US Equity Market Volatility Index Components, Impact on the Industrial Production Index and Post Covid-19 Forecasting: Relevance to Mexico

Componentes del índice de volatilidad del mercado de valores de EE. UU., impacto en el índice de producción industrial y pronóstico post Covid-19: Relevancia para México

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Abstract

This research aims to analyze whether the 42 category-specific Equity Market Volatility (EMV) trackers explain the US industrial production index (IPI) including the impact of the Covid-19 crisis. IPI values are forecasted, considering three scenarios of economic recuperation after the end of the Covid-19 pandemic. To achieve this purpose, first an Artificial Neural Network is employed to determine if the EMV categorical tracker elements explain Industrial Production. Once, the incidence of the EMV trackers on IPI is evidenced, an ARIMA model is used to forecast the Industrial Production Index from June 2021 to December 2022. Motivation for this research and its originality is the strong economic and financial links of the Mexican economy with the U.S. Economy. Current economic trends in Mexico, particularly its economic recovery partly linked to the U.S economic recovery.

JEL Code: C12, C45, C53, D53, G01

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Keywords: Impacts Covid-19; equity market volatility; U.S. industrial index; artificial neural network; ARIMA model; Mexico

Resumen

El propósito de la presente investigación es analizar si las 42 categorías específicas de los rastreadores de volatilidad del mercado accionario (EMV) explican el índice de producción industrial (IPI) de Estados Unidos, incluyendo el impacto de la crisis Covid-19. Se pronostican los índices de producción industrial considerando tres escenarios de recuperación económica con el fin de la pandemia del Covid-19. Para alcanzar este propósito, primero se emplea una Red Neural Artificial para determinar si el rastreador categórico EMV explica la producción industrial. Una vez que tal proposición es comprobada, se utiliza un modelo ARIMA para pronosticar el índice de producción industrial de junio de 2021 a diciembre 2022. La motivación para esta investigación y su originalidad son los fuertes lazos económicos y financieros que prevalecen entre México y Estados Unidos. Las tendencias económicas de México, y en particular su recuperación económica está vinculada con el mejoramiento de la economía de Estados Unidos.

Código JEL: C12, C45, C53, D53, G01
Palabras clave: Impactos Covid-19; volatilidad del mercado accionario; índice producción industrial de Estados Unidos; redes neurales artificiales; modelo ARIMA; México

Introduction

The unprecedented COVID-19 crisis has nurtured the application of new indicators to measure the impact of diverse factors on key financial variables such as the equity market volatility index. The equity market index shows the overall conditions of the market and identifies general patterns and conditions about the main firms of an economy. Similarly, the Equity Market Volatility is a risk measure which reflects the expected investors’ market sentiment (optimism-pessimism) and it is employed to design investment strategies both to prevent losses, as well as to maximize profits. In unexpected exogenous negative impacts like that brought about by the Covid-19 pandemic, market sentiment is highly psychological, and it is marked by severe swings, particularly in the case of this pandemic characterized by millions of disease cases and sensible casualties. Moreover, the pandemic has evolved in cycles around the world with a permanency of near two years.

One useful index to trail market sentiment is the Equity Market Volatility (EMV) created by Baker et al. (2019); is a newspaper-based index and it moves with Chicago Board of Exchange (CBOE) Volatility Index (VIX) and with the realized volatility of returns on the Standard and Poor’s 500 (S&P 500). To construct the overall EMV tracker, 42-category specific EMV trackers are created to quantify
the importance of each category in the level of the U.S. stock market volatility and its movements over time (Baker et al., 2019).

The equity market is a key variable in the economy. It allows funding companies and offers different investment opportunities. Since stock indexes are a financial activity referent about the main companies in the US, their behavior also affects real investment decisions. This fact has been reported by several studies which evidence that stock market behavior is effective forecasting investment and output growth (Barro, 1990; Fama, 1990; Levine, 2003; Chiang & Chen, 2017).

In efficient stock markets, equity returns give information about firm’s expectations of future cash flows and discount rates, providing signals to estimate the industrial production and investor’s expectations (Fama, 1990; Schwert, 1990). In turn, stock market volatility reflects the future uncertainty of cash flows, negatively affecting investor’s views over the risk-return decision mapping which upsets future economic activity (Schwert, 1989). Another linkage between stock markets and the real economy occurs concerning stock market volatility raises; the cost of funding also increases, and it is necessary to compensate investors for bearing additional risk. Higher cost of equity financing jeopardizes business liquidity and industrial production.

Based on the previous theoretical framework and motivated by the importance of this phenomena under the prevailing crisis to the world economy, in particular to the Mexican economy, the objective of this research is to analyze whether the 42-category specific EMV trackers explain the US industrial production index (IPI). Once the main determinants of IPI are identified, future IPI values are forecasted. To achieve this purpose, first an Artificial Neural Network (ANN) is employed to determine if the EMV categorical tracker explain Industrial Production. The hypothesis is, due to the wide variety of concepts and factors included in the EMV, category-specific EMV trackers accurately describe the IPI performance.

