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Article

Economic welfare in Mexican municipalities: A nonparametric analysis

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Abstract: This study determines the efficiency and productivity of Mexico's urban and rural municipalities in generating economic welfare between 1990 and 2020. It establishes the incidence of context and space on efficiency, using Data Envelopment Analysis, the Malmquist-Luenberger Metafrontier Productivity Index, and Nonparametric Regression. The results indicate that 4 of the 2456 municipalities analyzed were efficient, that productivity increased, and that context and space influenced efficiency. This highlights the need for policies that optimize resource utilization, enhance investment in education, stimulate local business development, encourage inter-municipal cooperation, reduce rural-urban disparities, and promote sustainability.

Keywords: economic welfare; municipalities; Mexico; DEA; MML; NPR

1. Introduction

The Human Development Index (HDI) in Mexico increased by 1.9% between 1990 and 2020; however, it remains below other countries with similar characteristics in the international HDI ranking (UNDP, 2024). The states with the highest HDI levels were Mexico City, Nuevo León, Baja California Sur, Baja California, and Coahuila, while Oaxaca, Chiapas, Guerrero, Puebla, and Veracruz ranked the lowest. At the municipal level, 15 of the 16 delegations of Mexico City and 4 urban municipalities of Nuevo León stood out as the most developed (Banxico, 2024; CONAPO, 2024; INEGI, 2024a–i; WB, 2024).

Mexico's performance, its states, and municipalities in the HDI is related to the behavior of income indicators (UNDP, 2024). During the 1990–2020 period, the per capita Gross Domestic Product (GDP) increased by 16%, driven by public spending, trade, and investment attraction policies. The entities with the highest levels of per capita GDP were Campeche, Mexico City, and Nuevo León, while Mexico City's delegations and some urban towns in Campeche stood out at the municipal level (Banxico, 2024; INEGI, 2024b, g, h). Public spending significantly increased from 94.6 million pesos in 1990 to 376.8 million pesos in 2020. Education also experienced progress during this period with a 63.7% increase in the average schooling grade in Mexican society. Likewise, the employed population grew by 163%, and the population living on income below the extreme poverty line decreased by 20% (Banxico, 2024; CONEVAL, 2024a–d; INEGI, 2024 a, b, d, e, g–i).

Despite this progress, the limited impact of the income dimension on the national, state, and municipal HDI, as well as the persistent disparity between urban and rural municipalities, highlight the need to design strategies to increase per capita income levels and reduce poverty to achieve greater economic and social welfare in the country. Thus, the objective of this research is to determine the efficiency and productivity of Mexico's urban and rural municipalities in generating economic welfare as well as to establish the incidence of contextual and spatial variables on efficiency between 1990 and 2020.

Human development is defined as the process by which the opportunities and welfare of individuals are expanded (Harttgen and Klasen, 2012). Its main goal is to expand the available options so that people can lead the lives they value. These basic opportunities include enjoying a long and healthy life, possessing skills and knowledge, having sufficient resources to maintain a decent standard of living, and actively participating in the community. The lack of these basic opportunities may hinder many other possibilities. To measure human development, the HDI, proposed by the United Nations Development Program (UNDP), stands out (Ayvar-Campos et al., 2017; Navarro et al., 2016). This index combines three key elements to assess the progress of countries and regions in terms of human development and social welfare: Education, income, and health (Desai, 1991; Harttgen and Klasen, 2012; León, 2002; López-Calva et al., 2003, 2004; Neumayer, 2001; Noorbakhsh, 1998; Ravallion, 2012; UNDP, 2016). In this context, and recognizing the complexity of the concepts of social welfare and human development, Murias et al. (2015) argue that the analysis of economic welfare should consider variables beyond income level, adopting a multidimensional approach.

Data Envelopment Analysis (DEA) was used to measure technical efficiency, the Malmquist-Luenberger Metafrontier Productivity Index (MML) was used to determine changes in efficiency and productivity, and Nonparametric Regression (NPR) was used to establish the influence of context and space. DEA presented by Charnes et al. (1978), as an alternative to parametric methods, is based on Farrell's (1957) concept of technical efficiency and applies linear programming (Bemowski, 1991). DEA compares an observed production unit with a virtual unit to maximize output (output orientation) or minimize the factors used in production (input orientation) (Banker et al., 1984; Charnes et al., 1978). The literature, starting with Pittman (1983), has emphasized incorporating undesirable outputs (bad outputs) into DEA measurements using Directional Distance Functions (DDF) (Cooper et al., 2007; Goto and Sueyoshi, 2010; Liu et al., 2010; Seiford and Zhu, 2002; Wang et al., 2013).

The Malmquist (1953) index calculates productivity changes between two periods. Färe et al. (1989) adapted it to the nonparametric context using DEA. To include bad outputs, the output-oriented Malmquist Index (MI) is combined with the DDF, creating the Malmquist-Luenberger Productivity Index (ML). This index measures changes in the productivity of good and bad outputs and can be decomposed into two components: Efficiency change and technological change (Chung et al., 1997). The Malmquist-Luenberger Metafrontier Productivity Index (MML) incorporates the concept of metafrontiers to address heterogeneity or differences in technological and productive capacities among the units of analysis (Battese et al., 2004; Battese and Prasada, 2002). The MML is developed on the referential global technological frontier and may be decomposed into three indicators: Efficiency Change (EC), Best Practice Change Gap (BPC), and Technological Gap Change (TGC) (Oh, 2010).

