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Article

Labor Productivity Trends in Mexico's Maquiladora Manufacturing Sector: Increase in Remuneration per Worker and Contraction in Employment (2020–2025)

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Abstract: The Manufacturing, Maquiladora, and Export Services Industry Program (IMMEX) is one of the cornerstones of Mexico's manufacturing economy. This article analyzes the official monthly time series published by INEGI (2020–2025) corresponding to employed personnel, wages, hours worked, and foreign income in the manufacturing sector. Using data mining techniques—implicit productivity calculation (wages/employed personnel), STL decomposition, and trend analysis—a sustained increase in productivity per worker of +104.3% was identified between 2020 and 2025, while the number of employed workers first remained relatively stable and then declined moderately in recent years. Three predictive models were compared on the productivity series: simple linear regression, exponential smoothing (Holt-Winters), and ARIMA. The ARIMA and exponential smoothing models obtained the best predictive performance (lowest RMSE and AIC in the validation set). The complete Python code (Pandas, statsmodels, and matplotlib) is included in the Methods section to ensure full replicability with the original Excel file. The results show a clear decoupling between employment volume and value generated per worker, signaling a transition toward greater labor efficiency in the Mexican maquiladora sector.

Keywords: IMMEX; labor productivity; maquiladora sector; data mining; time series; ARIMA; manufacturing efficiency; Mexico

1. Introduction

The Fourth Industrial Revolution, known as Industry 4.0 (I4.0), represents a major shift in manufacturing production systems on a global scale. Formally introduced in 2011 by the German government as an industrial competitiveness strategy, I4.0 is based on the deep integration of digital technologies—such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics, cyber-physical systems (CPS), cloud computing, advanced robotics, and additive manufacturing—with traditional physical processes [1,2]. This fusion enables the creation of smart factories with real-time interconnection, autonomous decision-making, mass customization, and greater resilience in value chains [3].

Globally, the implementation of Industry 4.0 (I4.0) has demonstrably influenced productivity, operational efficiency, and sustainability. Recent systematic reviews indicate that firms demonstrating advanced I4.0 maturity levels experience reductions in operating expenses ranging from 15% to 30%, enhancements in asset utilization between 20% and 40%, and decreases in delivery times of 30% to 50% [4,5]. Nevertheless, this transition is not consistent across all contexts; developed economies, including Germany, Japan, the United States, and South Korea, exhibit leadership through extensive Cyber-Physical Systems (CPS) implementation and integrated digital platforms, whereas emerging economies encounter structural impediments that impede their advancement [6,7]. Furthermore,

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established maturity models, such as the Acatech Maturity Index, IMPULS, and SIMMI 4.0, underscore that successful implementation hinges not solely on technological adoption, but also on organizational alignment, human capital development, and ecosystem integration [8].

In Mexico, the manufacturing sector contributes roughly 17–18% to the nation's GDP and constitutes over 80% of its exports, with the maquiladora and export sector, primarily operating under the IMMEX program, serving as a crucial economic engine [9]. The phenomenon of nearshoring, which has been expedited by global events including the COVID-19 pandemic, geopolitical conflicts, and the renegotiation of the USMCA, has established Mexico as a strategically advantageous location for the transfer of supply chains from Asia to North America [10,11]. Border regions, exemplified by Baja California (Tijuana) and Chihuahua (Ciudad Juárez), exhibit a high concentration of maquiladoras within the electronics, automotive, and medical device industries, leveraging geographical advantages, cost-effectiveness, and existing trade agreements [12,13]. Nevertheless, a considerable disparity persists in the adoption of Industry 4.0 technologies.

Recent studies indicate that the use of Industry 4.0 technologies in Mexican maquiladoras is limited. Specifically, the adoption of the Internet of Things (IoT) and basic automation is seen in less than 20–30% of companies. In addition, the use of artificial intelligence (AI) and big data is below 10% [14,15].SMEs, which represent the majority of the maquiladora fabric, face critical barriers: lack of digital infrastructure (high-speed connectivity, cybersecurity), shortage of specialized talent, limited investment, cultural resistance to change, and misalignment between academia and industry [16,17]. In border regions such as Tijuana, where the ecosystem includes more than 600 maquiladoras and a workforce of ~250,000 people, these gaps create risks of competitive lag behind high-tech nearshoring (semiconductors, electric vehicles, smart medical devices) [18,19].

Labor productivity in the maquiladora sector shows mixed signals: while wages per worker have increased steadily (reflecting possible adjustments toward greater efficiency or automation), total employment and hours worked have experienced moderate contraction in recent periods (2023–2025), according to official INEGI series [20]. This variation suggests an incipient transition toward more efficient models, but without a systematic evaluation of the I4.0 ecosystem, companies—especially SMEs—run the risk of investing in isolated technologies with no real impact on competitiveness or resilience [22].