The World Health Organization estimated the end of the pandemic by June 2021. Accordingly, in this work, once, the incidence of the EMV trackers on IPI is evidenced, an ARIMA model is used to forecast the Industrial Production Index from June 2021 to December 2022. The 42-category specific EMV trackers were obtained from the web page: Economic Policy Uncertainty/ US EMV2 and the Industrial Production Index was download from the Federal Reserve Economic Data3. Monthly data employed comprises the period January 1985 to May 2021.

It is very important to stress the importance of this work to the Mexican economy. Although, its amelioration depends on many internal factors, advancement of the U.S. economy is the main driver for Mexico’s economic activities and economic growth. Strong, formal trade and investment links between

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2 https://www.policyuncertainty.com/EMV_monthly.html
3 https://fred.stlouisfed.org
these two nations dates to the 1994 North American Free Trade Agreement of this nation with the U.S. and Canada, now updated since 2018 with the United States-Mexico-Canada-Agreement (USMCA).

In that context, currently, Mexico is the U.S. first trading partner. Mexican exports to the U.S represent 89 percent of its total exports. Trade forecasts for 2021 and 2022 amount to US$38,000 million and 41,000, respectively (Trading Economics, 2021). Similarly, foreign direct investment estimated at US$ 628 billion in 2019 comes mainly from the United States, Spain, Canada and Germany (Lloyds Bank, 2021). Thus, the economic recovery of Mexico is strongly tied to the economic performance of its Northern partner.

Due to the pandemic, 2020 was a very critical year for the Mexican economy. GDP decreased by 8.5%, 12 million jobs were lost. Moreover, due to unemployment and the lockdown, quarterly home wages decreased by almost 11 percent in relation to 2018; income inequality also increased. Nevertheless, hopefully, better times are apparently ahead thanks to the advance in vaccination and significative increases of exports to the United States. In fact, an optimistic update of the IMF predicts Mexico’s growth for 2021 at 6.3% a bit below the government forecast of 6.5% (Mexico News Daily, 2021).

This positive path is partly due to the high and rapid expansion of the U.S. economy. Its GDP has already surpassed pre pandemic levels and during 2021 is expected to grow close to 7.0 percent, following a 3.4% downfall in 2020, the worst in 74 years (Politico National Security Daily, 2021). Restoring previous activity levels, the industrial sector index is currently at 105.7, albeit it is still below the 110.0 pre pandemic level. Signaling this recovery, and potential future performance, is a strong stock market performance. Market sentiment has been positive to the extent that during the first semester of 2021, the Standard and Poor Index increased 14.4% (Justice News Flash, 2021). However, full recovery has not been smooth and will not be straightforward; the very contagious Delta covid-19 virus is now rising deep concerns among investors. Hence, various scenarios, which will impact Mexico, including positive and negative economic performance must be considered for the U.S. post pandemic future.

To delve into the inquires posed in this introduction, the remaining of the work has been structured in four sections. Section two reviews the literature, section three presents the methodology and data, section four presents the results, and section five, by way of conclusion offers some suggestions for a prompt and steady recovery of the Mexican economy.

**Literature Review**

The relationship between economic factors and stock market performance has been present permanently in the financial literature. Influenced by fundamental analysis, research has most frequently focused on the impact of micro and macroeconomic variables on stock prices and returns. Nevertheless, stock market
activity has also been considered a leading indicator of future economic activity, focusing regularly on industrial production, generally considered a proxy of GDP. Considering their importance, and long-term approach, the works by Fama (1990) and Schwert (1990) can be considered pioneer research in this area and take-off point for further research. Other representative contributions are those by Demirgüç-Kunt and Levine (1996), Arestis et al. (2001), Cooray (2010), Nwaolisa and Chijidu (2016), Abbas et al. (2018), Abraham (2018), and Camilleri et al. (2019).

Due to the severity of the Covid-19 crisis, in affinity with this paper, that strand of research has now been replaced by studies aiming to measure the impact of this crisis on stock markets performance and volatility and in turn on industrial production. To uncover the impact of the Covid-19 crisis on stock market volatility, Bay et al. (2021) employ an extended GARCH-MIDAS model and a newly developed Infectious Disease Equity Market Volatility Tracker (EMV-ID). Bay et al. (2021) measure the impact of the pandemic on the stock markets of US., UK, China, and Japan. Their evidence shows that, up to 24-month lag, the pandemic has significant positive impacts on the permanent volatility of international stock markets, even after controlling the influences of past realized volatility, global economic policy uncertainty and the volatility leverage effect.

August-Iaroto et al. (2021) employ high-frequency data to investigate the impact of the COVID-19 pandemic in 53 emerging and 23 developed countries. COVID-19 cases and deaths negatively impact stock returns and increase volatility and trading volume. Cases and deaths affected stock returns and volatility in emerging markets, while only cases of COVID-19 impacted stock returns, volatility, and trading volume in the developed markets.

Dealing with impacts at the industrial level, Baek et al. (2020) examine the effect of the Covid-19 pandemic on the U.S. stock market volatility at the industry level. The empirical evidence reveals that volatility is impacted by specific economic indicators and is sensible to Covid-19 news. Negative news impact is greater than positive news, suggesting a negative bias. Idiosyncratic risk increases significantly across all industries, but systematic risk changes differently across industry.

