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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 fuerte 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 EMV[2] and the Industrial Production Index was download from the Federal Reserve Economic Data[3]. 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

[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 loss. 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. Oher representative contributions are those by Demirgüç-Kunt and Levine (1996), Arestis et al. (2001), Cooray (2010), Nwaolisa and Chijiidu (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 1. 42
Category-specific EMV trackers

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

Macro – broad quantity indicators EMV tracker	Exchange rates EMV tracker	Regulation EMV tracker	Healthcare policy EMV tracker
Macro – inflation emv indicator	Healthcare matters EMV tracker	Financial regulation EMV tracker	Food and drug policy EMV tracker
Macro – interest rates EMV tracker	Litigation matters EMV tracker	Competition policy EMV tracker	Transportation, Infrastructure, and public Utilities EMV tracker
Macro – other financial indicators EMV tracker	Competition matters EMV tracker	Labor regulations EMV tracker	Elections and political Governance EMV tracker
Macro – labor markets EMV tracker	Labor disputes EMV tracker	Energy and environmental regulation EMV tracker	Agricultural policy EMV tracker
Macro – real estate markets EMV tracker	Intellectual property matters EMV tracker	Lawsuit and tort reform, supreme court decisions EMV tracker	Petroleum markets EMV tracker
Macro – trade EMV tracker	Fiscal policy EMV tracker	Housing and land management EMV tracker	
Macro – business investment and sentiment EMV tracker	Taxes EMV tracker	Other Regulation EMV tracker	

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.

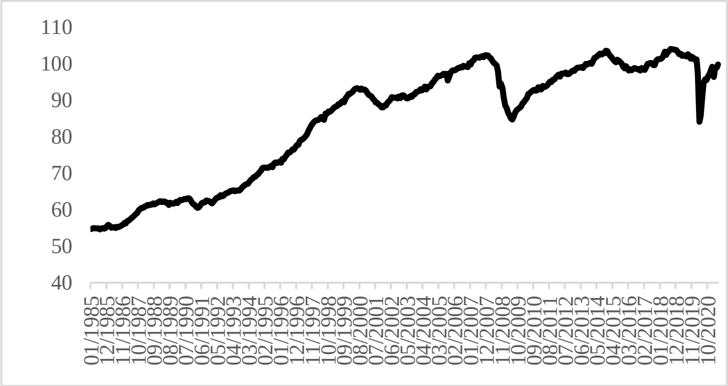

Figure 1. Industrial Production Index (1985-June/2020)
Source: Fred, Saint Louis

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.

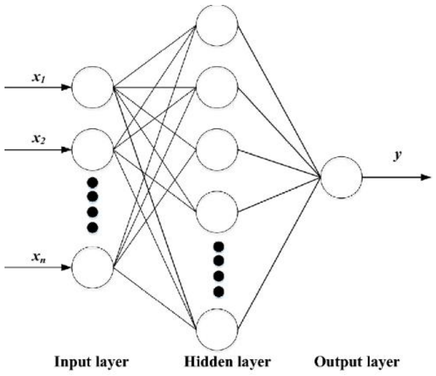

Figure 1. Architectural graph of multilayer perceptron
Source: You, et al. (2017)

Based on Vasylieva *et al.* (2021), the economic and mathematical model of the neural network is as follows:

$$f(x) = F\left(\sum_{i_N} w_{i_N j_N N} \dots \sum_{i_2} w_{i_2 j_2 2} F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right) - \theta_{j_2 2} \dots - \theta_{j_N N}\right) \tag{1}$$

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

$\sum_{i_2} w_{i_2 j_2 2} F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right) - \theta_{j_2 2}$ – layer 2;

$F\left(\sum_{i_N} w_{i_N j_N N} \dots \sum_{i_2} w_{i_2 j_2 2} F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right) - \theta_{j_2 2} \dots - \theta_{j_N N}\right)$– layer N;

i-input number

j-number of the neuron in the layer;

$x_{i_1 j_1 1}$ – i-input signal of j-neuron in the layer 1;

$w_{i_N j_N N}$ – weigh coefficient of the i-input of the j-neuron in layer N;

$\theta_{j_N N}$ – 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

$$E_D(w) = \frac{1}{2} \sum n \sum i \left(\left(t_i^{(n)} - y_i\left(x^{(n)}; w\right)\right)\right)^2 \tag{2}$$

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 $f(a) = tanh = \frac{e^a - e^{-a}}{e^a + e^{-a}}$, continuous and sigmoid. The activation functions for output layers are identity= $f(a) = a$ and softmax= $f(a) = \frac{\exp(a_{k)}}{(\sum jexp(a_j))}$.

