Regional energy and environmental performance of the Mexican manufacturing sector

Abstract

This study investigates the energy efficiency and environmental performance of Mexico's manufacturing sector across different regions. To achieve this objective, a non-radial directional distance function model that encompasses both desirable and undesirable outputs is employed. The dataset includes information from all Mexican states on production, capital, labor, and energy consumption. The measure of undesirable output involves quantifying greenhouse gas emissions from the manufacturing sector. The findings underscore the importance of including undesirable output in the analysis, as this leads to more precise conclusions about the economic efficiency of the manufacturing regions. The study's results indicate that, over the analysis period, the production frontier experienced only modest shifts. However, at the regional level, northern states have demonstrated significant strides in improving their energy and environmental efficiency, whereas their southern counterparts are lagging behind. The study highlights the potential for nationwide energy and emission savings if similar measures to those implemented in the most efficient states are adopted.

JEL Classification: C61, D24, Q43

Keywords: Undesirable output, Energy efficiency improvements, GHG emission performance, directional distance function.

1 Introduction

Mexico ranks twelfth worldwide in Greenhouse Gas (GHG) emissions, contributing around 1.5% of the global GHG emissions (The World Bank, 2021). The country's environmental goals, as outlined in the Paris Agreement in 2015, require a 22% reduction in GHG emissions by 2030 compared to a business-as-usual scenario (Iniciativa climática de México, 2021). This target corresponds to a reduction of approximately 211 million tons of CO2 (Iniciativa climática de México, 2021). It is estimated that the manufacturing industry is responsible for over 18% of the total emissions, primarily due to energy consumption during production (INECC, 2018).

The manufacturing industry sector is tasked with achieving a 25% reduction goal, despite accounting for 32% of the nation's total energy consumption (Secretaria de Energía, 2020; Iniciativa climática de México, 2021). This necessitates significant access to renewable energies, distributed generation, and the implementation of measures to enhance energy conservation and efficiency. The objective of this article is to assess the regional progression of energy efficiency within the manufacturing sector, coupled with the efficiency of emissions reductions. Consequently, companies could curtail their energy costs without impacting their output, leading to a net reduction in pollution. As highlighted by Wu et al. (2012), the conventional measurement of technical efficiency primarily emphasizes producing desired goods without adequately accounting for the environmental repercussions of these production processes.

The existing literature primarily investigates the technical efficiency of total production through the incorporation of undesirable output, often involving cross-country comparisons (e.g., Chiu et al., 2016; Zhou et al., 2012). However, a noticeable gap exists at the country level within Latin America, including Mexico. While prior studies have predominantly centered around China, comparing regional technical efficiency and environmental performance (e.g., Yao et al., 2015; Wang et al., 2013; Yan et al., 2020; Wu et al., 2012), the attention in this regard for Latin American nations, particularly Mexico, has been limited.

While some research has explored the technical efficiency of Mexico's manufacturing sector (e.g., Chávez and López Ornelas, 2014; Borrayo López et al., 2019; Vazquez-Rojas and Trejo-Nieto, 2014), these studies have yet to consider undesirable outputs within their regional analyses. Notably, a specific focus on regional assessments of the manufacturing sector's technical efficiency, particularly in relation to energy and environmental efficiency involving undesirable products, remains absent.

As depicted by INEGI (2020b), the regional dimension in Mexico assumes paramount importance, given the country's distinct characterization of highly industrialized northern and central regions, contrasting with the southern regions' higher reliance on oil and tourism.

The primary objective of this paper is to assess the regional variations in technical efficiency within the manufacturing sector, taking into account the impact of greenhouse gas emissions (GHG) emissions. By examining the integration of greenhouse gas emissions into the production framework, we aim to determine whether regions with previously identified high efficiency in manufacturing can maintain their advantageous positions as highlighted in earlier studies (e.g., Chávez and López Ornelas, 2014; Borrayo López et al., 2019; Vazquez-Rojas and Trejo-Nieto, 2014). To achieve this goal, we employ Data Envelopment Analysis (DEA), a non-parametric method used to evaluate the relative efficiencies and inefficiencies of a group of Decision-Making Units (DMUs). This technique establishes a production frontier that represents the best practices. DMUs that align with this frontier are considered efficient, while those positioned below the frontier are classified as inefficient. By comparing the efficiency values of DMUs below the best practices frontier with those on the frontier, we can accurately evaluate their performance. Moreover, as Yao et al. (2015) point out, by encompassing both desirable and undesirable outputs, it yields comprehensive efficiency metrics for energy and environmental performance. Thus, our secondary goal revolves around assessing the energy and environmental efficiencies within Mexico's regional manufacturing sector. We endeavor to gauge the extent of improvements over time in these aspects, alongside exploring the role these efficiencies play in reducing energy expenses and aiding the realization of national environmental targets.

Our findings indicate that there is significant potential for energy savings within the national manufacturing sector, with a possible reduction of up to 20.3% of the sector's total energy consumption. Additionally, from an environmental perspective, the sector could achieve a reduction in GHG emissions of up to 24.3% by implementing measures aimed at enhancing environmental performance.

The remainder of this paper is organized as follows. Section 2 provides some context of the regional use of the energy and emission intensity of the manufacturing sector. Section 3 provides a brief review of previous studies, including some applications for Mexico. In section 4 the non-radial directional distance function model is explained. Section 5 describes the variables used for the analysis and presents some descriptive statistics for selected variables. Section 6 reports the results of the directional, non-radial distance function model and the efficiency indices. Finally, section 7 provides some discussion of the results and concluding remarks.

2 Context

The manufacturing sector across Mexico's regions showcases considerable heterogeneity, with energy consumption exhibiting a strong correlation with activity levels. The country's thirty-two states are grouped into four major regions[1]: the Northern region, encompassing those bordering the U.S.; the North-Central region, comprising states below the northern region; the Central region, encompassing central states; and the Southern.

Of these, the Northern region's manufacturing industry commands the highest consumption of electricity and natural gas nationwide, representing a substantial 46.3%. Following closely are the North-Central and Central regions, accounting for 26.3% and 15.0%, respectively. The Southern region registers the lowest consumption at 12.4% (with information by Secretaria de Energía, 2020; INEGI, 2020b).

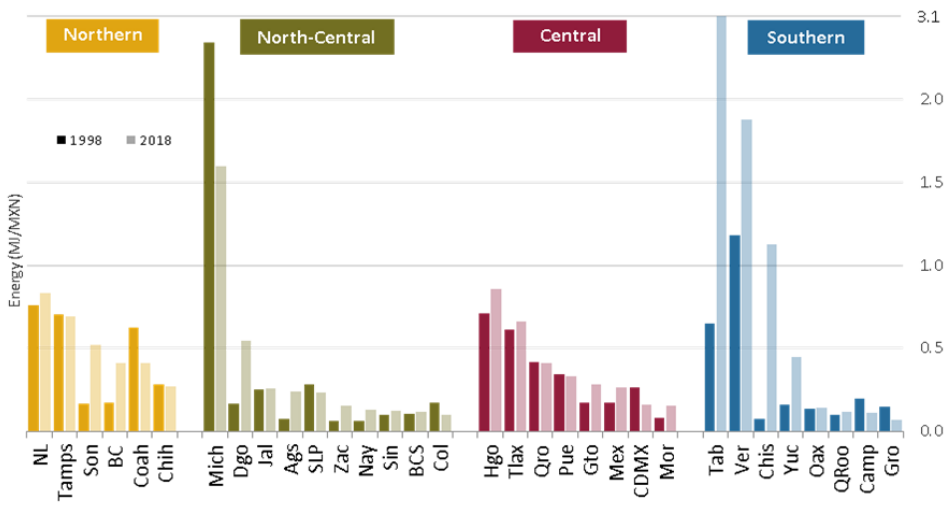
In terms of greenhouse gas (GHG) emissions, the Northern states emerge as the foremost contributors, responsible for 29.8% of total emissions within the manufacturing sector in 2018. The North-Central, Central, and Southern regions follow suit with 24.6%, 24.2%, and 21.4% contributions, respectively (with information by INECC, 2018). These disparities highlight the importance of analyzing regional variations, which is precisely the focus of this research.

The energy consumption within each state is significantly influenced by the manufacturing activities that necessitate substantial energy usage. Nevertheless, it's crucial to acknowledge that the level of energy use efficiency also plays a pivotal role. An apt metric for comprehending the present energy utilization status in each state, while considering its activity level, is energy intensity. This metric measures the amount of energy used to produce a given level of output, it is calculated specifically as the ratio of energy consumption to the gross value added by the manufacturing sector.