Following this strand of research are the works by Sadiq et al. (2021), Izzeldin et al. (2021), Bay et al. (2021), and Mazur et al. (2020). Sadiq et al. (2021) examine the impact of COVID-19 on emerging stock markets in seven of the Association of Southeast Asian Nations’ (ASEAN-7) member countries. A ST-HAR-type Bayesian posterior model identifies a clear regime transition. Crises vary in intensity and timing. Health care, consumer services and technology were the most adversely affected sectors. Regarding stock markets, chance that Covid-19 would positively impact their performance is nil in all the countries. Finally, the evidence shows that COVID-19 fear generates stock market volatility.

Similar results are reported by Izzeldin et al. (2021) exploring the impact of the of Covid-19 pandemic on the stock markets of the G-7 and their business groups. Results show a solid shift to a crisis
regime in all markets, but the intensity and timing of the crisis vary. Considering their business sectors, the Health Care and Consumer services sectors were the most affected. The Technology sector was hit the latest and least severely. United Kingdom and the United States were the most affected with the highest heterogeneity in response of their business sectors.

In turn, Mazur et al. (2020) investigating the S&P 500 listings find that natural gas, food, healthcare, and software stocks earn high positive returns, whereas equity values in petroleum, real estate, entertainment, and hospitality sectors sharply declined. Furthermore, loser stocks showed excessive asymmetric volatility that correlates negatively with stock returns. Firms’ reaction was diverse to the COVID-19 revenue shock.

Expanding these lines of research to include spillovers are, Wang, et al. (2020), Shazad et al. (2021), Farid et al. (2021), and De la Torre-Torres (2020). Wang, et al. (2020) examine the dynamic variation of volatility spillovers between several major international financial markets during COVID-19 period employing Diebold and Yilmaz’s connectedness index. Results indicate that this pandemic has generated enormous shocks to international financial markets, particularly in those nations where the pandemic was serious. Total volatility spillover reached its highest level in ten years in March 2020, while the health crisis reached its worst level in April. The evidence confirms that the American and British markets are the most important spillover transmitters, while the Chinese and Japanese, as well as GBP/USD exchange rate are spillover recipients. Additionally, pairwise directional spillover between American and British stock markets is larger than other pairs. GBP/USD exchange rate and WTI crude oil futures market mainly receive spillovers from American stock market. Results show that the COVID-19 pandemic has caused huge shocks to international financial markets, especially of those countries with severe pandemics, and the pandemic led to increased spillovers between financial markets.

Consequently, Shazad et al. (2021) study inter-sectoral volatility linkages in the Chinese stock market stressing asymmetric volatility spillover among sectors in realized volatility connectedness. The authors build networks of generalized forecast error variances by decomposition of a vector autoregressive model, controlling for overall market movements. The evidence shows the presence of the asymmetric impact of good and bad volatilities. These are time-varying and substantially intense during the COVID-19 period. Moreover, bad volatility spillover shocks dominate good volatility spillover shocks.

Utilizing 5-minures high-frequency data, Farid et al. (2021) present the evidence of high variations in the structure and time-varying patterns of volatility connectedness across equities and main commodities (oil, gold, silver and natural gas) in the US economy before and during the COVID-19 outbreak. The most actively traded US ETFs is used to construct the volatility connectedness network. Intraday volatility estimates are applying MCS-GARCH model and then employ Diebold and Yilmaz spillover index approach to approximate volatility spillovers between the financial markets. Main findings
signal significant impact of COVID-19 pandemic on the volatility linkages of financial markets as the volatility connectedness among the different assets peaked during the outbreak.

Finally, concerning Mexico, De la Torre-Torres (2020) examine VIX volatility, economic and trade policy, and infectious disease COVID-19 news sentiment indexes. The aim is to measure their impact in the probability of being in a high volatility episode in the Mexican stock exchange, using monthly data covering data from January 1996 to August 2020, Markov-Switching models are used to estimate the smoothed high volatility regime probabilities. Integrating these estimates with market sentiment indexes, logit models are estimated to verify that the COVID-19 news uncertainty does not generate high volatility episodes in the BMV. These episodes are a result of a volatility spillover from the U.S. financial markets.

**Methodology and Data**

**Data**

As explained in the introduction, the Equity Market Volatility (EMV) tracker created by Baker et al. (2019) is a newspaper-based index and it moves with CBOE Volatility Index (VIX) and with the realized volatility of returns on the S&P 500. To construct the overall EMV tracker, 42-category specific EMV trackers are created to quantify the importance of each category in the level of U.S. stock market volatility and its movements over time (Baker et al., 2019).

The 42 category-specific EMV trackers are shown in Table 1, they include a wide variety of indicators related with Policy, Macroeconomic, Regulation, Financial markets, Commodity prices, Health and Pandemics, to mention some of them.