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 has 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:

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

Where, Y_t is the actual value and ε_t is the random error at *t*, $\emptyset_i$ and θ_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),

$$RMSE = \sqrt{\sum_{t=1} \frac{T(P_t - Z_t)^2}{T}} \tag{4}$$

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)

$$MAE = \sum_{t=1} \frac{T|P_t - Z_t|}{T}$$

(5)

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

$$MAPE = 1T \sum_{t=1} TP_t - Z_t Z_t$$

(6)

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

Input layer							
Factors							
1	2	3	4	5	6	7	8
Policy-Related EMV Tracker	Infectious Disease EMV Tracker	Macroeconomic News and Outlook EMV Tracker	Macro – Broad Quantity Indicators EMV Tracker	Macro – Inflation EMV Indicator	Macro – Interest Rates EMV Tracker	Macro – Other Financial Indicators EMV Tracker	Macro – Labor Markets EMV Tracker
9	10	11	12	13	14	15	16

http://dx.doi.org/10.22201/fca.24488410e.2020.3457

Macro – Real Estate Markets EMV Tracker	Macro – Trade EMV Tracker	Macro – Business Investment and Sentiment EMV Tracker	Macro – Consumer Spending and Sentiment EMV Tracker	Commodity Markets EMV Tracker	Financial Crises EMV Tracker	Exchange Rates EMV Tracker	Healthcare Matters EMV Tracker
17	18	19	20	21	22	23	24
Litigation Matters EMV Tracker	Competition Matters EMV Tracker	Labor Disputes EMV Tracker	Intellectual Property Matters EMV Tracker	Fiscal Policy EMV Tracker	Taxes EMV Tracker	Government Spending, Deficits, and Debt EMV Tracker	Entitlement and Welfare Programs EMV Tracker
25	26	27	28	29	30	31	32
Monetary Policy EMV Tracker	Regulation EMV Tracker	Financial Regulation EMV Tracker	Competition Policy EMV Tracker	Labor Regulations EMV Tracker	Energy and Environmental Regulation EMV Tracker	Lawsuit and Tort Reform, Supreme Court Decisions EMV Tracker	Housing and Land Management EMV Tracker
33	34	35	36	37	38	39	40
Other Regulation EMV Tracker	National Security Policy EMV Tracker	Government-Sponsored Enterprises EMV Tracker	Trade Policy EMV Tracker	Healthcare Policy EMV Tracker	Food and Drug Policy EMV Tracker	Transportation, Infrastructure, and Public Utilities EMV Tracker	Elections and Political Governance EMV Tracker

41	Number of units
Petroleum Markets EMV Tracker	10168

Hidden and Output Layer Information

Hidden layer	Number of hidden layers	1
	Number of units in hidden layer	11
	Activation function	Hyperbolic tangent
Output lawyer	Dependent variables	Industrial Production Index
	Number of units	1

	Scale change method for the dependents of scale	Standardized
	Activation function	Identity
	Error function	Squared sum

Sample Data

		N	Percentage
Sample distribution	Training	149	60%
	Testing	74	30%
	Reserve	25	10%
Valid		248	100.00%
Excluded		189	
Total		437	

Source: own elaboration with estimation results

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.

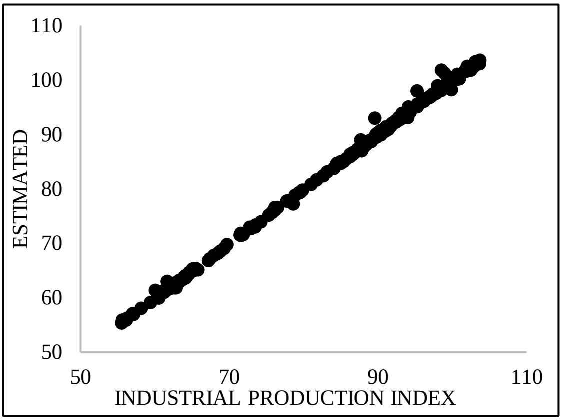

Figure 2.
ANN-Estimated data vs Industrial production index.

Table 3
Model summary

Training	Squared Errors Sum	.120
	Relative Error	.001
	Role used	The training error ratio was achieved (0.001)
	Training time	0:01:15.77
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.

