DEEP LEARNING FORECASTING AND THE GLOBAL US DOLLAR MONEY SUPPLY:

HOW A LONG-DATED US GOVERNMENT BOND CAN EXPLAIN U.S. ECONOMIC ACTIVITY AND THE GLOBAL RESERVE CURRENCY

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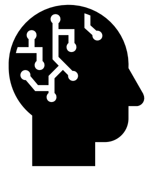
Abstract



Money is defined as U.S. Dollars in a narrative of Classical Financial Theory to justify the forecast of the Global Supply of U.S. Dollars. The classification of what is money and what is not money leads to the selection of the 10-year U.S. Treasury Bond Note as a dataset to signal the quantity of money and the U.S. Dollar as the Global Reserve Currency. The Neural Prophet model built on the tradition of Classical Time Series Models coupled with Contemporary Deep Learning methods is used to forecast daily, weekly, and monthly yield values with significant conclusions on the Global Monetary System.

Introduction

Money is easy to identify but difficult to understand. The more money we have in an economy, the more we spend, lend, invest, and do many other economic activities. The less money we have raises a financial concern of a possible recession, so both the presence and the usage work in tandem. If we identify money correctly, we can place the economy's current and maybe future state. According to the International Monetary Fund and the Federal Reserve of the United States, the U.S. Dollar is the most used money and accounts for 70% of international currency usage. By focusing on the largest economy in the world, the United States of America, and the Global Reserve Currency, the U.S. Dollar, we can identify the state of the U.S. economy. The more U.S. Dollars circulating worldwide, the better the U.S. Economy is and maybe the rest of the world.

However, a classification problem is common in academia and media that drives many issues and misunderstandings of money. The definition of money[§] used today initially comes from the classical description in the 1800s, which is used by monetary authorities, bankers, some academics, and others. William Stanley Jevons, a British Economist, provided the first three attributes of money in Table 1 below, which was the first attempt at an entity resolution when the British Pound Sterling was the Global Reserve Currency. Once the object was defined correctly, ideally, the next step would be identity resolution to map the journey of money in the global

[§] To this day, the Federal Reserve uses the three attributes of money in its educational materials, such as pages 3 to 5: https://www.dallasfed.org/~/media/documents/educate/everyday/money.pdf economy with various participants. The overall objective would be the Data Governance of the Global Reserve Currency, where the operations would be Data Management of the most commonly used money entity that flows non–stop around the world. The amount of money would be a function of the Global Economy and signal the economic health of dozens of countries.

Money Attribute	*Description*
Medium of Exchange	Money is used to trade goods and services as an acceptable payment or repayment of debts.
Store of Value	The value of money is not lost as economic participants receive money to spend on their interests and obligations to circulate money.
Unit of Account	Standardization of Economic Activity with the price quotation of products and services like a supermarket.

Table 1: Entity Resolution of Money

In short, there are three problems: the definition of money that drives entity resolution issues, the incomplete identity resolution of ignoring overseas non – U.S. Dollar money, and the common misclassification of Money Printing. To put it another way, defining money in multiple entities inflates its quantity. Feature Engineering multiple entities with incorrect classification would lead to many false conclusions, regardless of the model type. More importantly, we see later how we do not have a surplus quantity but a shortage of U.S. Dollar money that can be explained with much fewer money entities.