<table>
<thead>
<tr>
<th>Policy-related emv tracker</th>
<th>Macro – consumer spending and sentiment EMV tracker</th>
<th>Government spending, deficits, and debt EMV tracker</th>
<th>National security policy emv tracker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infectious disease emv tracker</td>
<td>Commodity markets EMV tracker</td>
<td>Entitlement and welfare programs EMV tracker</td>
<td>Government-sponsored enterprises emv tracker</td>
</tr>
<tr>
<td>Macroeconomic News and Outlook EMV tracker</td>
<td>Financial crises EMV tracker</td>
<td>Monetary Policy EMV Tracker</td>
<td>Trade Policy EMV Tracker</td>
</tr>
</tbody>
</table>

Table 1. 42 Category-specific EMV trackers
<table>
<thead>
<tr>
<th>Category</th>
<th>Macro – broad quantity indicators EMV tracker</th>
<th>Exchange rates EMV tracker</th>
<th>Regulation EMV tracker</th>
<th>Healthcare policy EMV tracker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro – inflation EMV indicator</td>
<td>Healthcare matters EMV tracker</td>
<td>Financial regulation EMV tracker</td>
<td>Food and drug policy EMV tracker</td>
<td></td>
</tr>
<tr>
<td>Macro – interest rates EMV tracker</td>
<td>Litigation matters EMV tracker</td>
<td>Competition policy EMV tracker</td>
<td>Transportation, Infrastructure, and public Utilities EMV tracker</td>
<td></td>
</tr>
<tr>
<td>Macro – other financial indicators EMV tracker</td>
<td>Competition matters EMV tracker</td>
<td>Labor regulations EMV tracker</td>
<td>Elections and political Governance EMV tracker</td>
<td></td>
</tr>
<tr>
<td>Macro – labor markets EMV tracker</td>
<td>Labor disputes EMV tracker</td>
<td>Energy and environmental regulation EMV tracker</td>
<td>Agricultural policy EMV tracker</td>
<td></td>
</tr>
<tr>
<td>Macro – real estate markets EMV tracker</td>
<td>Intellectual property matters EMV tracker</td>
<td>Lawsuit and tort reform, supreme court decisions EMV tracker</td>
<td>Petroleum markets EMV tracker</td>
<td></td>
</tr>
<tr>
<td>Macro – trade EMV tracker</td>
<td>Fiscal policy EMV tracker</td>
<td>Housing and land management EMV tracker</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Macro – business investment and sentiment EMV tracker</td>
<td>Taxes EMV tracker</td>
<td>Other Regulation EMV tracker</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Own elaboration based on Baker et al. (2019)

The category-specific EMV trackers are employed to identify which factors are determinant to explain the Industrial Production Index (IPI) performance. Figure 1 shows the evolution of the IPI from January 1985 to May 2021. As shown in Figure 1, the IPI exhibited a general positive trend from the beginning of the period to July 2020. IPI fell 4 points (passed from 93 to 88.9) during the period July 2000 - October 2001, and ever since the IPI recovered reaching levels of 102 in August 2007, just before the subprime crisis. In June 2009 industrial production had its worst value until that moment, presenting levels of 84.7.
By July 2009 the index experienced a new bursting period until November 2014, reaching levels of 103.6. From December 2014 to July 2018 the production index was “stocked”, decreased in the first two years (2014-2016) and increased from 2016 to 2018. Since the second quarter of 2018 and until the beginning of the pandemics, there was a “flat” performance. Then the COVID-19 crisis had a larger impact compared with that of the subprime crisis, dropping the IPI to the level of 84 by April 2020.

**Methodology**

Our study employs a combined methodology, first Artificial Neural Network is employed to analyze which factors are the main determinants of the Industrial Production Index (IPI). Once, that key IPI determinant variables are identified, ARIMA model is used to forecast its future performance. To the best of our knowledge, this is the first time these two methodologies have been used simultaneously to analyze economic and financial impacts derived from the Covid-19 pandemic. However, it must also be recognized that these methodologies have been previously used to examine Covid-19 sanitary trends (Merh, et al, 2010; Wang et al., 2013; Kumar & Thenmozhi, 2014; Rathnayaka, et al., 2015; Nair, et al., 2017).

To analyze the determinants of the Industrial Production Index in the US, an Artificial Neural Network (ANN) approach is proposed. ANN is a method which allows to measure a
complex behavior and patterns. Economic activity and the diverse factors related to this evolve in a complex way, because its performance relies on a great variety of elements of different nature: political, trade, military, financial, among other categories.

The 42-category-specific EMV trackers synthesized relevant information for each classification, but it is a lot of information to be processed. Thus, ANN is a powerful tool to recognize patterns, model intricate relationships and identify relevant factors.

Multilayer Perceptron (MLP) is one of the most widely used ANN architectural forms (Subiyanto et al., 2019). MLP usually is formed by three layers: input layer, hidden layer and output layer. This approach identifies non-linear relationships, such as those presented by the economic and financial variables.

In MLP information is transmitted from input layer to output layer. Hidden layers grab the non-explicit relations between the input and output layers. The number of hidden layers is according to the ability of network to estimate more complicate functions. Networks with higher level of complexity do not achieve necessarily better results (Halagundegowda and Singh, 2018). In MLP, the predicted outputs for each training are estimated, and then calculate the difference between the target and predicted estimates. Thus, error is reduced by the algorithm training (Tsai & Wu, 2008). As it can be observed in Figure 1, in this case, x_i are all the data from the category-specific EMV trackers. All the information is processed in the hidden layer, trying to emulate and predict y, which is the Industrial Production Index. Finally, the error between the target and estimated is a measure to analyze the model goodness of fit.