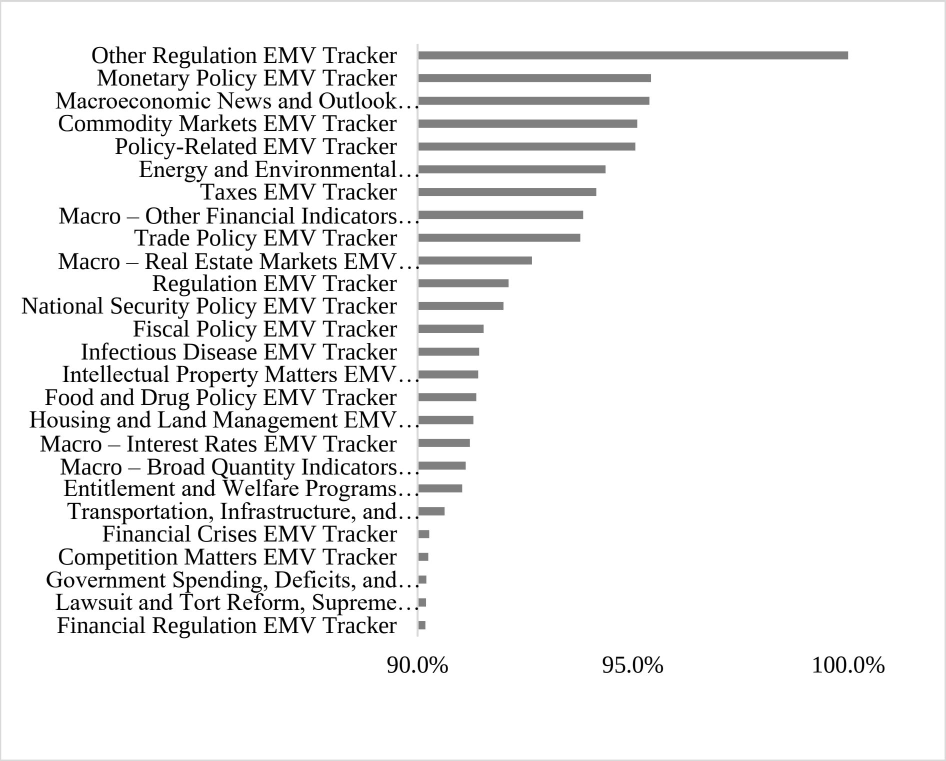

Figure 3.
Normalized importance (factors above 90% of importance)
Source: Own elaboration with estimation results.

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 to Andreou 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 4
Augmented dickey fuller test results

	Levels		Fist Diff	
	t-Statistic	Prob.*	t-Statistic	Prob.*
Intercept	-2.087698	0.2499	-14.90418	0.000
Intercept and trend	-1.085465	0.9291	-15.00352	0.000
None	2.426481	0.9966	-16.65696	0.000

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

					Estimation	SE	t	Sig.
IPI-Model	IPI	Without transformation	Constant		.001	.000	2.211	.028
			Diference		1			
			MA	Lag 1	-.263	.047	-5.560	.000
			AR, stationary	Lag 1	-.915	.166	-5.530	.000
			MA, stationary	Lag 1	-.964	.154	-6.267	.000

Table 6
ARIMA model statistics

Statistic	Mean
Stationary R^2	.061
R^2	.998
RMSE	.004
MAPE	.118
MaxAPE	3.039
MAE	.002
MaxAE	.059
Normalized BIC	-10.820

Source: Own elaboration with estimation results

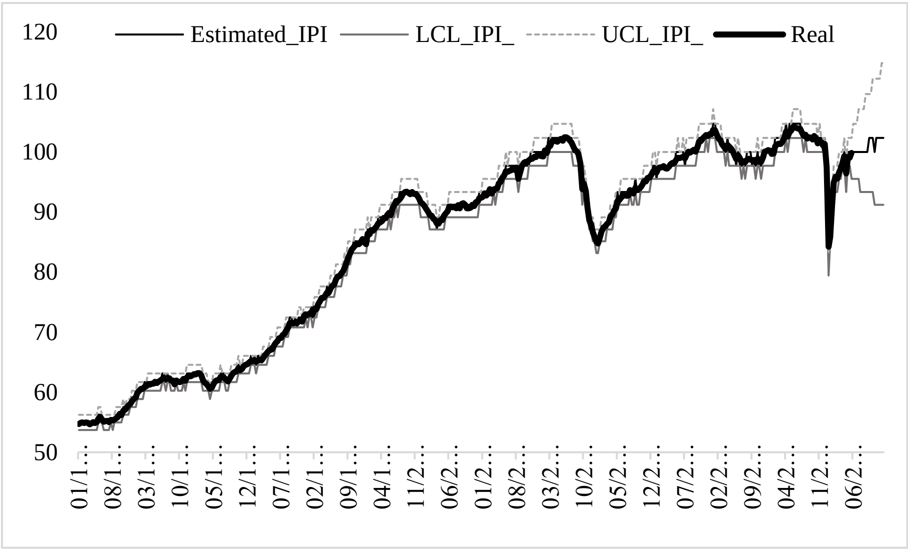

Figure 4. Industrial production index forecasting
Source: Own elaboration with estimation results

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.