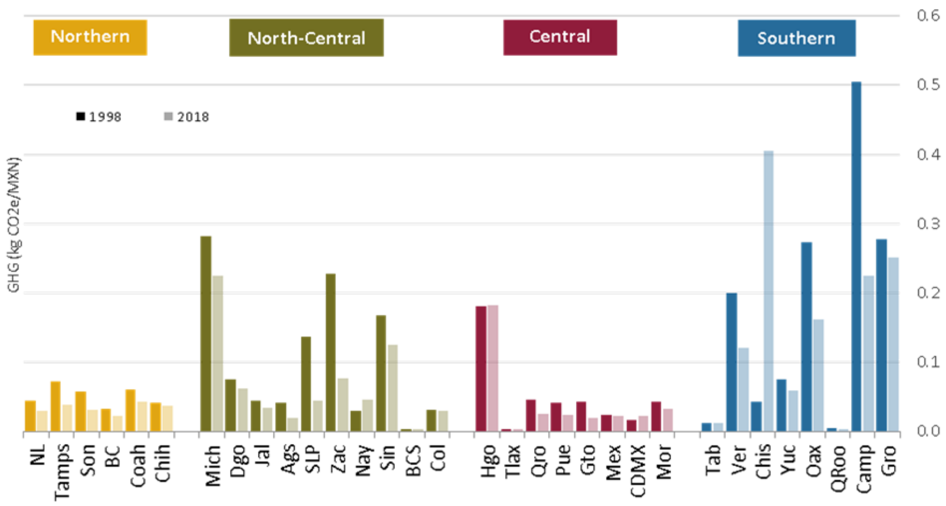
Figure 1(a) presents the energy intensity values for each state across regions in

[1] The Northern region includes Baja California (BC), Chihuahua (Chih), Coahuila (Coah), Nuevo León (NL), Sonora (Son) and Tamaulipas (Tamps); the North-Central region considers Aguascalientes (Ags), Baja California Sur (BCS), Colima (Col), Durango (Dgo), Jalisco (Jal), Michoacán (Mich), Nayarit (Nay), San Luis Potosí (SLP), Sinaloa (Sin) and Zacatecas (Zac); the Central region includes Mexico City (CDMX), Estado de México (Mex), Guanajuato (Gto), Hidalgo (Hgo), Morelos (Mor), Puebla (Pue), Querétaro (Qro) and Tlaxcala (Tlax); and the Southern region includes Campeche (Camp), Chiapas (Chis), Guerrero (Gro), Oaxaca (Oax), Quintana Roo (QRoo), Tabasco (Tab), Veracruz (Ver) and Yucatán (Yuc)

both 1998 and 2018. Of note, Michoacán (Mich) stands out with notably high energy intensities for both years, recording values of 2.34 and 1.60 MJ/MXN, respectively. Followed by this, Veracruz (Ver) displays elevated energy intensity in 2018 (1.88 MJ/MXN), significantly surpassing the value observed in 1998 (1.18 MJ/MXN). Similarly, Tabasco (Tab) only in 2018 shows the highest energy intensity with 3.1 MJ/MXN. Additionally, Nuevo León (NL), Hidalgo (Hgo), and Tlaxcala (Tlax) showcase elevated energy intensities, which have witnessed an increase from 1998 to 2018.



(a) Energy



(b) Environmental

Figure 1: Energy and Emissions Intensity

Note: Energy intensity refers to the amount of energy used to produce a given level of output, while emissions intensity refers to the CO2 emissions generated to produce a given level of output.

Beyond energy consumption, the emission intensity within each state is significantly influenced by the production process. This factor gauges the added value of the output concerning each additional unit of GHG emissions. In this context, it is computed by relating these emissions to the manufacturing value added.

As illustrated in Figure 1(b), Michoacán (Mich), Campeche (Camp) and Guerrero (Gro) stand out for their high emission intensities across both 1998 and 2018, boasting values exceeding 0.2 Kg CO2e/MXN, while Zacatecas (Zac), Veracruz (Ver) and Oaxaca (Oax) have high emission intensities in 1998. In particular, even though Hidalgo (Hgo), Nayarit (Nay) and Chiapas (Chis) had intensities around or below the average in 1998, unlike the remaining, have experienced an uptick in their emission intensity between 1998 and 2018. These states hold a substantial proportion of manufacturing value added within subsectors characterized by emission and energy-intensive activities, such as the production of oil and coal products, basic metal industries, and the chemical sector.

The savings computed within this study underscore the potential of each state to mitigate these intensities. These efficiencies can be achieved through measures enhancing energy and environmental efficiency, without detrimentally impacting their level of economic activity.

3 Literature Review

Considering undesirable outputs, such as CO2 emissions from fossil fuel use, is crucial for several reasons. First, neglecting these outputs leads to biased efficiency scores, as analyses that ignore them underestimate the true environmental impact (Wu et al., 2012; Yao et al., 2015). Several studies support this notion, demonstrating how excluding undesirable outputs misrepresents performance (e.g., Yao et al., 2015; Wang et al., 2013; Yan et al., 2020; Wu et al., 2012). For instance, models that do not account for these emissions might incorrectly label practices or technologies as efficient despite their negative environmental consequences. Therefore, incorporating undesirable outputs provides a more comprehensive and realistic assessment of energy efficiency, aligning it with broader environmental and sustainability goals.

Cross-country studies are abundant due to the availability of data at the national level. Analyzing undesirable outputs across countries reveals significant performance differences. Zhou et al. (2012) employed a dynamic efficiency analysis to evaluate energy use, carbon emissions, and integrated energy-carbon performance in OECD and non-OECD countries. They found countries like Switzerland, Lithuania, and Ukraine on the efficiency frontier, indicating their ability to manage both energy use and CO_2 emissions effectively. Conversely, nations with lower efficiency scores often relied heavily on coal and had lower generation efficiency, leading to higher undesirable outputs. Overall, the study suggests a gap between OECD and non-OECD countries, with the former generally exhibiting better energy and carbon performance. Additionally, their analysis indicates a link between generation efficiency and overall energy performance, and between lower carbon intensity and better CO2 emission performance. Chiu et al. (2016) explored productivity efficiency in G20 countries, highlighting variations in performance while considering undesirable outputs. While some countries like Turkey and Mexico showed significant improvements, others like Argentina and Germany experienced declines. Interestingly, the United States consistently ranked highest in productivity efficiency, while China and Saudi Arabia remained lower. This comparison underscores the importance of including undesirable outputs in efficiency analyses. It highlights that efficiency gains in some countries might come at the expense of increased undesirable outputs, whereas others have managed to improve both.

Prior research has focused on both specific sectors and entire economies. Studies like those by Zhou et al. (2012) and Wu et al. (2012) examine the electricity and industrial sectors, respectively, incorporating undesirable outputs into their analyses. Conversely, Chiu et al. (2016) consider the entire economy of G20 countries using GDP as an output variable. Notably, a significant portion of research has centered on China, comparing regional technical efficiency and environmental performance while considering undesirable outputs (e.g., Yao et al., 2015; Wang et al., 2013; Yan et al., 2020; Wu et al., 2012). For instance, Yao et al. (2015) conducted a detailed regional analysis for GDP and carbon emissions using data from China's provinces. Their findings suggest substantial potential for carbon emission reductions by improving efficiency in lagging provinces.

While research exists for various countries and lower levels like provinces or regions of a country, a gap remains at the national and regional levels within Latin America, including Mexico. Studies have explored the technical efficiency of Mexico's manufacturing sector but haven't yet considered undesirable outputs (e.g., Chávez and López Ornelas, 2014; Borrayo López et al., 2019; Vazquez-Rojas and Trejo-Nieto, 2014). For instance, Chávez and López Ornelas (2014) examined the contributions of factors like technical efficiency and technological change to labor productivity variations across Mexican states. However, their analysis did not include undesirable outputs. They used non-parametric techniques such as Kumar and Russell (2002)'s decomposition and Farrell (1957)'s index to measure the technical efficiency of the manufacturing industry in each state. Their findings indicate that labor productivity growth was primarily fueled by enhancements in technical efficiency in the northern and southern regions, whereas technological advancements were the main contributors to productivity increases in the central regions. Different methods have been also used, studies by Borrayo López et al. (2019) and Alvarez et al. (2017) employed stochastic frontier methods to evaluate efficiency in Mexico but also neglected undesirable outputs.

By integrating greenhouse gas emissions into the production framework, this research aims to investigate whether regions with previously identified high efficiency in the manufacturing sector (e.g., Chávez and López Ornelas, 2014; Borrayo López et al., 2019) can maintain their position when environmental considerations, specifically undesirable outputs, are included. This approach will provide a more accurate and holistic view of regional efficiency, aligning productivity assessments with environmental sustainability goals.

4 Methods

Data Envelopment Analysis (DEA) is a non-parametric method used to evaluate the relative efficiencies and inefficiencies of a group of Decision-Making Units (DMUs). This technique establishes a production frontier that represents the best practices. DMUs that align with this frontier are considered efficient, while those positioned below the frontier are classified as inefficient. To evaluate the performance of DMUs below the best practices frontier, their efficiency values are compared with those positioned on the frontier.

There are two approaches for constructing the frontier in data envelopment analysis: constant returns to scale (CRS) and variable returns to scale (VRS). CRS assumes that any linear combination of observed Decision Making Units (DMUs) is feasible, implying that proportionally scaling inputs and outputs of efficient DMUs could create even more efficient units. In contrast, VRS acknowledges heterogeneity within the data by considering only convex combinations of the observed DMUs as feasible. This approach ensures that efficient units cannot be surpassed simply by scaling up or down others. When dealing with a sample containing heterogeneous units over a long period, VRS is generally more appropriate. This is because the assumption of constant returns to scale might not hold over extended periods, where technological advancements or resource limitations can impact efficiency. VRS provides a more realistic assessment of efficiency under these circumstances by allowing for potential variations in scale economies.

DEA models can be categorized into two orientation types. On the one hand, we have input-oriented, which seeks to minimize input usage while maintaining the same output. On the other hand, we have output-oriented, which aims to maximize output yield while keeping input levels constant. For these two orientations we also have two measurement types. Firstly, the radial approach, which seeks a proportional way to optimize any orientation mentioned above. Secondly, the non-radial approach, which combines both orientations, with the objective of enhancing outputs while concurrently minimizing input consumption (Zhou et al., 2012).

The traditional DEA models mainly focus on desirable output or input, but in the actual production process, during the conversion of input to output undesirable byproducts may appear. The assumption is that an observed unit aligns with the production frontier when it can increase the production of certain desirable outputs (goods) without compromising the production of others, while also avoiding an increase in undesirable outputs (bads) or an increase in inputs. Similarly, if a unit can maintain the same outputs while using fewer inputs, it also indicates that it is operating efficiently and is aligned with the frontier. (Charnes et al., 1981; Seiford and Zhu, 2002).

