An RNN Model for Exploring the Macroeconomic and Financial Indicators in the Context of the COVID-19 Pandemic

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***Abstract*—**A recurrent neural network (RNN) was developed to explore the impact of the COVID-19 pandemic on the stochastic macroeconomic and financial indicators of the yield spread (Spread), crude oil prices (Oil), recession (USrec), and two stock market indices of the volatility index (VIX) and Wilshire 5000 total market index (Wil5000). A time-series dataset was obtained from the Federal Reserve Bank of St. Louis (for Jan/2/1990 – Feb/2/2022). For each indicator, separately, the dataset was partitioned into "before" and "during" the pandemic using the dataset's breakpoint (transition block) established based on the indicator behavior. The results revealed: (a) VIX was explained by Wil5000, Spread, Oil, and USrec more accurately before the pandemic, indicating that other observed and unobserved factors arising from the COVID-19 pandemic would affect the VIX more than the macroeconomic and financial indicators, (b) USrec is predicted less accurately compared to other indicators during the pandemic, which shows the sensitivity of this indicator to health and geopolitical challenges, and (c) effects of the indicators on the bond market diminished during the pandemic. The sensitivity analysis suggests that the results remain highly robust to the changes in the number of records chosen for the different test sets.

Keywords—*COVID-19 Impact on macroeconomic and financial indicators, Recurrent Neural Network, Stochastic modeling, Transition boundary, Robustness Analysis*

I. INTRODUCTION

Financial stability can be measured by financial outcomes (indicators), such as bond yield spread (Spread), crude oil prices (Oil), the stock market volatility index (VIX), Wilshire 5000 total market index (Wil5000), and the US recession indicator (USrec) [1] [2].

Spread is measured by the difference between rates of long-term (10-year US Treasury) and short-term (2-year US Treasury) bonds affecting economic activities and recessions [3]. Oil price is determined by OPEC-plus countries and influences recession [4][5] and inflation [6]. VIX is measured by the market expectation of the near-term volatility conveyed by stock index option prices [7]. Wil5000 is measured by the stock levels of publicly traded companies [8]. Both VIX and Wil5000 indices impact economic stability [9]. USrec, in general, is measured by a decline in economic activities, a high unemployment rate, and two successive periods of negative GDP growth [10]. Such a model is a stochastic one because the financial outcomes have stochastic behaviors.

The devastating effects of COVID-19 on society in terms of social interactions have put an enormous strain on all aspects of the economy such as supply chain, manpower, agriculture, education, etc. Such a strain has its impact on the economic and financial indicators.

The goal of this research effort is to develop an RNN model for exploring the impact of the COVID-19 pandemic on the individual macroeconomic and financial indicator by modeling the effects for two eras: the "before" and "during" pandemic. The identification of the data boundary between the two eras is a challenge because the indicator's behavior does not follow the official announcement of a pandemic by the World Health Organization (WHO).

The rest of the paper is structured as follows. The Previous Work is covered in Section Two. The Methodology is presented in Section Three. The Empirical results are the subject of Section Four. The Discussion, Conclusion and Future research are discussed in Section Five.

II. PRIVIOUS WORKS

Neural networks and deep learning have been used to predict economic business cycles. For example, Qi examines the predictive power of financial and macroeconomic indicators in predicting recessions through neural network models [11]. Joseph et al. also investigate the predictive ability of the interest rate spread in forecasting recession using neural networks and show that neural network models outperform conventional statistical models [12].

Recently, Puglia and Tucker developed a three-step method for cross-validating and conducted statistical inference on machine learning classifiers to examine the predictive power of yield spread and other macroeconomic outcomes in forecasting U.S. recessions [13]. They show that neural network classifiers identify essential features of recession distribution, whereas conventional statistical methods, such as probit and logit models, cannot capture these features. Longo et al. proposed an ensemble learning approach to forecast economic growth by combining a recurrent neural network and a dynamic factor model [14]. Wang et al. also compared different machine learning approaches for predicting recessions and found hat neural networks help predict economic business cycles [15].

The literature, however, lacks a study to account for the time series nature of the data. Our paper fills this void by proposing a recurrent neural network that addresses the autocorrelation property of macroeconomic and financial indicators.

III. METHODOLOGY

To meet the goal, the following steps are taken: (i) Pre-processing the dataset for imputing the missing data and discretization [16], (ii) Analyzing the structural change in data due to the external shock of the COVID-19 pandemic to find the breaking points in the data [17] and splitting the dataset into two for "before" and "during" the pandemic eras, accordingly, (iii) Analyzing and presenting the RNN. The details of the above steps are covered in the following three sub-sections.