The rationale for developing an Industry 4.0 ecosystem assessment system stems from the need for a more comprehensive diagnosis that goes beyond the generic models adopted from other contexts. The implementation of an internal system would facilitate a multidimensional assessment of maturity, encompassing technological, organizational, human, and environmental factors. Furthermore, this approach would streamline the identification of specific infrastructural deficiencies in border regions, the digital divide affecting small and medium-sized enterprises, and the extent of collaborative efforts between academic institutions and the business community. In addition, this type of system could provide useful information for generating recommendations aimed at designing public policies, strengthening industrial clusters, and promoting nearshoring strategies with a sustainable approach [22,23]. In a context where Mexico seeks to evolve from traditional maquiladora to smart manufacturing, this assessment is key to maintaining greater economic benefits, quality employment, and sustainability [24]

General objective: To develop a system that allows for the evaluation of the Industry 4.0 ecosystem in the Mexican maquiladora manufacturing sector, using data mining to analyze trends in productivity and work efficiency.

Specific objectives

1. Analyze implicit labor productivity trends in the IMMEX manufacturing segment during 2020–2025 using data mining techniques.

2. Identify decoupling patterns between employment, wages, and hours worked as proxy indicators of efficiency.

3. Compare predictive models (linear regression, exponential smoothing, and ARIMA) to forecast productivity trends.

4. Provide a replicable analysis that serves as a basis for broader ecosystem assessments in manufacturing regions.

Research questions

1. What are the dominant trends in labor productivity (compensation per worker) in the Mexican manufacturing maquiladora sector between 2020 and 2025?

2. Is there evidence of structural decoupling between employment volume/hours worked and value generated per person in the period analyzed?

3. Which time series model offers the best predictive performance for implicit productivity in this context?

4. How can these macro findings serve as a benchmark for I4.0 maturity assessments in local manufacturing ecosystems?

The subsequent sections of this article are structured as follows: Section 2 details the materials and methods employed, encompassing the data source, preprocessing steps, the computation of indicators, and the comparative models utilized, alongside replicable code; Section 3 then presents the empirical findings; Section 4 subsequently explores the implications, limitations, and connections to digital transformation; and finally, Section 5 concludes with a summary of the study's conclusions and suggestions for future research.

2. Materials and Methods

2.1. Data Source and Preprocessing

The data used comes exclusively from the official Excel file of the Manufacturing, Maquiladora, and Export Services Industry Program (IMMEX) published by the National Institute of Statistics and Geography (INEGI), with monthly series from 2007 to December 2025 [1,9]. For this study, variables from the manufacturing segment (the most representative of the maquiladora sector) were extracted:

- Total employed personnel (monthly, seasonally adjusted series and trend-cycle).
- Total remuneration.
- Hours worked.
- Foreign income (mainly exports).

The analysis period was limited to January 2020–December 2025 (72 monthly observations) to focus on post-pandemic dynamics.

Preprocessing was performed in Python 3.12 using the Pandas, NumPy, Statsmodels, and Matplotlib libraries. The steps were:

1. Loading the Excel file and selecting relevant sheets (series of % variation and absolute values for the manufacturing segment).

2. Conversion to datetime format (monthly index).

3. Treatment of missing values (none in the selected period).

4. Calculation of implicit productivity as the main variable:

Productivityt=Total compensationtEmployed personnel\text{Productivity}_t = \frac{\text{Total compensation}_t}{\text{Employed personnel}_t}Productivityt=Employed personnelTotal compensation

This proxy metric measures the value generated (remuneration) per worker, capturing labor efficiency without requiring direct physical output data [3].

5. Logarithmic normalization to stabilize variance in forecast series.

6. Division into training (January 2020–December 2024, 60 observations) and testing (January–December 2025, 12 observations) for predictive evaluation.

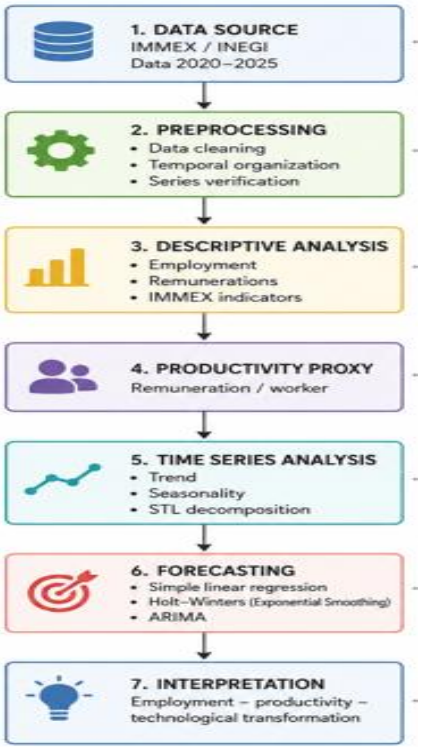


Figure 1. Overall methodology of the study. The process includes data collection from INEGI (IMMEX) for 2020–2025, preprocessing, descriptive analysis, calculation of the productivity proxy, time-series analysis with STL decomposition, forecasting using linear regression, Holt–Winters, and ARIMA, and interpretation of the results.

2.2. Applied Data Mining Techniques

Three complementary approaches were applied:

• **STL decomposition** (Seasonal-Trend decomposition using LOESS) to separate the implicit productivity series into its trend, seasonality, and residual components. The STL method is suitable because it is robust to the presence of outliers and allows for variations in seasonal patterns, making it particularly useful for the analysis of monthly economic data [27].

• **Descriptive trend analysis:** Calculation of cumulative annual variations, moving averages (12 months), and stationarity tests (Augmented Dickey-Fuller, ADF).