References

Abbas, G., Hammoudeh, S., Shahzad, S.J.H., Wang, S., and Wei, Y. (2018). Return and volatility connectedness between stock markets and macroeconomic factors in the G-7 countries. Journal of Systems Science and Systems Engineering, 28, 1–36. Https://doi.org/10.1007/s11518-018-5371-y

Abraham, H.K. (2018). A study on"The impact of industrial production on stock indices". Emperor International Journal of Finance and Management Research, UGC Jr.No. 45308, 123-130. Http://www.eijfmr.com/2018/feb_2018/Feb-2018-019.pdf

Andreou, E., Gagliardini, P., Ghysels, E., & Rubin, M. (2017). Is industrial production still the dominant factor for the US Economy?. CEPR Discussion Paper No. DP12219, Available at SSRN: https://ssrn.com/abstract=3018473

Arestis, P., Demetriades, P.O., and Luintel, K.B. (2001). Financial Development and Economic Growth: The Role of Stock Markets. Journal of Money, Credit and Banking, 33(1), 16-41. Https://doi.org/10.2307/2673870

Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In 2014 uksim-AMSS 16th International Conference on Computer Modelling and Simulation (106-112). IEEE. Https://ieeexplore.ieee.org/abstract/document/7046047

August-larioto, M., Rossi, F., Lee, R. , and Sergi, B.S. (2021). How do equity markets react to COVID-19? Evidence from emerging and developed countries. Journal of Economics and Business, 115, 105968. Https://doi.org/10.1016/j.jeconbus.2020.105966

Baek, S., Muhanty, S.K., and Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. Finance Research Letters, 37, 10148. Https://doi.org/10.1016/j.frl.2020.101748

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. J. (2019). Policy news and stock market volatility (No. W25720). National Bureau of Economic Research. Https://doi.org/10.3386/w25720

Barro, R. J., (1990). The stock market and investment, The Review of Financial Studies, 3, 115-131. Https://doi.org/10.1093/rfs/3.1.115

Bay, L., Wei, Y., Wei, G., Li, X., and Zhang, S. (2021) Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective. Finance Research Letters, 40, May, 101709. Https://doi.org/10.1016/j.frl.2020.101709

Blazsek, S., Escribano, Á., & Licht, A. (2019). Markov-switching score-driven multivariate models: outlier-robust measurement of the relationships between world crude oil production and US industrial production. Working paper. Economics

19-16 http://hdl.handle.net/10016/29030

Bruno, G., Crosilla, L., & Margani, P. (2019). Inspecting the Relationship Between Business Confidence and Industrial Production: Evidence on Italian Survey Data. Journal of Business Cycle Research, 15(1), 1-24. Https://doi.org/10.1007/s41549-018-00033-4

Camilleri, S.J., Scicluna, N., and Bai, Y. (2019). Do stock markets lead or lag macroeconomic variables? Evidence from select European countries.

The North American Journal of Economics and Finance, 48, 170-186. Https://doi.org/10.1016/j.najef.2019.01.019

CDC (Centers for Disease Control and Prevention) (2021). "Post-COVID Conditions" https://www.cdc.gov/coronavirus/2019-ncov/long-term-effects/index.html

Chiang, T. C., & Chen, X. (2017). Stock market activities and industrial production growth: Evidence from 20 international markets. In Advances in Pacific Basin business economics and finance. Emerald Publishing Limited. Https://doi.org/10.1108/S2514-465020170000001003

Cooray, A. (2010). Do stock markets lead to economic growth? Journal of Policy Modeling, 32(4), 448-460. Https://doi.org/10.1016/j.jpolmod.2010.05.001

De la Torre-Torres, O. V. (2020). Noticias del COVID-19 y contagio de volatilidad en la Bolsa Mexicana de Valores. Contaduría y Administración, 65 (5), Especial COVID-19, 2020, 1-20. Http://dx.doi.org/10.22201/fca.24488410e.2020.3088

