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Technical Progress and Sustainable Growth in the Manufacturing Sector of North American Countries, 1984–2022: A Stochastic Frontier Analysis

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Abstract: This article presents an estimation of a stochastic frontier model using a translog-arithmic production function to identify the impact of production factors—labor and capital—along with CO_2 emissions and technical progress on the value added of the manufacturing sector in North American countries over the 1984–2022 period. The model also provides estimates for technical efficiency, scale efficiency, and technological change, allowing for a comparative analysis of these indicators' evolution within the manufacturing sectors of Canada, Mexico, and the United States. The findings indicate that capital exerts the strongest influence on manufacturing value added, followed by labor. CO_2 emissions exhibit the anticipated negative effect on the sector's value added. Notably, the average technical efficiency of Mexico's manufacturing sector is higher than that of Canada and the United States over the studied period. Regarding technological change, the United States demonstrates the highest values, followed by Canada, with both nations displaying an upward trend throughout the years, while Mexico shows a declining trend in this indicator.

Keywords: stochastic frontier analysis; manufacturing sector; North America; CO_2 emissions; technical efficiency; technological change

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Academic Editor: Tsutomu Harada

Received: 19 December 2024
Revised: 16 February 2025
Accepted: 21 February 2025
Published: 25 February 2025

Citation: Navarro-Chávez, C. L. (2025). Technical Progress and Sustainable Growth in the Manufacturing Sector of North American Countries, 1984–2022: A Stochastic Frontier Analysis. *Economies*, *13*(3), 63. https://doi.org/10.3390/economies13030063

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1. Introduction

Manufacture is the engine of growth and the backbone of global economy, exerting its influence across various domains, ranging from the manufacturing of consumer products to the production of high-tech components. The continuous evolution of the manufacturing sector through the pursuit of efficiency and adaptability creates a context of flexibility and strategic development that transcends the economic sphere, reaching social and sustainable dimensions (Abeles et al., 2017; Fajnzylber, 1983; Khan & Ozturk, 2021; Wan et al., 2022).

The establishment of production centers has transformed the fabric of local communities by generating employment and stimulating regional economic development. Furthermore, the adoption of sustainable manufacturing practices has become an urgent necessity, as companies seek to balance production efficiency with environmental responsibility. In this scenario, the manufacturing sector stands as an integral component that drives economic progress, enhances the quality of life in contemporary societies, and promotes innovation and economic advancement, contributing significantly to the sustainable development of nations (Santeliz & Contreras, 2014; Yong, 2021).

Although the manufacturing sector positively impacts a country's economic growth, it is not without challenges. The negative consequences of production processes on the environment are significant, including the emission of air and water pollutants, fine particle emissions, chemical contaminants, and waste generation that harms soil quality. These

impacts represent one of the primary challenges that the industry faces, posing threats to both ecosystems and human health. To mitigate these impacts, it is essential to seek a balance between industry and conservation (IEA, 2024a).

Global carbon emissions reached 36.8 million metric tons in 2021, and the industrial sector generated 31% of these emissions (IEA, 2024a). According to the World Bank (2024a), climate change has had major consequences mainly due to greenhouse gas emissions, of which carbon dioxide has the largest share. For the 1990–2020 period, China has been the largest emitter of CO_2 with 22% of cumulative global emissions, followed by the United States with 19%. Meanwhile, Canada and Mexico have been relatively moderate emitters with 1.8% and 1.4% of cumulative global emissions, respectively (World Bank, 2024a).

Studies on sustainable manufacturing have been addressed by various authors, demonstrating that sustainability can help organizations achieve better operational performance and improvements in environmental outcomes (Abdul-Rashid et al., 2017; Daily et al., 2012; Z. Jiang et al., 2012; Millar & Russell, 2011). Since the publication of the United Nations' Sustainable Development Goals (SDGs) in 2015, research analyzing the sustainability of the manufacturing sector in enhancing productivity and efficiency has increased. These studies incorporate environmental factors such as waste reduction, energy consumption, CO_2 emissions, among others (Bayar et al., 2021; Hermann et al., 2016; Kiel et al., 2017; Sun et al., 2022; Waibel et al., 2017).

Other authors have focused on analyzing sustainable manufacturing practices and their impact on sustainable development (Abdul-Rashid et al., 2017; Aboelmaged, 2018; Ali et al., 2021; Darren et al., 2024; Hami et al., 2018; Rehman & Yu, 2021; Rochayatun et al., 2023; Yacob et al., 2019), environmental management practices and green production in the manufacturing sector (Baah et al., 2021; Famiyeh et al., 2018; Nazir et al., 2024; Hettiarachchi et al., 2022; Sadiku et al., 2023), as well as studies on sustainability and its relationship with financial performance (Cantele & Zardini, 2018; Sharma et al., 2021; Maldonado-Guzmán & Juárez-Del Toro, 2024; Tamaquiza et al., 2023; Roffé & González, 2023; Xu et al., 2021). Additionally, some research has addressed eco-innovation and technologies applied to industries to improve environmental sustainability (De Jesús Pacheco et al., 2018; Yudi & Wah, 2017; Jing et al., 2023; Javaid et al., 2022; W. Jiang et al., 2021; Mady et al., 2022).

Today's society is becoming aware that a new economic model of production and consumption must consider its environmental and social impact. Industries are under increasing pressure to be transparent in reporting on the environmental and social impacts of their operations. In this context, sustainable manufacturing must minimize negative environmental impacts and the consumption of energy and natural resources, while being socially responsible and economically viable. This is why the concept of sustainable manufacturing is gaining increasing attention in both the research community and organizations, especially in the industrial sector (Veleva & Ellenbecker, 2001; Ageron et al., 2012; Bonvoisin et al., 2017).

Various authors have incorporated sustainability into analyses of efficiency and technological change in the industrial sector through the stochastic frontier analysis methodology. A notable example is the model by Rao et al. (2019), which integrates environmental aspects into the endogenous variables. This study estimates Total Factor Productivity (TFP) in the Yangtze River Economic Belt in China. Using a panel data econometric model, the authors apply the stochastic frontier methodology with a translogarithmic production function, incorporating variables such as carbon capture and storage, CO_2 emissions, labor, capital, energy consumption, and industrial structure to assess climate change mitigation in the industrial sector.

Huanyi et al. (2015) obtained energy efficiency in China's automobile manufacturing sector by using stochastic frontier analysis with a translogarithmic function. They analyzed

in their results the performance of individual plants and their level of efficiency in input utilization and energy consumption. In this study, regional and climatic factors have significant impacts on energy efficiency.

In the same vein as Huanyi et al. (2015), the work of Boyd and Sotavento (2019) also focused on energy efficiency, in this case, for five different metal industries in the United States (U.S.) during the period 1987–2012. They similarly apply a stochastic frontier regression analysis model to calculate the level of efficiency. In the second stage, they calculate TFP and technological change using the Malmquist index.

It is crucial to address energy efficiency issues in the manufacturing sector. Lee and Jeon (2023) evaluated the energy efficiency of U.S. manufacturers through stochastic frontier analysis in the manufacturing sector in 20 sectors according to Standard Industrial Classification (SIC) codes. The results suggest that annual energy efficiency improved around 2010 in most manufacturing sectors. The manufacturing sectors classify them into three groups—increasing, stable, and decreasing—according to changes in energy efficiency after 2016.