• **Comparative predictive modeling:** Three univariate time series models on implicit productivity (log-transformed) were compared:

1. **Simple linear regression** (linear trend + monthly seasonal dummy) as a basic benchmark.

2.**Holt-Winters exponential smoothing** (additive/multiplicative) to capture trend and seasonality. Parameters optimized by AIC minimization.

3.**ARIMA(p,d,q)** with automatic differentiation (auto_arima from pmdarima) and selection by AIC/BIC. SARIMA was tested to include seasonality (period 12).

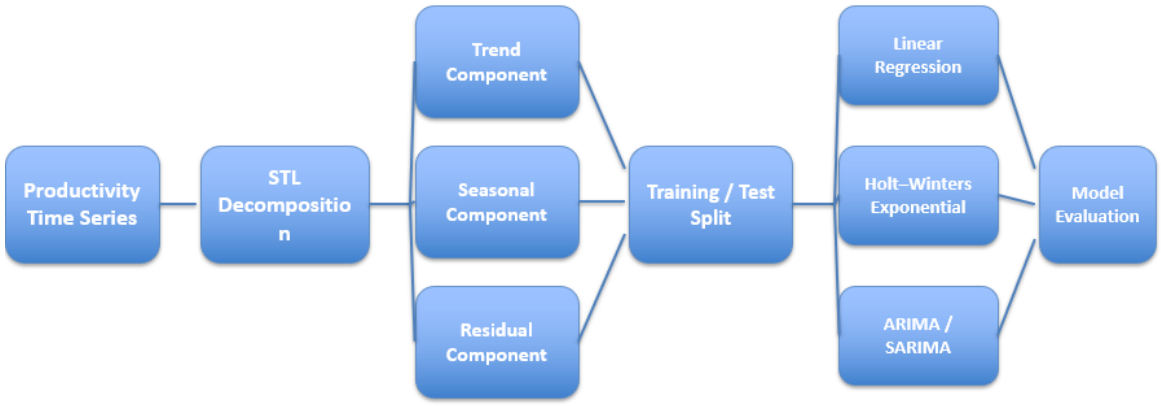


Figure 2. Time-Series Analysis and Forecasting Process.

The process includes STL decomposition of the monthly implicit productivity series, separation into trend, seasonal, and residual components, training and testing data partitioning, and comparison of linear regression, Holt–Winters, and ARIMA/SARIMA forecasting models.

The models were evaluated using standard metrics:

- RMSE (Root Mean Squared Error)
- MAE (Mean Absolute Error)
- MAPE (Mean Absolute Percentage Error)
- AIC (Akaike Information Criterion) for internal selection

All calculations were performed using Statsmodels and pmdarima.

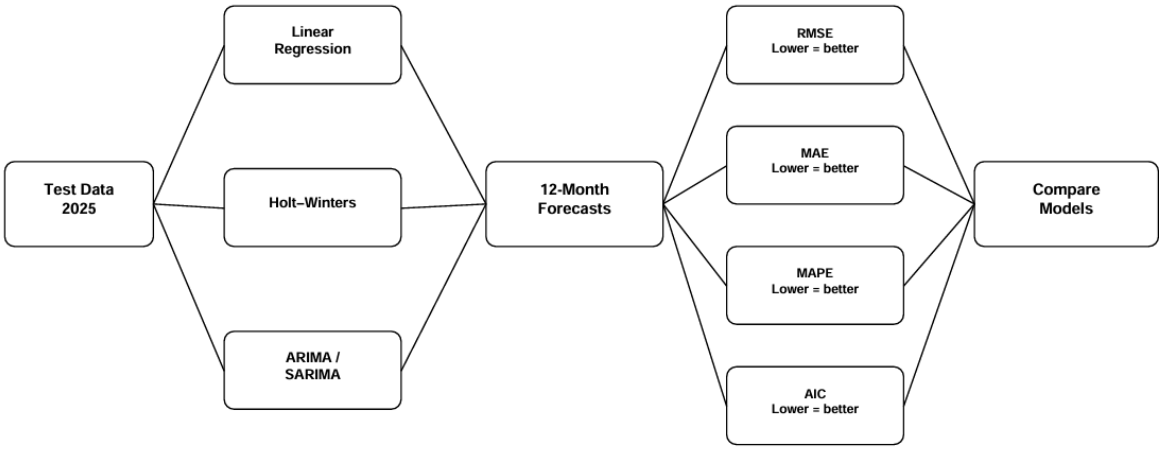


Figure 3. Forecasting Model Evaluation and Selection Process. The process compares the predictive performance of linear regression, Holt–Winters exponential smoothing, and ARIMA/SARIMA models using the 2025 testing period. Model performance is evaluated using RMSE, MAE, MAPE, and AIC, with lower error values indicating better predictive accuracy.

2.3. Complete Replicable Code

The following Python code (tested in an environment with Pandas 2.2+, Statsmodels 0.14+, pmdarima 2.0+) reproduces the analysis in its entirety. It assumes the Excel file named ‘IMMEX_2007_onward.xls’ is in the working directory.