When it comes to dealing with both desirable and undesirable outputs, within the DEA models, the Directional Distance Function (DDF) model is the optimal one to facilitate the simultaneous increase of desirable and reduction of undesirable outputs. Furthermore, the non-radial DDF method permits the non-proportional adjustment of input and output weights (Wang et al., 2013). Lastly, for our study, since we evaluate all the states of Mexico over a 20-year period, we cannot assume that the sample is quite homogeneous and all states operate under similar conditions during each period, so it is more appropriate to assume variable returns to scale and with this obtain a convex combination.

Following Zhou et al. (2012) and Zhang et al. (2013), to set a DEA model, let us assume that there are $i = 1, 2, ..., K$ DMUs (in our case DMUs are states) and for each DMU there is a production input vector $x \in \mathbb{R}_+^N$, to jointly produce desirable outputs $y \in \mathbb{R}_+^M$ and undesirable outputs $c \in \mathbb{R}_+^J$. We use these vectors to create the multi-output production technology, namely T, as defined in equation 1.

$$T = \{(x, y, c) : x \text{ can produce } y \text{ and } c\} \in \mathbb{R}_+^N \tag{1}$$

The production frontier is formed by the units that demonstrate the best practices using production factors efficiently. Following Zhang et al. (2013), the non-radial DDF is defined as in equation 2.

$$\overrightarrow{D}(x,y,c;g) = sup[\omega'\beta : \{(x,y,c) + g \times diag(\beta)\} \in T] \tag{2}$$

where $\omega = (\omega_n^x, \omega_m^y, \omega_j^c)'$ denotes a non-negative normalized weight vector, $g = (-g^x, g^y, -g^c)$ represents a directional vector, and $\beta = (\beta_n^x, \beta_m^y, \beta_j^c) \in \mathbb{R}_+^N \times \mathbb{R}_+^M \times \mathbb{R}_+^J$ is a vector of scaling factors with respect to inputs (x), desirable outputs (y), and undesirable outputs (c), respectively, that allows the set of inputs and the set of outputs to adjust non-proportionally as in Wang et al. (2013).

In technical terms, the model assumes that for the production technology, inputs and desirable outputs are strongly disposable, while undesirable output is weakly disposable, which means that a reduction of undesirable output may not always be possible without incurring in certain costs (Hua Z., 2007). This DEA model is equivalent to solve the linear programming problem for $\overrightarrow{D}(x,y,c;g)$ and mathematically can written as equation (3) .

$$\begin{aligned}
\overrightarrow{D}(x,y,c;g) =& \max_{\beta,\lambda}(\omega'\beta) \\
& s.t. \\
& \quad \sum_{i=1}^{K} \lambda_i x_{in} \leq x_n - \beta_n^x g_n^x, \qquad n = 1,...,N \\
& \quad \sum_{i=1}^{K} \lambda_i y_{im} \geq y_m + \beta_m^y g_m^y, \qquad m = 1,...,M \\
& \quad \sum_{i=1}^{K} \lambda_i c_{ij} = c_j - \beta_j^c g_j^c, \qquad j = 1,...J \\
& \quad \sum_{i=1}^{K} \lambda_i = 1 \\
& \quad \lambda_i \geq 0 \qquad i = 1,...,K \\
& \quad \beta_n^x, \beta_m^y, \beta_j^c \geq 0
\end{aligned} \tag{3}$$

The programming model in equation (3) provides the general form of non-radial DDF with variable return to scale, whose objective function maximizes the efficiency, this implies that when $\overrightarrow{D}(x,y,c;g) = 0$ the evaluated point is already located at the frontier of best practice and it is efficient in the g direction. For our case, we denote $x = (K,L,E)$ as inputs (Capital, Labor, and Energy), $y = Y$ as desirable output and $c = C$ as the undesirable output (Greenhouses gases emission). Assuming both inputs and undesirable outputs decrease and desirable outputs increase, the non-negative normalized weight vector is $\omega = (\omega_K, \omega_L, \omega_E, \omega_Y, \omega_C)'$ and the directional vector is $(-g^x, g^y, -g^c)$=(-K,-L,-E,Y,-C) following Yao et al. (2015). Thus, the left-hand side of the three first constraints uses the observed information for all DMUs, while the right-hand side allows the assessed DMU to adjust inputs and outputs along the direction of $g = (-K, -L, -E, Y, -C)$ in the proportion of $\beta = (\beta_K, \beta_L, \beta_E, \beta_Y, \beta_C)$ as Wang et al. (2013). In the case of the third constraint, the equal sign is due to weak disposability of undesirable output. The fourth constraint is for the variable return to scale, that is the frontier results in a convex set that allows that DMUs with different productivity to be considered efficient. [2]

Following the example proposed by Zhou et al. (2012) and Wang et al. (2022), we illustrate the non-radial directional distance function defined in equation (3) using Figure 2 that depicts the amount of desirable and undesirable outputs by unit of energy consumed. Points A, B, C and D are DMUs that form the frontier of best production practices, while point E represents an inefficient DMU below the frontier that could improve by moving along the frontier FBG, that is reducing C/E, increasing Y/E, or a combination of both. When using a non-radial DDF model, if vector g is assigned to these directions (called "directional vector"), E would move to the optimal point E' since is the best combination of reducing C/E, increasing Y/E, in a non-proportional way, which is determined by β_C and β_Y. This is the main contrast between radial and non-radial distance function, where in radial measure our reference point would be fixed in F or G, which implies that the non-radial measure is more flexible.

After solving the non-radial DDF problem in equation (3), we can use the resulting scaling factors and weight vector to calculate the energy and environmental potentials of each state in the country, as proposed by Zhou et al. (2012).

Following Zhou et al. (2012) and assuming β_E^*, β_Y^*, and β_C^* as the optimal scaling factors for energy, output, and GHG emissions (undesirable output), respectively to equation (3), four types of indices are proposed for energy efficiency and GHG emissions.

Energy Potential Savings (EPS) represent the amount of energy that can be reduced while maintaining the same production level. In other words, EPS indicates that the Decision Making Unit (DMU) is using more energy than necessary to produce the same amount of product. Therefore, EPS quantifies the reduction of this unnecessary

[2] In traditional DEA models, equation (3) has always a solution, but since optimal solutions for λ_i^* are multiple, then the solution cannot be unique. In addition, in the DDF model, the existence of multiple solutions for the lineal programming model in equation (3) will depend on the values assigned to ω. An example of this can be seen in the special cases provided by Zhou et al. (2012).

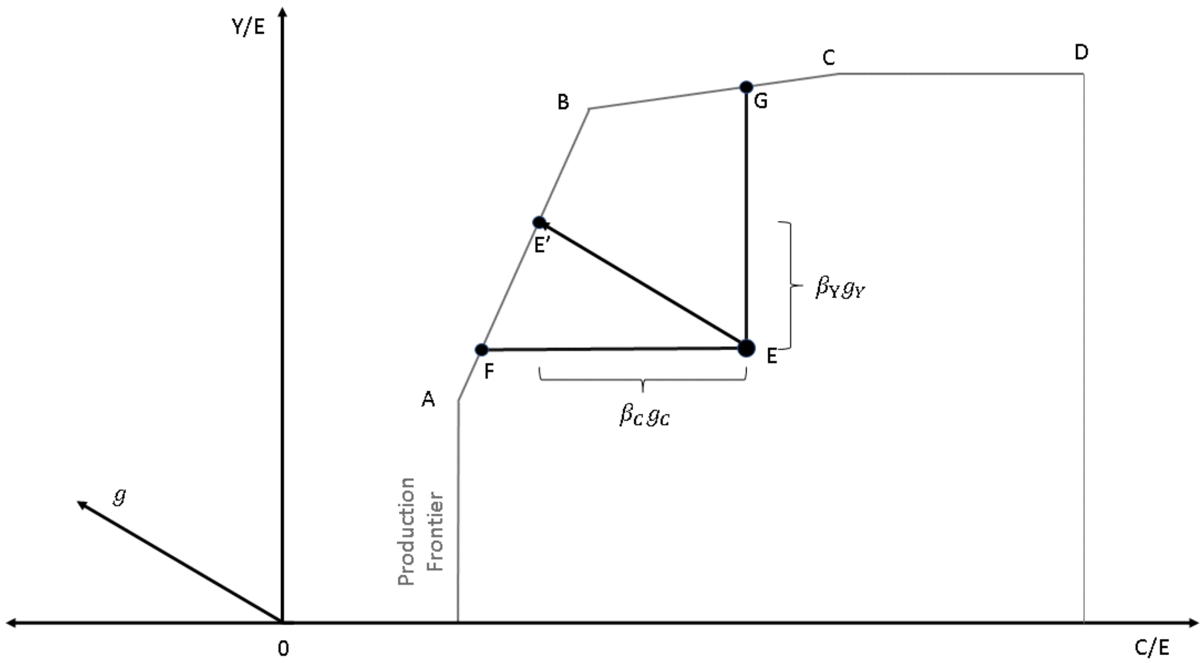


Figure 2: Graphical example of non-radial directional distance function.

