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Working Paper

Energy efficiency and mitigation of greenhouse gas emissions in Mexico's manufacturing sector

Working Papers, No. 2025-10

Provided in Cooperation with:

Bank of Mexico, Mexico City

Suggested Citation: Mata, Anna D.; Núñez, Héctor M. (2025) : Energy efficiency and mitigation of greenhouse gas emissions in Mexico's manufacturing sector, Working Papers, No. 2025-10, Banco de México, Ciudad de México

This Version is available at:

<https://hdl.handle.net/10419/322382>

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Banco de México

Working Papers

N° 2025-10

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June 2025

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Energy Efficiency and Mitigation of Greenhouse Gas Emissions in Mexico's Manufacturing Sector

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Abstract: This study examines the energy efficiency and environmental performance of Mexico's manufacturing sector across regions. We employ a Data Envelopment Analysis model that optimizes the weighted output-input ratio for each decision-making unit. Specifically, a non-radial directional distance function model is used to account for both desirable outputs and undesirable outputs, represented by greenhouse gas emissions. The findings show that including undesirable outputs reduces the estimated economic efficiency. Over the analysis period, the production frontier shifted only modestly. Regionally, northern states perform best, while southern states lag behind, revealing considerable potential for national energy and emission savings.

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

JEL Classification: C61, D24, Q43

Resumen: Este estudio examina la eficiencia energética y el desempeño ambiental del sector manufacturero de México en sus regiones. Empleamos un modelo de Análisis Envoltente de Datos que optimiza la razón ponderada entre producción e insumos para cada unidad de toma de decisiones. Específicamente, se utiliza un modelo de función de distancia direccional no radial para capturar tanto los productos deseables como los no deseables, representados por las emisiones de gases de efecto invernadero. Los resultados muestran que incluir los productos no deseables reduce la eficiencia económica estimada. Durante el período de análisis, la frontera de producción cambió solo modestamente. Regionalmente, los estados del norte tienen mejor desempeño, mientras que los del sur quedan rezagados, revelando un potencial considerable ahorro nacional en energía y emisiones.

Palabras Clave: Producto no deseable, Mejoras en la eficiencia energética, Desempeño en emisiones de GEI, Función de distancia direccional

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1 Introduction

México 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 status quo scenario. 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 (Secretaría 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 aim 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 affecting 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 México. 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 México, has been limited.

While some research has explored the technical efficiency of México'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, stays absent. As depicted by INEGI (2020b), the regional dimension in México 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.

By incorporating undesirable outputs—namely, greenhouse gas emissions—into the production framework, the main contribution of this study is to examine whether regions previously recognized for high efficiency in the manufacturing sector can sustain their performance when environmental impacts are considered. 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 sets up 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 México's regional manufacturing sector. We try 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 show 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. If all states reached the production frontier—maximizing efficiency in energy use and environmental impact—they could collectively contribute about 3% of the national target, equivalent to 6.4 million tons of CO₂e. At the regional level, results show that the northern states exhibit a promising capacity for energy savings, while the central-northern and southern states possess untapped potential to focus their efforts on reducing pollution.

The rest of this paper is organized as follows. Section 2 provides a brief review of

earlier studies, including some applications for México. Section 3 provides some context of the regional use of the energy and emission intensity of the manufacturing sector. 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 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 CO₂e 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 showing better energy and carbon performance. Additionally, their analysis shows a link between generation efficiency and overall energy performance, and between lower carbon intensity and better CO₂ emission performance. Chiu et al. (2016) explored efficiency in G20 countries, highlighting variations in performance while considering undesirable

outputs. While some countries like Turkey and México showed significant improvements, others like Argentina and Germany experienced declines. Interestingly, the United States consistently ranked highest in 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, while 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 on the manufacturing sector exists at lower levels, such as provinces or regions within a country, a gap persists at the national and regional levels in Latin America, including México. Studies such as Avile's-Sacoto et al. (2021) evaluate environmental performance across states by incorporating environmental outputs (e.g., water consumption, energy consumption, and pollution) within a DEA variable return to scale output-oriented framework for the entire economy. However, they do not account for both desirable and undesirable outputs simultaneously, and their study is not exclusively for the manufacturing sector. For the manufacturing sector in other countries, some studies have incorporated both desirable and undesirable outputs simultaneously. For instance, Zaim (2004) analyzed the manufacturing sector in U.S. states, employing a DEA distance function to assess efficiency while considering both output directions. Similarly, Wu et al. (2012) examined China's industrial sector using province-level data to estimate a meta-frontier non-radial directional distance function. Studies have explored the technical efficiency of México's manufacturing sector but haven't yet considered undesirable outputs (e.g., Bannister and Stolp, 1995; 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 show 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 also been employed; for instance, studies by Borrayo López et al. (2019) and Alvarez et al. (2017) used stochastic frontier methods to evaluate efficiency in México but also neglected undesirable outputs. By integrating the undesirable output, specifically greenhouse gas emissions, into the production framework, this research aims to investigate whether regions with high efficiency previously identified 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 taken into account. This approach will provide a more exact and comprehensive assessment of regional efficiency, aligning such evaluations with environmental sustainability goals.

3 Context

The manufacturing sector across México's regions showcases considerable heterogeneity, with energy consumption showing a strong correlation with activity levels. The country's thirty-two states are grouped into four major regions¹: the Northern region, encompassing those bordering the U.S.; the North-Central region, forming 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, being a substantial 46.3%.

¹The 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 México 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).

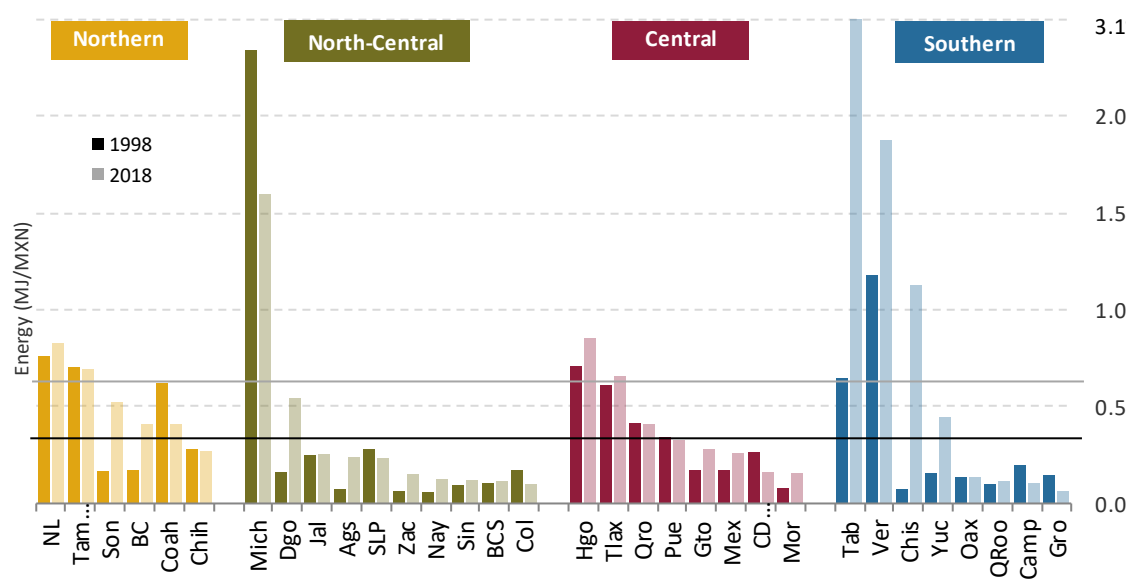
Following closely are the North-Central and Central regions, accounting for 26.3% and 15.0%, respectively. The Southern region registers the lowest consumption at 12.4% (with information by Secretaría de Energía, 2020; INEGI, 2020b).