NPR plots the relationship between variables without imposing a predefined model, allowing it to emerge from the data. It uses techniques such as moving averages, Kernel estimation, and locally weighted regression (Argüelles et al., 2019; Olaya, 2012). Kernel regression assigns greater weight to points close to x and less or no weight to points farther away from x, known as the Nadaraya-Watson estimator. In this sense, the Kernel smoother is understood as a locally constant polynomial fitting, that is, a locally linear regression. The best-known Kernel functions are the uniform, triangle, Epanechnikov, quartic, Gaussian, tricube, and Dirichlet (Olaya et al., 2014; Olaya and Reina, 2013; Rodríguez and Siado, 2003).

To meet the stated objective, and given the characteristics of DEA and MML measurements, the per capita GDP was established as the output; the population living on income below the extreme poverty line was considered the bad output; and public spending and employed personnel were the inputs. It is important to mention that the DEA model had an output orientation and worked with variable returns to scale. On the other hand, to determine the incidence of contextual and spatial variables, a multiple Kernel regression with the Epanechnikov function was established under the criterion of cross-validation of least squares, implementing a local linear estimator. In this regression, the results of the DEA model served as the dependent variable, whereas efficiency adjusted by the spatial weight matrix, average schooling grade, and economic units were used as the independent variables.

This research contributes to the existing literature by a) analyzing efficiency at the municipal level; b) conducting a multidimensional study of economic welfare; c) evaluating the evolution of productivity considering metafrontiers; and d) determining the incidence of context and space on the efficient use of resources in Mexican municipalities.

The research is structured into four sections. The first reviews the literature on social welfare, human development, and economic welfare. Next, the theoretical aspects of DEA, MML, and NPR are explored, detailing the methodological characteristics of the developed models. The third section presents and discusses the results obtained. Finally, a series of conclusions are presented, underlying the key elements of the study.

2. Literature review

2.1. Social and economic welfare: A conceptual analysis

The concept of development has been extensively explored and defined as the process aimed at creating conditions that expand the opportunities for active participation of various actors in the efficient management of natural, technological, and human resources. This seeks to foster a greater autonomous capacity for growth and modify the relationships between social groups to promote economic progress and improve welfare in a territory (Parra et al., 1982). On the other hand, social welfare encompasses the factors that allow individuals to meet their needs, from the most essential to the most superficial, promoting a life of satisfaction and tranquility (Duarte and Jiménez, 2007).

To measure social welfare, three approaches are used: Utility, economy, and social indicators (Pena-Trapero, 2009). Among them, the approach using synthetic indicators stands out for providing a global view of social welfare, such as the HDI. The HDI evaluates the level of development and welfare of a geographical entity, considering aspects such as income, health, and education (León, 2002; UNDP, 2011).

According to Murias et al. (2006, 2010, 2015), economic welfare, in this context, should be understood as a multidimensional phenomenon. Thus, a society's economic welfare depends not only on the level of income but also on its distribution, the accumulation of productive assets, and individuals' confidence in the future sustainability of that income. Therefore, measurements of economic welfare must seek to capture the multidimensionality of the concept.

2.2. Social and economic welfare: An empirical contextualization

The DEA has been applied to measure social welfare, human development and economic welfare. Examples include the research by Hashimoto and Ishikawa (1993) and Hashimoto and Kodama (1997) on social welfare. In the field of human development and the construction of synthetic indexes, significant studies include those by Arcelus et al. (2005), Despotis (2005a, 2005b), Mahlberg and Obersteiner (2001), Yago et al. (2010) and Zhou et al. (2006). Focused on examining specific aspects of well-being and human development, relevant studies are those of Álvarez-Ossorio et al. (1993), Araya and Miranda (2003), Cordero et al. (2016), Goñi (1998) and Martín (2008). In terms of economic welfare, prominent contributions are made by Deliktas and Gürel (2016), Jakšić et al. (2023), Malul et al. (2009), Murias et al. (2006, 2010, 2015), Poveda (2011), Ramos and Silber (2005), Stanković et al. (2021) and Valach and Vondrová (2016).

Based on Alkire's (2002) philosophy, Ramos and Silber (2005) used DEA to estimate economic welfare, finding that Great Britain exhibits high levels of welfare and low inequality. Murias et al. (2006) developed a synthetic index of economic welfare using DEA and evaluated 50 Spanish provinces, taking as a reference the postulates of Osberg (1985). Malul et al. (2009) measured the efficiency and government quality of 38 developed and 53 developing countries using DEA, noting that the inclusion of inequity and environmental performance affected the ranking of developing countries. Murias et al. (2010) assessed the economic welfare of 17 Spanish and 21 Italian regions using a synthetic index based on DEA, identifying Emilia-Romagna, Madrid, and Marche as the regions with the highest welfare rates.

Poveda (2011) analyzed economic development in Colombian regions (1993–2007) using DEA. The results showed that efficiency varied, and higher levels of development were associated with lower rates of poverty and violence. Deliktas and Gürel (2016) examined the relationship between resource use efficiency and economic growth in countries with different income levels (1991–2011), finding that low- and middle-income countries grew more by intensive input use than by efficiency. Murias et al. (2015) used DEA and the Malmquist index to assess the change in economic welfare in Spanish provinces (1996–2006). Although welfare improved, the disparity between provinces did not decrease, with the most innovative ones being primarily in the northeast. Valach and Vondrová (2016) measured the economic welfare of eleven OECD countries (2000–2013) using a multidimensional index with DEA. They concluded that economic welfare increased due to consumption and wealth, but overall welfare decreased due to inequality and economic security.

Stanković et al. (2021) evaluated the socioeconomic efficiency of 32 countries in 2018 considering bad outputs and found that most did not reach adequate levels of efficiency, with Northern and Western Europe being more efficient. Jakšić et al. (2023) analyzed the efficiency of the Western Balkan economies (2007–2021), comparing them with former socialist countries and found that the COVID-19 pandemic reduced efficiency, and that trade and scale inefficiencies affected relative efficiency.