Notes: Points A, B, C and D are DMUs that form the frontier of best production practices, while point E represents an inefficient DMU below the frontier that could improve by moving along the frontier FBG, that is reducing C/E, increasing Y/E, or a combination of both. When using a non-radial DDF model, the directional vector g causes E to move to the optimal point E' since is the best combination of reducing C/E, increasing Y/E, in a non-proportional way, which is determined by β_C and β_Y.

energy consumption. Formally, it is defined as in equation (4).

$$EPS = \omega_E \beta_E^* E \tag{4}$$

Energy Efficiency Performance (EEP), as defined in equation (5), quantifies the potential energy consumption savings per additional unit of output. Zhou et al. (2012) define it as the ratio of actual energy efficiency (Y/E) to potential energy efficiency.

$$EEP = \frac{\left(\frac{Y}{E}\right)}{\left(\frac{Y+\omega_Y \beta_Y^* Y}{E-\omega_E \beta_E^* E}\right)} = \frac{1-\omega_E \beta_E^*}{1+\omega_Y \beta_Y^*} \tag{5}$$

Similarly, the GHG Emissions Potential Savings (GEPS) represents the extent to which pollution should be reduced without affecting production.

$$GEPS = \omega_C \beta_C^* C \tag{6}$$

Finally, we follow Zhou et al. (2012) to define the GHG Emissions Performance (GEP) as the ratio of potential target emission intensity to actual emission intensity (C/Y).

$$GEP = \frac{\left(\frac{C-\omega_C\beta_C^*C}{Y+\omega_Y\beta_Y^*Y}\right)}{\left(\frac{C}{Y}\right)} = \frac{1-\omega_C\beta_C^*}{1+\omega_Y\beta_Y^*} \tag{7}$$

Both EEP and GEP lie between zero and unity. Zhou et al. (2012) states that, a larger GEP represents better reduction GHG emission performance. If GEP is equal to unity, it means that the DMU has the best reduction in GHG emission performance for the level of gross value added.

5 Data

This paper assesses the energy and environmental performance in the manufacturing sector across all thirty-two states of Mexico for different years between 1998 and 2018 . The economic activity data was sourced from the 31-32-33 NAICS sectors of economic censuses by INEGI (2020b)[3]. Notably, we omitted the 3241 and 3251 industry groups, encompassing the oil refining sector, given its substantial contribution to greenhouse gas emissions and energy consumption in manufacturing (16% and 9% in 2018, respectively, as indicated by CONUEE (2018)). While undergoing stringent environmental regulations, this sector has experienced heightened energy utilization. For this reason, we have excluded them from our analysis to avoid bias towards states including these industry groups.

Input variables, including capital (K), labor (L), and electricity consumption (E), alongside the desirable output (Y), were derived from INEGI (2020b). The desirable output (Y), representing gross value added (million MXN 2018=100), is the value generated during production. It was then adjusted using the corresponding manufacturing producer price index PPI (2013). Capital (K), measured in million MXN 2018=100, represents the total stock of fixed assets, encompassing movable and immovable property

[3]The National Institute of Statistics and Geography (INEGI from its acronym in Spanish) is responsible for obtaining statistical information from different projects such as censuses, surveys, and administrative records. For this case, use was made of the information generated with the Economic Censuses, which allow knowing and statistically measuring the state of the Mexican economy in a given period. This project is carried out every 5 years, taking data from the previous year. For example, the most recent for this document were the Economic Censuses 2019 which had information from 2018. Therefore, the years to consider in our analysis are: 1998, 2003, 2008, 2013 and 2018.

or enhancements enhancing productivity and useful life. It was adjusted using the appropriate producer capital formation price index. Labor (L), quantified in thousands of hours worked, includes both regular hours and overtime, dedicated to productive activities.

To ascertain the energy consumption input variable (E), we drew on electricity consumption data from INEGI (2020b), supplemented with natural gas consumption converted both to energy equivalent through a constant transformation to obtain the same units.[4] The data regarding natural gas usage was acquired from Secretaria de Energía (2020).

As a proxy for the undesirable output (C), we utilized data on CO2e emissions at the state level from SEMARNAT (2019), where each state reports emissions by activity type across various periods. However, these state-level emissions differed from national emissions published by INECC (2018), likely due to methodological variations. To reconcile these discrepancies, we employed a two-step approach, first, we calculated the proportion of each state's emissions relative to the national total, and second, we applied these weights to the national emissions data from the manufacturing sector. This approach ensures consistency between our state-level and national-level emissions data for the manufacturing sector.

Table 1 reports some descriptive statistics of the five variables for 1998 and 2018, which allows to illustrate clearer the change over the time. [5] As we can observe, all variables increased significantly during our sample period, highlighting how energy consumption increased by 114%, while GHG emissions were only 28%.

[4]Petajoules (PJ) were used as the unit of measurement for equivalent energy. To provide context, here are some conversion factors: 1 million kWh is equivalent to 0.0036 PJ and 1 million cubic feet is equivalent to approximately 0.0011 PJ (or 1.084597 x 10^{-3} PJ).

[5]Descriptive statistics and results for all years can be found in the appendices A.1, A.2, and A.3. Information at state level is available upon request.

Table 1: Descriptive Statistics

Variable	Unit	1998		2018		% change
		mean	sd	mean	sd	1998-2018
Value added (Y)	[1×10^6 MXN (2018)]	51,943	63,989	96,554	105,195	85.8
CO2e emissions (C)	[1×10^3 ton CO2e]	2,872	2,503	3,676	3,395	27.9
Energy (E)	[1×10^{15} Joules]	19.8	26.9	42.6	55.6	114.6
Capital (K)	[1×10^6 MXN (2018)]	71,132	81,548	86,010	89,863	20.9
Labor (L)	[1×10^3 hours worked)]	302,823	316,557	469,327	433,529	54.98

Note: Descriptive Statistics for years 1998 and 2018. The dataset comprised 32 observations for each of these years.

6 Results

6.1 Technical efficiency with and without undesirable output

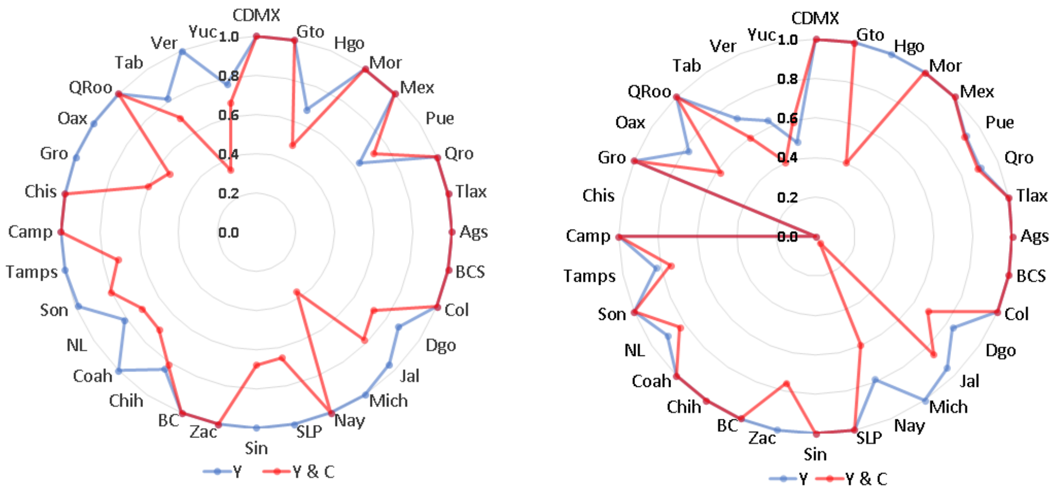
Upon applying the non-radial DDF model with a variable return to scale to the manufacturing sector of Mexico's states, to obtain $\overrightarrow{D}(x, y, c; g)$ with the optimal values, we solved equation (3) for five different years between 1998 and 2018, those are: 1998, 2003, 2018, 2013 and 2018. Subsequently, to simultaneously model energy and environmental performance, we set the directional vector $g = (-g^x, g^y, -g^c) = (-K, -L, -E, Y, -C)$ and changes in total technical efficiency are evaluated through a comparison of two scenarios. The first scenario exclusively considered the desirable output, denoted by the normalized weight vector $\omega = (\omega_n^x, \omega_m^y, \omega_j^c) = (\omega_K, \omega_L, \omega_E, \omega_Y, 0) = (1/9, 1/9, 1/9, 2/3, 0)$, with the directional vector for the undesirable output C set to $g_C = 0$. In contrast, the second scenario encompassed both desirable and undesirable outputs, utilizing $\omega = (1/9, 1/9, 1/9, 1/3, 1/3)$. [6]. The technical efficiency indexes ($\overrightarrow{D}$) obtained under both scenarios are illustrated in Figure 3. [7]

Our results demonstrate that, in general, technical efficiency is consistently higher or equal when focusing solely on the desired output rather than considering both outputs. Furthermore, instances where a state demonstrated inefficiency in the former scenario (depicted by the blue line in Figure 3(b) falling within the inner portion with values below 1.0) experienced an even further decline in efficiency under the latter scenario (illustrated by the red line), with the exception of Yucatán (noted as "Yuc" in Figure 3(b)).

Our analysis has uncovered a significant disparity in the number of efficient states based on whether only the desirable output is taken into account. Specifically, in 1998, we identified 23 states as efficient when focusing solely on the desirable output, a count that reduced to 15 when both outputs were considered (refer to Figure 3(a)). Similarly, for 2018, we observed 20 states exhibiting efficiency under the scenario of considering only the desirable output, compared to 17 states when incorporating both outputs (refer to Figure 3(b)).

[6] Following Zhang et al. (2013), we aim to improve economic efficiency by minimizing capital and labor inputs while maximizing desirable output and minimizing undesirable output. This approach suggests assigning equal weights to all inputs and outputs. However, since the inputs encompass three variables (capital, labor, and energy), the weight for inputs is divided equally among them, resulting in the vector $\omega = (1/9, 1/9, 1/9, 1/3, 1/3)$. Alternatively, we calculate results using a weight vector of $(0, 0, 1/3, 1/3, 1/3)$. This approach focuses solely on energy, desirable and undesirable outputs, isolating their impact without altering capital and labor inputs. This analysis is further explored in Section 6.3

[7] The technical efficiency indexes for the rest of the years are reported in Appendix A.2.