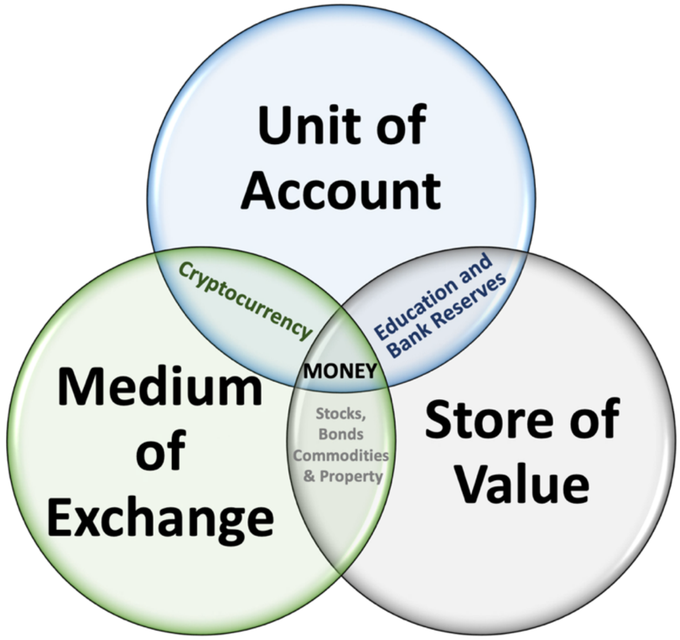


Image 1: Money and its Three Attributes♠

Most people would focus on the Central Bank, the Federal Reserve of the United States, but the Former Chair of the Federal Reserve of the United States, Alan Greenspan, testified to the U.S. Congress on the 28th of June, 2000 that the U.S. Central Bank cannot define money below. In terms of Data Science, there is an incomplete entity resolution with poor Data Governance, and the quantity of U.S. Dollar money has and continues to be unknown. Stocks, bonds, derivative contracts, repurchase agreements, and many other financial instruments, including real estate in the financial markets, are different forms of money or, as the quote implies below says, near money. It is too easy to over–classify money leading to many false conclusions and modeling mishaps.

♠ Cryptocurrency has no Store of Value attribute and is not money because it cannot be used, the vast majority of the time, for the purchase of goods and services to circulate in an economy. Its prices are too volatile. Also, Cryptocurrency is not a currency but an asset as there are no commonly accepted exchange rates for currencies like the U.S. Dollar, Euro, or Japanese Yen to any Cryptocurrency entity. .

> The problem is that we cannot extract from our statistical database what is true money conceptually, either in the transactions mode or the store-of-value mode. One of the reasons, obviously, is that the proliferation of products has been so extraordinary that the true underlying mix of money in our money and near money data is continuously changing. As a consequence, while of necessity it must be the case at the end of the day that inflation has to be a monetary phenomenon, a decision to base policy on measures of money presupposes that we can locate money. And that has become an increasingly dubious proposition. **- Alan Greenspan**

Quote 1: Incomplete Money Entity Resolution because of Over – Classification from the Meeting of the Federal Open Market Committee

Aside from the over-classification of money, there is the common mistake of under–classification because of non – U.S. Dollars outside the U.S. The Eurodollar market is a labeled entity of non – U.S. Dollars that is not to be confused with the Euro currency that came into existence in 1999. Starting in the 1950s, non–physical cash U.S. Dollars were lent and borrowed through telecommunications such as the standard SWIFT message or Society for Worldwide Interbank Financial Telecommunication‡ based in Belgium. After that came internet messages such as email and much more. Paul Einzig, a financial journalist and author of 57 books on global finance who did is a doctorate in Political and Economic Sciences at the University of Paris in 1923, wrote extensively about non – U.S. Dollars that the most commonly under–classified entity resolution of money in the Global Reserve Currency of U.S. Dollars.

> "The Eurodollar market was for years hidden from economists and other readers of the financial press by a remarkable conspiracy of silence. I stumbled on its existence by sheer accident in October 1959, and when I embarked on an enquiry about it in London banking circles several bankers emphatically asked me not to write about the new practice."
> – Paul Einzig

Quote 2: Under – Classification of the U.S. Dollar Money Entity because of overseas US Dollars

‡ To be clear, SWIFT is only a messaging system and does not send or receive money. It is only electronic promises to exchange money in a separate mechanism such as physical mail delivery, the current use of the internet, or other means.

In addition, this year, we do have quantity estimates of non – U.S. dollars outside the U.S. from a proprietary database demonstrated by the Bank of International Settlements, an international financial institution owned by several central banks. Senior Economist Egemen Eren, who has a Ph.D. in Economics from Stanford University below, shows the vast majority of U.S. dollars are not in the U.S. The significant takeaway for the under classification of U.S. Dollars is that outside the U.S., nobody can print U.S. Dollars because it is government issue paper by the United States Government, but you can issue debt as a digital book entry without the knowledge or consent of the United States Government.