In terms of greenhouse gas (GHG) emissions, the Northern states appear 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 National Institute of Ecology and Climate Change (INECC in Spanish), 2018). These disparities highlight the importance of analyzing regional variations, which is precisely the focus of this research.

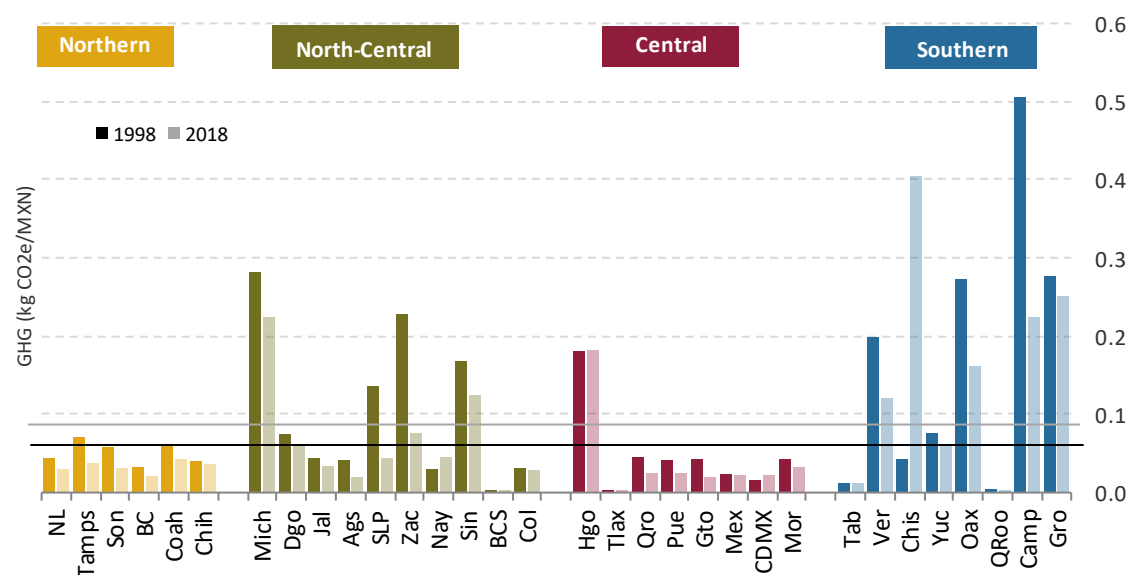
Energy consumption within each state is largely driven by manufacturing activities, which require substantial energy input. A key metric for understanding current energy usage compared to economic activity is energy intensity. This metric quantifies the energy consumed per unit of economic output and is calculated as the ratio of energy consumption to the gross value added by the manufacturing sector.

It is important to note that energy intensity is a macro-level indicator shaped by both the economic structure and energy efficiency. While energy intensity reflects overall energy usage patterns, energy efficiency specifically addresses the effectiveness of energy use by minimizing waste. Both factors are essential for comprehensive evaluation and improvement of energy performance across states.

Figure 1(a) presents the energy intensity values for each Mexican state across regions for the years 1998 and 2018. Energy intensity refers to the amount of energy used to produce a unit of economic output, measured here in megajoules per Mexican peso (MJ/MXN). The data for gross value added comes from INEGI (2020b), while energy consumption data—expressed in petajoules—combines electricity use from INEGI (2020b) and natural gas consumption from the Secretaría de Energía (2020).



(a) Energy Intensity



(b) Emission Intensity

Figure 1: Energy and Emission Intensity of the Manufacturing Sector

Notes: 1) 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. 2) The black and gray lines stand for the national average in 1998 and 2018, respectively. Source: Own elaboration with the data sources are as follows: Gross value added is from INEGI (2020b). Energy consumption, expressed in petajoules, is the sum of electricity (INEGI, 2020b) and natural gas consumption (Secretaría de Energía, 2020). CO₂e emissions are based on state-level data from SEMARNAT (2019) and the national emissions inventory from INECC (2018).

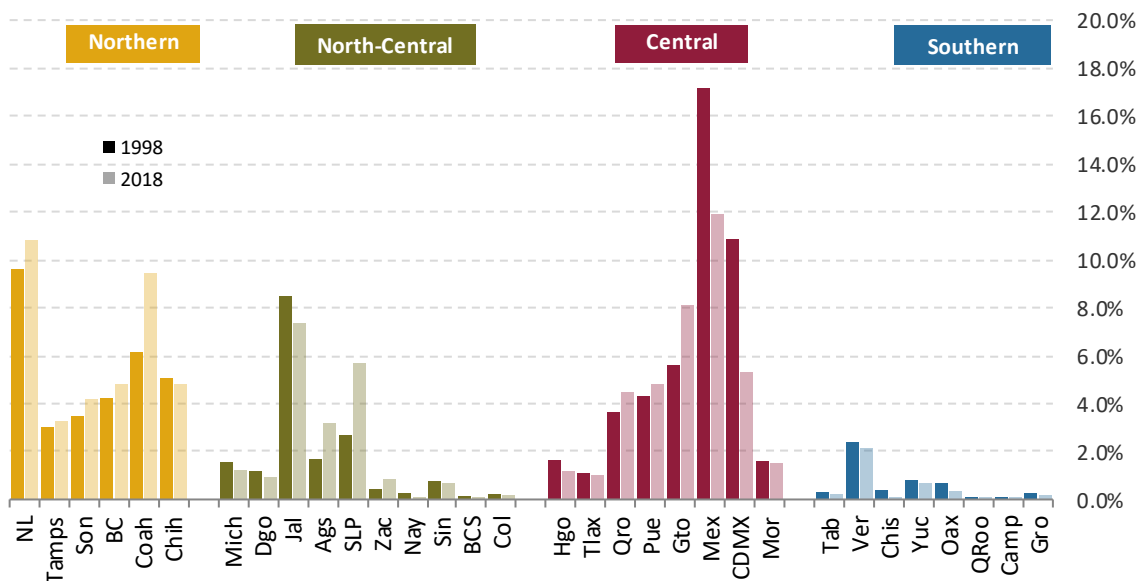


Figure 2: Value added participation in the manufacturing sector

Source: Own elaboration with the Gross value added from INEGI (2020b).

Among the states, Michoacán (Mich) stands out for having notably high energy intensities in both years, with values of 2.34 MJ/MXN in 1998 and 1.60 MJ/MXN in 2018. Veracruz (Ver) also exhibits a significant increase in energy intensity, rising from 1.18 MJ/MXN in 1998 to 1.88 MJ/MXN in 2018. Notably, Tabasco (Tab) records the highest energy intensity in 2018, reaching 3.10 MJ/MXN, despite not showing a comparable figure in 1998.

Other states such as Nuevo León (NL), Hidalgo (Hgo), and Tlaxcala (Tlax) also display elevated energy intensities, with notable increases over the 20-year period. These trends suggest rising energy use relative to output in these regions, which may reflect changes in industrial composition or energy efficiency.

It is important to contextualize these values with the scale of economic activity. Figure 2 illustrates each state's share in the national gross value added of the manufacturing sector. In some cases, high energy intensity may partly result from a low gross value added, rather than exceptionally high energy use. States with smaller industrial output can appear disproportionately energy-intensive when energy consumption is not matched by corresponding economic production.

Figure 1(b) illustrates emission intensity for each Mexican state in 1998 and 2018, where emission intensity is defined as the kilograms of CO₂ equivalent emitted per Mexican peso of gross value added in the manufacturing sector (Kg CO₂e/MXN).