(a) 1998 (b) 2018

Figure 3: Technical Efficiency with only desirable output (Y) and with both desirable and undesirable outputs (Y & C)

Notes: 1) Blue line represents total technical efficiency when only the desirable output is taking into account, while red line shows it when both desirable and undesirable outputs are taking into account. 2) The outer circle marked with 1.0 represents the production frontier, inner circles mean to locate below the frontier. 3) Average technical efficiencies in 1998 were 0.95 (Y) and 0.81 $(Y\&C)$, while in 2018 were 0.90 (Y) and 0.81 $(Y\&C)$. 4) Mann–Whitney–Wilcoxon test for 1998 shows a statistic $z = 2.556$ with $p\_value = 0.0106$ and for 2018: $z = 1.226$ and $p\_value = 0.22$.

Nonetheless, we contend that the evaluation of technical efficiency should encompass both desirable and undesirable outputs. This approach permits efficient strategies to account for the potential detrimental effects stemming from environmental factors. Recognizing the negative impact of emissions and energy consumption can help create more comprehensive and effective initiatives to promote sustainability within the manufacturing sector.

Moreover, a comparison of the average technical efficiency between 1998 and 2018 revealed an interesting trend. In 1998, the average technical efficiency was consistently higher under both scenarios than in 2018. To substantiate this, we employed the Mann–Whitney–Wilcoxon test to assess total technical efficiency,[8] uncovering significant differences at the 5% significance in 1998 but not in in 2018. This suggests that for the later year, there was no significant difference between the efficiencies achieved under these two scenarios.

Remarkably, our findings also unveiled that, although the number of inefficient states decreased from 1998 to 2018, the overall efficiency of the manufacturing sector

[8]The Mann-Whitney U Test, also known as the Wilcoxon Rank-Sum Test, is a non-parametric test used to compare differences between two independent groups under the null hypothesis that they come from populations with the same distribution (Mann and Whitney, 1947; Wilcoxon, 1992).

did not demonstrate improvement over this period. This intriguing outcome emphasizes that despite advancements in efficiency within some states, others experienced notable declines in their efficiency levels. For instance, states like Michoacán and Chiapas saw substantial reductions in their efficiency scores. This dynamic suggests that while certain regions have made progress, the overarching efficiency landscape in the manufacturing sector of Mexico still requires substantial attention.

6.2 Explaining technical efficiency with undesirable output

In this section, our objective was to discern the factors intricately linked with the technical efficiency index derived from both desirable and undesirable outputs. To achieve this, we construct a pseudo-panel utilizing the outcomes for obtained in Section 6.1, constituting a framework encompassing 32 states ($N = 32$) across a five-year span (specifically, $T =$ 1998, 2003, 2008, 2013, 2018). Delving into the analysis, we examined an array of variables (as detailed in Table 2) that could potentially drive improvements in energy and environmental efficiency.

These variables included educational attainment, sectoral specialization, investments, and a green tax for states that have already implemented it. [9] However, we must acknowledge that other factors might lead to outcomes of uncertain significance. For instance, variables such as whether states are natural gas producers and whether they have air quality systems in place can have different implications. This uncertainty arises from the fact that states lack ownership over local gas resources, and the enforcement of environmental regulations is relatively weak nationwide. To further ensure comprehensive analysis, we also incorporated population density as a control variable.

Given the bounded nature of the dependent variable, which ranges between zero and one, we opted for a fractional probit response model, which is well-suited for panel data analysis. In line with the approach suggested by Papke and Wooldridge (2008), we employed an exchangeable working correlation matrix. [10] We also followed Papke

[9] These taxes have been established by each state to target firms responsible for environmental damage. As of 2018, only five states have set such taxes: Estado de México, Querétaro, Oaxaca, Campeche, and Quintana Roo. For example, Estado de México introduced an environmental tax for the emission of pollutants into the atmosphere in 2018. More information by state and tax category can be found in the Mexican Environmental Taxes Guideline (https://explore.pwc.com/impuestosverdes2022).

[10] Papke and Wooldridge (2008) describe it as a situation where errors in data analysis tend to stay similarly connected over time, regardless of other factors. This is called an "exchangeable" pattern. Normally, these errors (represented by u_{it}) would change based on specific observations (i) and time periods (t and s), especially when the data being analyzed isn't a continuous, unrestricted variable. However, these error connections might not actually depend on the specific observations considered. Even if they did connect slightly, those connections would not change much based on the time period examined. In simpler terms, Papke and Wooldridge (2008) proposes that these errors behave in a

and Wooldridge (2008) methodology by using quasi-maximum likelihood estimation (quasi-MLE), which incorporates the temporal averages of explanatory variables. This adjustment helps to manage the correlation between individual fixed effects and the explanatory factors. By doing so, we can avoid the exclusion of unobservable effects that remained constant over time. Let z_{it} be the set of independent variables, equation (8) displays the model we aim to estimate.

$$Pr(\overrightarrow{D}_{it}|z_{i1}, z_{i2}, ..., z_{iT}) = \Phi(\gamma_t + z_{it}\delta + \bar{z}_i\psi) \tag{8}$$

where $\overrightarrow{D}_{it}$ is the optimal technical efficient coefficient for state i in year t, γ_t is for a different intercept in each year, and $\bar{z}_i$ is the average of z_{it} over time.

To obtain proxies for the variables mentioned above, we use for education, the average years of education of the employed population in the Educational characteristics of the population section from INEGI (2021a). Air quality monitoring systems [11] are a tool that some entities have that allows knowing the quality of the air with respect to certain pollutants, obtained by INECC (2018). The availability of a green tax was also considered, as obtained from each state's reports. Sectoral specialization index was calculated by determining the absolute difference between the three most important sectors (manufacturing, services, and trade) of each state in relation to the total of these sectors.[12] Natural gas production was also taken into account, as reported in Secretaria de Energía (2020). Population density was obtained from INEGI (2020a). Finally, we computed total public investments using information of "Public Domain Assets", "Productive Projects", and "Promotion Actions" sections from INEGI (2021b), along with information from the Economic Census published by INEGI (2020b) [13].

Table 2 presents the descriptive statistics. It's worth noting that for several variables, a value of 0 is observed in certain years. Consequently, we opted to work with these variables in their original levels rather than employing logarithmic transformations.

predictable way, regardless of the details of each data point or the specific time frame analyzed. This assumption aligns with the common idea in statistics that errors in a certain type of model (random effects) are independent and have a constant correlation structure.

[11] The quality of the air is monitored for specific pollutants using a series of computer programs in each station to gather reliable information. There are currently 34 air quality monitoring systems set up across the country, strategically placed in cities and metropolitan areas.

[12] This study adapts the specialization index originally proposed by Krugman (1991) to analyze regional economies within Mexico. The index measures the degree of industry specialization in a particular region. It essentially calculates the percentage of jobs in that region that would need to be shifted to different industries in order for the region's industrial makeup to mirror the national average. It is calculated in this case as $SI_{it} = \sum_{j=1}^{3} |b_{jit} - \bar{b}_{it}|$ where $b_{jit} = labor_{jit} / \sum_{j=1}^{3} labor_{jit}$, $\bar{b}_{it} = \sum_{i=1}^{N} labor_{jit} / \sum_{i=1}^{N} \sum_{j=1}^{3} labor_{jit}$, and i is for region and j for the sector: manufacturing, services, and trade.

[13] This calculation includes investments from the federal, state, and municipal governments

Table 2: Variable description and summary statistics

	mean	sd	min	max
Technical efficiency with undesirable output	0.77	0.26	0.00	1.00
Average years of education of the employed population	8.58	1.18	5.40	11.48
1 if state accounts with an air quality monitoring system	0.64	0.48	0.00	1.00
1 if state has a green tax	0.04	0.21	0.00	1.00
Sectoral specialization index	0.24	0.12	0.02	0.55
Natural gas production (Million cf)	0.04	0.10	0.00	0.50
Population density	295.9	1,025.4	2.2	6,160.5
Public investments per manufacturing unit (million MXN)	0.18	0.18	0.00	1.01

Note: Descriptive Statistics for years 1998, 2003, 2008, 2013, and 2018. The dataset comprised 160 observations.

We employed a fractional probit model with robust standard errors to identify factors correlated with the technical efficiency index derived from both desirable and undesirable outputs. The outcomes of our estimation are presented in the ”fractional probit coefficient” column of Table 3, along with the corresponding average partial effect in the final column.

Table 3: Effects on Technical Efficiency of the Manufacturing Sector

	Linear fixed effects	Fractional Probit	
	Coefficient	Coefficient	Average Partial Effect
Average years of education of the employed population	-0.077 (-0.521)	-0.044 (-0.560)	-0.009 (-0.554)
1 if state accounts with an air quality monitoring system	-0.029 (-0.540)	-0.092 (-0.550)	-0.018 (-0.558)
1 if state has a green tax	0.065 (0.748)	0.642**** (3.304)	0.123*** (3.067)
Sectoral specialization index	0.430 (0.986)	3.564** (2.128)	0.684** (1.992)
Natural gas production	1.304*** (2.982)	2.901*** (3.032)	0.557*** (2.886)
Population density	0.000 (0.507)	0.003**** (3.420)	0.001**** (4.240)
Total investments per manufacturing unit	0.137 (1.078)	0.762** (2.200)	0.146** (2.036)
Constant	-17.754 (-0.527)	-4.313**** (-3.712)	
Observations	160	160	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

To verify the robustness of our findings, we also estimated a linear model with fixed effects on the panel data. However, this approach has limitations, as it does not guarantee that the predicted values will fall within the necessary range of zero to one, which is necessary for our analysis. Despite this limitation, the results from the linear model and the fractional probit model showed consistency in terms of the direction (positive or negative) and magnitude of the coefficients. However, some coefficients that were statistically significant in the fractional probit model were not significant in the fixed effects model.

Given the limitations of the fixed effects model and the greater interpretability of the average partial effect from the fractional probit model's results within the zero-to-one range, we will focus on the estimates obtained from the fractional probit model for further analysis. The study's outcomes offer compelling insights into the drivers of technical efficiency within Mexico's manufacturing sector. Our analysis not only confirms the relevance of certain variables but also reveals intriguing nuances that are consistent with existing economic literature.