Demirgüç-Kunt, A., and Levine, R. (1996). Stock Markets, Corporate Finance, and Economic Growth: An Overview. The World Bank Economic Review, 10(2), 223-239. Https://www.jstor.org/stable/3990061

Fama, E. F. (1990). Stock Returns, Expected Returns, and Real Activity. The Journal of Finance, 4(5), 1089-1108. Https://doi.org/10.1111/j.1540-6261.1990.tb02428.x

Farid, S., Kayani, G.M., Naeem, M.A., and Shazad. S.J.H. (2021). Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic. Resources Policy, 72, 12101. Https://doi.org/10.1016/j.resourpol.2021.102101

Habibi, A. (2019). Non-linear impact of exchange rate changes on US industrial production. Journal of Economic Structures, 8(1), 1-17. Https://doi.org/10.1186/s40008-019-0172-0

Halagundegowda, G.R. and Singh, A., (2018). Multilayer Perceptron Method of Artificial Neural Network for Classification of Farmers Based on Adoption of Drought Coping Mechanisms, Int. J. Pure App. Biosci. 6(2): 1408-141. Doi: http://dx.doi.org/10.18782/2320-7051.6405

Hernandez-Matamoros, A., Fujita, H., Hayashi, T., & Perez-Meana, H. (2020). Forecasting of COVID19 per regions using ARIMA models and polynomial functions. Applied soft computing, 96, 106610. Https://doi.org/10.1016/j.asoc.2020.106610

IBM (2016, 2021). "ARIMA". IBM Watson Studio Desktop. SPSS Manual. Https://www.ibm.com/docs/en/wsd?Topic=sales-arima

Izzeldin, M., Muradoğlu, G., Pappas, V., and Sivaprasad, S. (2021). The impact of Covid-19 on G7 stock markets volatility: Evidence from a ST-HAR model. International Review of Financial Analysis, 74, 101671. Https://doi.org/10.1016/j.irfa.2021.101671

Kumar, M., & Thenmozhi, M. (2014). Forecasting stock index returns using ARIMA-SVM, ARIMA-ANN, and ARIMA-random forest hybrid models. International Journal of Banking, Accounting and Finance, 5(3), 284-308. Https://doi.org/10.1504/IJBAAF.2014.064307

Levine, R., (2003) . More on finance and growth: More finance, more growth? Review, Federal Reserve Bank of St. Louis, 85(4), 31-46. Https://n9.cl/4y2cx

Mazur, M., Dang, M., Vega, M. (2020). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. Finance Research Letters, 38, 101690. Https://doi.org/10.1016/j.frl.2020.101690Get rights and content

Merh, N., Saxena, V. P., & Pardasani, K. R. (2010). A comparison between hybrid approaches of ANN and ARIMA for Indian stock trend forecasting. Business Intelligence Journal, 3(2), 23-43. Https://n9.cl/34pf8

Nair, K. R., Vanitha, V., & Jisma, M. (2017, July). Forecasting of wind speed using ANN, ARIMA and hybrid models. In 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT) (170-175). IEEE. Https://doi.org/10.1109/ICICICT1.2017.8342555

Nwaolisa, E.F., and Chijindu, A.A. (2016). The relationship between index of industrial production and stock market liquidity: A cointegration evidence from Stock Market of Nigeria's value of stock traded ratio. Frontiers in Accounting and Finance, 1(1), 2-39. Http://lawarencepress.com/ojs/index.php/FAF/article/view/164

Ozturk, M., & Agan, Y. (2017). Determinants of industrial production in Turkey. Journal of Economics and Financial Analysis, 1(2), 1-16. Https://www.ojs.tripaledu.com/index.php/jefa/article/view/23

Rathnayaka, R. K. T., Seneviratna, D. M. K. N., Jianguo, W., & Arumawadu, H. I. (2015, October). A hybrid statistical approach for stock market forecasting based on artificial neural network and ARIMA time series models. In 2015 International Conference on Behavioral, Economic and Socio-cultural Computing (BESC) (54-60). IEEE. Https://doi.org/10.1109/BESC.2015.7365958.