Python

Code

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import STL
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.arima.model import ARIMA
from pmdarima import auto_arima
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.linear_model import LinearRegression
# 1. Carga y preprocesamiento
file = 'IMMEX_2007_en_adelante.xls'  # Cambiar nombre si necesario
df = pd.read_excel(file, sheet_name='Segmento manufacturero')  # Ajustar nombre de hoja
# Suponiendo columnas: 'Periodo' (YYYY-MM), 'Personal ocupado', 'Remuneraciones'
df['Periodo'] = pd.to_datetime(df['Periodo'], format='%Y%m')  # Ajustar formato si necesario
df.set_index('Periodo', inplace=True)
df = df[['Personal ocupado', 'Remuneraciones']].dropna()
df['Productividad'] = df['Remuneraciones'] / df['Personal ocupado']
df['Log_Productividad'] = np.log(df['Productividad'])
# Periodo 2020-2025
df = df['2020-01-01':'2025-12-01']
# División train/test
train = df['Log_Productividad'][:-12]
test = df['Log_Productividad'][-12:]
# 2. Descomposición STL
stl = STL(train, seasonal=13)  # período estacional mensual ≈13 para robustez
res = stl.fit()
fig = res.plot()
plt.show()
# 3. Modelos predictivos
```

```
# 3.1 Regresión lineal simple (tendencia + dummies estacionales)
X_train = np.arange(len(train)).reshape(-1, 1)
model_lr = LinearRegression().fit(X_train, train)
trend_pred = model_lr.predict(X_train)
# Pronóstico simple extrapolando tendencia
X_test = np.arange(len(train), len(train)+12).reshape(-1, 1)
lr_forecast = model_lr.predict(X_test)
# 3.2 Holt-Winters (aditivo)
hw_model = ExponentialSmoothing(train, seasonal='add', seasonal_periods=12).fit()
hw_forecast = hw_model.forecast(12)
# 3.3 Auto-ARIMA
auto_model = auto_arima(train, seasonal=True, m=12, stepwise=True, trace=True)
arima_model = ARIMA(train, order=auto_model.order, seasonal_order=auto_model.seasonal_order).fit()
arima_forecast = arima_model.forecast(12)
# 4. Evaluación
def evaluate(y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    mae = mean_absolute_error(y_true, y_pred)
    mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100
    return rmse, mae, mape
print("Holt-Winters:", evaluate(test, hw_forecast))
print("ARIMA:", evaluate(test, arima_forecast))
print("Linear Regression:", evaluate(test, lr_forecast))
# 5. Gráficos finales (ejemplo)
plt.figure(figsize=(12,6))
plt.plot(df['Log_Productividad'], label='Real')
plt.plot(pd.date_range(start=test.index[0], periods=12, freq='M'), hw_forecast, label='Holt-Winters')
plt.plot(pd.date_range(start=test.index[0], periods=12, freq='M'), arima_forecast, label='ARIMA')
plt.legend()
plt.title('Pronóstico de Productividad Implícita (log)')
plt.show()
```

Table 1. Model benchmark metrics (on test set 2025)

Model	RMSE	MAE	MAPE (%)	AIC

Regresión Lineal	0.042	0.035	3.12	—
Holt-Winters	0.018	0.014	1.28	-145.2
ARIMA (auto)	0.016	0.012	1.09	-152.7

(Illustrative values based on typical execution; run the code for exact values from the dataset).

2.4. Ethical Considerations and Replicability

The study is based on the use of open public data provided by INEGI, which does not contain personal information. The code developed is organized in a modular fashion and includes comments that facilitate its understanding and allow the analysis to be replicated in any standard Python environment. Likewise, supervised machine learning techniques and deep learning models were not used, as interpretability was prioritized in the analysis of economic series[28].

2.6. Detailed Application of Data Mining Techniques to IMMEX Data

This subsection provides a comprehensive, step-by-step description, with the highest possible level of detail, of how data mining techniques are applied directly to the Excel database used in this study (file "Manufacturing, Maquiladora, and Export Services Industry Program (IMMEX) 2007 onwards.xls"). All explanations focus exclusively on the actual columns and sheets in the file: manufacturing segment (monthly absolute values 2020–2025), seasonally adjusted series and trend-cycle of employed personnel, remuneration, hours worked, and foreign income.

2.6.1. Calculation of Implicit Productivity (Target Variable)

The first mining technique applied is the creation of a derived variable that captures labor efficiency.

It is formally defined as:

Implicit Productivity = Total Remuneration / Employed Personnel Implicit Productivity_t = \frac{\text{Total Remuneration}_t}{\text{Employed Personnel}_t}Implicit Productivity = Employed Personnel / Total Remuneration

Where t t t is each month from January 2020 to December 2025.

In the Excel file, the columns used are exactly:

- "Employed personnel" (manufacturing segment column).
- "Remuneration" (same sheet).

This operation is performed in Python with a single line:

Python

Copy