The results underscore the considerable influence of sectoral specialization on enhancing technical efficiency. This aligns with established economic theories, which assert that concentrating efforts in specific sectors can yield economies of scale and optimized resource allocation (Widodo et al., 2015; Alvarez et al., 2017). Furthermore, the substantial positive impact of combined public and private investments on technical efficiency resonates with empirical evidence showing that investments in modern technologies and infrastructure can foster productivity gains (Auci et al., 2021).

The presence of a green tax emerges as a pivotal factor that positively shapes technical efficiency. This finding aligns with the broader environmental economics literature, which underscores that incorporating environmental considerations into business practices can propel efficiency improvements (Böhmelt et al., 2018). However, the education coefficient's lack of significance challenges the conventional notion that a highly educated workforce inherently translates into heightened technical efficiency (Mohan, 2020).

The notable influence of local natural gas production on technical efficiency is particularly noteworthy (Tab, Tamps, Ver, NL, Chis, Coah, Pue, Camp, SLP). Having a natural gas well or a large storage point can significantly enhance energy efficiency and environmental performance for several reasons. First, these facilities allow for a stable and reliable supply of natural gas, which is a cleaner-burning fossil fuel compared to coal or oil. This results in lower greenhouse gas emissions and pollutants when used for electricity generation or heating. Second, large storage facilities enable the optimization of natural gas distribution, reducing the need for frequent transportation and associated emissions. They also help in balancing supply and demand, minimizing energy wastage and improving overall system efficiency. Additionally, the ability to store natural gas ensures that there is a backup supply during peak demand periods or supply disruptions, further enhancing energy security and reducing reliance on more polluting energy sources.

Conversely, the insignificance of the coefficient related to air quality monitoring systems underscores the challenges Mexico faces in enforcing environmental regulations, emphasizing the need for more robust enforcement mechanisms. In summary, the findings of this section not only affirm the role of established factors but also shed light on new perspectives on technical efficiency determinants in the manufacturing sector when considering the undesirable output.

6.3 Energy and Environmental Performance

Recognizing the significance of incorporating both desirable and undesirable outputs into our analysis, this section focuses on evaluating the energy and environmental potential while considering both output categories. However, we retained capital and labor as constant variables (i.e., $\omega = (0, 0, 1/3, 1/3, 1/3)$). The outcomes pertaining to the energy efficiency performance (EEP, vertical axis) and the GHG emission performance (GEP, horizontal axis) for the years 1998 and 2018 are displayed in Figure 4.

Our findings revealed a positive correlation between energy and environmental potential among inefficient states, comprising 17 in 1998 and 15 in 2018. This suggests that a higher energy efficiency potential corresponds to a greater ability to conserve energy, thereby resulting in reduced pollution and enhanced environmental performance.

In 1998, excluding the points on the frontier (i.e., those equal to 1), performance ranged from the pair (56%, 57%), representing the energy and environmental performance of Michoacán, to the pair (92%, 89%), corresponding to the energy performance of Sinaloa and the environmental performance of Chihuahua, respectively (refer to Figure 4(a)). By 2018, we observed an increased dispersion, with energy efficiency and environmental performance ranging from a minimum of 27% and 23% in Chiapas to a maximum of 97% and 92% in Nayarit and Nuevo León, respectively (see Figure 4(b)).

Notably, the black quadrant in the upper-right corner of the figure, located at coordinates (1,1), includes states on the production frontier. In 1998, there were 15 states in this quadrant, and by 2018, the number had increased to 17. These states had adopted optimal practices in terms of energy efficiency and environmental performance, achieving a balance between reducing energy consumption and pollution without compromising production. The states that moved to the frontier between 1998 and 2018 were mainly located in the Northern region (represented by yellow markers). In contrast, states that remained in the inefficient region or deviated from the frontier were mostly situated in the central-northern (green markers), southern (blue markers), and central (red markers) regions of the country.

Regarding the average performance, there were no substantial changes in energy and environmental performance between 1998 and 2018. The Energy Efficiency Performance (EEP) altered slightly from 0.9 to 0.88, and the Greenhouse Gas Emission Performance (GEP) remained steady at 0.87 for both years. However, Figures 4 and 5 revealed considerable variability (see Appendix A.3 for more information about EEP and GEP for the rest of the years).

Among the 15 states positioned below the frontier, six states (Nuevo León, Tamaulipas, Jalisco, Oaxaca, Puebla, and Veracruz) demonstrated enhanced production practices, edging closer to the frontier. Conversely, the remaining nine states moved further away from the frontier, indicating declining efficiency. Figure 5 illustrates the map detailing the percentage change in performance measures for each state between 1998 and 2018. Concerning EEP (Figure 5(a)), Coahuila emerged as the most improved state during this period, reaching the production frontier by 2018. Likewise, the GEP map (Figure 5(b)) highlighted noteworthy enhancements in five states: Sonora, Sinaloa, San Luis Potosí, Chihuahua, and Guerrero. Notably, Chiapas was the sole state that experienced a substantial decline in both EEP and GEP (Figure 5).

Utilizing a simple average for the analysis would result in an unfair representation. Instead, it is imperative to take into account the productive orientation of each state situated below the frontier. In Figure 4, the size of each marker corresponds to the sector's contribution to the national value added in the manufacturing sector. Given the exclusion of the oil refining industry from the analysis, this simplification aids in evaluating efficiency, considering the fluctuations in environmental regulations (CONUEE, 2018).

Nevertheless, it's important to note that according to CONUEE (2018) other industries such as iron and steel, cement, and paper also play a significant role in these states. These sectors exhibit substantial potential for improving their energy efficiency,can be effectively intervened upon, and have access to advanced technologies that can have positive environmental impacts. As such, evaluating efficiency in these states requires a detailed understanding of the specific characteristics of each sector and the broader regulatory environment (CONUEE, 2018).

Furthermore, the insights from Figure 4 underscore another dimension of this analysis. For instance, while states like Chiapas and Michoacán exhibit a significant potential for enhancing energy efficiency, their limited share in the national manufacturing value-added would lead to comparatively minor contributions to the overall national energy savings. Conversely, states such as Tamaulipas and Nuevo León, with higher proportions in the manufacturing value-added, hold the potential to make substantial contributions to national savings due to their greater influence.

Turning to the energy aspect, Table 4 presents a comprehensive view of the Energy Potential Savings (EPS) within the national manufacturing sector for the year 2018.[14] The EPS, amounting to 20.3% of total energy consumption, equivalent to 156 PJ of energy, highlights the considerable impact that energy efficiency enhancement measures could have. Notably, the table underscores the pivotal role of certain states in these potential energy savings. Among them, Nuevo León emerges as a significant contributor, accounting for 40.6% of the potential savings, closely followed by Veracruz (20.2%) and Tamaulipas (9.2%). This reinforces the idea that targeted improvements in energy efficiency could substantially drive national energy conservation goals, with the contribution varying based on a state's manufacturing prowess and energy consumption patterns.

Table 4: Energy Potential Savings in 2018

State name	State EPS (%)	EPS share (%)
Nuevo León	68.5	40.6
Veracruz	76.2	20.2
Tamaulipas	61.6	9.2
Michoacán	51.9	6.8
Querétaro	45.2	5.5
Rest of states*	12.5	17.7
Total**	20.3	100.0

*In the second and third columns, EPS refers to the rest of states' average. ** In the second column, EPS is for the country average, while in the third column, it represents the total sum.

In terms of environmental considerations, the insights gleaned from the GHG Emission Potential Abatement for the year 2018 underscore that enhancements in the manufacturing sector's environmental efficiency could potentially yield substantial reductions in GHG emissions. Nationally, a potential reduction of 24.3%, equivalent to around 6.4 Mt CO2e, could be achieved by implementing measures to improve the sector's environmental performance. These details are outlined in Table 5, where the results emphasize that the influential role of specific states in shaping the country's

[14] EPS and GEPS are reported in Appendix A.3 for the entire sample. From 1998 to 2018, there have been fluctuations in both EPS and GEPS, with values both increasing and decreasing over the years. However, no clear trend can be identified throughout this period.

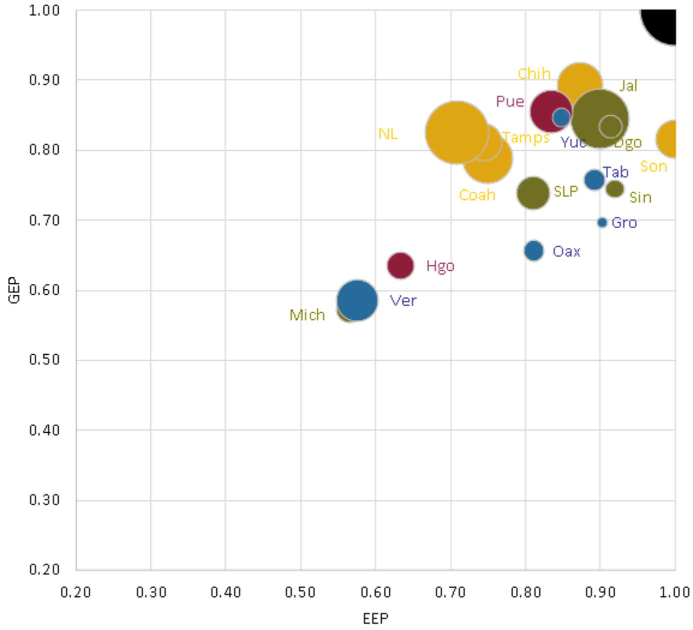
environmental savings. Hidalgo (17.6%), Veracruz (17.2%), and Michoacán (13%) are identified as key contributors to the envisioned national environmental savings, due to their substantial manufacturing value-added contributions.