Huynh and Hoang (2021) evaluated the growth of TFP in Vietnamese manufacturing industries during the period 2000–2019. They implemented stochastic frontier models with a translogarithmic function to decompose the sources of TFP into changes in technical efficiency, technological changes, allocative efficiency, and scale effects. It was observed that technological changes and the scale component effects have been the main driving forces behind productivity growth in two-digit manufacturing industries as well as in the manufacturing sector as a whole.

Hasan et al. (2021) estimated the growth of TFP and its components for the manufacturing industries of West Bengal and India as a whole for the period 1980–2017 using a stochastic frontier approach with a translogarithmic function. This study attempted to make a comparative analysis between the TFP growth of the manufacturing sector of West Bengal and the all-India level considering two phases: pre-World Trade Organization (WTO) and post-WTO. The estimates revealed that TFP growth increased marginally in the second phase for both West Bengal and India as a whole.

Zhu (2022) estimated the growth of TFP in Chinese manufacturing firms. To do this, he considered a stochastic frontier production function, where the growth of TFP is decomposed into technological change, scale economies, and changes in technical efficiency. The main findings show that the reduction in import tariffs has a positive impact on TFP growth by improving technological changes and technical efficiency.

For Mexico's manufacturing sector, Chávez and Fonseca (2012) estimated a translogarithmic slog stochastic frontier function to measure technical efficiency and technological development in the regional manufacturing sector in the 1988–2008 period. They concluded that technical efficiency increased in the period analyzed. At the level of technological development, they found considerable differences between the northern and central regions with respect to the south.

Borrayo et al. (2019) analyzed the main sources of TFP growth of regional industry in Mexico using a stochastic frontier and technical inefficiency model like Battese and Coelli (1992, 1995). They used a translogarithmic production function with the variables annual GDP, capital assets, and employment. The results show that technological change and a shift in technical efficiency are the two main sources explaining the observed trends in Mexico's regional TFP change rates between 1960 and 2013.

Basurto and Sánchez (2022) used the stochastic frontier method to examine the relationship between knowledge and technical efficiency in small- and medium-sized enterprises (SMEs) in the manufacturing, trade, and services industries in Mexico during the period 2014–2017. The main findings suggest that these companies exhibit decreasing

returns to scale, and that those with highly skilled workers tend to have higher levels of technical efficiency.

Guzmán et al. (2024) estimated the productivity and efficiency of the manufacturing sector in Mexico using annual data from 1993 to 2020. They applied a quadratic and logarithmic production function. The estimates, obtained through ordinary least squares, indicate lower efficiency in the sector's operations from 1993 to 2020.

Unlike previous works, this research focuses on applying a stochastic frontier model with a translogarithmic function to analyze the efficiency of the manufacturing sector in Mexico, the United States, and Canada from 1984 to 2022. Thus, it represents an important methodological contribution to this area of research.

This research contributes to the current state of knowledge by addressing the study of technical progress together with environmental variables—in this case, CO_2 emissions—in order to analyze their impact on economic growth, measured here through the added value indicator. To do this, a stochastic frontier model is estimated from a translogarithmic production function, thus highlighting the importance of considering the incorporation of environmental variables in the instrumentation of models of this nature, especially since empirical evidence shows that they are more oriented to studying the role of technical progress in economic growth, leaving these variables aside. If, in addition, the incorporation of the production factors labor and capital is considered, a more comprehensive approach is consequently obtained when addressing the analysis of sustainable growth, taking as a reference the set of variables considered here. Of equal importance is carrying out the study for the countries of North America in their manufacturing sector, due to what this region and its manufacturing industry represent in the global context. In this way, the aim is to cover a knowledge gap of great relevance when undertaking a comprehensive study in the terms set out here. Consequently, two objectives are derived from this to be covered in this research.

The first objective of this paper is to identify, through stochastic frontier analysis (SFA), the impact of production factors—labor and capital—, CO_2 emissions, and technical progress on the added value of the manufacturing industry in North American economies during the period 1984–2022.

The second objective, based on the validity of the SFA model implemented in the manufacturing sector of Mexico, Canada, and the United States, aims to calculate technical efficiency, scale efficiency, and technological change for these countries, and to analyze the evolution of these indicators in this sector during the period 1984–2022.

The document is structured in five sections. First, the introduction is presented. Next, in the Section 2, the theoretical and methodological elements of stochastic frontier analysis are outlined. The Section 3 discusses the development of the proposed model. The Section 4 presents the results and their analysis. The Section 5 provides a discussion of the results. Finally, the Section 6 presents the conclusions of the study.

2. Methods and Materials

The literature that has directly influenced the development of SFA began in the 1950s with the work of Koopmans (1951), Debreu (1951), and Shephard (1953). Koopmans (1951) provided a definition of technical efficiency: a producer is technically efficient if and only if it is impossible to produce more of any output without producing less of any other output or using more of some input. Later, Farrell (1957) proposed the estimation of the average values of the production function.

The measurement of efficiency began to be developed under a parametric approach with the works of Aigner and Chu (1968), Seitz (1971), Timmer (1971), Afriat (1972), and Richmond (1974). However, it was the contributions of Aigner et al. (1977) and Meeusen

and Van Den Broeck (1977) that developed the conceptualization of the stochastic frontier, which solidified the methodological reference for this line of research on efficiency. This approach is based on a function of efficient behavior, whether in production or costs.

$$Y = X\,\beta + \varepsilon \tag{1}$$

Y = Vector of outputs;
β = Vector of the parameters to be estimated;
X = Vector of all its inputs;
ε = Stochastic disturbance term.

Where it is assumed that the error term has two components $\varepsilon = v - u$ for the production functions, and $\varepsilon = v + u$ for the cost functions.

Generally, the production or cost function is based on a Cobb–Douglas or translogarithmic form, or some other form of the logarithmic model (Greene, 2003). The Cobb–Douglas form is the most commonly used.

$$lnY_i = \beta lnX_i + v_i - u_i \tag{2}$$

Y_i = Vector of the natural logarithm of the product obtained from the *i*-th firm;
β = Vector of the parameters to be estimated;
X = Vector of the natural logarithm of each of the inputs involved in the process.
Composite error as follows:

$$(v_i - u_i) \tag{3}$$

v_i = Random component (captures the stochastic noise);
u_i = Technical inefficiency.
Where $(u_i) > 0$ but v can take any value (Greene, 2003).

Although this stochastic frontier approach assumes that the error term has two components, one random (v_i) and one technical inefficiency (u_i), there are some approaches that focus their attention on this last component in order to analyze the productive efficiency of a firm. In this direction, Filippini and Greene (2016) consider that the productive efficiency of a firm is composed of two parts, one persistent and one transitory. The persistent part is related to the presence of structural problems in the organization of the production process of a firm or the presence of systematic deficiencies in management capabilities. Meanwhile, the transitory part is associated with the presence of non-systematic management problems that can be solved in the short term. In their work, Filippini and Greene (2016) present a general description of the most important stochastic frontier models for the estimation of the transitory and persistent parts of efficiency. It is certainly not the objective to develop this research with this approach, beyond the methodological similarities they have in common. This will certainly be a future line of research to consider.

Frontier models can be estimated with cross-sectional data, i.e., with data over a given time period, or with panel data. Panel data generally contain more observations than cross-sectional data because they combine the time series of cross-sectional observations (Coelli et al., 2005).