3. Methodology

3.1. Theoretical and methodological foundations of data envelopment analysis

Farrell (1957) proposed estimating the efficiency of Decision-Making Units (DMU) through the production function and the efficiency frontier, empirically validated using stochastic frontiers and DEA. The latter compares efficiency among similar units and assigns relative scores to each DMU, considering efficient those that generate more output without decreasing performance in other areas or those that use fewer inputs to create similar amounts of output. DEA also sets improvement targets for inefficient units based on the efficient ones (Bemowski, 1991). The main DEA models are constant returns to scale, variable returns to scale, additive, and multiplicative, oriented either to input or output. Additionally, the analysis of slacks in these models identifies the areas where further efficiency improvements are needed for the DMUs (Banker et al., 1984; Charnes et al., 1978; Coelli et al., 2002).

Pittman (1983) analyzed bad outputs by adapting the methodology of Caves et al. (1982) and establishing shadow prices. Subsequent studies, such as those of Färe et al. (1989), corroborated these findings (Sepúlveda, 2014). Hernández et al. (1998) proposed productivity indexes that use shadow prices and hyperbolic efficiency measures to incorporate bad outputs into efficiency and productivity assessments. This way, recent research seeks to maximize good outputs while minimizing bad outputs (Allen and Dyckhoff, 2001). Despite the technical complexity, certain models such as radial, slack-based, Russell, and those based on Directional Distance Functions (DDF), effectively address bad outputs (Cooper et al., 2007; Hernandez et al., 1998; Liu et al., 2010).

The efficiency model in the generation of economic welfare

The DEA model was established under the assumption of Variable Returns to Scale (VRS), considering the existence of bad outputs to capture the multidimensionality of economic welfare. The model focused on the output, seeking to maximize the good output while simultaneously minimizing the bad output. The mathematical formulation of the model is as follows (Goto and Sueyoshi, 2010; Seiford and Zhu 2002):

$$\vec{D}^t(x^t, y^t, b^t) = Max\ \phi \tag{1}$$

s.a.

$$\sum_{j=1}^{N} \lambda_j x_{ij}^t + s_i^+ = x_{io}^t \; i = 1, \ldots, I$$

$$\sum_{j=1}^{N} \lambda_j y_{dj}^t - s_d^- = (1+\phi) y_{do}^t \; d = 1, \ldots, D$$

$$\sum_{j=1}^{N} \lambda_j b_{zj}^t + s_z^+ = (1-\phi) b_{zo}^t \; z = 1, \ldots, Z$$

$$\sum_{j=1}^{N} \lambda_j = 1$$

$$\lambda_j, s_d^+, s_z^-, s_i^+ \geq 0, \phi \text{ sin restricción de signo}$$

where it is assumed that $j = (1 \ldots N)$ represent the *n DMUs*, each of which can use *i inputs* ($i = 1, \ldots, I$) to generate *d* good outputs ($d = 1, \ldots, D$) and *z* bad outputs ($z = 1, \ldots, Z$) in year *t*. Fixing to vector x_{ij}^t the *i* input used by *DMU j*, to vector y_{dj}^t *d* good output created by *DMU j*, and to vector d_{zj}^t *z* bad output produced by *DMU j*. ε is a non-archimedean constant; ϕ represents the maximum radial increase/decrease for the good and bad output, respectively; *s* indicates the slack of the variables; and λ_j is the intensity vector. Ultimately, the constraint $\sum_{j=1}^{N} \lambda_j = 1$ is incorporated to assume that the technology exhibits VRS.

In the DEA model, the good output was per capita GDP, while the bad output was the population living on income below the extreme poverty line. These were chosen for their theoretical relevance in explaining economic welfare and human development at both national and municipal levels. On the other hand, the selection of the inputs was based on theoretical principles that define economic welfare and the income factor of the HDI (Arcelus et al., 2005; Blancas and Domínguez-Serrano, 2010; Blancard and Hoarau, 2011; Deliktas and Gürel, 2016; Despotis, 2005a–b; Jahanshahloo et al., 2011; Jakšić et al., 2023; Malul et al., 2009; Murias et al., 2006, 2010, 2015; Poveda, 2011; Ramos and Silber, 2005; Stanković et al., 2021; Valach and Vondrová, 2016; Yago et al., 2010). Given the limited availability of statistical data for the 2456 Mexican municipalities analyzed between 1990 and 2020, the number of indicators was consequently reduced. With this data, a Spearman correlation matrix was created, and the results indicated that the model's inputs would be Public Spending (PS) and Employed Personnel (EP), as they were directly related to the performance of such good and bad outputs (see **Table 1**).

3.2. Theoretical and methodological aspects of the Metafrontier Malmquist-Luenberger productivity index

The Malmquist (1953) index establishes the variations in productivity between two periods. Färe et al. (1989) adapted it to the nonparametric context using DEA. To apply the Malmquist Index (MI) to the analysis of undesirable products, it is necessary to combine its output orientation, to visualize the variations of good and bad outputs, with a DDF, resulting in the Malmquist-Luenberger Productivity Index (ML) (Färe and Grosskopf, 2004; Goto and Sueyoshi, 2010; Tanaka and Watanabe, 2007). The ML indicates improvements in productivity when its values are greater than one and indicate a decrease if they are lower. Additionally, it can be decomposed into two components: Efficiency change and technological change (Chung et al., 1997).