It's worth noting that the synergy between energy and environmental efficiency is vital. The virtuous cycle of improvements in one area reinforcing the other is evident. For instance, advancements in energy efficiency translate into substantial energy savings, resulting in reduced pollution levels and consequently, amplified environmental efficiency. This holistic approach underscores the interconnectedness of energy and environmental dynamics within the manufacturing sector's performance landscape.

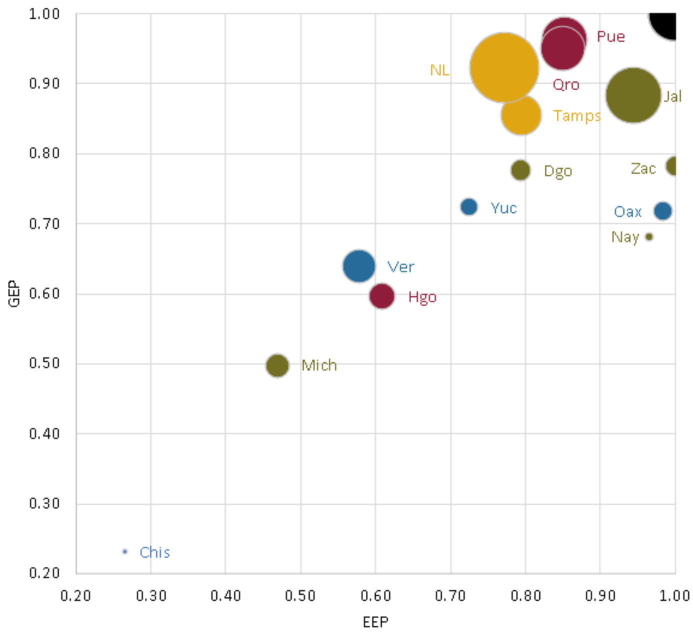
Table 5: GHG Emission Potential Savings in 2018

State name	State GEPS (%)	GEPS share (%)
Hidalgo	64.3	17.6
Veracruz	52.4	17.2
Michoacán	36.6	13.0
Jalisco	35.1	11.3
Nuevo León	23.1	9.5
Rest of states*	20.8	31.4
Total*	24.3	100.0

*In the second and third columns, GEPS refers to the average. ** In the second column, GEPS is for the country average, while in the third column, it represents the total.



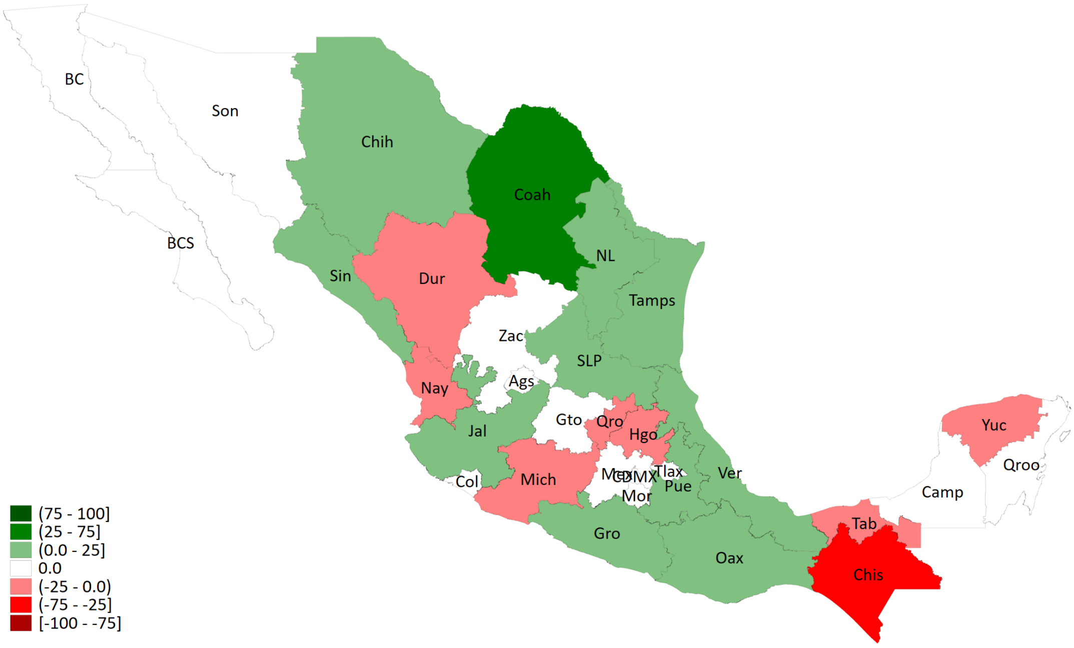
(a) 1998



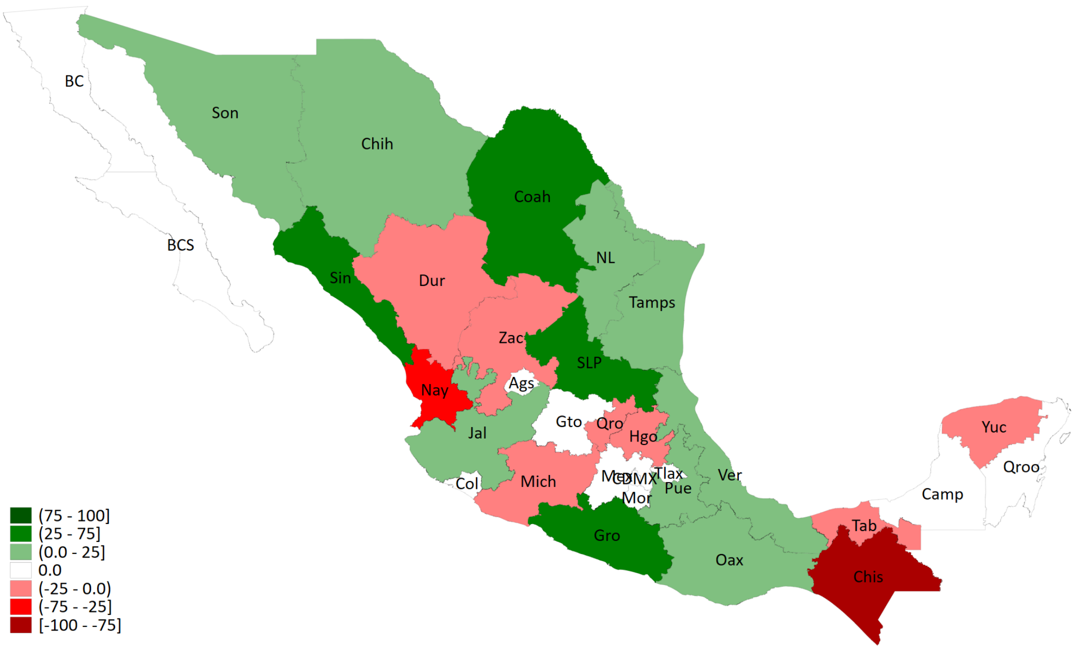
(b) 2018

Figure 4: Energy Efficiency Performance vs. GHG Emission Performance

Notes: 1) The black quadrant at (1,1) in the lower left corner illustrates the states on the production frontier, which were 15 (BC, BCS, Ags, Col, Zac, Nay, CDMX, Gto, Mex, Mor, Tlax, Qro, QRoo, Camp, Chis) in 1998 and 17 (Coah, Chih, Son, BC, BCS, Ags, Sin, Col, SLP, CDMX, Gto, Mex, Mor, Tlax, QRoo, Camp, Gro) in 2018. 2) States in the Northern region use yellow markers, in the Southern region blue markers, in the central-Northern region green markers, and in the central region red markers. 3) The size of each point represents the participation of the state's sector in the total domestic value added (VA). 4) Average EEP and GEP were 0.90 and 0.87, respectively, in 1998, and 0.88 and 0.87, respectively, in 2018.



(a) Energy Efficiency (EEP)



(b) GHG Emission (GEP)

Figure 5: % Change Performances 1998-2018

Notes: States in white remain in the frontier in both periods. States colored in green increased performance from 1998 to 2018, while in red means a reduction during the same period.

7 Discussion and concluding remarks

Mexico's ambitious commitment to curbing GHG emissions by an impressive 22% before 2030, equating to the substantial mitigation of over 211 million tons of CO2e, demonstrates a proactive approach towards combating climate change. Interestingly, an overlooked aspect of this endeavor is the potential embedded within the individual states of Mexico to significantly reduce emissions without compromising their manufacturing prowess, an aspect that warrants closer examination and strategic consideration.

To grasp this potential, assume each state reaches a position on the production frontier -— the hypothetical boundary where a state's production processes become as efficient as possible in terms of both energy consumption and environmental impact. If such an alignment were achieved, it could, in itself, contribute around three percentage points towards the nation's overarching target, corresponding to a substantial 6.4 million tons of the total 211 million tons. This analysis highlights that each state's position on the production frontier holds a latent power to create sizeable emissions reductions, irrespective of its current status.

However, this potential isn't uniform across all regions. The northern states exhibit a promising capacity for energy savings, reflecting the industrial heft and innovation-driven nature of these regions. Meanwhile, the central-northern and southern states possess untapped potential to focus their efforts on reducing pollution, aligning with their unique economic landscapes. These observations underscore the need for tailored strategies that address each region's specific strengths and opportunities.

Furthermore, envisioning a nationwide shift towards more efficient production practices, similar to those already demonstrated in certain regions, holds the promise of generating even more substantial energy savings and GHG reductions. The ripple effect of such a transformation, cascading across the nation's manufacturing landscape, could lead to a collective impact far greater than the sum of its parts.

However, it's important to acknowledge that these transformations don't come without their challenges. As energy prices continue to soar, the anticipated energy savings could potentially exert positive pressure on production costs. However, this hinges on the delicate balance between the savings realized and the necessary investments required to usher in these transformative changes. The feasibility of these investments would need to be carefully evaluated against the backdrop of broader economic considerations.

