMM, 324.70 TE, 314.13 TR, and 230.57 TGP, where its INV/TR is 67.72% and INV/TGP 92.26%.

Regarding the Mexican regions (Table 2), the highest efficiency of the investments is observed in the Centre North region (0.032), followed by the Northwest (0.032) and Southwest (0.031) regions. In the 1st stage, the worst evaluated region was the Southeast, which is also the worst evaluated in the 2nd stage with an efficiency of only 0.019 and SD 0.055. The level of investment across the regions resulted in no statistically significant differences ($P = 0.393$).

Economic Census 2019. In 2018, the average efficiency of the municipalities in the 1st stage was 0.479 with SD of 0.271. In this case, 20 municipalities reached an efficiency of 1.0 (1.2% of the sample). Compared to the results of the 1st stage in 2013, the average efficiency increased by 0.173, but the SD almost doubled and increased by 0.123. The efficiency growth is clearly visible in Figure 6 as the whole country darken in 2018.

Similarly, as in 2013, the best evaluated region is the Centre South (0.541, SD 0.2050). Its efficiency increased by 0.208 compared to 2013 and this improvement is the second highest among all the regions. The second best evaluated region is the Centre North (0.517, SD 0.210) with the highest growth of 0.210, followed by the West region (0.501, SD 0.251) with a growth of 0.192. These three regions report the smallest SD in the country. The worst evaluated region is the Southeast (0.413, SD 0.321), which recorded the smallest growth 0.127 (Table 3). Different levels of growth in the efficiency results resulted in statistically significant dif-

Table 2. Average efficiency by geographical regions in 2013, 1st and 2nd stage

Region	*n*	1st stage		2nd stage	
		mean	SD	mean	SD
Centre North	150	0.308	0.131	0.032	0.091
Centre South	158	0.334	0.131	0.022	0.060
East	431	0.308	0.159	0.027	0.079
Northeast	82	0.295	0.138	0.024	0.036
Northwest	123	0.313	0.150	0.032	0.097
Southeast	377	0.286	0.175	0.019	0.055
Southwest	110	0.319	0.122	0.031	0.099
West	241	0.308	0.108	0.026	0.058
Average	1 672	0.306	0.148	0.026	0.073

SD – standard deviation

https://doi.org/10.17221/172/2021-CJFS

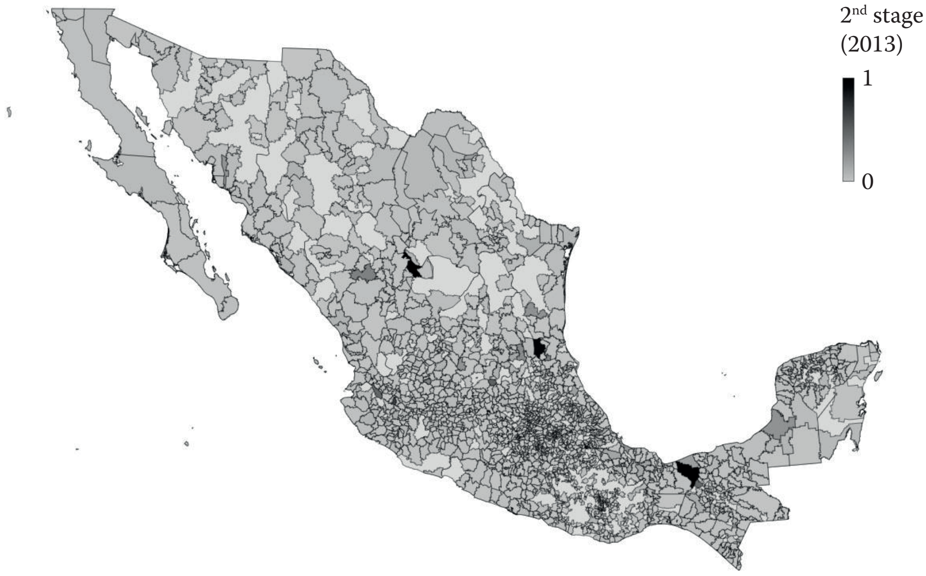

Figure 5. Efficiency in the Mexican food industry by municipalities in 2013 2nd stage

Source: Own elaboration using GeoNames, Microsoft tool

ferences between the regions ($P < 0.001$). The Centre South region has statistically higher efficiency compared to the Southeast region (0.129, $P < 0.001$), the Southwest region (0.087, $P = 0.097$) and the East region (0.057, $P = 0.093$). Similarly, the Centre North region has statistically higher efficiency compared to the Southeast region (0.105, $P = 0.001$); the West region has better evaluation compared to the Southeast region (0.088, $P < 0.004$).