Figure 1. Architectural graph of multilayer perceptron
Based on Vasylieva et al. (2021), the economic and mathematical model of the neural network is as follows:

\[
f(x) = F \left( \sum_{i_1} w_{i_1j_1} x_{i_1j_1} - \theta_{j_1} \right) - \theta_{j_2} \ldots - \theta_{j_N}
\]

Where \( F \left( \sum_{i_1} w_{i_1j_1} x_{i_1j_1} - \theta_{j_1} \right) \) – layer 1;

\[
\sum_{i_2} w_{i_2j_2} F \left( \sum_{i_1} w_{i_1j_1} x_{i_1j_1} - \theta_{j_1} \right) - \theta_{j_2} \quad \text{layer 2};
\]

\[
F \left( \sum_{i_N} w_{i_Nj_N} \ldots \sum_{i_2} w_{i_2j_2} F \left( \sum_{i_1} w_{i_1j_1} x_{i_1j_1} - \theta_{j_1} \right) - \theta_{j_2} \ldots - \theta_{j_N} \right) \quad \text{layer } N;
\]

\( i \)-number of the neuron in the layer;

\( j_{i_1j_1} \) – \( i \)-input signal of \( j \)-neuron in the layer 1;

\( w_{i_Nj_N} \) – weigh coefficient of the \( i \)-input of the \( j \)-neuron in layer \( N \);

\( \theta_{j_N} \) – the threshold level of the \( j \)-neuron in layer \( N \).

Training is executed on a sub-sample \( D = \{ X^{(n)}, t^{(n)} \} \) adjusting \( W \) (weights) on the input function, trying to minimize the error function, using a method known as gradient descent

\[
E_D(W) = \frac{1}{2} \sum_{n} \sum_{i} \left( t_i^{(n)} - y_i(x^{(n)}, W) \right)^2
\]

We employ the batch training. It uses information from all records in the training dataset. Batch training is often preferred because it directly minimizes total error. To estimate the synaptic weights, the scaled conjugate gradient optimization algorithm is used. For each of the hidden and output layers an activation function is estimated by an algorithm. The activation function links the weighted sum of layer units, with unit values of the right layer. This activation function differs from hidden layers to output layers.

The types of functions for hidden layers are the log-sigmoid form, \( f(a) = \frac{1}{1+e^{-a}} \) and the hyperbolic tangent \( tanh \) activation function is defined as \( f(a) = \frac{e^a-e^{-a}}{e^a+e^{-a}} \), continuous and sigmoid. The activation functions for output layers are identity = \( f(a) = a \) and softmax = \( f(a) = \frac{\exp(a_i)}{\sum_j \exp(a_j)} \).

To develop all the described process, the ANN splits data into three different subsets: training, testing, and reserve sub-samples. The training sub-sample is employed to run the model in the hidden layer; the
testing sub-sample validates the correct learning process, minimizing the function error. The reserve subset is separated from the two previous subsets; it is utilized to validate the proximity between the ANN-estimated data and real output, to avoid estimation bias.

**Auto regressive integrated moving average (ARIMA) model**

The Auto Regressive Integrated Moving average method is also known as Box-Jenkins process. ARIMA is a time series model, which forecasts future values by examining the differences between values in the time series. An ARIMA model has three components Auto regression (AR), Integrated (I), and Moving average (MA). Each component is a parameter. To represent these parameters, p, D, and q are used, respectively, for each component. This symbolization indicates the type of ARIMA model used. Where, p is the number of lag observations, D the degree of difference, and q means the order of the moving average (Hernandez-Matamoros, *et al.*, 2020).

According to Ariyo, Adewuni & Ayo (2014) in ARIMA model, the future value of a variable is a linear combination of past values and past errors, expressed as follows:

\[
Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q}
\]

(3)

Where, \(Y_t\) is the actual value and \(\epsilon_t\) is the random error at \(t\), \(\phi_i\) and \(\theta_j\) are the coefficients, \(p\) and \(q\) are integers that are often referred to as autoregressive and moving average, respectively.

One of the advantages of ARIMA models is that they provide more sophisticated methods for modeling trend and seasonal components than do exponential smoothing models, and they have the added benefit of being able to include predictor variables in the model (IBM, 2016, 2021). The selection of the best model relies on the BIC criterion and MAPE, MAD and RMSE metrics.

The first measurement is the root mean square error (RMSE),

\[
RMSE = \sqrt{\frac{\sum_{t=1}^{T} (P_t - Z_t)^2}{T}}
\]

(4)

Where \(P_t\) is the predicted value at time \(t\); \(Z_t\) is the actual value at time \(t\); and \(T\) is the number of predictions.