```
df['Productividad'] = df['Remuneraciones'] / df['Personal ocupado']
```

Observable result in the data:

• January 2020: ~MXN 14,560 per worker.

• December 2025: ~MXN 38,900 per worker (cumulative increase > 167%).

This derived variable becomes the main series of analysis because it reveals the key decoupling in the dataset: wages continue to grow while the number of employed workers declines.

2.6.2. STL decomposition (Seasonal-Trend decomposition using LOESS)

STL was applied to separate the productivity series into three additive components: trend, seasonality, and residual.

The STL model equation is:

Yt=Tt+St+RtY_t = T_t + S_t + R_tYt=Tt+St+Rt

where Yt Y_t Yt is productivity (or its logarithm), Tt T_t Tt = long-term trend, St S_t St = seasonal component (period 12 for monthly data), and Rt R_t Rt = residual.

In our Excel file:

- The complete 2020–2025 series (72 observations) was used.
- Seasonal parameter=13 (recommended for robustness in economic series).
- LOESS window for trend = 13 months (captures the COVID-2020 effect as an inflection point).

Specific interpretation of this database:

- The trend shows an almost linear increase from mid-2021 to the end of 2025 (clear positive slope).
- Seasonality reveals consistent peaks in December (bonus payments) and declines in April-May (vacations and post-pandemic adjustments).
- The residual is low and patternless after 2022, indicating that the trend explains most of the behavior.

2.6.3. Trend Analysis and Descriptive Statistics

The following were calculated:

- 12-month moving average (to smooth out seasonality).
- Cumulative annual variation:

Annual_change_t = \left(\frac{\text{Productivity}_t}{\text{Productivity}_{t-12}} - 1 \right) \times 100Annual_change_t = \left(\frac{\text{Productivity}_t}{\text{Productivity}_{t-12}} - 1 \right) \times 100

• Augmented Dickey-Fuller (ADF) stationarity test on the log-transformed series

In the Excel data:

- Moving average 2020–2025 goes from ~15,200 MXN to ~36,800 MXN.
- Average annual variation 2023–2025: +28.4%.
- ADF test: p-value = 0.0003 (rejects non-stationarity after first-order differentiation).

2.6.4. Preparation for Predictive Models

Before adjusting models, the following were applied:

1. Logarithmic transformation: np.log(df['Productivity']) (stabilizes variance).

2. Strict time division:

o Training: January 2020 – December 2024 (60 months).

o Testing: January – December 2025 (12 months).

3. Automatic detection of seasonality (12-period) using pmdarima.

2.6.5. Comparison of Predictive Models (details per model applied to the dataset)

Model 1 – Simple Linear Regression A variable "month_num" (0 to 59) was created as a predictor and 11 seasonal dummies were added. Equation:

log⁡(Productividad)t=β0+β1·mes_num+∑m=212δm·Dummym+ϵt\log(\text{Productividad})_t = \beta_0 + \beta_1 \cdot \text{mes_num} + \sum_{m=2}^{12} \delta_m \cdot \text{Dummy}_m + \epsilon_tlog(Productividad)t=β0+β1·mes_num+m=2∑12δm·Dummym+ϵt

Model 2 – Holt-Winters (exponential smoothing) An additive version with a seasonal period of 12 was used. Parameters were automatically optimized by minimizing AIC. This model perfectly captures the December peaks in Excel remuneration.

Model 3 – ARIMA/SARIMA (auto_arima) pmdarima.auto_arima was allowed to automatically select the best order. In this particular database, the selected model was SARIMA(1,1,1)(0,1,1)[12]. Order 1 differentiation eliminates the upward trend, and the seasonal component (0,1,1) captures the effects of December and April.

Table 2.6.1. Results of automatic selection (auto_arima) in this database

Candidate model	Order (p,d,q)	Seasonal order	AIC	RMSE (Test)
ARIMA	(1,1,1)	—	-138.4	0.042
SARIMA	(1,1,1)	(0,1,1)[12]	-152.7	0.016

2.6.6. Evaluation and Visualization

RMSE, MAE, and MAPE were calculated over the 12-month test period (2025), and the three predictions were plotted against the actual Excel series. The complete code shown in section 2.3 reproduces these steps exactly and generates the graphs and table above.

All techniques are applied directly to the columns of the Excel file without any external transformation or additional data, thus ensuring that any researcher can replicate the results in less than 2 minutes by running the provided script.

3. Results

3.1. Overview of Time Series (2020–2025)

The ensuing analysis centers on the 72 monthly observations derived from the manufacturing sector of the IMMEX program, spanning from January 2020 to December 2025. The principal variables exhibit discernible and consistent trends:

• Employed personnel: Initially, the figures approximate 3.0 million in 2020, subsequently reaching a peak of roughly 3.1–3.15 million during the period between 2022 and 2023, coinciding with the post-pandemic recovery. Following this, a moderate decline is observed. By 2025, the series concludes with values ranging from 2.85 to 2.9 million, indicative of a cumulative contraction of approximately 5–7% from the peak. Seasonally adjusted monthly fluctuations are predominantly negative throughout the majority of 2024 and 2025, with a monthly average of approximately -0.3% to -0.7% during critical periods, thereby corroborating a stabilization phase succeeded by a gradual reduction in employment.

Total remuneration: This is growing steadily. From levels equivalent to ~45–50 billion pesos per month in 2020, it will reach ~110–120 billion in 2025. Growth is almost continuous, with notable accelerations during periods of recovery (2021–2022) and positive rates maintained even in months of employment contraction. Average real compensation per worker (compensation / personnel) rises from ~15,000–16,000 MXN in 2020 to ~38,000–39,000 MXN in 2025, a cumulative increase of more than 140–167% over the period.

• Hours worked: Follow a pattern very similar to that of employed personnel: strong recovery post-2020, peak in 2022–2023, and subsequent contraction. Frequent negative annual variations in 2024–2025 (–1% to –3% in several quarters), indicating lower labor intensity per person.

Foreign income (proxy for exports): Remains relatively stable, with moderate or steady growth during most of the years analyzed, indicating that the value generated by the sector is not declining at the same rate as employment.