The Metafrontier Malmquist-Luenberger Productivity Index (MML) combines the ML with the concepts of metafrontiers, which are introduced in efficiency and productivity analyses to address the problem of heterogeneity in the technological and productive capacities among the units of analysis (Battese et al., 2004; Battese and Prasada, 2002). The MML is developed on the referential global technological frontier and may be decomposed into three indicators: Efficiency change, best practice change gap, and technological gap change (Oh, 2010).

The Metafrontier Malmquist-Luenberger productivity model

The mathematical expression of the MML, on which this research is based, is as follows (Oh, 2010):

$$MML(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + \vec{D}^G(x^t, y^t, b^t)}{1 + \vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})}$$

$$= \frac{1 + \vec{D}^t(x^t, y^t, b^t)}{1 + \vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{\dfrac{\left(1 + \vec{D}^I(x^t, y^t, b^t)\right)}{\left(1 + \vec{D}^t(x^t, y^t, b^t)\right)}}{\dfrac{\left(1 + \vec{D}^I(x^{t+1}, y^{t+1}, b^{t+1})\right)}{\left(1 + \vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})\right)}} \quad (2)$$

$$\times \frac{\dfrac{\left(1 + \vec{D}^G(x^t, y^t, b^t)\right)}{\left(1 + \vec{D}^I(x^t, y^t, b^t)\right)}}{\dfrac{\left(1 + \vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})\right)}{\left(1 + \vec{D}^I(x^{t+1}, y^{t+1}, b^{t+1})\right)}} = \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t}$$

$$= EC \times BPC \times TGC.$$

where the contemporaneous distance function $\vec{D}^s(x, y, b) = inf\left\{\beta\middle|(x, y + \beta y, b - \beta b) \in P^s_{R_h}\right\}$, $s = t$, $t + 1$, is established on the referential contemporaneous technological frontier $P^s_{R_h}$ of group R_h; the intertemporal distance function $\vec{D}^I(x, y, b) = inf\left\{\beta\middle|(x, y + \beta y, b - \beta b) \in P^I_{R_h}\right\}$ is established on the referential intertemporal technological frontier $P^I_{R_h}$ of group R_h; and the global distance function $\vec{D}^G(x, y, b) = inf\{\beta|(x, y + \beta y, b - \beta b) \in P^G\}$ is established on the referential global technological frontier P^G. All distance functions described above can be calculated by fitting model (1).

In the above equation, *TE* represents the technical efficiency of period *s*; *BPR* is the Best Practice Gap between the contemporaneous technological frontier and the intertemporal technological frontier in period *s*; *TGR* symbolizes the technological gap between the intertemporal technological frontier and the global technological frontier in period *s*. These elements are calibrated to maximize good outputs and minimize bad outputs. Efficiency Change (*EC*) indicates how close a *DMU* moves toward the contemporaneous technological frontier from period *t* to *t*+1, with $EC > 1$ indicating efficiency gain (moving closer) and $EC < 1$ indicating loss (moving apart). The Best Practice Change Gap (BPC) measures the change in BPR; $BPC > 1$ indicates that the frontiers have come closer together and $BPC < 1$ indicates that they have moved further apart, thus capturing the innovation effect. The Technological Gap Change (TGC) reflects the change in TGR; $TGC > 1$ shows a decrease in the technology gap and $TGC < 1$ denotes an increase, thus expressing the technical leadership effect of a group of DMUs. Finally, $IMML > (<) 1$ implies a gain (loss) in productivity (Oh, 2010).

3.3. Theoretical and methodological features of nonparametric regression

Classical regression theory assumes that observations are independent and normally distributed. However, in cases where these assumptions do not hold, nonparametric methods offer an alternative with less stringent assumptions. Nonparametric regression identifies the relationship between variables without imposing a prior model, using techniques such as moving averages, nuclear estimation (Kernel), and locally weighted regression. These techniques are useful for modeling complex relationships, complementing parametric regression if necessary (Argüelles et al., 2019; Olaya, 2012).

NPR is positioned between graphical analysis and parametric inference, well known for its flexibility. In a bivariate model, NPR estimates the relationship between *y* and *x* using local smoothing techniques applied to observation pairs (x_i, y_i). This method allows for estimating a smooth function *m(x)* that describes the conditional mean value of *y* given *x*, with decreasing weights assigned to the observations located farther away from the center of the interval (Argüelles et al., 2019; Brufman et al., 2008).

The multiple nonparametric regression model estimates the conditional mean value of the response variable as a smooth function of the predictor variables, without imposing restrictions on its form, except that it is continuous. This approach relaxes the linearity assumption, allowing the conditional mean value of variable y to be a continuous function of predictors x_k. The goal is to estimate this function similarly to how parametric regression estimates parameters β_k (Brufman et al., 2008).

The nonparametric regression model

The NPR used in this research employs the Kernel regression method, which analyzes bi-dimensional independent variables (X_i, Y_i). Assuming a relationship $Y_i = r(X_i) + \varepsilon_i$, and $E(\varepsilon_i | X_i) = 0$, the best approximation to Y_i, in terms of minimizing the mean squared error, is obtained by the conditional expectation $r(x) = E(Y_i | X_i = x)$, $x \in R$. The Kernel estimate of *r(x)* is defined as a weighted average of the *Y* values, assigning greater weight to the points closest to *x*. This method is named the Nadaraya-Watson estimator. The best-known Kernel functions are the uniform, triangle, Epanechnikov, quartic, Gaussian, tricube, and Dirichlet. In estimating the regression function, the choice of Kernel type is less important, provided that the smoothing parameters are determined by minimizing the mean integrated squared error (Olaya et al., 2014; Olaya and Reina, 2013; Rodriguez and Siado, 2003).