In the 2nd stage of the evaluation, the average efficiency of the municipalities is 0.020 (SD 0.059), which is even lower by –0.006 compared to 2013 results. Even though the average level of investments increased by 26.93% from 9.21 million pesos in 2013 to 11.69 million pesos in 2018 (Table 1), this growth was not higher than the growth of the total average revenues (28.44%) and the average gross production (26.88%). As a result, the average ratio of investments to income (INV/TR) decreased from 1.55% in 2013 to 1.53% in 2018, whereas the ratio of investments to gross production remains literally unchanged (1.59% in both years). The only 1.0 efficient municipality in 2018 is Quintana Roo in Yucatán, which is again a very small municipality with 0.203 RMM, 0.271 TE, 0.615 TR, and 0.615 TGP, with INV/TR of 79.67% and INV/TGP of 79.67%.

Considering the regions (Figure 7), all regions report lower efficiency in 2018 compared to 2013. The biggest decrease can be observed in the Centre North re-

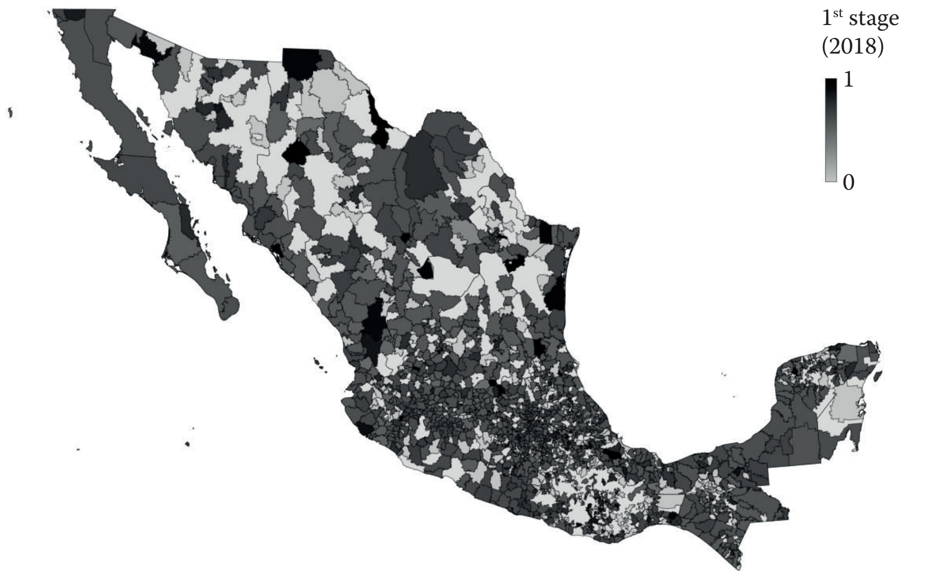

Figure 6. Efficiency in the Mexican food industry by municipalities in 2018 1st stage

Source: Own elaboration using GeoNames, Microsoft tool

https://doi.org/10.17221/172/2021-CJFS

Table 3. Average efficiency by geographical regions in 2018, 1st and 2nd stage

Region	n	1st stage		2nd stage	
		mean	SD	mean	SD
Centre North	150	0.517	0.233	0.016	0.024
Centre South	158	0.541	0.205	0.013	0.024
East	431	0.484	0.251	0.020	0.051
Northeast	82	0.500	0.286	0.022	0.042
Northwest	123	0.497	0.283	0.025	0.056
Southeast	377	0.413	0.321	0.018	0.076
Southwest	110	0.454	0.275	0.031	0.106
West	241	0.501	0.251	0.020	0.049
Average	1 672	0.479	0.271	0.020	0.059

SD – standard deviation

gions (–0.016), which was evaluated as the best region in 2013. The smallest decrease (almost none) in the efficiency occurred in the Southwest region (–0.00003), Southeast (–0.001), and the Northeast (–0.002) regions. The highest efficiency can be observed in the case of the Southwest (0.031, SD 0.106), Northwest (0.025, SD 0.056), and Northeast (0.022, SD 0.042) regions, but with no statistically significant difference compared to the rest of the regions.

The obtained results revealed significant differences between regions and growth in the production efficiency (1st stage) from 2013 to 2018, this is mainly due to the economic structure in Mexico. The southern regions, eminently agricultural, send their largest production to the northern regions for processing. In 2013–2014, international oil prices increased and, as the major transportation of goods in Mexico is done by roads, this was the reason why the northern regions, further from the agricultural production, were less efficient than those in the south closer to the agricultural centres. After the consolidation of the oil prices, the northern regions reached higher efficiency in 2018. This observation corresponds with Becerril-Torres et al. (2011), who observed the average technical efficiency of the agricultural sector in Mexico of 0.49, where the northern states (Aguascalientes, Baja California, Coahuila, Colima, Nuevo León, Sinaloa, and Sonora) are the highest efficiency.