2.1. Stochastic Frontier Estimations

For the estimation of the production frontier, maximum likelihood (ML) or Modified Ordinary and Least Squares (MOLS) can be used. The estimation procedure proposed by Aigner et al. (1977), is ML, as it requires the maximization of the likelihood function to obtain the maximum likelihood estimators of the parameters; we are interested in findings

in the production frontier model. In order to structure the likelihood function, we need the density function of the following:

$$\varepsilon_i = (v_i - u_i) \tag{4}$$

The density function arises from the following integral (Greene, 1999):

$$\begin{gathered} f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \int_0^\infty \frac{2}{2\pi\sigma_u\sigma_v}\, exp\left[-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon-u)^2}{2\sigma_v^2}\right]du = \\ f(\varepsilon) = \frac{2}{\sigma}\,\phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right) \end{gathered} \tag{5}$$

where $\sigma^2 = \sigma_u^2 + \sigma_{v,}^2$ $\lambda = \frac{\sigma_u}{\sigma_v}$, $\phi(.)$ y $\Phi(.)$ are probabilistic and cumulative density functions of the standard normal. Using the above equation, the likelihood function is obtained.

$$In\ L = -\frac{1}{2}\ In\left(\frac{\pi}{2}\right) - In\ \sigma + \sum In\ \phi\left\{\frac{\varepsilon_i\lambda}{\sigma}\right\} - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2 \tag{6}$$

2.2. Assuming a Distribution

Once the estimation of the stochastic frontier by ML is performed, the next step is to obtain the efficiency measure. In order to decompose the random term and establish which part corresponds to noise and which part corresponds to inefficiency, it is necessary to assume some distribution for both components.

For the case of v_i there is a general consensus that this variable is assumed to be independent and identically distributed as a normal distribution.

$$N\left(0,\ \sigma_v^2\right);$$

Several distributions were proposed for the inefficiency term, the most common of which are the following (Greene, 2003):

- Normal distribution (Aigner et al., 1977).
- Truncated normal distribution (Stevenson, 1980).
- Exponential distribution (Meeusen & Van Den Broeck, 1977).
- Gamma distribution (Greene, 1990).

2.3. An Estimation of the Term u_i

The inefficiency term u_i cannot be estimated directly; its estimation is carried out indirectly. The main authors who have established an estimator to obtain the value of u_i are the following:

- JLMS (Jondrow et al., 1982).
- BC (Battese & Coelli, 1988).

Estimation of u with the Jondrow et al. (1982)'s formula, based on the mean distribution $E[u \mid v_i - u_i]$. This procedure calculates the inefficiency of each firm or production unit based on the estimated value for the disturbance.

$$E\ (u_i|e_i) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(\frac{e_i\lambda}{\sigma}\right)}{\Phi\left(-\frac{e_i\lambda}{\sigma}\right)} - \frac{e_i\lambda}{\sigma}\right] \tag{7}$$

where $\phi(.)$ is the standard normal distribution density, and $\Phi(.)$ is its distribution function.

$$\lambda = \frac{\sigma_u}{\sigma_v}, \qquad e_i = v_i - u_i \qquad \sigma = \sqrt{\sigma_u^2+\sigma_v^2} \tag{8}$$

Once the estimate of u_i is obtained, Jondrow et al. (1982) calculate the technical efficiency as follows:

$$TE_i = 1 - E(u_i|e_i) \tag{9}$$

On the other hand, Battese and Coelli (1988, 1992) calculate efficiency using the mean distribution of exp $(-u \mid e)$, E exp$(-u \mid e)$, and it is deduced that the following occurs:

$$E\{exp(-\mu_{it}U_i|E_i = e_i)\} \tag{10}$$

The average technical efficiency of firms in an industry is the following:

$$E(\exp(-u_i)|e_i) = \left\{ \frac{1 - \Phi\left[\sigma - \left(\frac{\mu}{\sigma}\right)\right]}{1 - \Phi\left(-\frac{\mu}{\sigma}\right)} \right\} exp\left(-\mu + \frac{1}{2}\sigma^2\right) \tag{11}$$

2.4. Technical Efficiency

Once the estimate of u_i is obtained, the estimate of technical efficiency (TE) is given by the quotient between the observed production and the estimated stochastic frontier, as shown in the following formula (Greene, 2003).

$$ET_i = \frac{Y_i}{f(x_{1i,}x_{2i,\ldots}x_{ki};\beta)\exp(v_i)} = \exp(u_i) \tag{12}$$

The stochastic production frontier has two parts: deterministic and stochastic. $f(x_{1i,},\beta)$, is the deterministic part of the production frontier; $x_{1i,}$ is the vector of inputs; v is the stochastic part, which captures the random effects; and u is the technical inefficiency. The translogarithmic and Cobb–Douglas functional forms are the most common forms found in the applied economics literature when representing production functions. The authors recommend a series of criteria that allow for discriminating between the different functional forms to be used, noting that, while both are similar in terms of parameter linearity and regularity, the translogarithmic one is superior in flexibility (Coelli et al., 2005).

For the purposes of this research, a panel data model with a translogarithmic specification of the production function proposed by Kumbhakar and Lovell (2004) is considered. The translogarithmic production function is more flexible than other functional forms, such as the Cobb–Douglas form, because it allows for a greater number of interactions and changes in the substitution elasticities between production factors. This is crucial in manufacturing, where technology and inputs can interact in complex ways.

$$\begin{aligned} \ln y_{it} = \beta_0 + \sum_n \beta_n lnx_{nit} + \beta_t t + \tfrac{1}{2}\sum_n \sum_j \beta_{nj} lnx_{nit} \ln x_{jit} + \tfrac{1}{2}\beta_{tt} t^2 \\ + \sum_n \beta_{nt} lnx_{nit} t + v_{it} - u_{it} \end{aligned} \tag{13}$$

where y_{it} represents the observable output in period t; x_{it} is the set of production factors; t is a time trend component; β are the unknown parameters to be estimated; v_{it} is the random noise error component; and u_{it} is the technical inefficiency error component.

2.5. Technological Change

Technological change is associated with the shift in the production possibility frontier of the sector or industry to which it belongs. The following translogarithmic function involves, in addition to the independent effect of t, the interaction between the trend term and the production inputs, through which non-neutral technological change can be

calculated (Kumbhakar & Lovell, 2004). In this model, output is assumed as a function of two inputs: capital (K) and labor (L).

$$\begin{aligned} lny_{it} = \beta_L lnL_{it} + \beta_K\, lnK_{it} + \tfrac{1}{2}\beta_{LL}(lnL_{it})^2 + \tfrac{1}{2}\beta_{KK}(lnK_{it})^2 \\ +\beta_{LK}(lnL_{it})\ (lnK_{it}) + \beta_t t + \tfrac{1}{2}\beta_{tt}t^2 + \beta_{Lt}(lnL_{it})t \\ +\beta_{Kt}\ (lnK_{it})t + v_{it} - u_{it} \end{aligned} \tag{14}$$

$$\Delta TC_{it} = \frac{\partial lnf(x_{it}, t; \beta)}{\partial t} = \hat{\beta}_t + \hat{\beta}_{tt}t + \hat{\beta}_{Lt}\ L_{it} + \hat{\beta}_{Kt}\ K_{it} \tag{15}$$

Technological change (TC) is represented by the derivative of the production function in relation to time. Technological change ΔTC_{it}, can be positive or negative, reflecting the upward or downward shift in the production frontier. When the result is greater than zero, $\Delta TC_{it} > 0$, it means that there was technological progress; on the contrary, when the result is less than zero, $\Delta TC_{it} < 0$, there has been technological backward movement, and when the result is equal to zero, $\Delta TC_{it} = 0$, the frontier remains constant during the periods analyzed and therefore technology has not changed.