Greenhouse gas emissions data at the state level are sourced from SEMARNAT (2019) and the national inventory from INECC (2018), while gross value-added figures come from INEGI (2020b).

Among the states, Michoacán (Mich), Campeche (Camp), and Guerrero (Gro) consistently exhibit the highest emission intensities in both years, each exceeding 0.20 Kg CO₂e/MXN. In 1998, Zacatecas (Zac), Veracruz (Ver), and Oaxaca (Oax) also registered relatively high values. Notably, Hidalgo (Hgo), Nayarit (Nay), and Chiapas (Chis) began around or below the national average in 1998 but experienced clear increases in their emission intensities by 2018. These states typically concentrate their manufacturing output in subsectors with energy- and emission-intensive processes—such as oil and coal product refining, basic metal production, and chemicals manufacturing—explaining their above-average intensities. Figure 2 shows that between 1998 and 2018, many of the high-emission-intensity states (Mich, Camp, Gro, Zac, Ver, Oax, Hgo, Nay, Chis) saw declines in their manufacturing value-added participation. In other words, even though their emission intensity rose or remained elevated, their overall contribution to the country's manufacturing output diminished. By contrast, Tabasco (Tab) in 2018 presents a case of high energy intensity but relatively low emission intensity. Overall, while energy intensity and emission intensity often move in tandem, factors such as fuel mix, industry structure, technology adoption, regulatory frameworks, and data quality can create significant deviations. Also, when interpreting Figure 1(b) alongside Figure 2, it is crucial to recognize that a high emission intensity may reflect both a state's industrial profile and shifts in its contribution to national manufacturing output.

Building on the previous discussion of energy and emission intensities, the savings computed in this study underscore each state's potential to reduce energy intensity. These improvements can be achieved through measures that enhance energy and environmental efficiency without adversely affecting their economic activity.

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) based on their inputs and outputs. This technique constructs a production frontier that is the best practices observed among the DMUs. DMUs located on this frontier are

considered efficient, while those positioned below it are classified as inefficient. The efficiency of DMUs below the frontier is evaluated relative to the efficient DMUs, using measures that compare their performance to those positioned on the frontier.

There are two main 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 lengthy 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 affect 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 keeping 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).

Traditional DEA models focus mainly on desirable outputs or inputs. However, in the actual production process, undesirable byproducts can appear in the conversion of input to output. The key assumption in DEA is that a Decision-Making Unit (DMU) is considered efficient if it can increase the production of certain desirable outputs (goods) without sacrificing the production of others, while also avoiding an increase in undesirable outputs (bads) or the need for additional inputs. Similarly, if a unit can maintain the same outputs while using fewer inputs, it also indicates that it is operating efficiently and aligned with the frontier. (Charnes et al., 1981; Seiford and Zhu, 2002).

Since the main contribution of this study is to examine whether regions previously recognized for high efficiency in the manufacturing sector can sustain their performance when environmental impacts are considered, the Directional Distance Function (DDF) model, within the DEA models, 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 México 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.

To define the DEA model, we adopted the approach of Zhou et al. (2012) and Zhang et al. (2013), who proposed a non-radial directional distance function (non-radial DDF) to measure energy efficiency and environmental performance considering undesirable outputs. While Zhang et al. (2013) originally applied this framework to compare coal- and oil-fired power plants in Korea, we adapt it to assess regional manufacturing efficiency in México, where technological heterogeneity across states is equally critical for understanding energy and environmental performance disparities. Following their formulation, let us assume that there are $i=1, 2, \dots, K$ 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).

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

Set T represents all possible combinations of inputs and outputs for all DMU_i , feasible under the available technology, and the production frontier corresponds to the upper limit of T , where no further improvements can be made without moving outside the feasible set. The efficient production frontier is directly constructed from the constraints of the model, which ensures that T includes all combinations of inputs and outputs derived from the observed DMUs and their convex combinations. That is, it is made up of units that cannot improve their efficiency without compromising other dimensions of performance (units that demonstrate the best practices using production factors efficiently). Following

Zhang et al. (2013), the non-radial DDF adapted to include CO2 emissions is defined as follows:

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

where $\omega = (\omega_n^x, \omega_m^y, \omega_j^c)'$ denotes the set of vectors that group non-negative normalized weight vectors, that is, $\omega_n^x = (\omega_1^x, \omega_2^x, \dots, \omega_N^x)$, $\omega_m^y = (\omega_1^y, \omega_2^y, \dots, \omega_M^y)$, $\omega_j^c = (\omega_1^c, \omega_2^c, \dots, \omega_J^c)$. $g = (-g^x, g^y, -g^c)$ represents the set of vectors that group directional vectors, i.e., denote the desired reductions or expansions in the inputs and outputs. That is, $g_n^x = (g_1^x, g_2^x, \dots, g_N^x)$, $g_m^y = (g_1^y, g_2^y, \dots, g_M^y)$, $g_j^c = (g_1^c, g_2^c, \dots, g_J^c)$. $\beta = (\beta_n^x, \beta_m^y, \beta_j^c)$ is a vector of scaling factors with respect to inputs, desirable outputs, and undesirable outputs, i.e., it indicates the non-proportional adjustment of how much should be reduced or increased to project the assessed DMU towards the efficient frontier, that is, $\beta_n^x = (\beta_1^x, \beta_2^x, \dots, \beta_N^x)$, $\beta_m^y = (\beta_1^y, \beta_2^y, \dots, \beta_M^y)$, $\beta_j^c = (\beta_1^c, \beta_2^c, \dots, \beta_J^c)$.

In technical terms, the model assumes that inputs and desirable outputs are strongly disposable for production technology, while undesirable output is weakly disposable. As Hua and Bian (2007) pointed out, this means that reducing undesirable output may not always be possible without incurring certain costs. Then, this DEA model is equivalent to solve the following linear programming problem for $\vec{D}(x, y, c; g)$:

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

$$\begin{aligned}\sum_{i=1}^K \lambda_i &= 1 \\ \lambda_i &> 0 \quad i = 1, \dots, K \\ \beta_n^x, \beta_m^y, \beta_j^c &\geq 0\end{aligned}$$

The programming model in equation (3) —based on the formulation of Zhang et al. (2013)—, provides the general form of non-radial DDF with variable return to scale, whose objective function seeks to maximize the total weighted adjustment required by the evaluated DMU to achieve its technical efficiency. Specifically, in the first three restrictions, x_n, y_m, c_j represent the n^{th} input, m^{th} desirable output and j^{th} undesirable output of the evaluated DMU. Whereas x_{in}, y_{im}, c_{ij} denote the n^{th} input, the m^{th} desirable output and the j^{th} undesirable output, respectively, of the i^{th} DMU, with $i = 1, \dots, K$. This implies that when $\vec{D}(x, y, c; g) = 0$ 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 (Greenhouse gas emissions). 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 $g = (-K, -L, -E, Y, -C)$ 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 evaluated 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), i.e., each β_g represents the amount by which inputs or outputs are adjusted. In the case of the third constraint, the equal sign is due to the weak disposability of undesirable output. The fourth constraint is for the variable return to scale, which is the frontier results in a convex set that allows that DMUs with different productivity to be considered efficient.²

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).