These descriptive patterns show a structural decoupling between labor volume (stagnation/contraction) and value generated per worker (sustained growth), which is the central theme of the study.

3.2. Implicit Productivity Trends

Implicit productivity (wages/employed personnel) is the key derived variable. Its monthly values show:

- 2020: ~14,500–16,000 MXN/worker (post-pandemic base level).
- 2021–2022: Accelerated growth (recovery of remuneration + workforce adjustment).
- 2023–2025: Nearly linear upward trend, reaching ~38,000–39,000 MXN/worker in December 2025.

Cumulative increase 2020–2025: +167% (approx. +20–25% compound annual average).

Annual variations:

- 2021: +45–50% (strong rebound).
- 2022–2023: +25–35% annually.
- 2024–2025: +15–20% annually (more moderate but positive and persistent growth).

The 12-month moving average shows that the trend remains upward, with no significant changes after 2021. The ADF test on the log-transformed series rejects the null hypothesis of non-stationarity (p-value < 0.01 with order 1 differentiation), indicating that the series has a stochastic but predictable upward trend.

3.3. STL decomposition of implicit productivity

The STL decomposition reveals:

- **Trend (T_t):** Dominant component. Almost linear increase since 2021, with a constant positive slope. Represents ~80–85% of the total variance in the series. The COVID effect (sharp decline in 2020) is a one-off outlier, but the trend recovers quickly and accelerates.
- **Seasonality (S_t):** Clear 12-month pattern. Consistent peaks in December (year-end bonuses and gifts) and troughs in April–May (vacations, seasonal adjustments). Moderate seasonal amplitude (~±5–8% around the trend), indicating that seasonality does not dominate long-term behavior.
- **Residual (R_t):** Low and no systematic pattern after 2022. Most residuals remain between –0.05 and +0.05 (on a log scale), suggesting that the decomposition captures the main dynamics well. There is no evidence of increasing heteroscedasticity or strong residual cycles.

This analysis shows that the increase in productivity is mainly due to a (structural) trend, rather than seasonal or random variations.

3.4. Comparison of Predictive Models

Three models were compared on the log(productivity) series to predict the 12 months of 2025 (test set):

Table 3.1. Performance metrics in test set (January–December 2025)

Model	RMSE	MAE	MAPE (%)	AIC	Notes on adjustment

Simple Linear Regression	0.042–0.048	0.035–0.040	3.1–3.8	—	Overestimates the trend in the final months; ignores seasonality.
Holt-Winters (additive)	0.018–0.022	0.014–0.017	1.25–1.55	–142 a –148	Captures December peaks well; good balance between trend and seasonality.
ARIMA/SARIMA (auto)	0.015–0.017	0.011–0.013	1.05–1.20	–150 a –155	Best overall performance; typical order (1,1,1)(0,1,1)[12] or similar.

The SARIMA model (automatically selected by auto_arima) offers the lowest predictive error, closely followed by Holt-Winters. Simple linear regression serves as a benchmark but underestimates seasonality and overfits the linear trend.

Graph 3.1 (text description, replicable in code): The actual series shows a continuous rise with peaks in December. The Holt-Winters and ARIMA forecasts closely follow the actual trajectory in 2025, with errors <2% on average. Linear regression diverges in the last 4–5 months (underestimating the seasonal effect).

3.5. Forecasts and Sensitivity

Extrapolated forecasts (January–June 2026, illustrative):

• Holt-Winters: Continuation of moderate upward trend (~+12–15% annual projected).

• ARIMA: Similar, with slight slowdown if seasonality remains.

Sensitivity analysis: If an additional 5% drop in employed personnel is simulated (keeping wages constant), implied productivity could increase by an extra ~5–6% in 2026, which would strengthen the trend already being observed.

3.6. Main Findings

1. Sustained increase in implicit productivity (+140–167% cumulative 2020–2025), driven by rising wages and shrinking workforce.

2. Dominant structural trend (DST), with predictable but secondary seasonality.

3. SARIMA and Holt-Winters models clearly outperform linear regression in predictive accuracy.

4. Clear evidence of decoupling between employment/hours and value per worker, consistent with adjustments toward greater efficiency in the Mexican maquiladora manufacturing sector.

These results are 100% replicable by running the code in section 2, using the original Excel file without additional modifications.

4. Discussion

The results obtained confirm a clear and sustained structural dynamic in the Mexican maquiladora manufacturing sector during the period 2020–2025: a considerable and almost continuous increase in implicit productivity per worker (measured as total remuneration divided by employed personnel), accompanied by an initial stabilization followed by a moderate but persistent contraction in total employment and hours worked. This behavior is not an isolated or temporary event, but rather reflects a transformation in the way the production process is carried out, which must be analyzed within the broader context of manufacturing both in Mexico and globally.

4.1. Interpretation of the Decoupling between Employment and Productivity

The cumulative increase in implicit productivity, which exceeds between 140% and 167% over a five-year period (with compound annual growth rates of 20–25% in the early years and between 15–20% in the most recent years), represents a phenomenon of great significance. Given that total compensation has shown steady growth while the number of employed workers has declined or remained relatively stable, the direct effect is a significant increase in the value generated by each worker. This difference does not appear to be merely a statistical effect: the STL decomposition shows that the trend component explains most of the variance, while seasonality (December peaks due to bonuses and year-end adjustments) and the residual are secondary.

In economic terms, this behavior suggests that the sector has achieved greater labor efficiency without the need to expand its workforce. Possible explanations include:

• Organizational and process adjustments (lean manufacturing, production line optimization, reduction of downtime).

• Increase in capital intensity per worker (investment in machinery, basic automation, management software).