The improvements in efficiency can be done in several ways. For example, to minimise the differences between the regions it is important to develop industrial centres, particularly food centres, that can have positive results in the municipality efficiencies. This, together with an active industrial development policy, would have a positive impact on regional economic development and would combat the regional asymmetries (Revilla et al. 2015; Raut et al. 2019).

It is also necessary to increase the level of investments and innovations in the sector. As Becerril-Torres et al. (2011) and Ayvar Campos et al. (2018) stress out, the Mexican agricultural sector needs technological improvements and investments, which would generate greater production with an added value. This is in line with the obtained results as the level of investment efficiency is very low across the whole industry with a negative tendency. This is a consequence of incorrect resource management of small farms as they do not have the capacity to evaluate their efficient allocation. The most efficient farms are those that present the best management

Figure 7. Efficiency in the Mexican food industry by municipalities in 2018 2nd stage

Source: Own elaboration using GeoNames, Microsoft tool

https://doi.org/10.17221/172/2021-CJFS

of resources (Dios-Palomares and Martínez-Paz 2011). For example, Meena et al. (2019) observed that one of the biggest weaknesses in the agri-food supply chain is related to the lack of modern technologies for managing production, which negatively affects its efficiency.

In this case, it is important to provide training to the employees, as this has a positive effect on the efficiency of the production. The more unskilled workers a firm has, the lower its efficiency is (Dios-Palomares and Martínez-Paz 2011). The necessity of investments in farmers' education was observed by Raheli et al. (2017) applying the two-stage DEA model. The higher level of investments would help to increase the competitiveness in the sector as the companies (municipalities) would expand their production capacities, diversify the production, and optimise the use of their resources (Bagchi et al. 2019). However, such investments must be carefully assessed in the long-term perspectives as they do not attain their full utility during a period of increased expenditures (Krejčí et al. 2019).

Therefore, the intervention of public policies in the municipalities with greater rural concentration is needed to allow technology and knowledge transfer (TKT). This transfer should be done in cooperation with universities or local educational institutions, as proposed by Isiordia-Lachica et al. (2020). Local networking, partnership and collaboration with local municipalities are important to strengthen agricultural education in rural areas (Tomšíková et al. 2019).

CONCLUSION

The results revealed the productive and investment precariousness in the Mexican food industry and, therefore, it can be concluded that a regional development policy must be first implemented to meet the needs of the municipalities that show greater fragility and, also, to reinforce those in which a certain relative advantage is reported. Similarly, an active industrial policy must be created to promote improvements in the food industry and other sectors of the economy. Once virtuous circles are created in most sectors, an improvement in production and investment efficiency can be sustained. Currently, in Mexico these two great policies are absent and, although there are initiatives to promote specific industries, sectors and regions, these measures are disconnected, have limited resources allocated, are not part of a state policy and are not properly carried out with a long-term perspective aimed at promoting authentic national development.

REFERENCES

Atici K.B., Podinovski V.V. (2015): Using data envelopment analysis for the assessment of technical efficiency of units with different specialisations: An application to agriculture. Omega, 54: 72–83.

Ayvar Campos F.J., Navarro Chávez J.C.L., Zamora Torres A.I. (2018): The Mexican agricultural sector in the context of APEC: A data envelopment analysis with presence of 'bad outputs' (El sector agropecuario Mexicano en APEC: Un análisis a través de la envolvente de datos con presencia de bad outputs). Análisis Económico, 33: 125–143. (in Spanish)

Bagchi M., Rahman S., Shunbo Y. (2019): Growth in agricultural productivity and its components in Bangladeshi regions (1987–2009): An application of bootstrapped data envelopment analysis (DEA). Economies, 7: 37.

Becerril-Torres O.U., Rodríguez Licea G., Ramírez Hernández J.J. (2011): Technical efficiency of the agricultural sector in Mexico: An overview of data envelopment analysis (Eficiencia técnica del sector agropecuario de México: Una perspectiva de análisis envolvente de datos). Economía, 31: 85–110. (in Spanish)

Carbajal Suárez Y., de Jesús Almonte L. (2017): Manufacturing labor in the Central Region of Mexico. An estimation by great division. Contaduria y Administracion, 62: 902–923.

Charnes A., Cooper W., Rhodes E. (1978): Measuring the efficiency of decision making units. European Journal of Operational Research, 2: 429–44.

Cooper W., Seiford L., Zhu J. (2011): Handbook on Data Envelopment Analysis. New York, US, Springer: 1–40.