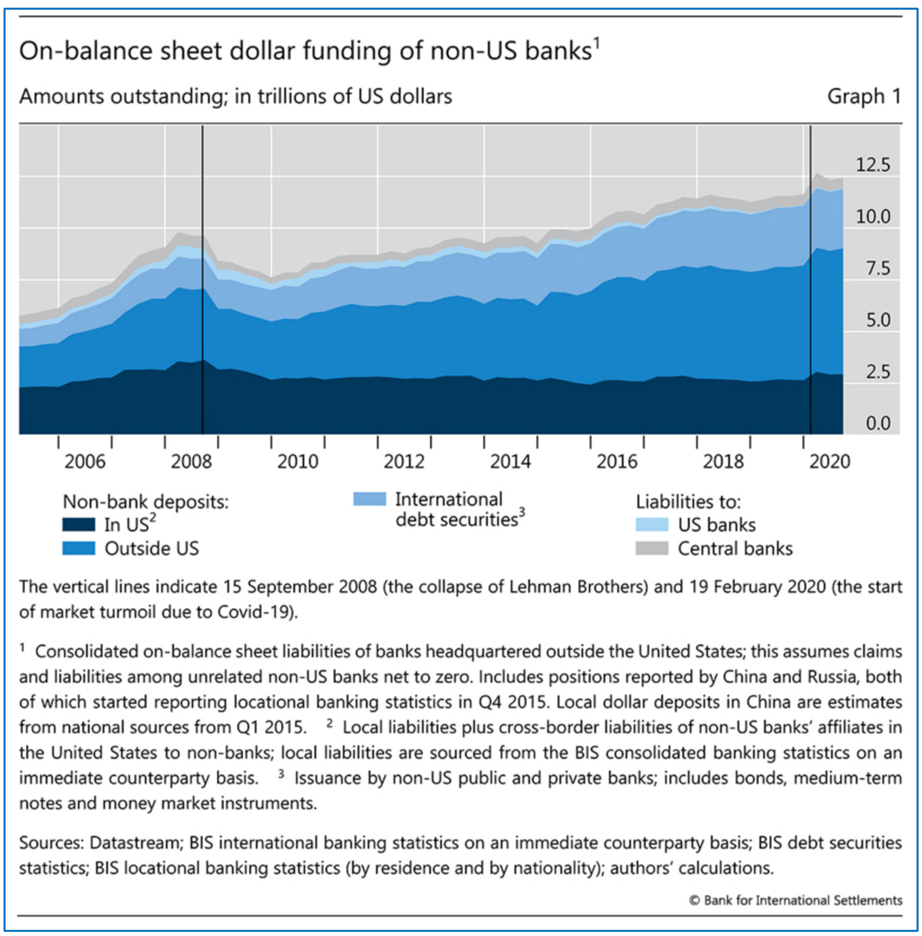


Image 2: Bank of International Settlements on U.S. Dollars in and outside the U.S.

Lastly, aside from the over-classification and under–classification, there is widespread misclassification with money printing in terms of money. To make a long story short, the US Central Bank, the Federal Reserve, has an expansionary monetary policy called Quantitative Easing, labeled as Money Printing[±] in countless media outlets to grow the economy. In other words, more money, more economic growth. The overall objective is to cause Big Commercial Banks to lend money into existence, but money printing is neither money nor printing. The operations of the U.S. Central Bank purchase financial instruments like the US Government Treasury Bonds, then store them in their account. The central problem of misclassification is that it violates the Medium of Exchange attribute of the entity of money. No one can download the data of so-called Money Printing to analyze it other than a single dealer with a particular Federal Reserve account. Purchasing already printed money is not printing, and the so-called money does not circulate in the economy because money printing is bank reserves, not money.