Sadiq, M., Hsu, CH-CH, Zhang, Y., and Chien, F. (2021). COVID-19 fear and volatility index movements: empirical insights from ASEAN stock markets. Environmental Science and Pollution Research https://doi.org/10.1007/s11356-021-15064-1

Schwert, G. W. (1990). Stock returns and real activity: A century of evidence. The Journal of Finance, 45(4), 1237-257. Https://doi.org/10.1111/j.1540-6261.1990.tb02434.x

Schwert, G.W. (1989). Why Does Stock Market Volatility Change Over Time? The Journal of Finance, 45(5), 115-153. Https://doi.org/10.1111/j.1540-6261.1989.tb02647.x

Seip, K. L., Yilmaz, Y., & Schröder, M. (2019). Comparing sentiment-and behavioral-based leading indexes for industrial production: When does each fail?. Economies, 7(4), 104. Https://doi.org/10.3390/economies7040104

Shahzad, S.J.H., Naem, M.A., Peng, Z., and Bouri, E. (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. International Review of Financial Analysis, 75, May, 101754. Https://doi.org/10.1016/j.irfa.2021.101754

Śmiech, S., Papież, M., & Dąbrowski, M. A. (2019). How important are different aspects of uncertainty in driving industrial production in the CEE countries?. Research in International Business and Finance, 50, 252-266. Https://doi.org/10.1016/j.ribaf.2019.05.008

Subiyanto, S., Sukmono, A., Bashit, N., & Amarrohman, F. J. (2019, November). The use of a MLP neural network for analysis and aodeling of land use changes with variations variable of physical and economic social. In IOP Conference Series: Earth and Environmental Science (Vol. 389, No. 1, p. 012029). IOP Publishing. Https://iopscience.iop.org/article/10.1088/1755-1315/389/1/012029/meta

Tavani, D. (2021). Path dependence, the COVID-19 crisis, and inequality in the United States. European Journal of Economics and Economic Policies: Intervention, 18(2), 198-206. Available at SSRN: https://ssrn.com/abstract=3873367

Tsai, C. F., & Wu, J. W. (2008). Using neural network ensembles for bankruptcy prediction and credit scoring. Expert systems with applications, 34(4), 2639-2649. Https://doi.org/10.1016/j.eswa.2007.05.019

Tseng, F. M., Yu, H. C., & Tzeng, G. H. (2002). Combining neural network model with seasonal time series ARIMA model. Technological Forecasting and Social Change, 69(1), 71-87. Https://doi.org/10.1016/S0040-1625(00)00113-X

Vasilyeva, T., Kuzmenko, O., Kuryłowicz, M., & Letunovska, N. (2021). Neural network modeling of the economic and social development trajectory transformation due to quarantine restrictions during COVID-19. Economics and Sociology, 14(2), 313-330. Https://doi.org/10.14254/2071-789X.2021/14-2/17

Wang, D., Li, P., and Huang, L. (2020). Volatility Spillovers between Major International Financial Markets During the COVID-19 Pandemic (June 21, 2020). Https://dx.doi.org/10.2139/ssrn.3645946

Wang, L., Zou, H., Su, J., Li, L., & Chaudhry, S. (2013). An ARIMA-ANN hybrid model for time series forecasting. Systems Research and Behavioral Science, 30(3), 244-259. Https://doi.org/10.1002/sres.2179

You, H., Ma, Z., Tang, Y., Wang, Y., Yan, J., Ni, M., Cen, K., & Huang, Q. (2017). Comparison of ANN (MLP), ANFIS, SVM, and RF models for the online classification of heating value of burning municipal solid waste in circulating fluidized bed incinerators. Waste management, 68, 186-197. Https://doi.org/10.1016/j.wasman.2017.03.044

Web sites

Justice News Flash (2021). Wall Street rises for the fifth consecutive quarter | Wall Street Journal Business and Economic News. Justice News Flash, June 30, 2021. Https://www.wsj.com/articles/global-stock-markets-dow-update-06-30-21-11625038923

Lloyds Bank (2021). Investing in Mexico: https://www.lloydsbanktrade.com/en/market-potential/mexico/investment

Mexico News Daily. (2021). IMF raises Mexico growth forecast to 6.3% for 2021. Mexico Daily News, July 31, 2021: https://mexiconewsdaily.com/news/imf-raises-mexico-growth-forecast-to-6-3-for-2021/

Politico National Security Daily. (2021). U.S. economy surpasses prepandemic size with 6.5% Q2 growth. July 29, 2021: accessed August 1, 2021: Https://www.politico.com/news/2021/07/29/us- economy-accelerated-65-percent-501510

Trading Economics (2021). Mexican Exports: https://tradingeconomics.com/mexico/exports#:~:text=In%20the%20long-term%2C%20the%20Mexico%20Exports%20is%20projected,Million%20in%202022%2C%20according%20to%20our%20econometric%20models