A: Data Preprocessing

We discretize the continuous macroeconomic and financial indicators using the *k*-mean clustering technique [16]. The *k*-means algorithm identifies *k* cluster centers known as centroids and allocates the data to the nearest mean while minimizing the within-cluster sum of squares.

B: COVID-19 Pandemic effects on Dataset Structure

Let us assume that we deal with a dataset that contains N macroeconomic and financial indicators of (EF1, . . ., EFn) for the period of the time starting from date dt_0 and ending at the date dt_s. Somewhere within this period, the COVID-19 pandemic starts and continues. Let us also assume that DT is the date announced by the World Health Organization (WHO) as the beginning of the pandemic. We try to extract the starting date of the COVID-19 pandemic through the analysis of data in reference to the macroeconomic and financial indicators which may be different from DT.

The actual starting date of the pandemic is fuzzy, and it may be different for different indicators. Therefore, it makes sense that, for a given indicator, we do not designate one day as the starting time of the pandemic, but a block of several days that are collectively referred to as the *transition Block*. To identify the starting and ending dates for this block, it is logical to assume that the shocking behavior of the indicator for days within the block are much bolder than for days outside of the block. Plotting of data for the indicator may reveal the strong shocking behavior of the indicator for more than one time interval. We know for the fact that one such strong shocking behavior of the indicator belongs to the global financial crisis of 2008 [18][19][20][21]. Aside from that, the next strongest shocking behavior interval is due to the pandemic because there is not another noticeable economic and financial event that takes place between 2008 and the pandemic. The starting and ending dates of this interval make the starting and ending dates for the transition block of the indicator. Let the transition blocks for the N macroeconomic and financial indicators be b1, . . . , bn. Also, let the starting and ending dates for the transition block bi be Sbi and Ebi, respectively. Considering all the indicators, the starting date (SB) and the ending date (EB) for the *overall* transition block(B) of the dataset are given by formula 1.

$$SB = Min(Sb1, . . ., Sbn) \qquad (1)$$
$$EB = Max(Eb1, . . ., Ebn)$$

Considering the transition block, bi, for the i-th indicator, divides the dataset into three partitions of the normal, transition, and pandemic as follows. The normal partition (Before Pandemic) starts from the first record of the dataset and ends at the record for the date Sbi-1 . The transition partition contains the records for the dates within the block bi. The pandemic partition (During the Pandemic) starts from the record of date Ebi+1 and ends at the last record of the dataset.

We set aside the transition partition and we compare the macroeconomic and financial indicators' behavior for the two partitions of the normal and pandemic. This is done by comparing the rate of the correct predictability of the indicators using the partitions separately.

To have a comparable result, the cardinality of both partitions must be the same. If the cardinality of the normal partition is higher, then we remove the records from the partition normal starting from the first record. If the cardinality of the Pandemic partition is higher, then we remove the records starting from the last record going upward. One may ask why removing records from the top of the normal partition and not from the bottom. The answer is that we need to compare the two partitions based on the recent history.

C: RNN

Our time-series dataset has a property that influences the architecture of our recurrent neural network. This property says that the record at time t, X(t), has influence on the record at time t+1, X(t+1). We introduce the RNN architecture that fully supports this property.

The RNN has two layers of input and output displayed in Figure 1. The input layer is composed of two sets of nodes: *X-set and C-set*. The nodes in the X-set receive dataset's records one at a time starting from record X2. The nodes in C-set receives the output of the Q-set as input. This provides for the property of the dataset. The initial input to the C-set nodes is the first record (X1) of the dataset.

Since a record (Xi) of the dataset carries values for the N macroeconomic and financial indicators, (x1, . . ., xn), then there are N nodes in each one of the X-set and C-set. We also add a biased node, B, to the input layer. As a result, the number of nodes in the output layer are 2N+1.

The output layer is also composed of two sets of nodes: Y-set and Q-set. The number of nodes in each set is N. The output of the Y nodes (y1, . . ., yn) are considered as the output for the RNN. If the input to the X-set is the record Xi, then the target output for Y-set is the record Xi+1.