2.6. The Sustainable Model

Sustainable models in the manufacturing sector were analyzed with the aim of ensuring that sustainable production is carried out and remains viable over time (Rao et al., 2019; Molina & Castro, 2015).

One of the most analyzed elements is CO_2 emissions, which are considered an undesirable factor. CO_2 is a greenhouse gas that traps heat in the Earth's atmosphere. This creates the so-called greenhouse effect, which is essential for maintaining the conditions necessary for life on our planet. However, human activities such as the burning of fossil fuels and deforestation have increased CO_2 levels in the atmosphere at an alarming rate. This excessive increase in CO_2 is causing global warming and drastic changes in our climate (Baah et al., 2021; Famiyeh et al., 2018; Sadiku et al., 2023).

Therefore, sustainability in manufacturing production is a relevant issue that should be analyzed from different perspectives. One way to measure the relationship and impact of the environmental factor, which in this case is CO_2 emissions with the production factors, is through a translogarithmic production function, where the environmental effect can be calculated together with the production factors, labor (L) and capital (K), to determine their impact on the value of production.

The model developed in this paper considers production factors L and K in a translogarithmic production function (Kumbhakar & Lovell, 2004). Additionally, the environmental factor (CO_2) (Borrayo et al., 2019; Rao et al., 2019; Huanyi et al., 2015) is incorporated into the value added function (Y) of the manufacturing sector, with the equation represented as follows:

$$\begin{aligned} \ln y_{it} = \beta_L lnL_{it} + \beta_K lnK_{it} + \beta_{co2} lnco2_{it} + \beta_t t + \tfrac{1}{2}\beta_{LL}(lnL_{it})^2 + \tfrac{1}{2}\beta_{KK}(lnK_{it})^2 \\ +\tfrac{1}{2}\beta_{co2co2}(lnco2_{it})^2 + \beta_{LK}(lnL_{it})(lnK_{it}) \\ +\beta_{Lco2}(lnL_{it})(lnco2_{it}) \\ +\beta_{kco2}(lnk_{it})(lnco2_{it}) + \tfrac{1}{2}\beta_{tt}t^2 + \beta_{Lt}(lnL_{it})t + \beta_{Kt}(lnK_{it})t \\ +\beta_{co2t}(lnco2_{it})t + v_{it} - u_{it} \end{aligned} \tag{16}$$

This way, the goal is to develop a translogarithmic model where the possibility to obtain technical inefficiency is initially verified; furthermore, technological progress can be identified through factor *t*, which represents a time trend (Chávez & Fonseca, 2012; Molina & Castro, 2015).

3. Modeling

In this research, the estimation of a stochastic frontier is carried out using a translogarithmic production function to initially identify the impact of production factors labor and capital, technological progress, and CO_2 emissions on the value added in the manufacturing sector of Mexico, the United States, and Canada during the period 1984–2022. In a second stage, based on the validity of the stochastic frontier analysis model, technical efficiency, scale efficiency, and technological change are obtained for the manufacturing sector of these countries during the study period.

3.1. Model Development

The starting point is the translogarithmic production function by Kumbhakar and Lovell (2004), incorporating the environmental factor (CO_2) (Borrayo et al., 2019; Rao et al., 2019; Raza et al., 2024; Huanyi et al., 2015), so Equation (16) is applied again as follows:

$$\begin{aligned}\ln y_{it} = {} & \beta_L lnL_{it} + \beta_K lnK_{it} + \beta_{co2} lnco2_{it} + \beta_t t + \tfrac{1}{2}\beta_{LL}(lnL_{it})^2 + \tfrac{1}{2}\beta_{KK}(lnK_{it})^2 \\ & + \tfrac{1}{2}\beta_{co2co2}(lnco2_{it})^2 + \beta_{LK}(lnL_{it})(lnK_{it}) \\ & + \beta_{Lco2}(lnL_{it})(lnco2_{it}) \\ & + \beta_{kco2}(lnk_{it})(lnco2_{it}) + \tfrac{1}{2}\beta_{tt}t^2 + \beta_{Lt}(lnL_{it})t + \beta_{Kt}(lnK_{it})t \\ & + \beta_{co2t}(lnco2_{it})t + v_{it} - u_{it}\end{aligned} \tag{17}$$

where:

- i = A subindex representing the manufacturing sector for each country in year t.
- $\ln y_{it}$ = Logarithm of the value added of the manufacturing sector for each country in year t.
- lnL_{it} = Labor factor represented by the logarithm of the wages in the manufacturing sector for each country in year t.
- lnK_{it} = Capital factor represented by the logarithm of the adjusted capital stock of the manufacturing sector for each country in year t.
- $lnco2_{it}$ = Logarithm of CO_2 emissions of the manufacturing sector for each country in year t.
- β = Coefficients of the inputs.
- t = Variable representing the time trend.
- v_{it} = Random noise error component.
- u_{it} = Error component of technical inefficiency.

In addition to the independent effect of t, this translogarithmic production function involves the interaction between the trend term and the production inputs through which non-neutral technological change can be calculated (Kumbhakar & Lovell, 2004).

To calculate the technical efficiency as expressed, the procedure is carried out in two stages. First, a stochastic production frontier is specified and estimated. Second, the efficiency is measured. To estimate the stochastic production frontier, a panel data model using maximum likelihood is proposed. Based on the validity of the model, the estimator of Jondrow et al. (1982) is considered in the second stage, and a normal mean distribution is assumed.

3.2. Variables and Data Sources

The variables selected for the model are as follows:

- Dependent variable = Value added at constant 2012 prices of the manufacturing sector for each country.
- Independent Variables:

- Capital = Adjusted capital stock of the manufacturing sector for each country at constant 2012 prices.
- Labor = Wages of workers in the manufacturing sector for each country at constant 2012 prices.
- CO_2 = CO_2 emissions from the manufacturing sector of each country.

The data were obtained from the statistics of the UNIDO (2024), OECD (2024), World Bank (2024b), and the IEA (2024b).

3.3. Descriptive Statistics of the Variables

Descriptive statistics are shown in Table 1, which presents the mean, standard deviation, and minimum and maximum values of each of the variables considered in the model. Where Y represents the value added, L is wages, K is the capital stock, and finally, CO_2 is the CO_2 emissions from the North American manufacturing sector during the period 1984–2022.

Table 1. Descriptive statistics.

	Mean	Std. Dev.	Min	Max
Y	192,977.351	465,020.86	327.70	2,954,356.88
L	59,565.74	141,588.65	10.41	1,364,034.69
K	257,684.65	670,471.44	707.14	4,593,322.37
CO_2	2121.52	2355.495664	276.649	6132.183

Source: Author's design based on statistical calculations of the variables.

4. Results

The initial estimates of the parameters of the translogarithmic production function of Equation (14) are presented in Table 2, where all coefficients were significant at 5% and 1%.

Table 2. Results of stochastic frontier model.

Variable	Parameters	Coefficients	z	P > |z|
lnL	β_L	0.214	5.234	0.000
lnK	β_K	0.808	3.776	0.013
lnco2	β_{Co2}	−0.192	−2.53	0.000
t	$\beta_t t$	−0.023	−4.442	0.039
lnL2	β_{LL}	0.059	2.977	0.003
lnK2	β_{KK}	0.047	1.615	0.011
lnco22	β_{co2co2}	−0.681	−7.611	0.000
t2	$\beta_{tt}t^2$	−0.001	−7.125	0.000
lnLK	β_{LK}	0.033	3.72	0.054
lnLco2	β_{Lco2}	0.042	1.813	0.058
lnKco2	β_{kco2}	−0.0216	−8.744	0.037
lnLt	β_{Lt}	0.071	4.605	0.018
lnKt	β_{Kt}	−0.043	−2.358	0.000
lnco2t	β_{co2t}	−0.013	−6.801	0.000
σ_v		0.224		
σ_u		0.731		
λ		1.538		

Source: Author's design based on results from SFA methodology.