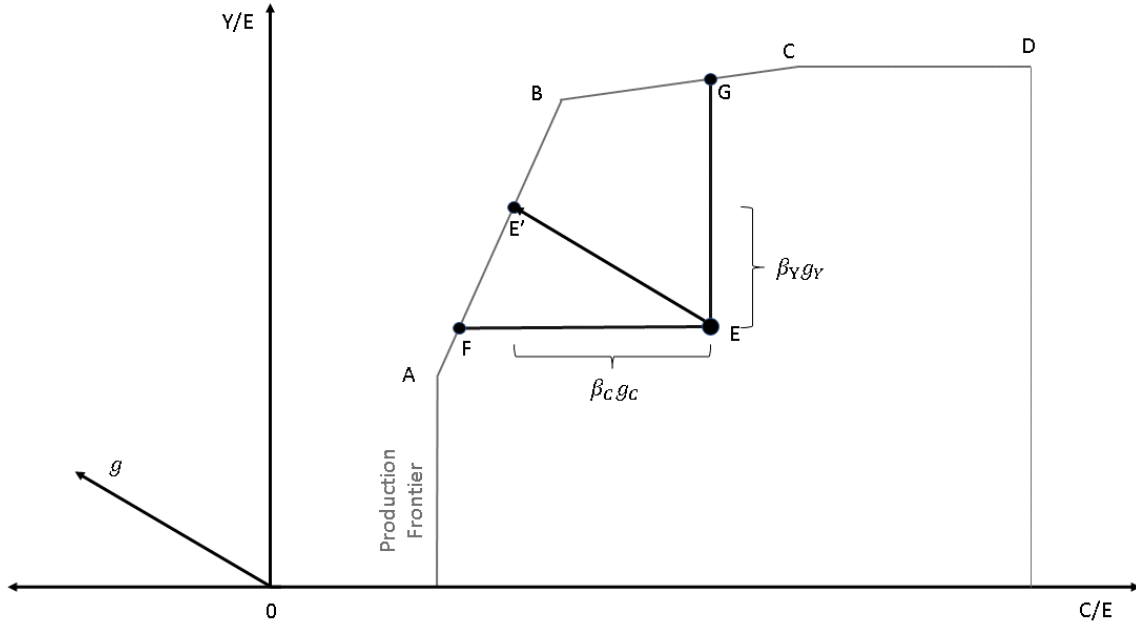


Figure 3: Graphical example of non-radial directional distance function.

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 . Source: Own elaboration.

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

$$EPS = \beta_E^* E \quad (4)$$

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.

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

Similarly, the GHG Emissions Potential Savings (GEPS) represents the extent to which pollution should be reduced without affecting production as defined in equation (6).

$$GEPS = \beta_C^* C \quad (6)$$

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) as in equation (7).

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

Both *EEP* and *GEP* lie between zero and one. 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 México for different years between 1998 and 2018. The economic activity data was sourced from the 31-32-33 NAICS sectors of economic censuses by the National Institute of Statistics and Geography (INEGI, by its Spanish acronym) conducts economic censuses every five years, using data from the previous year. For example, the most recent census referenced in this document is the 2019 Economic Census, which contains information from 2018. Consequently, the years included in our analysis are 1998, 2003, 2008, 2013, and 2018. For clarity, the results section concentrates on a comparison between 1998 and 2018. Additionally, the analysis excludes the 3241 and 3251 industry groups—which encompass the oil refining sector—due to their substantial contributions to greenhouse gas emissions (16%) and energy consumption (9%) in 2018 according to the National Commission for the Efficient Use of Energy (CONUEE in Spanish) (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.

The input variables, including capital (K) and labor (L), alongside the desirable output (Y), were derived from INEGI (2020b). The desirable output (Y), representing gross value added (measured in million MXN 2018=100), reflects 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 both movable and immovable property or as well as improvements that enhance productivity and extend the useful life of assets. 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 determine the energy consumption input variable (E), we used electricity

consumption data from INEGI (2020b) and supplemented it with natural gas consumption data from Secretaría de Energía (2020). Both data sets were converted to energy equivalents using a constant transformation to ensure consistency in units.³

Table 1: Descriptive Statistics

Variable (Unit)	1998		2018		% change 1998-2018
	mean	sd	mean	sd	
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	55.0

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

As a proxy for the undesirable output (C), we used state-level CO2e emissions data from the National Inventory of Emissions of Greenhouse Gases and Compounds (INEGyCEI) published by SEMARNAT (2019), where each state reports emissions by activity type across various periods. This inventory includes emissions from fixed sources (such as industrial plants and electricity generators), mobile sources (land, air, and maritime transport), and diffuse sources (fertilizer use, biomass burning, and fugitive emissions). However, not all states report their data in sufficient detail to allow for the selection of specific subsectors, which, in turn, these state-level emissions differed from national emissions inventory published by INECC (2018), likely due to methodological variations. To reconcile these discrepancies and align with the sectors studied in this document, we employed a two-step approach. First, we calculated the proportion of each state's emissions relative to the national total. Second, we applied these proportions to the national emissions data for the manufacturing sector. This approach ensures consistency between our state-level and national-level emissions data for the manufacturing sector.

³ 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 1.084597×10^{-3} PJ).

Table 1 reports some descriptive statistics of the five variables for 1998 and 2018, which allows to illustrate clearer the change over the time.⁴ 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%.

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 México's states, we aimed to obtain the optimal values of $\vec{D}(x, y, c; g)$. To achieve this, we solved Equation (3) for five different years between 1998 and 2018 (1998, 2003, 2018, 2013 and 2018) to analyze changes over time. Subsequently, to model energy and environmental performance simultaneously, we defined the directional vector $g = (-g^x, g^y, -g^c) = (-K, -L, -E, Y, -C)$, where negative values for inputs K, L, E represent the reduction of resources, while positive values for outputs Y and negative for undesirable outputs C aim to minimize emissions.

Two scenarios were considered to evaluate technical efficiency. In the first scenario, only desirable outputs were taken into account, with the normalized weight vector $\omega = (\omega^x, \omega^y, \omega^c) = (\omega_K, \omega_L, \omega_E, \omega_Y, 0) = (1/9, 1/9, 1/9, 2/3, 0)$, and the directional vector for the undesirable output C set to $g_C = 0$. In contrast, the second scenario incorporated both desirable and undesirable outputs, using the weight vector $\omega = (1/9, 1/9, 1/9, 1/3, 1/3)$.⁵ The technical efficiency indexes (\vec{D}) obtained under both scenarios are illustrated in Figure 4.⁶

Our results demonstrate that, in general, technical efficiency is consistently higher or

⁴ 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.

⁵ Following Zhanget 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.

⁶ For clarity of presentation, we use a figure that represents 1 minus the efficiency score, meaning that values closer to 1 indicate higher efficiency. The technical efficiency indexes for the rest of the years are reported in Appendix A.2.

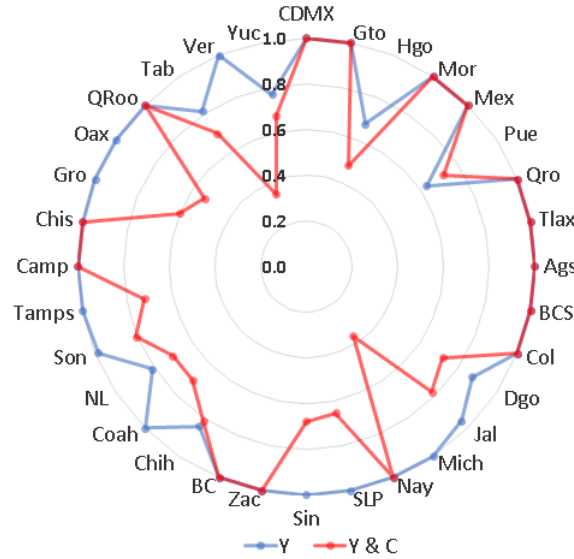
equal when focusing solely on the desired output rather than considering both outputs. Furthermore, in most of the instances where a state demonstrated inefficiency in the former scenario (depicted by the blue line in Figure 4(b) falling within the inner portion with values below 1.0) experienced an even further decline in efficiency under the latter scenario (illustrated by the red line).