Object	Unit of Account	Store of Value	Medium of Exchange	Explanation
Bank Reserves	✓	✓	✗	Money Printing is an inert form of money
Cryptocurrency	✓	✗	✓	Nothing is priced into it
Stocks, Bonds, Commodities, & Property	✗	✓	✓	Limited functions for the use of money
Education	✓	✓	✗	Not tradeable
U.S. Dollar	✓	✓	✓	Global Reserve Currency

Table 2: Money Entity Resolution of Money and Non - Money

[±] You can read an explicit declaration that the U.S. Central Bank does not print money from the FED360, the Federal Reserve Bank Services, which is a subsidiary that provides critical payment processes and securities services of the U.S. Banking System here: https://www.frbservices.org/news/fed360/issues/101521/fed-facts-4-myths-federal-reserve

Literature Review

No specific literature uses Deep Learning to forecast money as the definition of money is falsely argued. In addition, the original Neural Prophet publication was on November 21^{st}, 2021, and has only nine citations as of August 2022. Nonetheless, plenty of non–deep learning articles and countless media channels, too many to cite, have tried to forecast money, but with several fundamental errors. Not comprehensive, but below are the most common issues.

Error Type	Implication

Over – Classification	• **High Bias**
	  ○ Too much data leads to less usefulness
	  ○ For example, classifying non–money as money such as bank reserves.

Misclassification	• **Type I Statistics Error**
	  ○ False Positive
	  ○ An accurate model, for instance, on non–money about money.

Under–Classification or Missing Data	• **Incomplete and non – representative dataset**
	  ○ You are ignoring the overseas U.S. Dollars that are greater in number than domestic U.S. Dollars, whose prices are driven by different factors.
	  ○ For example, whether you use M1 and M2 datasets or both from the U.S. Central Bank that are only domestic U.S. Dollars, regardless of whether it properly fulfills the money classification.

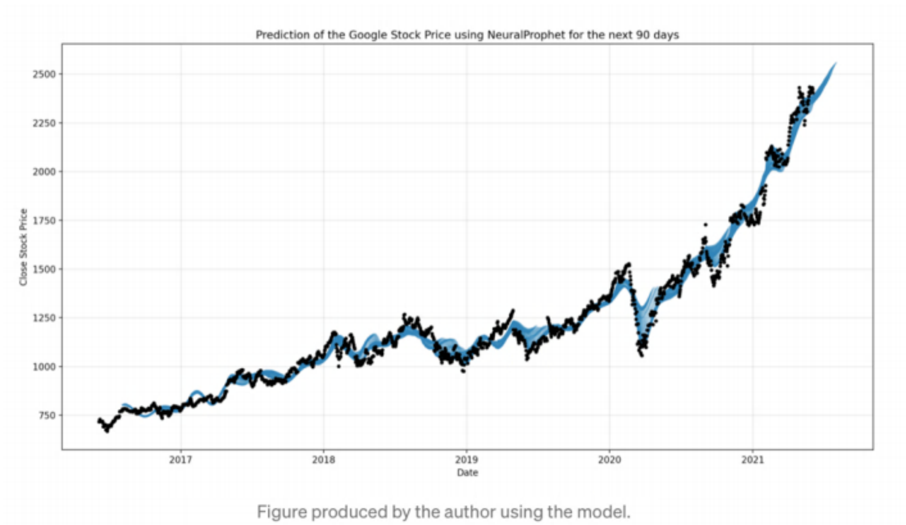
Same Model, but Different Results	• **High Variance** ○ The same model yields different results on different (non) money datasets
Always Inaccurate	• **Reselect features** • **Change the Model** ○ Restrictive assumptions of the classical model ARIMA is one example.

Table 3: Most Common Issues on Forecasting U.S. Dollar Money

Nonetheless, I have chosen one author trying to forecast the price of near-money stocks, a different dataset with Neural Prophet, and another that forecasts the same dataset but with a different model. Serafeim Loukas is a Postdoctoral Research Scientist at the University of Geneva, and Nick Hallmark, a Senior Data Scientist with experience at the International Monetary Fund working in the private sector in the investment services industry, are my literature review.