In this context, the present research employs a multiple Kernel regression with the Epanechnikov function, applying the least squares cross-validation (CV) criterion and establishing a local linear estimator (Hayfield and Racine, 2008). The mathematical expression of the regression used, for a sample of data $\{(x_i, y_i)\}_{i=1}^{n}$ where $x_i \in R^p$ represents the vector of independent variables and $y_i \in R^p$ is the vector of the dependent variable, is as follows (Bishop, 2006):

$$\hat{f}(x) = \sum_{i=1}^{n} \alpha_i K\left(\frac{x - x_i}{h}\right) \quad (3)$$

where K is the Epanechnikov Kernel function, defined as $K(u) = \frac{3}{4}(1 - u^2)$ for $|u| \leq 1$ and $K(u) = 0$ for $|u| > 1$, where $u = \frac{x - x_i}{h}$; h is the smoothing parameter or bandwidth, determined as a function of $CV(h) = \frac{1}{n}\sum_{i=1}^{n}\left[y_i - \hat{f}_{-i}(x_i)\right]^2$ where $\hat{f}_{-i}(x_i)$ is the estimator obtained by excluding the i-th value; α_i are the coefficients to be determined; x is the point of interest; and x_i are the observed data points (Hastie et al., 2009; Schölkopf and Smola, 2002).

The dependent variable in the NPR model is represented by the efficiency results of Mexico’s urban and rural municipalities in generating economic welfare between 1990 and 2020. The selection of contextual independent variables was initially based on the significance of socioeconomic variables from the HDI income dimension and economic welfare in explaining efficiency (Ávila and Cárdenas, 2012; Balcilar and Deliktas, 2005; Deliktas and Gürel, 2016; Dutta, 2011; Hauner and Kyobe, 2010; Jakšić et al., 2023; Jayasuriya and Wodon, 2005; Malul et al., 2009; Méon and Weill, 2005; Morrison, 1993; Murias et al., 2015; Poveda, 2011; Ramos and Silber, 2005; Rayp and Van, 2007; Stanković et al., 2021; Thompson et al., 2016; Valach and Vondrová, 2016). Subsequently, due to the limited availability of statistical data for the 2456 Mexican municipalities analyzed from 1990 to 2020, the number of variables was reduced. With this information, a Spearman correlation matrix was performed, indicating that the most relevant contextual variables were the average schooling grade and the economic units (see **Table 1**).

Table 1. Description of variables.

Variable	Indicator	Description	Source
Gross Domestic Product per capita, annual	GDPpc	Pesos at constant prices, base 2010	Banco de México and INEGI
Population living on income below the extreme income poverty line	PopY	# People	CONEVAL
Employed Personnel	EP	# People	INEGI
Public Spending	PS	Thousands of pesos at constant prices, base 2010	INEGI
Average Schooling Grade	ASG	Years	INEGI
Economic Units	EU	Companies	INEGI

Source: Authors’ design based on data published by Banxico (2024), CONAPO (2024), CONEVAL (2024a–d), INEGI (2024a–i) and WB (2024).

To determine the spatial independent variable, the efficiency results and a physical contiguity-based weight matrix were employed through a first-order Queen neighbor’s approach. This method defines neighbors as units that share either a side or a vertex with the analyzed entity (Moreno and Vayá, 2000). An exploratory spatial data analysis was then conducted using global and local contrasts. Upon identifying a correlation between space and the efficiency results, the latter were used, adjusted by the spatial weight matrix, as the spatial independent variable in the NPR model:

3.4. Characteristics and descriptive analysis of variables in DEA, MML, and NPR models

The descriptive statistics of the variables used in the research showed significant variability and inequality between 1990 and 2020. The average per capita GDP grew from 56,185 in 1990 to 65,990 in 2020; however, the wide interquartile ranges indicate an unequal distribution of wealth. The population living on income below the extreme poverty line showed a slight decrease, meaning that many people still live on significantly low incomes. The average number of employed personnel increased substantially, from 9625 in 1990 to 25,300 in 2020, but variability in access to employment remained notable. Public spending grew substantially, denoting greater government investment but with significant variability across sectors and regions. The mean average schooling grade improved from 4.5 in 1990 to 7.8 in 2020, indicating progress in the population's educational level and a more uniform distribution of it. The mean number of economic units increased from 718 in 1990 to 2066 in 2020, reflecting an expansion of economic activity, albeit with significant regional disparities (see **Table A1** in the Appendix).

4. Analysis and discussion of results

4.1. Determination of efficiency in generating economic welfare

To capture the complexity of the economic welfare concept, this research developed an efficiency model that includes both a good output (per capita GDP) and a bad output (population living on income below the extreme poverty line). By using an output-oriented DEA model, the results identified Mexico's urban and rural municipalities that were efficient and inefficient in generating income and reducing the population living on income below the extreme poverty line during the 1990–2020 period.

Between 1990 and 2020, the efficient municipalities in utilizing their inputs to generate economic welfare were: Santa Magdalena Jicotlán, San Juan Chicomezúchil, and Santiago Tepetlapa in Oaxaca; as well as San Javier in Sonora. In contrast, the most inefficient municipalities were: Ocosingo, Las Margaritas, and Palenque in Chiapas; and Chilapa de Álvarez in Guerrero. This shows how these municipalities did not effectively manage their resources (employed personnel and public spending) to increase per capita GDP and reduce the population in income poverty during the mentioned period (see **Figure 1**).

From a rural-urban comparative perspective, efficiency results show that during the analyzed period, rural municipalities had an average efficiency of 0.881, while urban municipalities had an average efficiency of 0.948. The above suggests that during the 1990–2020 period, rural municipalities demonstrated greater efficiency than urban municipalities in generating economic welfare.