The results for Chiapas ("Chis") and Michoacán ("Mich") warrant specific commentary. The issue with Chiapas primarily stems from the value-added data reported by INEGI, which highlights significant economic challenges within the state. For instance, in 1998, Chiapas reported a value-added of \$6,670, emissions of 289, and inputs of 0.5 for energy, 70,449 for labor, and \$8,248 for capital. By 2018, these values had changed dramatically: value-added dropped by 86% to \$894, emissions increased by 25% to 362, and inputs rose significantly—energy doubled to 1.0, labor increased to 152,463, and capital rose to \$20,620. Without needing DEA, it is evident that such a drastic decline in value-added alongside increases in emissions and inputs signals a severe inefficiency in economic and environmental performance. For Michoacán, a similar pattern emerges but with important differences. Between 1998 and 2018, value-added and emissions increased by 38% and 17%, respectively, while labor and capital inputs more than doubled. However, energy input showed only a minimal increase of 1%. In the model without undesirable outputs (blue line), this balance allowed Michoacán to achieve an efficiency score of 1, as the proportional changes in desirable outputs relative to inputs indicated full efficiency under that scenario.

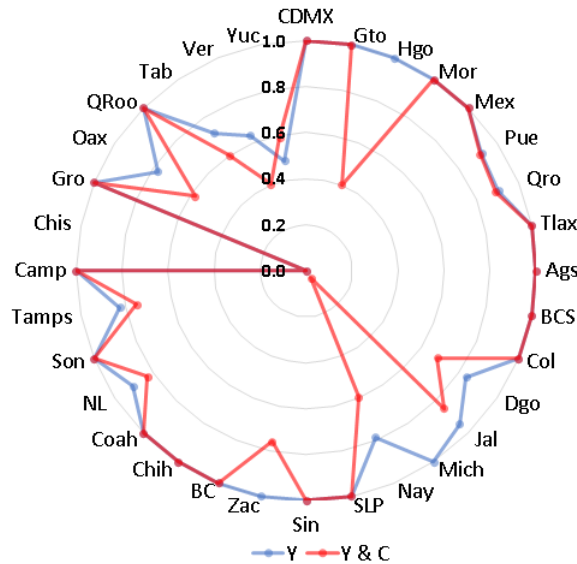
Our analysis reveals a significant disparity in the number of efficient states based on whether only the desirable output is considered. Specifically, in 1998, 23 states were identified as efficient when focusing solely on the desirable output, but this number dropped to 15 when both outputs were considered (refer to Figure 4(a)). Similarly, in 2018, 20 states were classified as efficient under the scenario of considering only the desirable output, compared to 17 states when incorporating both outputs (refer to Figure 4(b)).

Nonetheless, we contend that the evaluation of technical efficiency should encompass both desirable and undesirable outputs. This approach allows 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.



(a) 1998



(b) 2018

Figure 4: 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 considered, while red line shows it when both desirable and undesirable outputs are considered. 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. Source: Own elaboration.

Moreover, we compared the average technical efficiency between 1998 and 2018 under two scenarios: one considering only desirable outputs and the other including both desirable and undesirable outputs. For each year, we calculated the average technical efficiency across the 32 states for both scenarios and conducted separate Mann–Whitney–Wilcoxon tests to evaluate the differences.⁷ The results revealed significant differences at the 5% level in 1998, highlighting a notable disparity between the two scenarios that year. However, no significant differences were found in 2018, suggesting similar levels of efficiency under both scenarios in the later year.

Interestingly, our findings also showed that, although the number of inefficient states decreased from 1998 to 2018, the overall efficiency of the manufacturing sector did not demonstrate improvement over this period. This surprising outcome underscores that, despite efficiency gains in some states, others experienced notable declines. For example, states such as Michoacan and Chiapas recorded 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 México still requires substantial attention and improvement.

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 include educational attainment, investments, and a green tax for states that have already implemented it.⁸ However, we must acknowledge that other factors

⁷ 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).

⁸ 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>).

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, as well as the efficiency scores generated in the previous stage can be biased due to the nature of non-parametric frontier methods, we employ two techniques: 1) the Simar and Wilson (2000) estimator and 2) a two-part fractional probit response model. Both of which are well-suited for second-stage DEA analysis, as highlighted by Ramalho et al. (2010).

The approach proposed by Simar and Wilson (2000) employs a two-stage truncated regression to model the relationship between efficiency scores and explanatory variables, while accounting for the bounded nature of the dependent variable. It then applies bootstrapping to generate confidence intervals and assess the statistical significance of the regression parameters. This method addresses the issue of statistical dependence between the estimated DEA scores from the first stage and the explanatory variables.

On the other hand, the two-part fractional probit response model offers a complementary approach. First, it employs a probit model for the efficiency scores to identify factors that drive DMUs to reach the efficient frontier. For observations with efficiency scores strictly between 0 and 1, a fractional probit regression is applied to further analyze the relationship. This two-part structure effectively captures the dynamics of both boundary and interior efficiency scores. Let z_{it} be the set of independent variables, equation (8) displays the model we aim to estimate under this method.

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

where \vec{D}_{it} is the optimal technical efficient coefficient for state i in year t , $\Phi()$ is the standard normal cumulative distribution function, 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 are a tool that some entities have that allows knowing the quality of the air with respect to certain pollutants, obtained by INECC (2018).⁹ The availability of a green tax was also considered, as obtained from each state's reports. Natural gas production was also taken into account, as reported in Secretaría 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).¹⁰

Table 2 presents the descriptive statistics. It is 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. The outcomes of our estimation are presented in Table 3, along with the corresponding marginal effect for the two-part model in the final column.

Table 2: Variable description and summary statistics

Variable	mean	sd	min	max
Technical efficiency with undesirable output	0.77	0.26	0	1
Average years of education of the employed population	8.58	1.18	5.4	11.48
1 if state accounts with an air quality monitoring system	0.64	0.48	0	1
1 if state has a green tax	0.04	0.21	0	1
Natural gas production (Million cf)	0.04	0.1	0	0.5
Population density (inhabitants per km ²)	295.9	1,025.4	2.2	6,160.5
Public investments per manufacturing unit (million MXN)	0.18	0.18	0	1.01

Note: The dataset comprises 160 observations, representing data from 32 states over the years 1998, 2003, 2008, 2013, and 2018, with descriptive statistics computed across all states and years.

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

⁹ 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.

¹⁰ This calculation includes investments from the federal, state, and municipal governments.

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, Simar & Wilson and fractional probit models showed consistency in terms of the direction (positive or negative) for almost all coefficients. However, some coefficients that were statistically significant in either Simar & Wilson or the fractional probit model were not significant in the fixed effects model.

Table 3: Effects on Technical Efficiency of the Manufacturing Sector

	Linear fixed effects	Simar & Wilson	Fractional Probit		
			1st part	2nd part	Marginal effect
Average years of education of the employed population	0.164*** (4.949)	0.155*** (3.843)	0.241 (1.255)	-0.399* (-1.746)	0.003 (0.065)
1 if state accounts with an air quality monitoring system	-0.023 (-0.467)	0.099* (1.826)	0.368** (2.009)	0.660** (2.038)	0.164*** (2.663)
1 if state has a green tax	0.091 (0.913)	0.228 (1.274)	0.399 (1.342)	-0.093 (-0.138)	0.076 (0.556)
Natural gas production	-0.002 (-0.011)	0.368* (1.673)	1.472* (1.863)	2.932** (1.969)	0.692*** (2.641)
Population density	-0.000 (-1.011)	-0.000 (-0.286)	-0.001 (-1.14)	-0.004*** (-4.041)	-0.001*** (-3.116)
Public investments per manufacturing unit	0.099 (0.77)	-0.064 (-0.393)	-0.656 (-1.06)	-1.799** (-2.146)	-0.370** (-2.117)
Constant	-0.317 (-1.299)	-0.405 (-1.494)	-1.507 (-1.33)	3.405** (2.092)	
Observations	160	91	160	91	160

t statistics in parentheses

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

Given the limitations of the fixed effects model and the greater interpretability of the marginal effect from the fractional probit model's results, we will focus on the estimates obtained from this model for further analysis. The study's outcomes offer compelling insights into the drivers of technical efficiency within México'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.