Loukas does a detailed walkthrough with the Neural Prophet Model implementation with the Google Company Stock, an indicator of the Global Technology sector, with reasonable accuracy, in "NeuralProphet For Time – Series Forecasting: Predicting Stock Prices Using Facebook's New Model" in 2021. Several hyperparameters are explicitly assigned without clear explanations, so Serafeim Loukas comes from the most common tradition of counting money with high bias over - classification. The preconceived notions are not discussed, and instead, only a link to the documentation is provided because the reader is supposed to know ahead of time.

```
from neuralprophet import NeuralProphet

# m = NeuralProphet() # default model

# our model

m = NeuralProphet(
    n_forecasts=60,
    n_lags=60,
    n_changepoints=50,
    yearly_seasonality=True,
    weekly_seasonality=False,
    daily_seasonality=False,
    batch_size=64,
    epochs=100,
    learning_rate=1.0,
)

metrics = m.fit(data, freq="D")  # fit the model using all data

# with cross-validation
# metrics = m.fit(data,
#                 freq="D",
#                 valid_p=0.2, # validation proportion of data (20%)
#                 epochs=100)
```



Images 3 and 4: Author Nick Hallmark on Deep Learning Forecasting on the U.S. Treasury 10 – Year Bond

Hallmark compares the Convolutional Neural Network (CNN) and Long–Short Term Memory (LSTM) to the GS10 monthly dataset, the U.S. Treasury 10 – Year Bond but in isolation from the Global Monetary System. CNN typically works well with image and speech data by taking advantage of spatial correlation and temporal dependencies in data. In other words, the connection in the intermediate steps of fitting the model between the targeted prediction values from the averaged inputs and the impact of previous data points to current data points when processing over time, respectively. LSTM is different because it processes sequential data to make predictions as a variant of a Recurrent Neural Network (RNN) model by feeding information back onto itself in the next step. Given the history of at least rhyming or at the most repeating exact yield values in GS10, then LSTM makes sense in model selection.

Turning to the dataset, it only represents the US Bond Market. According to Hallmark, it influences the US macro economy for policymakers with a generalization of both expansionary and contractionary economies. He correctly outlines the behavior of lower yields, high prices of a weakening or recessionary economy, and the opposite of a growing economy. However, the

Global Economy is ignored in the Global Reserve Currency and non–US Dollars, so money is misclassified. The US Economy may be growing, and non – US Economies are contracting as the latter is selling their US Dollar Bonds for US Dollar cash money. The Global Economy may or may not grow and contract together.

Regardless, his “Deep Learning in Macroeconomics – Treasury Bonds” in 2020 by Nick Hallmark on the Long – Short–Term Memory (LSTM) forecasts monthly average 10-year rates of impressive validation metrics.

	Convolutional-LSTM Model				DARM 2001:Q3 - 2019:Q3		SPF 2001:Q3 - 2019:Q3	
Time Horizon	**Overall RMSE**	**Overall MAE**	**Test RMSE**	**Test MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
T +1	0.00306	0.02144	0.00006	0.00635	0.19150	0.14367	0.17920	0.14000
T +2	0.00319	0.02090	0.00004	0.00581				
T +3	0.00287	0.01928	0.00003	0.00467	0.47483	0.36030	0.49209	0.38815
T +4	0.00292	0.02208	0.00006	0.00704				
T +5	0.00283	0.02030	0.00004	0.00479				
T +6	0.00287	0.02092	0.00004	0.00479	0.58901	0.46775	0.65749	0.52018
T +7	0.00293	0.01861	0.00001	0.00289				
T +8	0.00314	0.02105	0.00006	0.00708				
T +9	0.00280	0.02004	0.00004	0.00526	0.67786	0.54166	0.79831	0.65085
T +10	0.00330	0.02209	0.00006	0.00717				
T +11	0.00314	0.01954	0.00002	0.00409				
T +12	0.00332	0.02170	0.00004	0.00557	0.81477	0.66682	0.96095	0.79311
Average (T+1,3,6,9,12)	**0.00298**	**0.02067**	**0.00004**	**0.00533**	**0.54959**	**0.43604**	**0.61761**	**0.49846**