Coefficients $\beta_t t$ and $\beta_{tt}t^2$ indicate that the neutral part of technical progress has negative effects on production, with values of −0.023 and −0.001, respectively. To achieve (positive) technical progress, it is necessary for the non-neutral part of the technical progress to offset said effects.

The signs of β_{Lt} and β_{Kt}, respectively, indicate that the non-neutral part of technical progress goes hand in hand with labor supply (positive sign of β_{Lt}), and inversely with capital accumulation (negative sign of β_{Kt}). That is, technical progress is capital-saving and occurs with greater intensity in those countries where labor is abundant, in this case, the countries of North America.

The coefficients obtained in the production factors have the expected sign: the highest positive value was presented by the capital stock variable with 0.808, followed by the labor variable, which had a positive coefficient of 0.214. Finally, CO_2 emissions obtained the expected sign, with a value of -0.192, which shows the negative impact that this indicator has on the value added in the manufacturing sector of North American economies.

As indicated in Table 2, the value of lambda is close to 2, which means that the stochastic frontier model is appropriate for calculating inefficiency. Meanwhile, the value of sigma u is close to 1, suggesting that inefficiency is explained by the residual in the model.

Table 3 shows the likelihood test; it allows us to verify whether the restrictions are valid or not. The null hypothesis posed is that the model does not contain the inefficiency component. In this case, by rejecting the null hypothesis, it indicates that the restrictions are valid and that the inefficiency component is present in the stochastic frontier analysis model.

Table 3. Likelihood test.

H0 = No Efficiency Component:	LR Test of Sigma_u = 0:	chibar2(01)=	Prob >= chibar2=
		60.89	0.000

Source: Author's design based on results from SFA methodology.

These tests together validate the model and thus provide evidence that the results from the stochastic frontier model can be used to estimate technical efficiency, scale efficiency, and technological change using the Jondrow et al. (1982) estimator.

4.1. Technical Efficiency

This section presents the results obtained for the average technical efficiency of the manufacturing sector in North American countries. In the case of Canada, the average value for the entire study period was 0.752. The technical efficiency of the manufacturing sector in this country shows stable behavior, except for the drop in this indicator for the years 2008 and 2009 during the world financial crisis, and the drop in 2020 during the COVID-19 pandemic, recovering again in 2022 (see Figure 1).

The efficiency of the manufacturing sector in this country during the reviewed period, while exhibiting a certain level of stability, still shows a downward trend, largely explained by the financial crisis and the COVID-19 pandemic. However, it should not be overlooked that the combinations of production factors labor and capital were not optimal to achieve better efficiency values. Moreover, the negative synergies of CO_2 emissions, which are present in the model's results, also affect the efficiency of this sector. It is worth noting, however, that CO_2 emissions in this country do not reach the levels observed in the manufacturing sector in the United States (see Figure 2).

In the case of Mexico, the average technical efficiency of the manufacturing sector in the period was 0.76—a value very close to that of Canada—. It is evident that the evolution of this efficiency has been very similar to that of Canada, i.e., it drops down in the years of the financial crisis and the COVID-19 pandemic, with the difference that in Mexico, the efficiency of the sector has a significant drop in 1995, with a value of 0.404, as a result of the economic crisis that this country went through in that year. After 1995, technical efficiency showed a significant recovery, reaching its highest level in 1997 with a value of

0.866. It should not be forgotten that Mexico was already part of the North American Free Trade Agreement (NAFTA) by this time, which came into force in January 1994. In terms of trend, it remains largely stable throughout the period. While the values of this indicator are higher than those of Canada and the United States—particularly toward the end of the 1990s and much of the 21st century—the greater instability of the sector, having gone through three critical periods (the 1995 economic crisis, the 2008–2009 financial crisis, and the COVID-19 pandemic), dampens this positive trend. As a result, the technical efficiency of the manufacturing sector in Mexico during this period follows a consistent trend overall (see Figure 1).

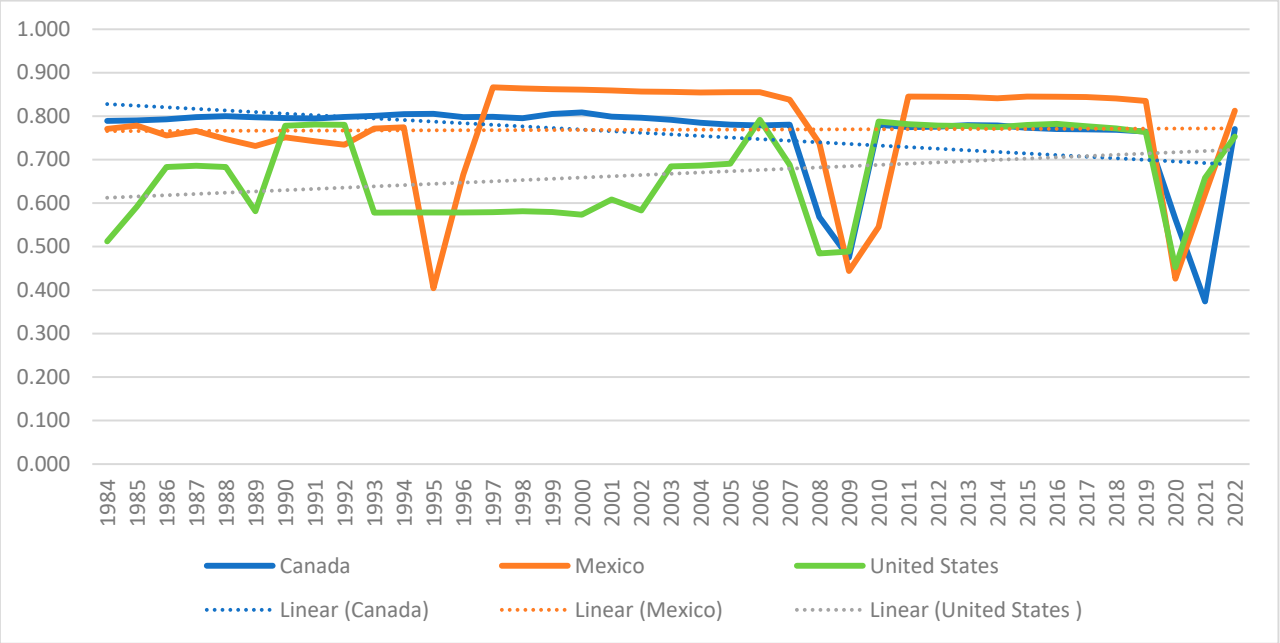

Figure 1. Technical efficiency in North American manufacturing sector, 1984–2022. Source: Author's design based on results from SFA methodology.