Dios-Palomares R., Martínez-Paz J. (2011): Technical, quality and environmental efficiency of the olive oil industry. Food Policy, 36: 526–534.

Duman G.M., Tozanli O., Kongar E., Gupta S.M. (2017): A holistic approach for performance evaluation using quantitative and qualitative data: A food industry case study. Expert Systems with Applications, 81: 410–422.

Hoang V.N., Alauddin M. (2012): Input-orientated data envelopment analysis framework for measuring and decomposing economic, environmental and ecological efficiency: An application to OECD agriculture. Environmental and Resource Economics, 51: 431–452.

Ibrahim M.D., Ferreira D.C., Daneshvar S., Marques R.C. (2019): Transnational resource generativity: Efficiency analysis and target setting of water, energy, land, and food nexus for OECD countries. Science of the Total Environment, 697: 134017.

INEGI (2014): Mexico – Economic Censuses 2014 (México – Censos Económicos 2014). National Institute of Statistics

https://doi.org/10.17221/172/2021-CJFS

and Geography [Instituto Nacional de Estadística y Geografía (INEGI)]. Available at https://www.inegi.org.mx/programas/ce/2014/ (accessed June 1, 2021). (in Spanish)

INEGI (2019): Mexico – Economic Censuses 2019 (México – Censos Económicos 2019). National Institute of Statistics and Geography [Instituto Nacional de Estadística y Geografía (INEGI)]. Available at https://www.inegi.org.mx/rnm/index.php/catalog/547 (accessed June 1, 2021). (in Spanish)

INEGI (2020): Mexico – System of National Accounts (México – Sistema de Cuentas Nacionales). National Institute of Statistics and Geography [Instituto Nacional de Estadística y Geografía (INEGI)]. Available at https://www.inegi.org.mx/sistemas/bie/ (accessed June 1, 2021). (in Spanish)

Isiordia-Lachica P.C., Valenzuela A., Rodríguez-Carvajal R.A., Hernández-Ruiz J., Romero-Hidalgo J.A. (2020): Identification and analysis of technology and knowledge transfer experiences for the agro-food sector in Mexico. Journal of Open Innovation: Technology, Market, and Complexity, 6: 59.

Jiménez-Bandala C.A. (2018): Development in Southern Mexico: Empirical verification of the 'seven erroneous theses about Latin America'. Latin American Perspectives, 45: 129–141.

Kao C., Hwang S.N. (2008): Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. European Journal of Operational Research, 185: 418–429.

Krejčí I., Moulis P., Pitrová J., Tichá I., Pilař L., Rydval J. (2019): Traps and opportunities of Czech small-scale beef cattle farming. Sustainability, 11: 4245.

Kuo H.F., Chen H.L., Tsou K.W. (2014): Analysis of farming environmental efficiency using a DEA model with undesirable outputs. APCBEE Procedia, 10: 154–158.

Marcikić-Horvat A., Radovanov B., Popescu G.H., Panaitescu C. (2019): A two-stage DEA model to evaluate agricultural efficiency in case of Serbian districts. Economics of Agriculture, 66: 965–974.

Mardani M., Salarpour M. (2015): Measuring technical efficiency of potato production in Iran using robust data envelopment analysis. Information Processing in Agriculture, 2: 6–14.

Meena S.R., Meena S.D., Pratap S., Patidar R., Daultani Y. (2019): Strategic analysis of the Indian agri-food supply chain. OPSEARCH, 56: 965–982.

Moreno-Moreno J., Velasco Morente F., Sanz Díaz M.T. (2018): Assessment of the operational and environmental efficiency of agriculture in Latin America and the Caribbean. Agricultural Economics, 64: 74–88.

Raheli H., Rezaei R.M., Jadidi M.R., Mobtaker M.B. (2017): A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. Information Processing in Agriculture, 4: 342–350.

Raut R.D., Luthra S., Narkhede B.E., Mangla S.K., Gardas B.B., Priyadarshinee P. (2019): Examining the performance oriented indicators for implementing green management practices in the Indian agro sector. Journal of Cleaner Production, 215: 926–943.

Revilla D., García-Andrés A., Sánchez-Juárez I. (2015): Identification of key productive sectors in the Mexican Economy. Expert Journal of Economics, 3: 22–39.

Toma E., Dobre C., Dona I., Cofas E. (2015): DEA applicability in assessment of agriculture efficiency on areas with similar geographically patterns. Agriculture and Agricultural Science Procedia, 6: 704–711.

Tomšíková K., Hudečková H., Tomšík K. (2019): Enhancing attractiveness of secondary agricultural education in the Czech Republic. Journal on Efficiency and Responsibility in Education and Science, 12: 135–145.

Received: August 16, 2021
Accepted: February 16, 2022
Published online: April 6, 2022