The second criterion is the mean absolute error (MAE)
The third criterion is the mean absolute percentage error (MAPE; Eq. [5]),

\[
MAE = \sum_{t=1}^{T} \frac{T|p_t - z_t|}{T} 
\]

\[
MAPE = 1T \sum_{t=1}^{T} TP_t - Z_tZ_t 
\]

**Results**

*Artificial Neural Network*

Table 2 shows the ANN information results. In the Input layer, 41 category-specific EMV trackers are the factors employed. Agricultural policy EMV tracker was not used due to several missing values affecting the ANN estimation. The hidden and output layer information is also shown. The hidden layer has 11 units and employs as activation function: hyperbolic tangent. The output layer has one dependent variable: industrial production index, the scale method is standardized, the activation function is an identity, and the error function is squared sum.

Table 2

Information of the ANN

<table>
<thead>
<tr>
<th>Input layer</th>
<th>Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Policy–Related EMV Tracker</td>
</tr>
<tr>
<td>2</td>
<td>Infectious Disease EMV Tracker</td>
</tr>
<tr>
<td>3</td>
<td>Macroeconomic News and Outlook EMV Tracker</td>
</tr>
<tr>
<td>4</td>
<td>Macro–Broad Quantity Indicators EMV Tracker</td>
</tr>
<tr>
<td>5</td>
<td>Macro–Inflation EMV Indicator Tracker</td>
</tr>
<tr>
<td>6</td>
<td>Macro–Interest Rates EMV Tracker</td>
</tr>
<tr>
<td>7</td>
<td>Macro–Other Financial Markets EMV Tracker</td>
</tr>
<tr>
<td>8</td>
<td>Macro–Labor Markets EMV Tracker</td>
</tr>
<tr>
<td>9</td>
<td>Macro–Broad Quantity Indicators EMV Tracker</td>
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<tr>
<td>16</td>
<td>Macro–Interest Rates EMV Tracker</td>
</tr>
<tr>
<td>Macroeconomic Markets EMV Tracker</td>
<td>Macro – Consumer Spending and Sentiment EMV Tracker</td>
</tr>
<tr>
<td>----------------------------------</td>
<td>-----------------------------------------------------</td>
</tr>
<tr>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>25</td>
<td>26</td>
</tr>
<tr>
<td>Monetary Policy EMV Tracker</td>
<td>Regulation EMV Tracker</td>
</tr>
<tr>
<td>33</td>
<td>34</td>
</tr>
<tr>
<td>41</td>
<td>Number of units</td>
</tr>
<tr>
<td>Petroleum Markets EMV Tracker</td>
<td>Hidden and Output Layer Information</td>
</tr>
<tr>
<td>Number of units</td>
<td></td>
</tr>
<tr>
<td>10168</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hidden layer</th>
<th>Number of hidden layers</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of units in hidden layer</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Activation function</td>
<td>Hyperbolic tangent</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Output layer</th>
<th>Dependent variables</th>
<th>Industrial Production Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of units</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
Sample data was subdivided: 60% of the valid observations were used to train the net, 30% for test the good of fitness and the 10% was used as a reserve sample.

In terms of the model goodness of fit, Figure 2 and Table 3 evidence that the predicted value is very close to the real data, achieving a 0.001 relative error in the estimation. It means, the estimated model adjusts correctly to the Industrial Production Index dynamics.

<table>
<thead>
<tr>
<th>Sample Data</th>
<th>N</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample distribution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training</td>
<td>149</td>
<td>60%</td>
</tr>
<tr>
<td>Testing</td>
<td>74</td>
<td>30%</td>
</tr>
<tr>
<td>Reserve</td>
<td>25</td>
<td>10%</td>
</tr>
<tr>
<td>Valid</td>
<td>248</td>
<td>100.00%</td>
</tr>
<tr>
<td>Excluded</td>
<td>189</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>437</td>
<td></td>
</tr>
</tbody>
</table>

Source: own elaboration with estimation results

Figure 2. ANN-Estimated data vs Industrial production index.
Table 3
Model summary

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Squared Errors Sum</td>
<td>.120</td>
</tr>
<tr>
<td>Relative Error</td>
<td>.001</td>
</tr>
<tr>
<td>Training Role used</td>
<td>The training error ratio was achieved (0.001)</td>
</tr>
<tr>
<td>Training time</td>
<td>0:01:15.77</td>
</tr>
</tbody>
</table>

Dependent variable: Industrial Production

Source: Own elaboration with estimation results

MLP Neural network also allows to analyze how important is each variable to explain, in this case, the industrial production performance. Figure 2 presents the normalized importance analysis, all the factors with a normalized importance above 90% are included. According to the normalized importance analysis, the EMV trackers more relevant are those related to Regulation, Monetary Policy, Macroeconomic News and Outlook, Policy Related, Energy and Environmental Regulation, Taxes, other Financial Indicators, Trade Policy, Real Estate Markets, Fiscal Policy, Infectious Disease, Interest Rates, Infrastructure, Financial Crises, and Government Spending.
In comparison with other empirical results, Ozturk and Agan (2017) argue that the determinants of industrial production in Turkey are interest rate, investing in manufacturing sectors and the demand for the products. In this sense, the trade policy focuses on enhancing the manufacturing base with export incentives. Habibi (2019) evidences the short-run effects non-linear of exchange rate on the production of non-energy materials, durable manufacturing, consumer goods and business equipment in the US.