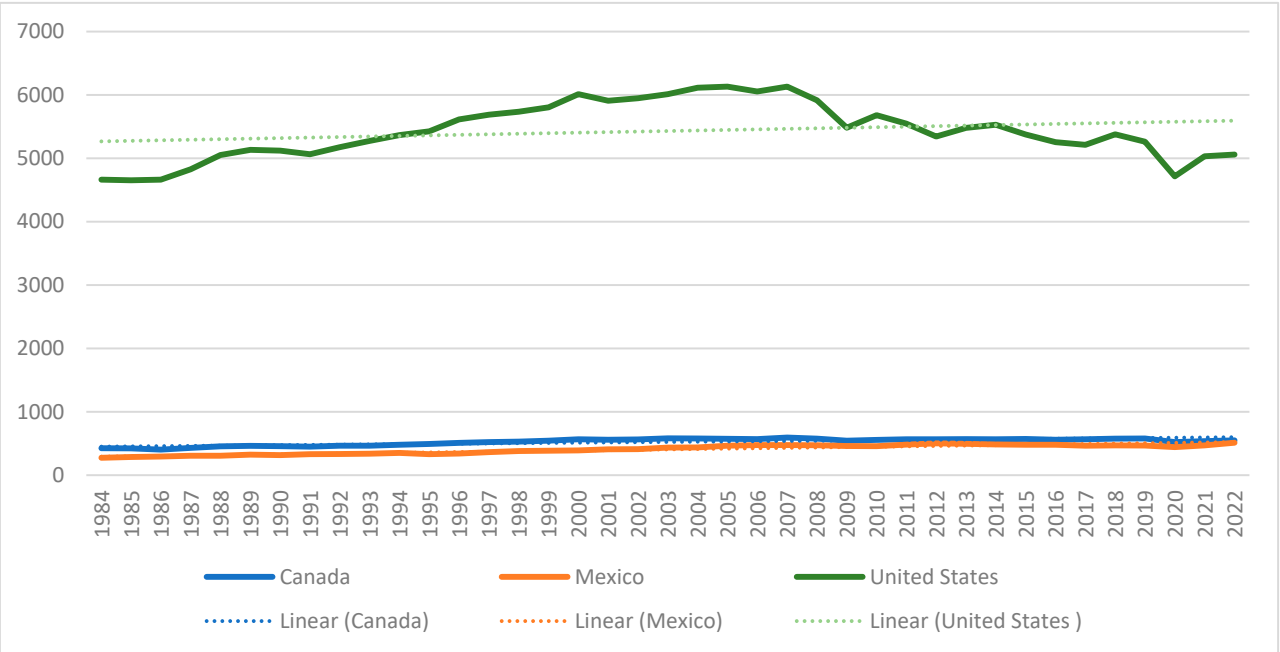

Figure 2. CO_2 emissions in North American manufacturing sector, 1984–2024. Millions of tons. Source: Author's design based on IEA (2024b).

Of the three North American countries, the United States is the one with the lowest levels of technical efficiency in the manufacturing sector, with an average value of 0.671 for the study period. The behavior of efficiency in the sector for the years reviewed in this country is more erratic, with greater instability than Canada and Mexico, concurring with these countries in their drops during the financial crisis and the pandemic. The highest level of efficiency was reached in 2006 with a value of 0.792. One of the explanations for these low levels of efficiency that cannot be overlooked is that it is the country with the highest CO_2 emissions in North America (see Figure 2), together with the inadequate combination of production factors to achieve optimal technical efficiency. Although it is the country with the lowest levels of technical efficiency in the manufacturing sector of the three countries, it is also the only one with an upward trend in this indicator (see Figure 1).

4.2. Scale Efficiency

As for scale efficiency in the manufacturing sector, as expected, the highest efficiencies are found in the U.S. economy, followed by Canada and Mexico, in that order. However, unlike what happens with technical efficiency, in this case, all three economies show a decreasing trend in scale efficiency throughout the period. What remains consistent are the sharp declines in scale efficiency during the financial crisis of 2008–2009 and during the COVID-19 pandemic years. In particular, for the Mexican economy, there was also a significant drop during the 1994–1995 economic crisis. The scale efficiency of manufacturing in Mexico reached its highest values in the years leading up to the 2008–2009 financial crisis, as well as in 2022, just after the COVID-19 pandemic. It is worth noting that the scale efficiency in Canada's manufacturing sector, unlike the United States and Mexico, shows greater instability during the 1990s and early 2000s (see Figure 3).

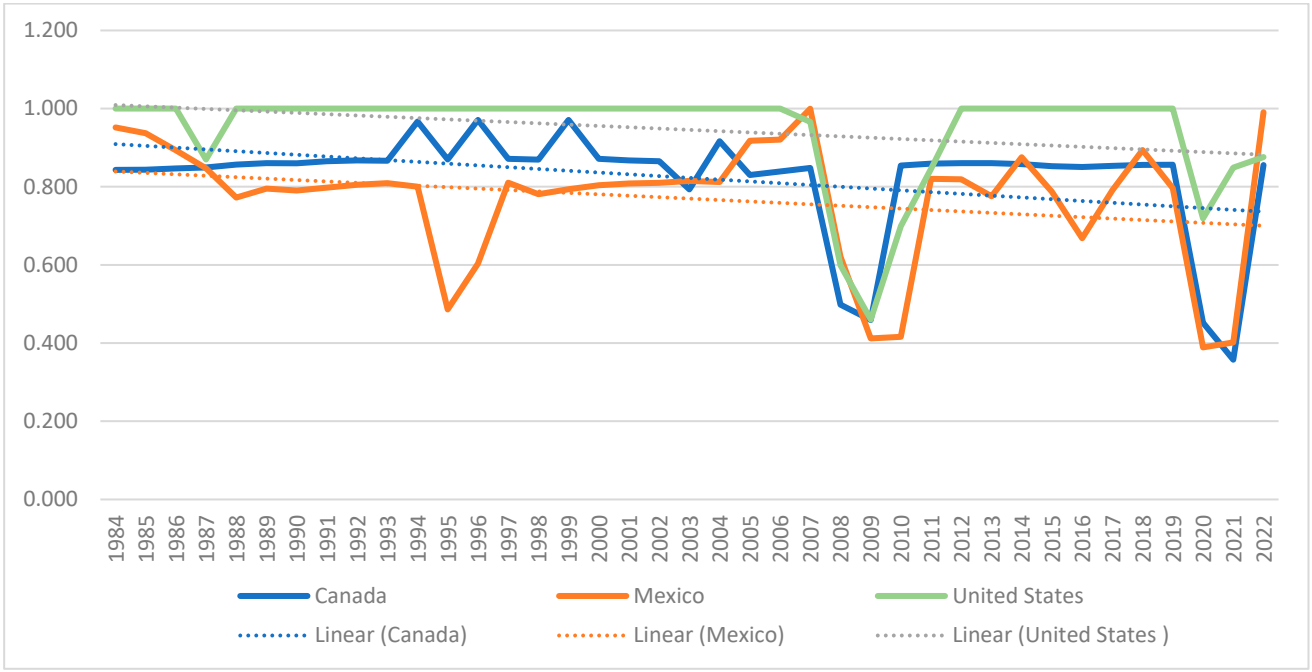

Figure 3. Scale efficiency in North American manufacturing sector, 1984–2022. Source: Author's design based on results from SFA methodology.

4.3. Technological Change

As for this indicator, although each country has its own particularities, in general terms, Canada and the United States show a trend in their manufacturing sector that reflects technological progress in these countries during the period under study. Mexico's sector

shows a trend of technological regression, although this trend is not highly significant (see Figure 4).