In conclusion, Mexico's journey towards a greener future entails multifaceted implications. The potential for emissions reduction within each state offers a compelling pathway towards meeting national goals. By leveraging regional strengths, fostering innovation, and adopting efficiency-enhancing practices, Mexico could indeed turn the tide on emissions while simultaneously redefining its manufacturing landscape. This dual benefit – a substantial environmental contribution and a potential economic advantage – underscores the critical intersection between sustainable practices and a resilient, forward-looking economy.

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A Appendix

A.1 Descriptive Statistics

Variable	Unit	1998		2003	
		mean	sd	mean	sd
Value added (Y)	[1×10^6 MXN (2018)]	51,943	63,989	61,965	68,1132
CO2e emissions (C)	[1×10^3 ton CO2e]	2,872	2,503	2,659	2,125
Energy (E)	[1×10^{15} Joules]	19.8	26.9	19.4	28.7
Capital (K)	[1×10^6 MXN (2018)]	71,132	81,548	75,564	81,380
Labor (L)	[1×10^3 hours worked)]	302,823	316,557	306,172	304,121
Observations		32	32	32	32

Variable	Unit	2008		2013	
		mean	sd	mean	sd
Value added (Y)	[1×10^6 MXN (2018)]	68,782	76,252	65,760	71,398
CO2e emissions (C)	[1×10^3 ton CO2e]	3,320	2,615	3,546	2,831
Energy (E)	[1×10^{15} Joules]	21.9	32.0	25.6	36.0
Capital (K)	[1×10^6 MXN (2018)]	70,495	68,650	78,128	82,402
Labor (L)	[1×10^3 hours worked)]	324,316	310,070	359,963	337,214
Observations		32	32	32	32

Variable	Unit	2018	
		mean	sd
Value added (Y)	[1×10^6 MXN (2018)]	96,554	105,195
CO2e emissions (C)	[1×10^3 ton CO2e]	3,676	3,395
Energy (E)	[1×10^{15} Joules]	42.6	55.6
Capital (K)	[1×10^6 MXN (2018)]	86,010	89,863
Labor (L)	[1×10^3 hours worked)]	469,327	433,529
Observations		32	32

A.2 Technical Efficiency

Region	State	1998		2003		2008		2013		2018	
		Y	Y & C	Y	Y & C	Y	Y & C	Y	Y & C	Y	Y & C
Central	CDMX	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Central	Gto	1.00	1.00	0.92	0.75	0.84	0.70	0.84	0.78	1.00	1.00
Central	Hgo	0.68	0.48	0.87	0.45	1.00	0.56	1.00	0.07	1.00	0.40
Central	Mor	1.00	1.00	1.00	1.00	1.00	1.00	0.71	0.51	1.00	1.00
Central	Mex	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Central	Pue	0.63	0.72	0.88	0.81	0.79	0.69	1.00	1.00	0.92	0.91
Central	Qro	1.00	1.00	0.77	0.56	1.00	1.00	0.66	0.64	0.91	0.89
Central	Tlax	1.00	1.00	0.65	0.69	1.00	1.00	1.00	1.00	1.00	1.00
North-Central	Ags	1.00	1.00	0.67	0.53	0.96	0.95	0.37	0.47	1.00	1.00
North-Central	BCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
North-Central	Col	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.49	1.00	1.00
North-Central	Dgo	0.87	0.72	0.00	0.34	0.91	0.63	0.34	0.33	0.84	0.69
North-Central	Jal	0.96	0.78	1.00	0.71	1.00	0.69	1.00	1.00	0.94	0.85
North-Central	Mich	1.00	0.37	1.00	0.06	1.00	0.45	1.00	0.00	1.00	0.04
North-Central	Nay	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.54	0.79	0.60
North-Central	SLP	1.00	0.65	1.00	0.47	1.00	0.65	0.82	0.61	1.00	1.00
North-Central	Sin	1.00	0.68	0.85	0.57	1.00	0.67	0.85	0.24	1.00	1.00
North-Central	Zac	1.00	1.00	1.00	1.00	1.00	1.00	0.81	0.48	1.00	0.76
Northern	BC	1.00	1.00	0.92	0.89	1.00	1.00	0.87	0.86	1.00	1.00
Northern	Chih	0.84	0.81	1.00	1.00	1.00	0.70	0.78	0.77	1.00	1.00
Northern	Coah	1.00	0.70	0.87	0.68	1.00	1.00	1.00	1.00	1.00	1.00
Northern	NL	0.81	0.70	1.00	0.69	1.00	0.87	1.00	0.81	0.91	0.83
Northern	Son	0.99	0.81	0.77	0.56	1.00	0.74	1.00	1.00	1.00	1.00
Northern	Tamps	1.00	0.72	0.69	0.65	1.00	1.00	0.48	0.57	0.83	0.75
Southern	Camp	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Southern	Chis	1.00	1.00	0.84	0.77	0.83	0.64	1.00	1.00	0.00	0.00
Southern	Gro	1.00	0.60	0.81	0.54	0.88	0.48	1.00	1.00	1.00	1.00
Southern	Oax	1.00	0.54	1.00	0.31	1.00	0.49	1.00	0.00	0.78	0.58
Southern	QRoo	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Southern	Tab	0.82	0.70	1.00	1.00	0.80	0.78	0.77	0.81	0.72	0.60
Southern	Ver	1.00	0.34	0.89	0.44	1.00	0.69	1.00	0.65	0.63	0.41
Southern	Yuc	0.77	0.67	0.52	0.54	0.61	0.56	0.41	0.38	0.49	0.59
National		0.95	0.81	0.87	0.72	0.96	0.81	0.87	0.69	0.90	0.81

Note: 1) The showed values represent total technical efficiency. Y variable describes total technical efficiency when only the desirable output is taking into account. $Y\&C$ variable shows it when both desirable and undesirable outputs are taking into account. 2) The value 1.00 represents the production frontier. Hence, the closer to this value more efficient could be. 3) National variable is the average technical efficiencies in each year.

A.3 Energy Efficiency and GHG Emission Performance

Region	State	1998		2003		2008		2013		2018	
		EEP	GEP	EEP	GEP	EEP	GEP	EEP	GEP	EEP	GEP
Central	CDMX	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Central	Gto	1.00	1.00	0.92	0.79	0.81	0.79	0.84	0.86	1.00	1.00
Central	Mex	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Central	Mor	1.00	1.00	1.00	1.00	1.00	1.00	0.64	0.67	1.00	1.00
Central	Tlax	1.00	1.00	0.70	0.84	1.00	1.00	1.00	1.00	1.00	1.00
Central	Pue	0.83	0.86	0.92	0.89	0.76	0.82	1.00	1.00	0.85	0.96
Central	Qro	1.00	1.00	0.74	0.69	1.00	1.00	0.71	0.78	0.85	0.95
Central	Hgo	0.63	0.64	0.70	0.60	0.75	0.69	0.48	0.49	0.61	0.60
North-Central	BCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
North-Central	Ags	1.00	1.00	0.91	0.68	0.98	1.00	0.67	0.71	1.00	1.00
North-Central	Sin	0.92	0.74	0.92	0.75	1.00	0.74	0.62	0.50	1.00	1.00
North-Central	Col	1.00	1.00	1.00	1.00	1.00	1.00	0.82	0.59	1.00	1.00
North-Central	SLP	0.81	0.74	0.74	0.63	0.80	0.77	0.75	0.73	1.00	1.00
North-Central	Zac	1.00	1.00	1.00	1.00	1.00	1.00	0.75	0.64	1.00	0.78
North-Central	Nay	1.00	1.00	1.00	1.00	1.00	1.00	0.80	0.62	0.97	0.68
North-Central	Jal	0.90	0.84	0.90	0.78	0.83	0.76	1.00	1.00	0.94	0.88
North-Central	Dur	0.91	0.83	0.74	0.55	0.82	0.71	0.56	0.57	0.79	0.78
North-Central	Mich	0.56	0.57	0.46	0.46	0.64	0.64	0.41	0.44	0.47	0.50
Northern	Coah	0.75	0.79	0.80	0.79	1.00	1.00	1.00	1.00	1.00	1.00
Northern	Chih	0.87	0.89	1.00	1.00	0.84	0.79	0.79	0.90	1.00	1.00
Northern	Son	1.00	0.82	0.87	0.70	0.91	0.78	1.00	1.00	1.00	1.00
Northern	BC	1.00	1.00	0.98	0.94	1.00	1.00	0.80	0.99	1.00	1.00
Northern	Tamps	0.74	0.81	0.75	0.78	1.00	1.00	0.69	0.73	0.79	0.86
Northern	NL	0.71	0.82	0.75	0.82	0.79	0.95	0.79	0.89	0.77	0.92
Southern	Qroo	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Southern	Camp	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Southern	Gro	0.90	0.70	0.93	0.67	0.84	0.63	1.00	1.00	1.00	1.00
Southern	Oax	0.81	0.66	0.71	0.55	0.83	0.61	0.48	0.40	0.98	0.72
Southern	Yuc	0.85	0.85	0.91	0.65	0.85	0.66	0.60	0.60	0.72	0.72
Southern	Tab	0.89	0.76	1.00	1.00	0.83	0.91	0.75	0.96	0.70	0.73
Southern	Ver	0.58	0.59	0.67	0.64	0.78	0.80	0.71	0.78	0.58	0.64
Southern	Chis	1.00	1.00	1.00	0.88	0.97	0.74	1.00	1.00	0.27	0.23

Note: 1) The showed values represent Energy Efficiency (EEP) and GHG Emission Performance (GEP). 2) We can see Mexico City, Mexico, Baja California Sur, Quintana Roo and Campeche maintain through five periods the optimal energy efficiency and GHG emissions performance

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used openai in order to check grammar and improve readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.