States with air quality monitoring systems experience roughly a 16.4 percentage point increase in technical efficiency. This positive effect likely reflects enhanced environmental oversight and management practices that promote more efficient production, even when accounting for undesirable outputs such as greenhouse gas emissions. Although the coefficient for green taxes is positive, its lack of statistical significance suggests that simply having a green tax does not robustly impact technical efficiency. This may imply that variations in design, enforcement, or economic scale across states limit their overall effect.

Natural gas production, on the other hand, shows a strong positive effect—with nearly a 70-percentage point improvement per unit change. This robust relationship likely stems from the benefits of a reliable, cleaner-burning energy source. Facilities such as natural gas wells and storage points ensure a stable supply, optimize distribution, reduce transportation emissions, balance supply and demand, and provide backup during peak periods. Together, these factors lower operational costs and enhance both energy use and environmental performance.

Higher population density is associated with a modest yet significant decline in technical efficiency, likely reflecting challenges such as congestion, increased competition for resources, and infrastructural strain. Similarly, the negative marginal effect of public investments per manufacturing unit suggests that higher investments correlate with lower efficiency—potentially due to inefficiencies in fund allocation or because underperforming states receive more investments as remedial measures.

The education coefficient is near zero and statistically insignificant, indicating that average years of education do not meaningfully influence technical efficiency after controlling for other factors. In other words, higher educational attainment alone does not drive efficiency improvements when undesirable outputs are considered.

Overall, air quality monitoring systems and local natural gas production emerge as the most robust and policy-relevant determinants. Both factors enhance technical efficiency by fostering better environmental management and ensuring a stable, cleaner energy supply. In contrast, the anticipated benefits from higher education levels and green tax policies are not evident, challenging conventional expectations. For education, this contradicts the notion that a more educated workforce inherently boosts efficiency

(Mohan, 2020), and for green taxes, their limited impact may reflect their sparse implementation. A more widespread or effectively designed green tax might, however, play a crucial role in driving efficiency improvements (Böhmelt et al., 2018).

Contrary to the findings of Auci et al. (2021), who report that investments in modern technologies and infrastructure foster productivity gains, our results indicate that higher population density and elevated public investments are linked to lower technical efficiency. In densely populated states, challenges such as congestion may impede production, and the negative association with public investments suggests that these funds might be deployed reactively in states already struggling with performance rather than serving as a proactive strategy for enhancing productivity.

In summary, the analysis of Table 3 indicates that, when both desirable and undesirable outputs are considered, enhancing technical efficiency should center on improving environmental monitoring and leveraging local natural gas resources. Meanwhile, the expected benefits of higher education and green tax policies remain unproven, and the negative associations with population density and public investments warrant further investigation. These findings not only reinforce established determinants but also offer new insights into the factors influencing technical efficiency in México's manufacturing sector.

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. When performing this analysis, we treat capital and labor as constant variables (i.e., $\omega = (0, 0, 1/3, 1/3, 1/3)$). The outcomes related to the energy efficiency (*EEP*, vertical axis) and GHG emission performance (*GEP*, horizontal axis) for the years 1998 and 2018 are displayed in Figure 5.

Our findings revealed a positive correlation between energy and environmental potential among inefficient states, comprising 17 in 1998 and 14 in 2018. This suggests that a higher energy efficiency potential corresponds to a greater ability to conserve energy, resulting in reduced pollution and enhanced environmental performance.

In 1998, excluding the dots on the frontier (i.e., those equal to 1), performance ranged from the pair (7.0%, 8.8%), representing the energy and environmental performance of

Michoacán, to the 100% of *EEP* in Sonora and the 67.7% of *GEP* in Chihuahua (see Figure 5(a)). In 2018, we observed a slightly higher dispersion, with energy efficiency and environmental performance ranging from a minimum of 10.8% and 6.4% in Chiapas to a maximum of 100% *EEP* in Zacatecas and 89% in Puebla (see Figure 5). Notably, the black dot 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 dot, and by 2018, the number had increased to 18. 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 average Energy Efficiency Performance (*EEP*) altered slightly from 0.73 to 0.75, and the Greenhouse Gas Emission Performance (*GEP*) from 0.66 to 0.72. 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 17 states positioned below the frontier in 1998, 12 demonstrated improved production practices, moving closer to the frontier in both dimensions from 1998 to 2018. Two states made progress in only one direction, while the remaining three states moved farther away from the frontier in both dimensions, indicating a decline in efficiency. Figure 6 illustrates the map detailing the percentage change in performance measures for each state between 1998 and 2018. Concerning *EEP* (Figure 6(a)), Coahuila in the Northern region emerged as the most improved state during this period, reaching the production frontier by 2018. Likewise, the *GEP* map (Figure 6(b)) highlighted noteworthy enhancements in six states: Sonora, Sinaloa, San Luis Potosí, Coahuila, Michoacán, and Guerrero. Notably, Chiapas, Tabasco, and Yucatán, all in the Southern region experienced a substantial decline in both *EEP* and *GEP* (Figure 6).

Utilizing a simple average for the analysis would result in an unfair representation. Instead, it is imperative to consider the productive orientation of each state situated below

the frontier. In Figure 5, 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).

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

*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.

Furthermore, the insights from Figure 5 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, Veracruz, 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 2018.¹¹ The

¹¹ 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,

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.

Interestingly, when comparing proportions, Wu et al. (2012) identifies a national energy potential savings of 19% for China's industrial sector, calculated as an average for the period 1997–2008. This comparison highlights the substantial opportunities for energy efficiency in both countries. 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 at national level, 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 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
Jalisco	35.1	11.3
Nuevo León	23.1	9.5
Rest of states*	20.8	31.4
Total*	24.3	100

*In the second and third columns, GEPS refers to the average.

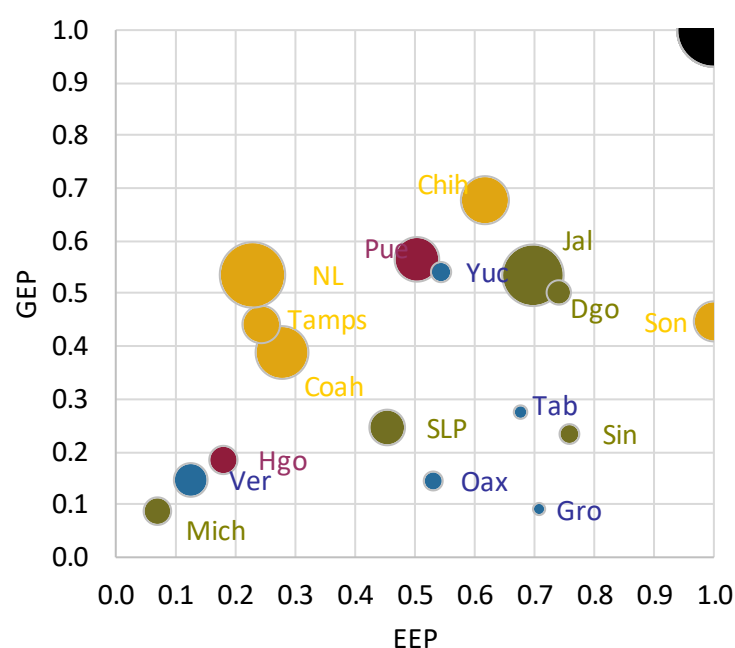
** In the second column, GEPS is for the country average, while in the third column, it represents the total.