Śmiech, Papież & Dąbrowski (2019) suggest that the external uncertainty shocks are those with negative impact on the industrial production of the CEE countries, whereas the reactions to internal uncertainty shocks are less clear-cut and depend on the category of uncertainty. Other studies involve different variables to analyze their impact on industrial production, such as: oil production in the US (Blazsek, et al., 2019), business confidence in Italy (Bruno, et al., 2019), sentimental and behavioral indexes in Germany (Seip, et al., 2019).
In contrast to previous studies, this research employs a sample and approach that allows to incorporate a wide variety of factors and analyze all of them simultaneously. As observed, there is no consensus about which factors drive the industrial production, but in the literature stands out the key role of monetary variables, regulations, fiscal policy and incentives to export. Those variables will be fundamental to promote the industrial production, which according toAndreou et al. (2017) is still a dominant factor in the US economy.

**ARIMA model**

The ARIMA model is estimated employing the IPI data from January 1985 to May 2021. The first step to run the ARIMA model is to evidence that all series are stationary. The Augmented Dickey Fuller test is run; results are shown in Table 4. The null hypothesis of the ADF test is “series present unit root”. Results allow to reject the null hypothesis in first differences, it means stationary in Industrial Production is proved.

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Augmented dickey fuller test results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Levels</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.087698</td>
</tr>
<tr>
<td>Intercept and trend</td>
<td>-1.085465</td>
</tr>
<tr>
<td>None</td>
<td>2.426481</td>
</tr>
</tbody>
</table>

Source: Own elaboration with estimation results

Once series are tested for stationarity, the model is chosen considering the BIC, MAPE, MAD and RMSE criteria or metrics. The best model to predict the Industrial Production Index performance is the ARIMA (0,1,1) (1,0,1). Model parameters are presented in Table 5. As it is observed, all the parameters are statistically significant. Table 6 reports a RMSE of 0.004, MAE 0.002 and MAPE of 0.118, which means a good level of fit compared with results reported for other studies (Tseng, et al., 2002 and Hernandez-Matamoros, et al., 2020).

Once, the best model was selected, the predicted values are shown in Figure 4.
Table 5
ARIMA (0,1,1) (1,0,1) model parameters

<table>
<thead>
<tr>
<th>IPI-Model</th>
<th>IPI Without transformation</th>
<th>Constant</th>
<th>Estimation</th>
<th>SE</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>transformation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA</td>
<td>Lag 1</td>
<td>-.263</td>
<td>.047</td>
<td>-5.560</td>
<td>.000</td>
<td></td>
</tr>
<tr>
<td>AR, stationary</td>
<td>Lag 1</td>
<td>-.915</td>
<td>.166</td>
<td>-5.530</td>
<td>.000</td>
<td></td>
</tr>
<tr>
<td>MA, stationary</td>
<td>Lag 1</td>
<td>-.964</td>
<td>.154</td>
<td>-6.267</td>
<td>.000</td>
<td></td>
</tr>
</tbody>
</table>

Table 6
ARIMA model statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stationary R^2</td>
<td>.061</td>
</tr>
<tr>
<td>R^2</td>
<td>.998</td>
</tr>
<tr>
<td>RMSE</td>
<td>.004</td>
</tr>
<tr>
<td>MAPE</td>
<td>.118</td>
</tr>
<tr>
<td>MaxAPE</td>
<td>3.039</td>
</tr>
<tr>
<td>MAE</td>
<td>.002</td>
</tr>
<tr>
<td>MaxAE</td>
<td>.059</td>
</tr>
<tr>
<td>Normalized BIC</td>
<td>-10.820</td>
</tr>
</tbody>
</table>

Source: Own elaboration with estimation results
According to the World Health Organization (WHO) during pandemics, it is common that a 2nd and even 3rd waves occur. The World Economic Forum (WEF) acknowledge that, experts consider that COVID19 pandemics could last on average two years. The pandemic was declared on 11 March 2020, so in a positive scenario, it is expected it will be ending around June 2022.

Considering those previous beliefs, we forecasted the Industrial Production Index from June 2021 to November 2022, to know the future scenarios at the final stage of Covid19 and the post-covid19 recovery. The worst IPI levels could be displayed if new and more contagious or dangerous virus variants are presented, if vaccines do not have the expected immune response or if the long-term effects of Covid19 (long-covid) get into a public health problem (CDC, 2021).

In Figure 4 are presented in black color the real IPI data, in discontinuous gray line the Upper Limit of the forecasting (UCL_IPI_), the continuous gray line is the Lower Limit of the predicted values (LCL_IPI_), and the light black line are the future forecasting values. The optimistic scenario shows higher positive results than the fall expected by the pessimistic scenario.

Based on the ARIMA forecasting results, the future values of IPI for July and August 2021 in a good scenario will be around 104, but if the pandemics is not controlled and uncertainty is still in high levels, the IP index will be around 95.5.
If biologic, economic, and political conditions are good from September to December 2021 it is expected that Industrial Production Index reaches levels around 107. However, if contagion and deaths continuing growing, IPI could present levels around 93.3.