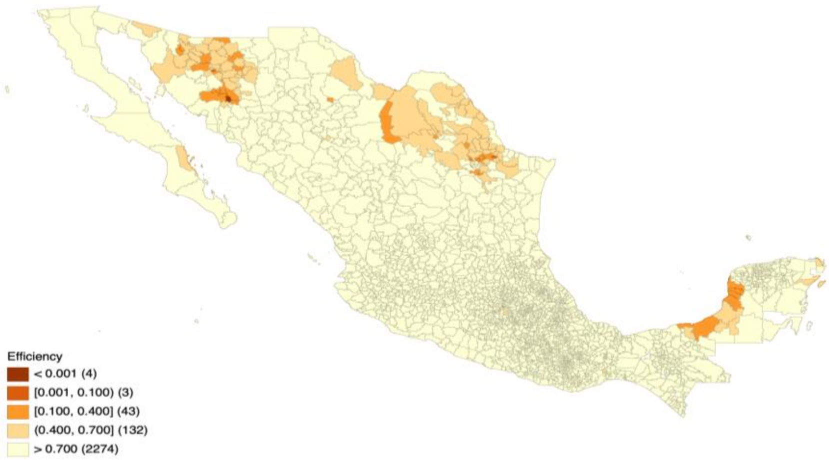

Figure 1. Average efficiency results for Mexican municipalities, 1990–2020.

Note: Efficiency represents the average efficiency of Mexico's urban and rural municipalities between 1990 and 2020. Source: Authors' design based on data published by Banxico (2024), CONAPO (2024), CONEVAL (2024a–d), INEGI (2024a–i) and WB (2024), using *R* software.

4.2. Evolution of efficiency and productivity

The MML results indicate that the productivity of rural and urban municipalities decreased during the 1990–2020 period due to the widening of the Best Practice Change Gap (BPC).

During the same period, the rural and urban municipalities that showed the greatest gains in MML were: La Magdalena Contreras, Cuajimalpa de Morelos, and Iztacalco in Mexico City; China, Gral. Bravo, and Cerralvo in Nuevo Leon; Calkiní, Tenabo, Carmen in Campeche; and Cumpas in Sonora. This increase was due to positive evolution in terms of Efficiency Change (EC) and Technological Gap Change (TGC). In contrast, the municipalities with greater losses in the MML were: Santiago el Pinar in Chiapas; Santos Reyes Yucuná, Santa María Tlalixtac, San Francisco Logueche, Santa Cruz Xitla, and Santo Domingo Teojomulco in Oaxaca; Nicolás Bravo and Huehuetlán el Grande in Puebla; Solidaridad in Quintana Roo; and Tehuipango in Veracruz. These losses were due to setbacks in EC, BPC, and TGC (see **Figure 2**).

Figure 2. MML results for Mexican municipalities, 1990–2020.

Note: IMML represents the MML of Mexico's urban and rural municipalities between 1990 and 2020. Source: Authors' design based on data published by Banxico (2024), CONAPO (2024), CONEVAL (2024a–d), INEGI (2024a–i) and WB (2024), using R software.

The MML also reveals that the productivity of rural municipalities decreased during the study period, driven mainly by losses in EC and the widening of BPC. The rural municipalities that presented gains in the MML were: Metapa de Chiapas, Santa Isabel de Chihuahua; Agualeguas, Doctor Coss, Los Herreras, and Vallecillo in Nuevo León; San Pedro and San Pablo Teposcolula in Oaxaca; and San Damián Texóloc, San Lorenzo Axocomanitla, and Santa Isabel Xiloxoxtla in Tlaxcala. Conversely, the municipalities that recorded the greatest losses were: Santiago el Pinal in Chiapas; as well as Santo Domingo Teojomulco, Santa Cruz Xitla, San Francisco Logueche, Santa María Tlalixtac, Santos Reyes Yucuná, Santo Domingo Ozolotepec, Santiago Apoala, San Lorenzo Cuaunecuiltitla, San Mateo Nejápam, and Santo Domingo Albarradas in Oaxaca.

As for urban municipalities, productivity decreased during the same period, driven by an increase in BPC. The urban municipalities that showed productivity gains were: La Magdalena Contreras, Cuajimalpa de Morelos, and Iztacalco in Mexico City; China, General Bravo, Cerralvo, and Lampazos de Naranjo in Nuevo León; Calkiní, Tenabo, and Carmen in Campeche; and Cumpas in Sonora. Meanwhile, the municipalities with the greatest productivity losses were: Tehuipango and Agua Dulce in Veracruz; Huehuetlán el Grande and Nicolás Bravo in Puebla; Solidaridad and Cozumel in Quintana Roo; Coicoyán de las Flores, San Martín Peras, and San Sebastián Tutla in Oaxaca; and Carmen in Nuevo León.

The MML results show that during the 1990–2020 period, rural municipalities presented a productivity index of 0.879, while urban municipalities reached an index of 0.971. From a comparative perspective, this implies that although both types of municipalities experienced productivity losses during the analyzed period, the MML of rural municipalities is lower. Furthermore, rural municipalities have lower levels of EC, BPC, and TGC compared to urban municipalities. These results indicate that the rural municipalities in Mexico operated below the production frontier established by urban municipalities between 1990 and 2020.

4.3. The incidence of context and space on efficiency

Table 2 highlights the importance and impact of context and space on the efficiency of resource utilization to generate income while reducing the population living on income below the extreme poverty line in Mexico's urban and rural municipalities between 1990 and 2020.