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 Metric tons (Mt) of 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 environmental savings. Hidalgo (17.6% with respect to the national level),

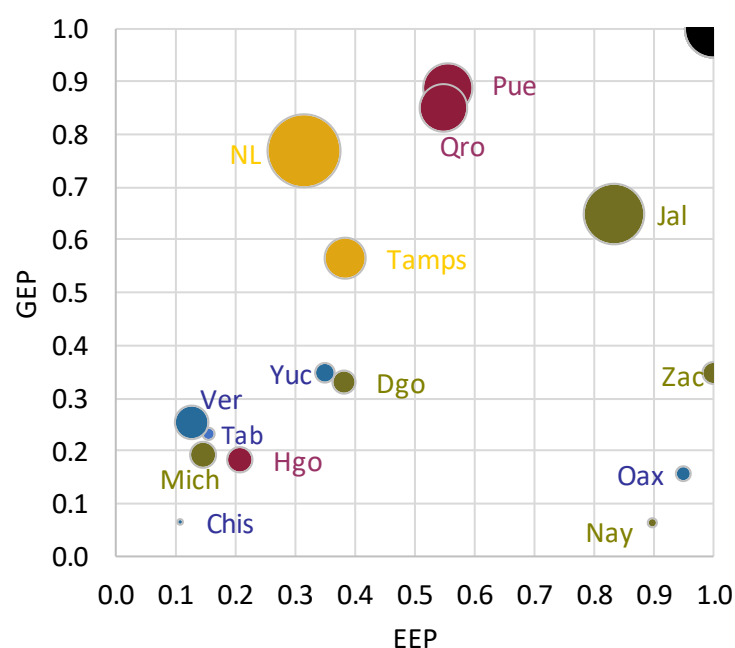
no clear trend can be identified throughout this period.

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 is 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.



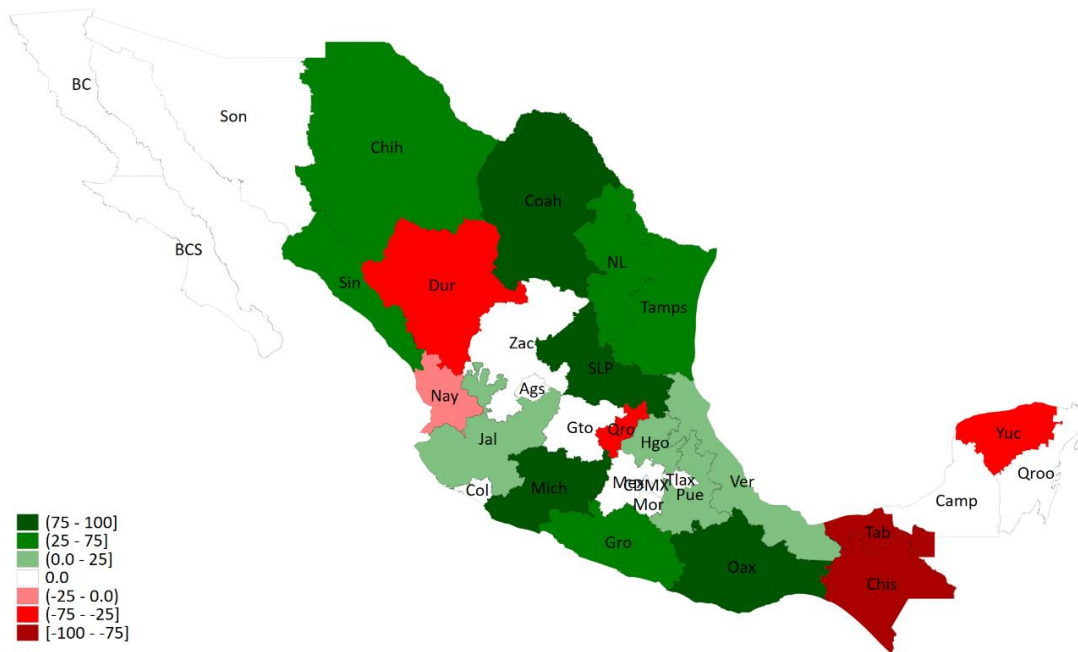
(a) 1998



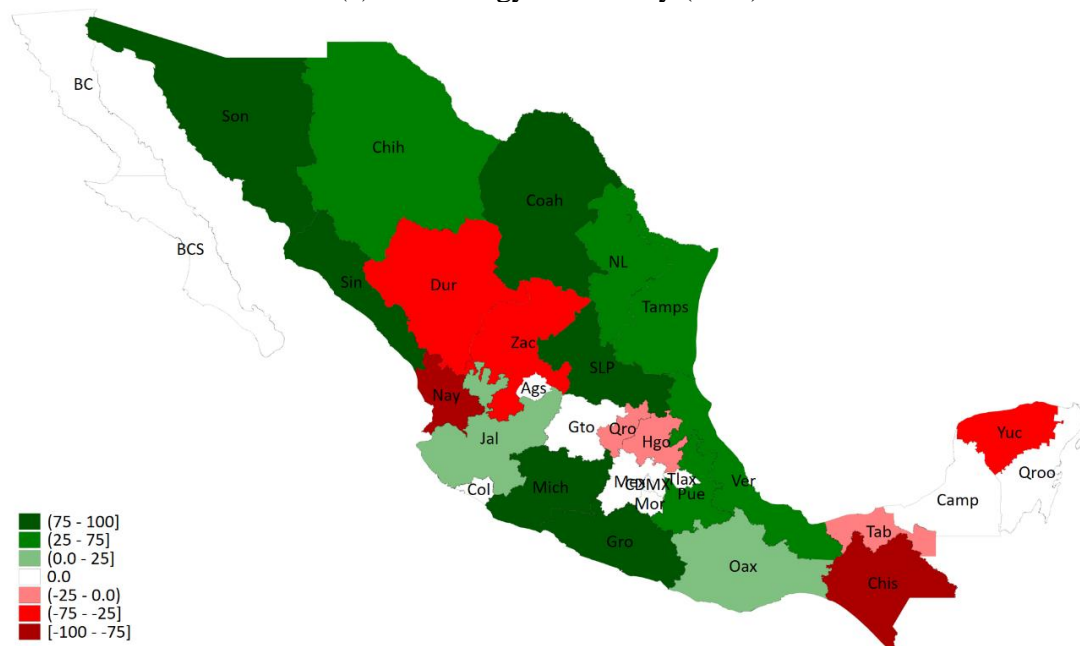
(b) 2018

Figure 5: Energy Efficiency Performance vs. GHG Emission Performance

Notes: 1) The black dot at (1,1) in the lower left corner illustrates the states on the production frontier, which were 15 (Ags, BC, BCS, Camp, CDMX, Chis, Col, Gto, Mex, Mor, Nay, Qro, Qroo, Tlax, Zac) in 1998 and 17 (Ags, BC, BCS, Camp, CDMX, Chih, Coah, Col, Gro, Gto, Mex, Mor, Qroo, Sin, SLP, Son, Tlax) 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 dot represents the participation of the state's sector in the total domestic value added (VA). 4) Average EEP and GEP were 0.73 and 0.66, respectively, in 1998, and 0.75 and 0.72, respectively, in 2018. Source: Own elaboration.