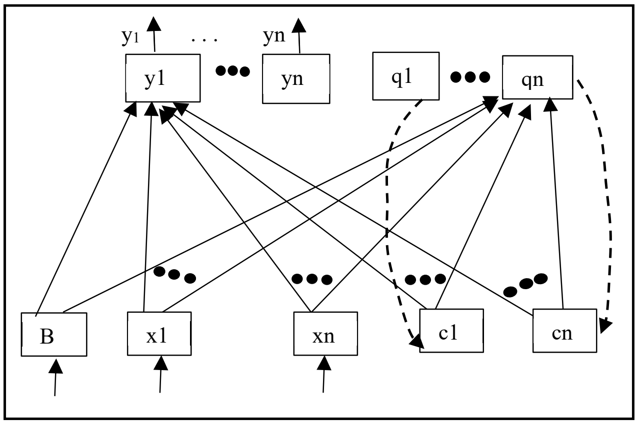

Figure 1: The RNN architecture

The output for the Q nodes (q1, . . ., qn) are considered as the context output of the RNN. The first record (X1) of the dataset is used as the initial input to the C-set nodes and for the rest of iterations the output of Q-set is used as the input to the C-set nodes. However, the target output for the nodes in Q-set starts with X2 and continues with the next record of the dataset for each iteration.

The RNN has a weight matrix of (N) X (N+1) and uses the activation function of the Gaussian Error Linear Unit (GELU), [22] that is expressed by the Formula 2.

$$Out = \frac{Net}{1+e^{-1.702Net}} \quad (2)$$

Where Out is the output for a given node and Net is the weighted sum of inputs to the node.

IV. EMPERICAL RESULTS

A time-series dataset (named ORIGIN) has already obtained from FRED, Federal Reserve Bank of St. Louis and it includes the daily financial outcomes from Jan. 2, 1990, through Feb. 2, 2022. Each record of the dataset carries a date along with five financial outcomes of Spread, Oil, VIX, Wil5000, and the USrec indicators.

By use of the *k*-mean clustering technique, the indicators are discretized and the intervals along with the number of observations for each discrete value is shown in Table 1. For VIX and Wil5000, the 5th percentile is added to cluster 1, and the 95th percentile is added to cluster 3. The USrec is a binary indicator, and it does not participate in the discretization process.

To meet the goal of this research effort, six copies of the original dataset are created. Five of these copies are named after the five indicators (F-VIX, F-Spread, F-Oil, F-Wil5000, and F-USrec). The transition block for each indicator is determined using the indicator's plot. (Plots for the five indicators are shown in Figures 2 to 6).

Table 1: *k*-means clustering: Intervals and the number of observations for each discrete value

Indicator	1	2	3
VIX	[9.14,19.6)	[19.6,34.5)	[34.5,82.7]
	4,815	2,768	356
Wil5000	[7.35,69.8)	[69.8,150)	[150,234]
	5,785	1,713	441
Spread	[-0.52,0.758)	[0.758,1.75)	[1.75,2.91]
	3,163	2,429	2,347
Oil	[9.1,42.1)	[42.1,84.8)	[84.8,144]
	3,882	2,799	1,258