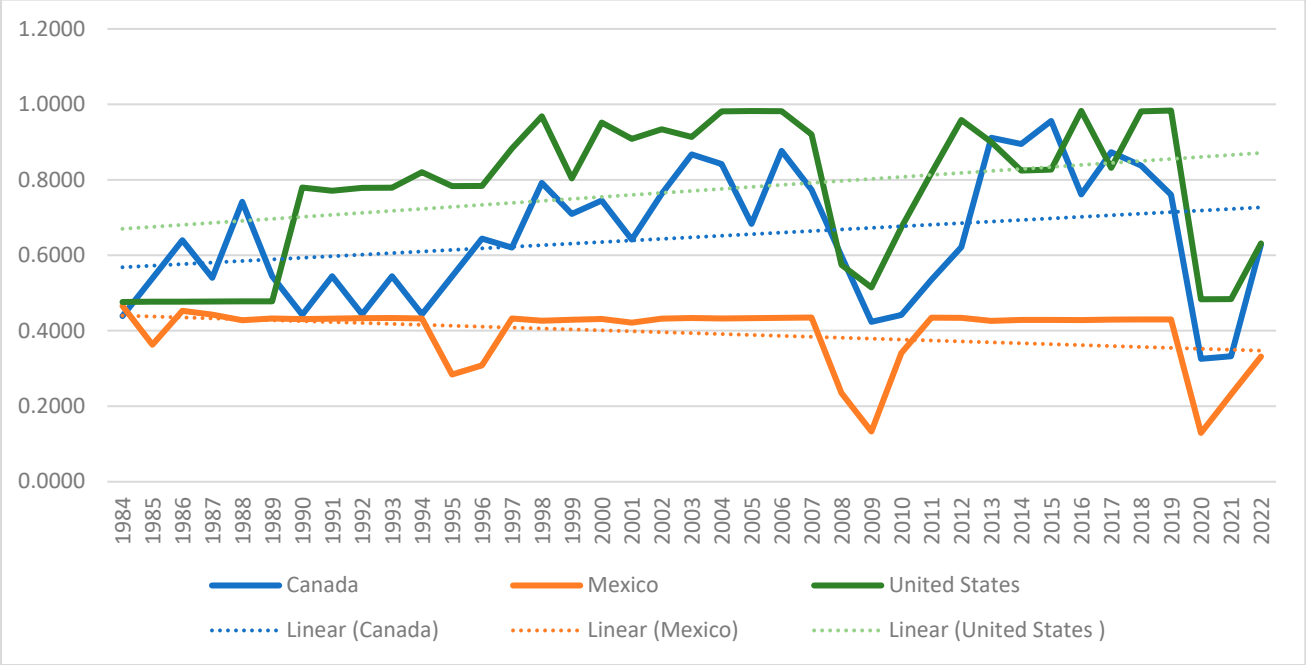

Figure 4. Technological change in North American manufacturing sector, 1984–2022. Source: Author's design based on results from SFA methodology.

The manufacturing sector in the three countries shows a very significant technological regression in the years of the financial crisis and the COVID-19 pandemic, with the lowest values for these years. For 2009, which was one of the years of the financial crisis that began in 2007 and 2008, the values of technological change in the North American countries were 0.4233 for Canada, 0.5147 for the United States, and 0.1329 for Mexico. While for the years of the COVD-19 pandemic, the drop was even deeper, so that Canada had values of 0.3258 and 0.3324 for 2020 and 2021, respectively; while in the United States, their values were 0.4834 in 2020 and 0.4837 for 2021; finally, in Mexico, their values were 0.1294 in 2020 and 0.2312 for 2021. In the year 2022, the three countries were in a clear recovery, i.e., they were already in a situation of technological progress.

The United States has the highest values of the three countries for technological change in the manufacturing sector, followed by Canada. These two countries are also distinguished by their constant technological progressions and regressions, but, in general, they show an increasing trend during these years.

Mexico, like Canada and the United States, experienced its greatest technological regressions in the manufacturing sector during the years of the financial crisis and the COVID-19 pandemic. Similarly to the other two North American countries, the most significant deterioration occurred during the pandemic years. However, in Mexico, it is particularly noteworthy that there was also technological regression during the economic crisis that began in late 1994 and deepened in 1995, where the value of technological change was 0.2839. In general, for Mexico, during the study period, technological change in the manufacturing sector remained largely unchanged, except for the years of the economic crisis, the financial crisis, and the COVID-19 pandemic. These events ultimately led to a downward trend in technological change for the country (see Figure 4).

5. Discussion

The manufacturing sector has been extensively studied by various authors from different perspectives. Below, some works are discussed within a comparative framework alongside the results obtained in this research.

In the study by Rao et al. (2019), the growth of TFP is analyzed with the inclusion of carbon capture as an endogenous variable. A stochastic frontier model with a translogarithmic production function is implemented to examine TFP growth in the Yangtze River Economic Belt (YREB) in China, across three watershed segments. The results indicate a 26.74% improvement in TFP growth due to carbon capture, with positive changes in technical efficiency, technological progress, and scale efficiency, compared to traditional TFP growth that excludes environmental variables. The findings of this research align with Rao et al. (2019) in that both studies evaluate technical efficiency, scale efficiency, and technological progress using the stochastic frontier methodology and a translogarithmic production function, while incorporating environmental variables. However, this study focuses on the manufacturing sector in North American countries, investigating the effect of endogenous variables—labor, capital, technological progress, and CO_2 emissions—on the sector's added value. Additionally, it examines the evolution of technical efficiency, scale efficiency, and technological progress within this sector.

Huanyi et al. (2015), through stochastic frontier analysis, developed two models, an output efficiency model (production frontier) and an input efficiency model (energy demand frontier), to analyze the energy efficiency performance in 12 globally distributed automotive companies. The results show that regional or climate effects could have a significant impact on energy efficiency performance, while plant size and product type have less effect on energy consumption efficiency and manufacturing performance. As in this study, the methodology used is stochastic frontier analysis and the presence in the translogarithmic function of the environmental component. However, the differences are found in the object of study: in this work, the analysis is for the manufacturing sector of the three North American economies and, consequently, the variables and indicators used are also different.

Molina and Castro (2015) estimate technical efficiency through a stochastic frontier analysis in the manufacturing sector for five South American economies—Bolivia, Colombia, Ecuador, Peru, and Venezuela—during the 1995–2008 period. Their results indicate that during these years, there were no improvements in technical efficiency or technological changes in the manufacturing sector of these countries. The differences with the work of these authors are found in the variables considered, particularly with regard to the environmental variables—CO_2 emissions—which are incorporated in this study. Likewise, the period reviewed and the countries studied make the results different. In both studies, a translogarithmic production function is used.

For the case of Mexico, Borrayo et al. (2019) analyzed the main variables that explain the TFP of regional manufacturing during the 1960–2013 period, through a stochastic frontier model. The results show that technological change and a shift in technical efficiency are the two main sources that explain the change rates in the TFP of Mexico's regional manufacturing between 1960 and 2013. For these authors, it was also observed that the economic growth of national manufacture, averaging 4.5%, was sustained by an accelerated increase in capital assets (6.3%) and slower growth in employment generation (3.8%). The present study shares similarities with these authors: first, it employs a stochastic model with a translogarithmic production function; second, in the coefficients obtained from the model, the capital variable has the greatest impact on added value, followed by labor; and third, both studies consider technical efficiency and technological change. The differences with these authors are as follows: (a) this study includes the environmental variable CO_2 in

the translogarithmic production function; (b) the study focuses on the manufacturing sector in North American countries; (c) the time frame analyzed is 1984–2022; and (d) finally, the goal is not to identify the sources of TFP, but rather to analyze the impact of the endogenous variables labor, capital, technical progress, and CO_2 emissions on the added value of North America's manufacturing sector.