The regression analysis shows that contextual variables, such as the Average Schooling Grade (ASG) of the population and the number of Economic Units (EU), are statistically significant with confidence levels of 95% and 90%, respectively. Additionally, a positive impact of these indicators on efficiency is observed. Thus, it can be concluded that contextual variables have a positive and significant influence on the efficiency of Mexico's municipalities. In other words, during the 1990–2020 period, municipalities with higher ASG and a greater number of EU tended to utilize resources more effectively (EP and PS) to increase per capita GDP and reduce the population living on income below the extreme poverty line (see **Table 2**).

Table 2. Results of the nonparametric regression model.

Variable	*p* value	Impact
ASG	0.037**	Positive
EU	0.060*	Positive
WEF	0.001***	Positive
R2	0.2988	

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Average Schooling Grade (ASG), Economic Units (EU), and Efficiency Adjusted by the Spatial Weights Matrix (WEF). Source: Authors' design based on data published by Banxico (2024), CONAPO (2024), CONEVAL (2024a–d), INEGI (2024a–i) and WB (2024), using R software.

Table 2 also demonstrates that the variable reflecting the impact of space Efficiency Adjusted by the Spatial Weights Matrix (WEF)—is statistically significant at a 99% confidence level. In addition, it is noted that space has a positive effect on efficiency. This suggests that the spatial variable holds a positive and significant influence on the efficiency of municipalities in Mexico. Therefore, proximity to municipalities with good performance in resource management improved the ability of municipalities to efficiently use EP and PS, increasing per capita GDP and reducing the population living on income below the extreme poverty line between 1990 and 2020. Overall, these findings indicate that efficiency in resource use for generating economic welfare between 1990 and 2020 was influenced by the contextual characteristics of the municipalities and their geographical proximity to other municipalities with good economic and social performance.

The results of the DEA, MML, and NPR models align with findings from Sánchez (2006), who identified that only a few units affect supranational behavior when a smaller scale efficiency analysis is performed. Furthermore, they correspond with Malul et al. (2009) and Murias et al. (2015). They stressed the need to consider variables other than per capita income to analyze economic welfare in a multidimensional way, recognizing the influence of context and space on economic welfare. Similarly, they echo the perspectives of Baquero (2004) and Despotis (2005a, 2005b) in the need for state intervention through specific actions in education, income, and health to reverse negative trends in social welfare and human development. Likewise, these results resonate with the arguments of Deliktas and Gürel (2016), Reig and Soler (2009) and Stanković et al. (2021), who highlighted the North-South and, therefore, Urban-Rural distinction among the studied units. The results of this research also concur with Yago et al. (2010) in the classification of the most and least efficient Mexican entities and the need to increase socioeconomic investment to optimize the generation of social welfare and human development. Finally, they are consistent with analyses by Poveda (2011), Ramos and Silber (2005) and Valach and Vondrová (2016), who pointed out that high levels of economic and social welfare are associated with high levels of income, education, and health, as well as low levels of inequality.

5. Conclusion

During the 1990–2020 period, Mexico's HDI grew, although it remains below that of other similar economies. Similarly, social welfare is very unequal, with states and municipalities showing significantly different HDI levels. Despite increases in income and reductions in poverty indicators, there are still great challenges to enhance economic welfare in the country's states and municipalities. This denotes a need to design strategies that will address these issues.

In this vein, the research determines the efficiency and productivity of Mexico's urban and rural municipalities in generating economic welfare and establishes the incidence of contextual and spatial variables on efficiency during the 1990–2020 period. To do so, an output-oriented DEA model with variable returns to scale was first developed, measuring efficiency in terms of increasing the good output and decreasing the bad output. The model variables were: Per capita GDP as output, PopY as bad output, and PS and EP as inputs. Then, the MML was used to evaluate changes in efficiency and productivity between 1990 and 2020. This allowed comparisons of the evolution of the country's urban and rural municipalities, both among themselves and as a whole, and identified whether variations were due to efficiency changes, best practice change gap, or the technological gap. Finally, to determine the incidence of contextual and spatial variables on efficiency between 1990 and 2020, a multiple Kernel regression model was designed using the Epanechnikov function, the least squares cross-validation criterion, and a local linear estimator. In this regression, the results of the DEA model served as the dependent variable, while ASG, EU, and efficiency adjusted by the spatial weight matrix were the independent variables.

The results of the DEA model revealed that the municipalities of Santa Magdalena Jicotlán, San Juan Chicomezúchil, and Santiago Tepetlapa in Oaxaca, as well as San Javier in Sonora, were efficient in generating economic welfare. Thus, during the 1990–2020 period, only 4 out of the 2456 municipalities analyzed were efficient. Additionally, it was observed that rural municipalities were more efficient than urban municipalities. On the other hand, the MML revealed that the productivity of Mexico's urban and rural municipalities decreased between 1990 and 2020 due to an expanding best practice change gap. Municipalities with progress in the MML were located in Mexico City, Nuevo León, Campeche, and Sonora, whereas the greatest losses occurred in Chiapas, Oaxaca, Puebla, Quintana Roo, and Veracruz. Similarly to urban municipalities, rural towns experienced a decline in productivity driven by a setback in efficiency and an increase in the best practice change gap. Comparatively, the productivity of rural towns was lower than that of urban municipalities.

The nonparametric regression analysis indicated that the contextual variables ASG and EU had a positive and significant impact on the efficiency level of Mexico's urban and rural municipalities between 1990 and 2020, with confidence levels of 95% and 90%, respectively. Additionally, the spatial variable, measured by efficiency adjusted by the spatial weight matrix, is significant at 99%, indicating that proximity to municipalities with good resource management performance improves efficiency levels. In summary, during the study period, efficiency in the use of resources to increase per capita GDP and reduce the population located below the extreme income poverty line was influenced by contextual and spatial factors.