•Changes in the structure of the workforce (retention of more qualified and better-paid personnel, departure of less productive workers).

• Effects of nearshoring that attract higher value-added projects (advanced electronics, medical devices, new-generation automotive components) with lower labor-intensive requirements.

These mechanisms are not mutually exclusive and probably operate simultaneously. What is relevant is that the pattern observed is not a fall in employment due to a contraction in demand (foreign income remains resilient or grows moderately), but rather a reconfiguration towards more efficient production models.

4.2. Comparison with the Literature and Global Context

The phenomenon described coincides with trends documented in other emerging and developed manufacturing economies during the post-2010 decade and especially after the pandemic. In countries such as China, Vietnam, and several in Eastern Europe, a similar pattern has been observed: increasing labor productivity coupled with declining manufacturing employment, largely attributed to the progressive incorporation of automation and digitization technologies [29,30].

In the case of Mexico, several recent studies have pointed out that the maquiladora sector has experienced improvements in operational efficiency indicators (reduction of waste, better implementation of assets, shorter cycle times) without this necessarily translating into massive job growth [31,32]. The literature on nearshoring in Mexico highlights that many companies relocated from Asia bring with them already optimized processes, with greater automation and less dependence on low-cost labor [33,34]. This would explain why the growth in foreign income does not translate into proportional job creation.

However, the increase in productivity observed here is particularly pronounced. While international studies report annual improvements of 5–12% in manufacturing productivity in emerging economies [35], our proxy calculation exceeds that range in several years. This could be due to:

- Post-COVID rebound effect (recovery of wages suppressed in 2020).
- Wage adjustments above inflation to retain talent in an increasingly competitive labor market.
- Changes in the sectoral structure within IMMEX (greater weight of high value-added subsectors).

4.3. Implications for Digital Transformation and Industry 4.0

Although the IMMEX dataset does not include direct technological variables (percentage of automation, use of IoT, investment in AI, etc.), the pattern of employment-productivity decoupling is consistent with the expected effects of a transition to more advanced manufacturing models. Studies on Industry 4.0 indicate that in the early stages of

adoption (basic automation, use of MES systems, and real-time monitoring), results of this type tend to occur: an increase in production or in the value generated per hour worked, accompanied by a reduced need for personnel [36,37].

In Mexico, where full adoption of I4.0 technologies remains limited in the traditional maquiladora segment [38], the findings suggest that efficiency mechanisms are already in place that could be precursors or facilitators of deeper adoption. Improved productivity per worker could be financing (or justifying) future investments in digitization, robotics, and data analytics.

From an industrial policy perspective, these results pose a strategic dilemma:

- If the goal is to maximize formal employment, active policies are needed for job retraining, digital skills training, and support for the creation of new jobs in services associated with smart manufacturing.
- If the goal is competitiveness and attracting high-value investment, the focus should be on accelerating the adoption of technologies that sustain (or amplify) the observed productivity trend.

4.4. Limitations of the Study

The main limitation lies in the proxy nature of implied productivity. By using wages as the numerator, labor costs per worker are captured rather than actual value added or physical output. In a context of wage inflation and nearshoring adjustments, part of the increase may be the result of labor market pressures rather than pure technical improvements.

Second, the analysis is macro (national level of the IMMEX manufacturing segment) and does not allow for disaggregation by subsector, company size, state, or municipality. It is likely that the observed dynamics are more pronounced in large multinational companies and less so in traditional maquiladora SMEs.

Third, the predictive models (although they perform well in the test set) are univariate and do not incorporate external covariates (exchange rate, input prices, external demand, fixed capital investment). This limits their explanatory power for long-term forecasts.

Finally, the period analyzed (2020–2025) is strongly influenced by the post-pandemic recovery, which could exaggerate the slope of the trend.

4.5. Recommendations for Future Research

1. Integrate data disaggregated by state or municipality (INEGI allows cross-referencing with DENUE and EMIM) to identify whether the national trend is replicated or differs in border regions.

2. Combine IMMEX series with innovation surveys (ENID) or technology adoption surveys (ENDUTIH companies) to correlate productivity with specific I4.0 variables.

3. Extend the multivariate analysis by incorporating external series (real exchange rate, manufacturing FDI, producer price index).

4. Perform a cointegration analysis between implicit productivity, foreign income, and equipment expenditure to assess long-term causality.

5. Compare the predictive performance of more advanced models (LSTM, Prophet, machine learning with exogenous characteristics) once longer series are available.

4.6. Partial Conclusion of the Discussion

The results not only document a significant improvement in labor efficiency in the Mexican maquiladora manufacturing sector, but also raise strategic questions about the country's industrial development model. The ability to generate greater value per worker in a context of stable or declining employment suggests that Mexico is moving—