Chávez and Fonseca (2012) analyzed the technical efficiency of the manufacturing sector across different regions of Mexico for the period 1988–2008. They estimated a stochastic translogarithmic frontier function to measure this efficiency and its impact on productivity and economic growth in the manufacturing sector. According to these authors, technical efficiency acted as a mechanism that reduced the labor productivity gap among states. They highlight significant differences in the level of technological development between the northern and central regions compared to the south, partially explaining the labor productivity gap across the country's regions. The authors do not address environmental variables in their study, which are considered in this research. Similarly, differences include the time frame analyzed and the regional focus of their study. An additional difference is that this research encompasses the economies of North America as a whole. However, there is alignment with these authors in the methodology employed, particularly the use of a stochastic frontier through a translogarithmic production function.

The study by Valderrama et al. (2015) shows the greatest methodological and variable-based similarities with this research. In both models, technical efficiency is estimated through stochastic frontier analysis using a translogarithmic production function. Additionally, in both studies, the dependent variable is the value added of the manufacturing sector. However, there are differences in the independent variables. In particular, these authors do not include environmental variables in their study, unlike this research, which considers CO_2 emissions. Furthermore, in this study, capital contributes more significantly to the determination of value added than labor, whereas for Valderrama et al. (2015), labor plays a larger role than capital in determining value added. Notably, for these authors, human capital is the variable that contributes the most to value added in the Mexican manufacturing sector. This is a key distinction as this research focuses on the manufacturing sector of all three North American economies.

In summary, this research represents a significant contribution to the study of the manufacturing sector in North American countries—United States, Canada, and Mexico—during the 1984–2022 period, using an advanced stochastic frontier methodology and a translogarithmic production function. This study not only identifies the incidence of the production factors labor and capital, CO_2 emissions, and technical progress on the value added of the manufacturing sector but also evaluates technical efficiency, scale efficiency, and technological change, providing a more comprehensive perspective on the performance and evolution of the sector.

6. Conclusions

In the first stage, a stochastic frontier model with a translogarithmic production function is used to identify the incidence of the production factors labor and capital, CO_2 emissions, and technical progress on the value added of the manufacturing sector in Mexico, the United States, and Canada for the 1984–2022 time frame. In a second stage, technical efficiency, scale efficiency, and technological change are estimated based on the validity of the stochastic frontier model in order to comparatively analyze the evolution of these indicators in the manufacturing sector of these countries.

The selected variables from the manufacturing sector of each country to be included in the model were value added, worker wages, adjusted capital stock—this being another contribution of the study—and CO_2 emissions as the environmental variable.

In the estimates of the translogarithmic production function, all coefficients were found to be significant. Coefficients β_t t and β_tt t^2 indicate that the neutral part of technical progress has negative effects on production. Therefore, to achieve positive technical progress, the non-neutral part of technical progress compensates for these effects. The signs of β_(Lt) and β_(Kt) show that the non-neutral part of technical progress aligns with the labor supply (positive sign of β_(Lt)), and inversely with capital accumulation (negative sign of β_(Kt)). This suggests that technical progress is capital-saving and occurs more intensely in countries where labor is abundant, as is the case in North American countries during the study period, particularly in recent years when migration flows have intensified.

As for the coefficients obtained for the production factors, they have the expected sign. The highest positive value is held by capital stock, with a value of 0.808, followed by labor, which also has a positive coefficient of 0.214. Finally, in the case of CO_2 emissions, the expected sign is also present, with a value of −0.192, which clearly shows the negative impact that this indicator has on the value added in the manufacturing sector of North American economies.

The other parameters obtained, such as the lambda value with a coefficient close to 2, show that the stochastic frontier model is adequate to calculate inefficiency, and the value of sigma u2 close to 1 indicates that the inefficiency component is present and therefore can be calculated using the stochastic frontier analysis model. That is, once the stochastic frontier model was validated, it was possible to obtain the technical efficiency, scale efficiency, and technological change for the manufacturing sector of the North American economies—Mexico, United States, and Canada—through the Jondrow et al. (1982) estimator.

Technical efficiency for the manufacturing sector throughout the study period had an average value of 0.758. It shows stable behavior, except for the decline in this indicator during the years 2008 and 2009 due to the global financial crisis, and the drop in 2020 during the COVID-19 pandemic, after which it began to recover in 2022. Although the manufacturing sector's efficiency in this country shows a certain level of stability, it still exhibits a downward trend, largely explained by the financial crisis and the COVID-19 pandemic.

In the case of Mexico, the average technical efficiency of the manufacturing sector in the period was 0.769—a value very close to that of Canada—. The evolution of this efficiency has been very similar to that which occurred in this sector in Canada, i.e., a decline in the years of the financial crisis and the COVID-19 pandemic, with the difference that in Mexico, the efficiency of the sector has a significant drop in 1995, where its value was 0.404, as a result of the economic crisis that this country went through in that year. The values of this indicator are above those of Canada and the United States, particularly at the end of the 1990s and most of the years considered in the 21st century.

The United States is the North American country with the lowest levels of technical efficiency in the manufacturing sector, with an average value of 0.670 for the study period. The efficiency in this sector over the years in the U.S. shows greater instability compared to Canada and Mexico, although it concurs with these countries during the declines caused by the financial crisis and the pandemic. The highest level of efficiency was reached in 2006, with a value of 0.792. Among the explanations for these low efficiency levels that cannot be overlooked is the fact that it is the country with the highest CO_2 emissions in North America, coupled with the inadequate combination of production factors to achieve optimum technical efficiency. Even though it has the lowest levels of technical efficiency in the manufacturing sector among the three countries, it is also the only one showing an upward trend in this indicator.

As for scale efficiency in the manufacturing sector, as expected due to the size of the economies, the highest efficiencies are observed in the United States, followed by Canada and Mexico, in that order. However, unlike what happens with technical efficiency, in this case, a decreasing trend in scale efficiency is observed across all three economies throughout the period. The scale efficiency of manufacturing in Mexico reaches its highest values in the years leading up to the 2008–2009 financial crisis, as well as in 2022, almost at the end of the COVID-19 pandemic.

Of the three countries, the United States has the highest values in technological change in the manufacturing sector, followed by Canada. These two countries are also characterized by constant technological progressions and regressions, but they generally show an increasing trend over the years of the study. For Mexico, technological change in the manufacturing sector remains virtually unchanged, except for the years of the economic crisis, the financial crisis, and the COVID-19 pandemic, situations that ultimately define a downward trend in terms of technological change. The largest technological regression during the reviewed period in Mexico occurred in 2020, with a value of 0.1294.

The results show that incorporating CO_2 emissions as an environmental variable makes it clear that a manufacturing sector with lower emissions tends to be more efficient. This leads to the need to consider not only traditional factors such as capital and labor, but also the environmental impact in the evaluation of efficiency and technological change. Integrating environmental variables in these studies makes it possible to identify more sustainable sectors and develop policies that promote both economic growth and carbon emissions reduction. This is essential to ensure a balanced development of the manufacturing sector in North America, without compromising environmental and sustainability goals.

Although this research focused on identifying the impact of production factors—labor and capital—technical progress, and CO_2 on the added value of the manufacturing industry in North American countries, it is important to consider other variables for future studies, such as productivity, a key variable in determining the economic growth of countries. Similarly, it would be advisable to address the analysis at the level of divisions of the manufacturing industry, given the implications that this has on the design of industrial policy in economies.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The author declares no conflicts of interest.

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