The research results are consistent with those of Baquero (2004), Deliktas and Gürel (2016), Despotis (2005a, 2005b), Malul et al. (2009), Murias et al. (2015), Poveda (2011), Ramos and Silber (2005), Reig and Soler (2009), Sánchez (2006), Stanković et al. (2021), Valach and Vondrová (2016) and Yago et al. (2010). These authors stress the need to analyze efficiency on a smaller scale, consider additional variables beyond per capita income to assess economic welfare, include context and space, and recognize differences between units of analysis for comparative studies.

The findings of this research emphasize the need to optimize the management of socioeconomic resources in Mexico's urban and rural municipalities. Improving such management will increase economic welfare in both the municipalities and their surrounding areas. Therefore, it is essential to implement policies tailored to each municipality, aimed at optimizing resource use, increasing investment in education, fostering local business development, encouraging inter-municipal cooperation, reducing rural-urban disparities, and promoting sustainability. These efforts will collectively strengthen the nation's economic and social welfare.

As a result of the scarcity of similar studies, this research is considered a significant contribution to the state of the art. It measures economic welfare not only through per capita GDP but also by considering the population in extreme income poverty, thus offering a multidimensional view of the concept. Moreover, it conducts an empirical analysis in specific municipalities, allowing for a better estimation of any country's economic welfare. The study also differentiates the efficiency and productivity analysis by municipality type (urban-rural). Finally, it identifies the incidence of contextual and spatial variables on the efficiency of municipalities.

Finally, considering the limitations of this research, such as the availability of data at the municipal level and the multidimensional nature of economic well-being, it is essential to continue advancing this line of study. This will allow future research to consider incorporate additional variables, employ diverse analytical tools, and address the impact of recent events, such as the COVID-19 pandemic, on the dynamics of economic well-being.

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Appendix

Table A1. Descriptive statistics of variables, 1990–2020.

Year	Statistic	GDPpc	PopY	EP	PS	ASG	EU
1990	Mean	56,185	13,076	9626	38,810	4.51	718
	p25	29,879	1860	919	1510	3.48	29
	p50	47,862	4718	2575	5432	4.37	107
	p75	73,308	13,507	6303	13,438	5.38	373
	Max	557,350	489,207	547,683	5,197,482	11.11	44,702
	Min	530	0	2	26	0.55	2
1995	Mean	48,916	11,411	11,691	41,679	4.95	889
	p25	26,618	1945	1044	3082	3.89	39
	p50	41,050	4563	2955	7913	4.78	137
	p75	61,270	12,466	7475	18,282	5.85	478
	Max	283,793	406,556	617,107	3,573,549	11.60	55,746
	Min	3733	1	32	148	0.94	3
2000	Mean	56,000	9746	13,755	63,039	5.38	1088
	p25	30,006	1885	1177	5326	4.32	49
	p50	48,105	4344	3330	15,201	5.20	173
	p75	71,763	10,949	8439	39,148	6.33	605
	Max	296,626	323,906	705,741	3,374,786	12.09	68,441
	Min	4712	1	33	516	1.11	3
2005	Mean	59,731	9398	15,982	93,981	6.02	1340
	p25	29,635	1851	1294	10,004	4.96	66
	p50	49,788	4399	3845	26,043	5.85	226
	p75	73,325	10,432	9894	61,741	6.95	758
	Max	1,226,713	269,182	749,019	4,407,013	12.81	80,076
	Min	4935	4	33	791	1.72	3
2010	Mean	61,823	9049	18,204	127,533	6.65	1597
	p25	32,288	1685	1376	15,224	5.59	86
	p50	53,577	4100	4297	37,015	6.51	288
	p75	77,674	9634	11,227	84,541	7.60	950
	Max	1,012,282	214,459	792,297	6,238,270	13.52	87,016
	Min	4507	7	33	1087	2.03	3
2015	Mean	66,919	9106	21,752	151,892	7.24	1813
	p25	34,437	1733	1511	19,551	6.22	108
	p50	58,078	3947	5064	43,889	7.11	357
	p75	87,010	9232	13,621	105,813	8.16	1128
	Max	1,234,122	366,908	874,162	5,323,614	14.04	90,005
	Min	4889	4	38	1260	2.72	3

Table A1. (*Continued*).

Year	Statistic	GDPpc	PopY	EP	PS	ASG	EU
2020	Mean	65,990	10,503	25,300	153,461	7.83	2066
	p25	33,081	1313	1646	19,718	6.81	123
	p50	57,432	3658	5798	45,932	7.72	411
	p75	86,287	10,068	16,008	107,541	8.75	1328
	Max	1,865,149	362,871	1,051,417	5,997,791	14.55	88,689
	Min	4017	11	42	1080	3.40	0
Total	Mean	59,366	10,327	16,616	95,771	6.08	1359
	p25	30,271	1743	1230	6496	4.71	61
	p50	50,348	4252	3722	21,082	5.99	223
	p75	76,059	10,784	10,104	60,342	7.35	788
	Max	1,865,149	489,207	1,051,417	6,238,270	14.55	90,005
	Min	530	0	2	26	0.55	0

Note: Mean = Average, p25 = 25th Percentile, p50 = 50th Percentile, p75 = 75th Percentile, Max = Maximum value, and Min = Minimum value. Source: Authors' design based on data published by Banxico (2024), CONAPO (2024), CONEVAL (2024a–d), INEGI (2024a–i) and WB (2024), using R software.