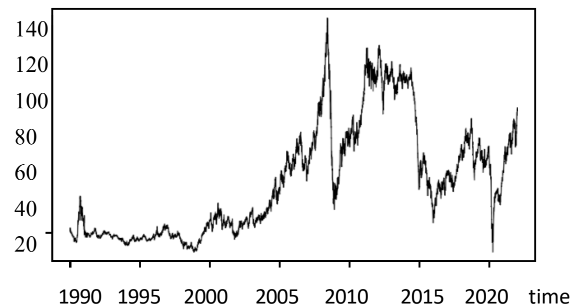

Figure 2: Oil plot

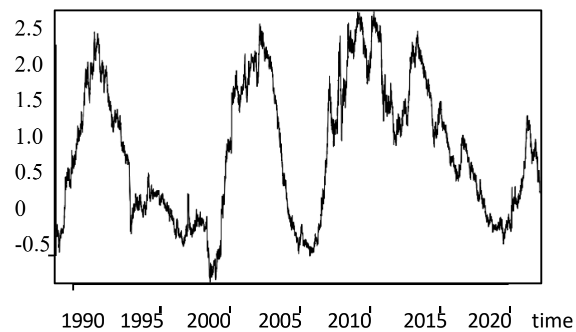

Figure 3: Spread Plot

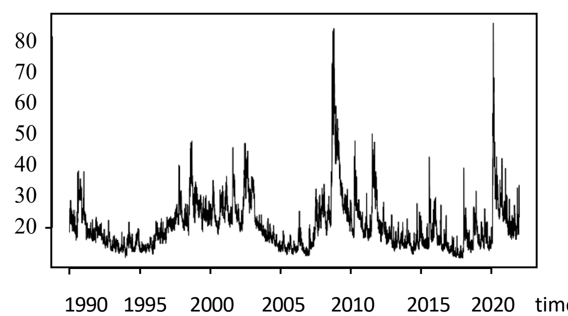

Figure 4: Vix Plot

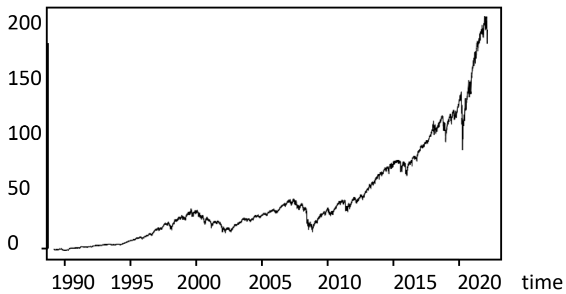

Figure 5: Wil5000 Plot

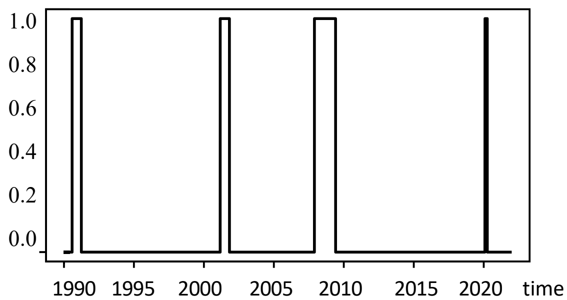

Figure 6: USrec Plot

The sixth copy is named F-All. The transition block for this dataset is obtained using formula (1) and it so happened to be the same as the transition block for USrec. F-All always has the largest transition block. The transition blocks of each indicator along with the F-All are shown in Table 2.

Table 2: Transition blocks of the Macroeconomics and Financial Indicators

Indicator	Transition block
VIX	[3/12/2020 to 3/27/2020]
Wil5000	[3/9/2020 to 3/23/2020]
Spread	[3/16/2020 to 3/20/2020]
Oil	[3/16/2020 to 4/21/2020]
USrec	[3/2/2020 to 4/30/2020]
All	[3/2/2020 to 4/30/2020]

We divide each file of F-VIX, F-Spread, F-Oil, F-Wil5000, and F-USrec into Before and During pandemic by removing the records from the corresponding transition block of the indicator associated with the file names. We also divide the file F-All into Before and During by removing the records of the overall transition block. As a result, we generate 6 pairs of files (VIX-b, VIX-d), (Spread-b, Spread-d), (Oil-b, Oil-d), (Wil5000-b, Wil5000-d), (USrec-b, USrec-d), and (All-b, All-d).

We have observed that the cardinality of Before files are much higher than the cardinality of their corresponding During files. After adjusting the cardinality of all the Before files the cardinality for the six pairs are shown in Table 3.

Two facts govern the selection of a pair of training and test sets. The first fact is related to the nature of data. Since we analyze a time-series dataset, prediction of the indicators for the date of dt_i is produced by the indicators for the date of dt_{i-1}. Based on this fact, records for a test set cannot be selected randomly. In fact, the records of a test set must be time-wise in sequence. When a record, Ri, of the test set is presented to the model, then the model assumes this new record is the next record (time-wise) to the last input record that model encountered. When the record Ri+1 of the test set is presented to the model, then the model has already learned the features of Ri and this learning is manifested in modification of the weight matrix by the features of Ri. In other words, a dynamic learning is always in progress. This leads us to the second observed fact that as the model encounter more input records, it becomes more trained.

Due to this fact, the ratio of the number of records in the test set to the number of records in the training set must be as small as possible. Therefore, the last λ records of the dataset are selected as the test set (based on the first fact), λ is as small as possible (based on the second fact) and λ makes the 10% of the records in the file.