Model and benchmark error results

Image 5: Validation Metrics on the U.S. Treasury 10 – year Bond Note on the CNN and LSTM Models

Literature in the future on forecasting U.S. Dollar money with Deep Learning methods should require the absence of both incomplete entity and identity resolution as we can only measure the signals to estimate the quantity and not its quantity itself. Nobody knows the total amount of U.S. Dollars in the world and where it is because we do not have a Global Central Bank or a Global Government that requires anybody to reveal their amounts of U.S. Dollars.

Data

The dataset is the 10-year constant maturity of a U.S. Treasury Bond Note created or officially issued by the U.S. Department of Treasury and then routinely auctioned by the U.S. Central Bank, the Federal Reserve Bank of New York, every month depending on demand in the global financial markets. U.S. Government Bonds are classified as money or deferred money as they represent physical cash but with a term length and rate. The constant maturity refers to the average yield over time in the conveyor belt of newly created 10-year bond notes in each auction, simultaneously to each 10-year bond note that matures or stops existing. Making a new 10-year to an about to be destroyed nine years eleven month 10-year bond note has different yields, so a constant maturity averages all the differences. Not to mention all the live bond notes in between.

More importantly, each auction plays a critical role in the quantity of U.S. Dollar money as individuals or institutions can bid for the price for deferred money, including foreign bidders. The auction presents an amount for acceptance or tendered in an official global auction, and after the auction, there is an acceptable amount. Less would be accepted if too much were tendered, or all would be taken if the same amount were, but most of the time, it is something in between. The critical takeaway is that the workaround for not knowing the total quantity of Global U.S. Dollars is to read the signal in the auctions that routinely every month tell us if we are low in quantity or at comfortable levels.

Specifically, each bidder acts on their quantity of U.S. Dollar money, and collectively the bidders provide a sample of the total amount of Global U.S. Dollars. The auctions drive the U.S. Dollar Currency as the Global Reserve Currency as a primary market, but even more, the Secondary Markets that have already auctioned U.S. Dollar deferred money bought at auction and sold later are influenced by the monthly activity of what is tendered and what is accepted in the official auction. Suppose the gap between the tendered and accepted keeps widening. In that case, the Global Economy is okay, so keep your Secondary Market holdings of U.S. dollars and do not sell them for U.S. Dollar cash money. Otherwise, a narrowing trend of tendered and accepted in multiple auctions signals that the total quantity of Global U.S. Dollars is dear, and the Global Economy is in trouble. These are generalized observations, but numerous consecutive outcomes signal U.S. Dollar shortages and surpluses in the Global Economy under the Global Reserve Currency of the U.S. Dollar money even though nobody knows the total number of U.S. Dollar money. Nonetheless, an outline of the data files incorporating the description above is below.

Frequency	Dataset Label	Start Date	End Date	Number of Observations
Monthly	GS10	April 1953	July 2022	832
Weekly	WGS10YR	January 1962	July 2022	3,161
Daily	DGS10	January 2, 1963	July 29, 2022	15,130

Table 4: Dataset Details

Methods

About half a century ago, the statisticians George Box and Gwilym Jenkins developed the Auto-Regressive Integrated Moving Average or ARIMA model. It sets in motion time series modeling when a single column dataset can be processed and forecasted. The classical approach expanded to other model types with various applications with high interpretability but restrictive assumptions and a lack of scalability. As long as you assume the stability in the first two moments of the dataset's distribution, mean, and variance, you have a workable solution but with limited extensibility. Also, the parametric assumption only allows a restrictive range of numerical values.

Contemporary models like Deep Learning with relaxed assumptions of data distributions coupled with non – parametricity at the expense of interpretability raised the accuracy and applicability. The opening between interpretable classic and highly accurate contemporary deep learning models is an open research topic. A model's optimal positive and negative attributes are the ideal or the best of both worlds.