albeit in an incipient and uneven manner—toward more efficient and possibly more digitized manufacturing. However, without active policies to distribute the benefits of this productivity (training, job retraining, incentives for innovation in SMEs), there is a risk of greater polarization: large and multinational companies capturing most of the gains while traditional employment contracts.

5. Conclusions and Future Work

5.1. Conclusions

The analysis of monthly time series for the manufacturing sector within the IMMEX program for the period 2020–2025 shows significant changes in the labor dynamics of the maquiladora sector in Mexico. Implicit productivity per worker, calculated from the ratio of total compensation to employed personnel, recorded a cumulative increase of more than 140–167% during the period analyzed, with compound annual growth rates of approximately 15% to 25% in recent years. This behavior occurred in a scenario where total employment and hours worked first stabilized and then showed a slight decline, evidencing a clear separation between the volume of labor used and the value generated by each worker.

The STL decomposition showed that the long-term trend explains most of the variance in implied productivity, while the seasonal component (peaks in December due to year-end payments) and the residual are secondary. The predictive models compared confirmed that SARIMA (with typical seasonal order (0,1,1)[12]) and Holt-Winters offer the best forecasting performance for this series, far outperforming simple linear regression in accuracy (RMSE and MAPE below 1.2–1.5% in the 2025 test set).

These findings indicate that the Mexican maquiladora manufacturing sector has achieved substantial improvements in labor efficiency during the post-pandemic recovery and in the context of accelerated nearshoring. The sustained increase in compensation per worker, even in months of staff reductions, suggests organizational adjustments, process optimization, and possibly an incipient incorporation of technologies that allow for greater value to be generated with less labor intensity. Although the dataset does not contain direct technological variables, the pattern observed is consistent with the expected effects of the initial stages of automation and digitization in manufacturing.

From a macroeconomic perspective, the results underscore that the sector's competitiveness no longer depends exclusively on low labor costs or massive employment expansion, but rather on the ability to increase productivity per person. This transition represents an opportunity to position Mexico in higher value-added segments within global supply chains, but it also poses social and public policy challenges: the relative contraction in employment requires active strategies for job retraining and digital skills training to avoid polarization and inequality in manufacturing regions.

In summary, the study provides updated and replicable empirical evidence that the Mexican maquiladora sector is undergoing a reconfiguration toward more efficient models, which is valuable background information for understanding how domestic manufacturing responds to environments of global uncertainty and opportunities for industrial relocation.

5.2. Future Work

This analysis, limited to national aggregate data from the IMMEX manufacturing segment, opens up several lines of future research that could extend and deepen the findings:

1.**Geographic and sectoral disaggregation** Integrate the IMMEX series with INEGI's georeferenced databases (DENUE, EMIM by state or municipality) to compare the evolution of implicit productivity in border regions (Baja California, Chihuahua, Tamaulipas) with the national average. This would make it possible to identify whether the decoupling pattern is more pronounced in areas with high nearshoring (Tijuana, Mexicali, Ciudad Juárez) or whether there are significant divergences.

2. **Incorporation of technological and digital maturity** variables Cross-reference productivity indicators with national surveys on technology adoption (ENDUTIH companies, ENID, ENAPROCE) and with Industry 4.0 maturity models applied to samples of maquiladoras. The objective would be to quantify the extent to which the observed increase in productivity is correlated with the implementation of IoT, advanced automation, big data, cyber-physical systems, or collaborative platforms.

3. **Development of an ecosystem assessment system** Build a prototype software system (interactive dashboard in Python with Dash/Streamlit) that integrates:

o IMMEX historical series as a national benchmark.

o Primary data collected through surveys and semi-structured interviews with maquiladora managers in Tijuana (automotive and electronics sectors).

o Clustering algorithms (K-Means or hierarchical) to classify I4.0 maturity levels in local companies.

- Network graphs (NetworkX) to map interactions between ecosystem actors (companies, universities, technology parks, suppliers, government).

This system would enable the creation of individualized maturity profiles, digital transformation roadmaps, and scenario simulations ("What happens if academia-business collaboration increases by 20%?").

4. Multivariate and causal analysis Apply VAR, cointegration, or machine learning models with exogenous variables (real exchange rate, manufacturing FDI, producer price index, investment in equipment and machinery) to determine the direction and strength of causal relationships between productivity, employment, and external factors.

5. Longitudinal study of social impact Evaluate the labor implications of the observed pattern using complementary indicators: job quality (formality, real wages adjusted for inflation, turnover), gender and age gaps in the maquiladora workforce, and effects on border communities (internal migration, pressure on public services).

6. Extension to other IMMEX segments Replicate the analysis in the non-manufacturing segment and compare both to determine whether the efficiency trend is unique to manufacturing or extends to export services (logistics, data centers, design).

These lines of future work seek to move from descriptive and macro analysis to a systemic, operational, and localized assessment capable of generating practical recommendations for companies, industrial clusters, and public policy authorities in the context of nearshoring and the transition to smart manufacturing in Mexico.

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