(a) Energy Efficiency (*EEP*)



(b) GHG Emission (*GEP*)

Figure 6: % 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. Source: Own elaboration.

7 Discussion and concluding remarks

México'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 an initiative-taking approach towards combating climate change. Interestingly, an overlooked aspect of this endeavor is the potential embedded within the individual states of México to significantly improve energy practices and reduce emissions without compromising their manufacturing prowess, an aspect that warrants closer examination and strategic consideration.

Currently, many states operate below their optimal efficiency levels, leaving room for substantial improvements. If all states were to improve their practices and move closer to the production frontier—the hypothetical boundary where energy use and environmental impact are minimized for a given level of output—the manufacturing sector could theoretically reduce energy consumption by 20.3% while maintaining the same production levels. This estimate highlights inefficiencies in current energy use that can be addressed through advancements in production technologies, process improvements, and better energy management strategies.

The driving forces behind these findings are diverse. The analysis assumes that firms operating below the frontier can optimize their energy use without altering their production capacity. This does not imply a substitution of capital or labor for energy but rather a focus on improving energy efficiency within the current production framework.

In addition, the sector could achieve a 24.3% reduction in GHG emissions. This reduction primarily arises from lower energy consumption, as using less energy directly translates into fewer emissions. Some of the emissions reductions may also stem from cleaner energy sources or process optimizations that decrease emissions intensity. While our study does not explicitly model a transition to renewable energy, it underscores that energy efficiency improvements alone could generate significant environmental benefits. 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 is not 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.

Nonetheless, it is important to acknowledge that these transformations do not come without their challenges. Under a scenario of steadily rising energy prices, 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, México's journey towards a greener future entail multifaceted implication. 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, México 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		2008		2013		2018	
		mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Value added (Y)	$[1 \times 10^6 \text{ MXN (2018)}]$	51,943	63,989	61,965	681,132	68,782	76,252	65,760	71,398	96,554	105,195
CO2e emissions (C)	$[1 \times 10^3 \text{ ton CO2e}]$	2,872	2,503	2,659	2,125	3,320	2,615	3,546	2,831	3,676	3,395
Energy (E)	$[1 \times 10^{15} \text{ Joules}]$	19.8	26.9	19.4	28.7	21.9	32.0	25.6	36.0	42.6	55.6
Capital (K)	$[1 \times 10^6 \text{ MXN (2018)}]$	71,132	81,548	75,564	81,380	70,495	68,650	78,128	82,402	86,010	89,863
Labor (L)	$[1 \times 10^3 \text{ hours worked}]$	302,823	316,557	306,172	304,121	324,316	310,070	359,963	337,214	469,327	433,529
Observations		32		32		32		32		32	

A.2 Technical Efficiency

Region	State	1998		2003		2008		2013		2018	
		Y	YC	Y	YC	Y	YC	Y	YC	Y	YC
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
NCentral	Ags	1.00	1.00	0.67	0.53	0.96	0.95	0.37	0.47	1.00	1.00
NCentral	BCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NCentral	Col	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.49	1.00	1.00
NCentral	Dgo	0.87	0.72	0.00	0.34	0.91	0.63	0.34	0.33	0.84	0.69
NCentral	Jal	0.96	0.78	1.00	0.71	1.00	0.69	1.00	1.00	0.94	0.85
NCentral	Mich	1.00	0.37	1.00	0.06	1.00	0.45	1.00	0.00	1.00	0.04
NCentral	Nay	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.54	0.79	0.60
NCentral	SLP	1.00	0.65	1.00	0.47	1.00	0.65	0.82	0.61	1.00	1.00
NCentral	Sin	1.00	0.68	0.85	0.57	1.00	0.67	0.85	0.24	1.00	1.00
NCentral	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. The *Y* variable describes total technical efficiency when only the desirable output is considered. The *YC* variable shows it when both desirable and undesirable outputs are considered. 2) The value 1.00 stands for the production frontier. Hence, the closer to this value more efficient could be. 3) National variable is the average technical efficiencies in each year. NCentral is for the North-Central region.

A.3 Energy Efficiency and GHG Emission Performance

Region	State	1998		2003		2008		2013		2018	
		EE P	GE P	EE P	GE P	EE P	GE P	EE P	GE P	EE P	GE P
Central	CDM X	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	0.76	0.36	0.49	0.42	0.52	0.57	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	0.11	0.18	1.00	1.00
Central	Tlax	1.00	1.00	0.23	0.61	1.00	1.00	1.00	1.00	1.00	1.00
Central	Pue	0.50	0.57	0.77	0.66	0.33	0.49	1.00	1.00	0.56	0.89
Central	Qro	1.00	1.00	0.30	0.17	1.00	1.00	0.22	0.39	0.55	0.85
Central	Hgo	0.18	0.18	0.30	0.06	0.28	0.09	0.08	0.10	0.21	0.18
NCentral	BCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NCentral	Ags	1.00	1.00	0.74	0.04	0.94	1.00	0.07	0.18	1.00	1.00
NCentral	Sin	0.76	0.23	0.77	0.25	1.00	0.21	0.28	0.06	1.00	1.00
NCentral	Col	1.00	1.00	1.00	1.00	1.00	1.00	0.58	0.01	1.00	1.00
NCentral	SLP	0.45	0.25	0.35	0.07	0.41	0.31	0.25	0.18	1.00	1.00
NCentral	Zac	1.00	1.00	1.00	1.00	1.00	1.00	0.35	0.07	1.00	0.35
NCentral	Nay	1.00	1.00	1.00	1.00	1.00	1.00	0.49	0.01	0.90	0.06
NCentral	Jal	0.70	0.53	0.70	0.34	0.55	0.37	1.00	1.00	0.83	0.65
NCentral	Dur	0.74	0.50	0.44	0.02	0.46	0.15	0.05	0.09	0.38	0.33
NCentral	Mich	0.07	0.09	0.06	0.05	0.07	0.08	0.03	0.09	0.15	0.19
Northern	Coah	0.28	0.39	0.39	0.37	1.00	1.00	1.00	1.00	1.00	1.00
Northern	Chih	0.62	0.68	1.00	1.00	0.54	0.39	0.37	0.70	1.00	1.00
Northern	Son	1.00	0.45	0.61	0.10	0.73	0.34	1.00	1.00	1.00	1.00
Northern	BC	1.00	1.00	0.93	0.81	1.00	1.00	0.39	0.96	1.00	1.00
Northern	Tamps	0.24	0.44	0.26	0.34	1.00	1.00	0.12	0.25	0.38	0.57
Northern	NL	0.23	0.54	0.26	0.46	0.37	0.84	0.37	0.66	0.31	0.77
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	0.71	0.09	0.81	0.15	0.56	0.01	1.00	1.00	1.00	1.00
Southern	Oax	0.53	0.14	0.45	0.15	0.60	0.08	0.20	0.08	0.95	0.16
Southern	Yuc	0.54	0.54	0.75	0.03	0.65	0.22	0.13	0.13	0.35	0.35
Southern	Tab	0.68	0.28	1.00	1.00	0.48	0.72	0.25	0.87	0.16	0.23
Southern	Ver	0.13	0.15	0.17	0.08	0.34	0.41	0.14	0.35	0.13	0.25
Southern	Chis	1.00	1.00	1.00	0.64	0.90	0.21	1.00	1.00	0.11	0.07

Notes: 1) The shown values stand for Energy Efficiency (EEP) and GHG Emission Performance (GEP). 2) We can see México City, México, Baja California Sur, Quintana Roo and Campeche keep through five periods the optimal energy efficiency and GHG emissions performance. NCentral is for the North-Central region.

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.