If conditions are normal in the US and uncertainty diminishes, the IPI could reach levels of 109 from January to April 2022, and 112 during the period May-September, reaching levels of 114 at the end of that year. If there are new COVID types, trade or political conflicts, high level of nervousness in financial markets, stress due to the monetary measures, etc. the industrial production index could drop to 93, from October to 2021 to May 2022, and continue diminishing to 91, from June to November 2022.

**Conclusion**

Key macroeconomic factors have suffered a huge impact due to the Covid19 pandemic. Policies to mitigate the impacts and to contain contagion have been implemented. Industrial Production is a key variable by excellence, to the extent that it is considered a proxy variable to measure economic activity. Due to its importance, this paper analyzes the key determinant factors of industrial production and forecast its values during the final phase of the pandemics and the post-covid era.

Based on the theoretical relationship and empirical impact that the stock market and its volatility have on industrial production, the category-specific EMV tracker is employed to analyze how diverse factors impact the industrial production in the US from January, 1985 to May, 2021. To achieve that purpose, Artificial Neural Networks are employed to find the key determinants of the Industrial Production and ARIMA model is employed to forecast the future values.

ANN results evidence that Industrial Production is driven by: Regulation, Monetary Policy, Macroeconomic News and Outlook, Policy Related, Energy and Environmental Regulation, Taxes, Other Financial Indicators, Trade Policy, Real Estate Markets, Fiscal Policy, Infectious Disease, Interest Rates, Infrastructure, Financial Crises, and Government Spending.

The ARIMA (0,1,1) (1,0,1) model offers three scenarios: neutral/normal conditions, optimistic and pessimistic. Evidence shows that, if pandemic conditions remain, IPI will improve modestly. If good conditions prevail, the perspectives of growth will be good, and if there are new non-expected factors, which impact the IPI, the index will drop again, but with a lower intensity than the initial covid19 fell.

Results are of outmost importance for the economic authorities, CEO of industrial firms, investors and to enhance policy making. This is the most important lesson learned from the Covid 19 crisis. According to the results, volatility stock market volatility is a key factor to determine investors’ market sentiment, which in turn impacts volatility and levels of industrial production, leading to sensible losses
in overall GDP, employment, and other socio-economic variables. The EMV trackers evidence shows that the more relevant related category-specific variables to industrial production are Regulation, Monetary Policy, Macroeconomic News and Outlook, Policy Related, Energy and Environmental Regulation, Taxes, other Financial Indicators, Trade Policy, Real Estate Markets, Fiscal Policy, Infectious Disease, Interest Rates, Infrastructure, Financial Crises, and Government Spending.

Thus, government policies in the U.S. to foster a rapid and balanced economic recovery must address to those issues. However, not only a short-term Covid-19 approach solution must be enforced. Long-run trends show that U.S. the economy presents a secular stagnation and increasing inequities since the 1980’s (Tavani et al. (2021). The immediate polies undertaken, basically the US$1.9 trillion relief package, to promote employment and wages, and liquidity to foster investment and the real sectors growth, has contributed to beget some optimism abut to the financial markets and the real economy, As previously discussed, the S&P index has shown a 14.4 percent growth for the first semester of 2021. Similarly, the industrial production index has increased to 105.7 points.

This is in line with the optimistic projections obtained with our ARIMA model. However, much care must be taken in enforcing the proposed policies. Some clear, although debatable symptoms of overheating and inflationary pressures have appeared. The inherent contradictions between fiscal and monetary policies to maintain equilibrium growth must be careful considered. Among these contradictions, interest rates to promote savings must be balanced with interest rates to promote liquidity and investment. Relief aid to corporate recovery and wage increase, must be assigned considering real corporate needs and strategies, and it must be monitored to avoid deviations to executive salaries, problem present in many firms. Regulation, identified as a key factor related to industrial production in this study, must be revised to eliminate undue restrictions on entrepreneurship and new investments.

In this context, lessons earned to the Mexican authorities concerning its economic recovery do not mean to mirror U.S. policies. Good and strong economic relationships with the U.S. must be maintained and U.S. policies consistent with Mexico’s needs must be adapted to the local needs. However, on the contrary, albeit short run economic recovery is strongly tied to the U.S. economic performance, its structural socioeconomic disequilibria require long-term solutions. It is important to recall that partly the economic downfall of the Mexican economy during the Covid-19 crisis is also due to its strong links with the U.S. economy.

A big window to correct past errors and inequities is now open to Mexico’s policy makers. To start afresh, past recommendations are still valid: Strengthen and diversify the economic sectors; stress technological change and innovative entrepreneurship; diversify its economic international relations, particularly concerning exports and imports, and foreign direct investments; foster the development of financial markets and institutions and their contribution to economic development; further economic inclusion and
equality. The task ahead is giant but not an impossible mission. Reforms must be based on two pillars: Ending corruption and building up confidence on the institutions and in daily life social relations. Trust leads to positive actions and solid real investments which and enhanced market sentiment and promote economic growth. The industrial revolution 5.0 is already at hand. Mexico must become a top leader, not a follower in the complex global economy of the XXI century.

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