About 30 years ago, the econometricians Andrew Charles Harvey and Simon Peters built a univariate structural time series model on-trend, seasonal, and irregular components. After that, the model was improved with Facebook Prophet, developed by practitioners Benjamin Letham and Sean Peters with backgrounds in Operational Research and Information Science, respectively, in 2017. The Prophet model is a modular and non–linear regression model that separates and recombines a single dataset of history. Also, there was practical commercial appeal like holiday processing without needed imputation. Yet, Facebook Prophet does not look for causal relationships between the past and the future.

Image 6: The Neural Prophet Banner

Enter Neural Prophet with flexibility, automation, interpretability, and scalability. There are 25 hyperparameters with automatic selection and are independently configurable. Beyond Facebook Prophet, there is also auto–regression when future behavior is based on past behavior and lagged covariates or delayed predictors. Research on short–term future values depending on the current state would find this helpful as the long–term input values have a long–term downtrend. Moreover, the restrictive assumptions from ARIMA are removed as the distribution of the dataset can evolve with regime switching coupled with dozens or even hundreds of training passes to increase fitting for accuracy. Six authors introduced Neural Prophet from Stanford University, Monash University, Skoltech University, and Facebook last year, but it is an ongoing open–source development project. Below are the additive components that can be selected and assembled in various combinations as $\hat{y}_t$ is the predicted value at time *t*.

$$\hat{y}_t = T(t) + S(t) + E(t) + F(t) + A(t) + L(t)$$

Variable	Description at time t
$\boldsymbol{T(t)}$	Trend
$\boldsymbol{S(t)}$	Seasonal effects
$\boldsymbol{E(t)}$	Event and Holiday effects
$\boldsymbol{F(t)}$	Regression effects for future known exogenous variables
$\boldsymbol{A(t)}$	Auto – Regression effects based on past observations
$\boldsymbol{L(t)}$	Regression effects for lagged observations of exogenous variables

Image 7: The General Equation for the Neural Prophet Model

Below are the hyperparameter settings for the three frequencies. Some can be manually configured, such as those colored in green, but others are automated.

	Parameter	Default Value	Daily	Weekly	Monthly
1	growth	linear			
2	Changepoints	None			
3	n_changepoints	10		24	12
4	changepoints_range	0.9			
5	trend_reg	0			
6	trend_reg_threshold	FALSE			
7	yearly_seasonality	auto			
8	weekly_seasonality	auto	disabled	disabled	disabled
9	daily_seasonality	auto	enabled	disabled	disabled
10	seasonality_mode	additive			multiplicative
11	seasonality_reg	0			
12	n_forecasts	1			
13	n_lags	0			
14	num_hidden_layers	0		1	2
15	d_hidden	None			
16	ar_sparsity	None			
17	learning_rate	None	0.1		
18	epochs	None	92	139	206
19	batch_size	None	64	32	16
20	loss_func	Huber			
21	optimizer	AdamW			
22	train_speed	None			
23	normalize	auto			
24	impute_missing	TRUE			
25	collect_metrics	TRUE			

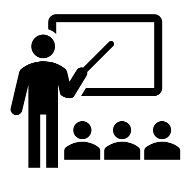
Table 5: Hyperparameter Settings for the Neural Prophet Model.
Green-colored values are manually set, and the rest are automated.

Both domain knowledge from the business side can configure the hyperparameters like the daily seasonality set to true for the daily yield values of the 10-year U.S. Treasury Bond Note and the

Deep Learning approach to setting the learning rate to a higher 0.1 for more significant updates to changes in the Neural Networks weight management at each pass in the epochs. Nonetheless, eighty percent of the datasets were used for training to fit the data, and the other twenty percent to validate the test set.

I used Exploratory Data Analysis and essential Statistical Testing to add value to the Neural Prophet Model selection. Monthly, Weekly and Daily have line plots and histograms followed by one test for stationarity, Augmented Dickey-Fuller, on how stable the dataset is and then how normally distributed the datasets are with the Jarque – Bera test. The results of the statistical methods used to drive the use of the Neural Prophet Model.