Table 3: Cardinality of Before and During files for each indicator

Pair	Cardinality
(VIX-b, VIX-d)	455
(Spread-b, Spread-d)	460
(Oil-b, Oil-d)	440
(Wil5000-b, Wil5000-d)	455
(USrec-b, USrec-d)	433
(All-b, All-d)	433

Table 4: Results for 6 pairs of Before and During and Original dataset

Indicator's file for Before Pandemic	λ	**BEFORE-PANDEMIC**				
		% of the correct classification				
		VIX	Wil5000	Spread	Oil	USrec
VIX-b	45	84	78	80	71	67
Wil5000-b	45	78	73	76	67	62
Spread-b	46	87	74	70	76	63
Oil-b	44	77	73	77	70	66
USrec-b	43	74	77	70	58	56
All-b	43	74	77	70	58	56
Indicator's file for During Pandemic	λ	**DURING-PANDEMIC**				
		% of the correct classification				
		VIX	Wil5000	Spread	Oil	USrec
VIX-d	45	69	71	67	56	58
Wil5000-d	45	73	69	71	69	62
Spread-d	46	67	65	65	61	48
Oil-d	44	70	68	68	64	60
USrec-d	43	56	53	53	51	47
All-d	43	56	53	53	51	47
		Original dataset				
		% of the correct classification				
		VIX	Wil5000	Spread	Oil	USrec
ORIGIN	800	91	90	93	89	85

The statistics obtained from applying the RNN on the 12 files of Before and During are shown in Table 4. We also applied the RNN on the original dataset as one file and the accuracy of predicting the indicators are also shown in Table 4.

V. DISCUSSION, CONCLUSION, AND FUTURE RESEARCH

Let us assume that TRi and TRj, are two training sets of the same size with the same set of attributes that are collected in two different time periods of ti and tj, respectively. Let us also assume that the prediction model of PM, at time ti, uses the training set and test set pair of (TR_i, TSi) and delivers predictions with the accuracy rate of α. The same PM, at time tj, uses the training set and the test set pair of (TRj, TSj) and delivers predictions with the accuracy rate of β. If $\beta << \alpha$, then one can conclude that data in the first pair are less chaotic than data in the second pair.

Table 4 presents the percentage of the correct classifications for the before-pandemic files of (•-b) and during-pandemic files of (•-d) using the proposed RNN model. Table 4 also presents the accuracy prediction for the entire dataset. The range of prediction accuracy is 85 to 93 for the entire dataset, while they decline after splitting the dataset. This result is expected since the entire dataset includes a larger number of records and combines the normal and recessionary periods, alleviating the pandemic impact.

The following points are noteworthy by comparing the results of the before-pandemic and during-pandemic files.

a) The accuracy of predicting the indicators during the pandemic, on average, is 10% less than the accuracy of predicting the indicators before the pandemic. This means that the behaviors of the macroeconomic and financial indicators are more chaotic during the pandemic.
b) Macroeconomic and financial indicators influence each other simultaneously. So, we should consider the joint influence of these indicators in predicting each one. The proposed RNN model considers this simultaneity, as explained in Section III.
c) VIX is explained by Wil5000, Spread, Oil, and USrec more accurately before the pandemic. This finding indicates how other observed and unobserved factors arising from the COVID-19 pandemic would affect the VIX more than just the financial and macroeconomic indicators.
d) USrec is predicted less accurately compared to other indicators after the pandemic, which shows the sensitivity of this indicator to health and geopolitical challenges.
e) USrec's forecast accuracy is lowest for the pre-pandemic (56%) and during-pandemic (47%) periods, while accuracy measures of VIX and Wil5000 are highest for the two subsamples. This finding is consistent with findings of Malladi [23], who utilizes machine learning techniques to forecast recessions and stock market crashes.
f) Before-pandemic results suggest that the Spread could be explained by VIX, Wil5000, Oil, and USrec with an accuracy of 80 percent. This accuracy fell to 67 percent during the pandemic, indicating that the effects of financial and macroeconomic factors on the bond market diminished after the pandemic. Our findings are aligned with the findings of the Zaremba et al. [24].

As a robustness check, various values are considered for λ, which are led to different size training and test sets. The robustness check includes λ values ranging from 7 to 12. Although the percent of correct classification is increased as expected due to a larger training set and smaller test set, the patterns for Before and During pandemic periods remain unchanged and consistent with the results presented in Table 4. This sensitivity analysis suggests that the results remain highly robust to the change in λ.

As future research development of a hybrid Markov model is in progress which makes it easier: (i) to predict the behavior of the macroeconomic and financial indicators of N days from the current date, (ii) to determine the ceiling for the value of N, and (iii) to entertain “what if” scenarios proposed by the user of the system.

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