Results



There are strong outcomes from start to finish on the Exploratory Data Analysis, Statistical Testing, and the Neural Prophet Model validation metrics for all three frequencies. The highest yield values are north of the 10 percent rate of return as most yield values are below 10 percent for the past 40 years and up until 2022. Since the early 1980s, the consistent long–term downtrend with short-term up swings has been non–linear and complex. The US Economy and non – US Economies add, reduce or remove their influences over different frequencies over time. More U.S. Dollar flows because of globalization of trade and finance, plus various new financial instruments add to the complexity.

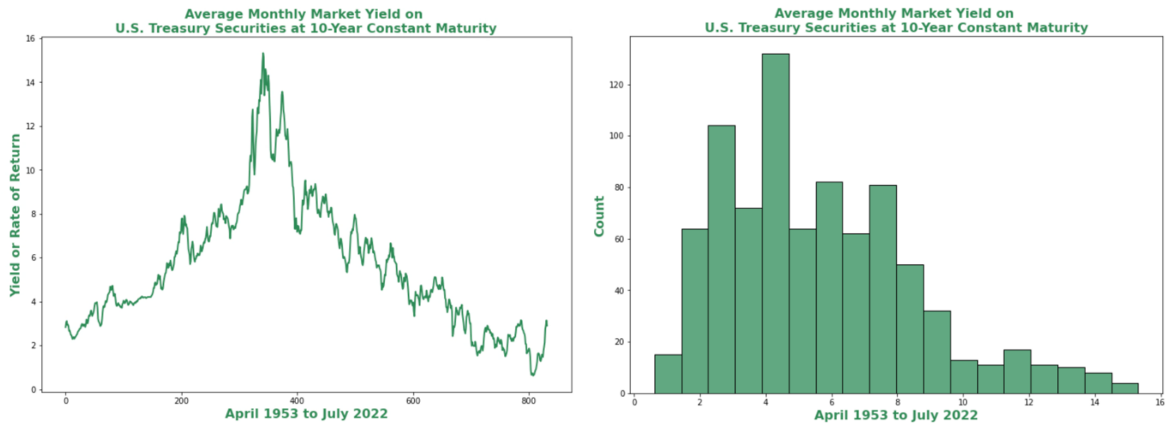


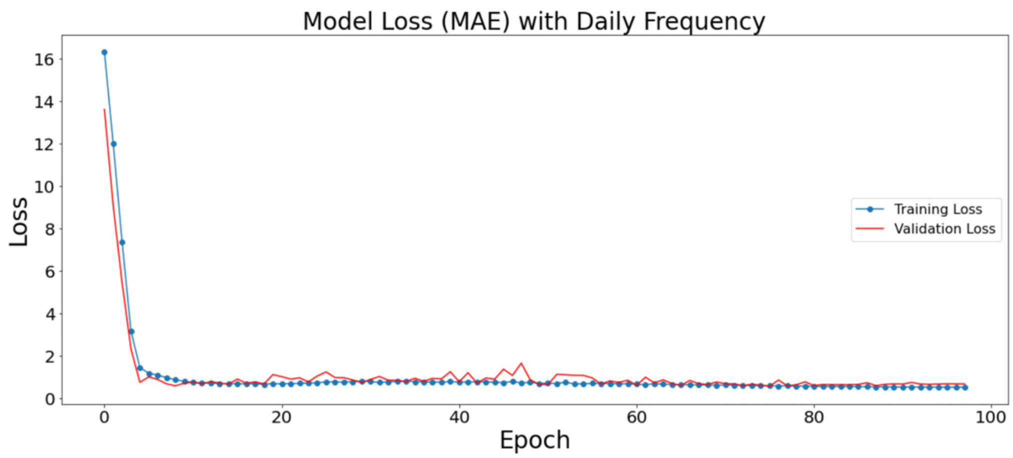
Image 8: The Exploratory Dataset Analysis of the Monthly Average Yield Dataset

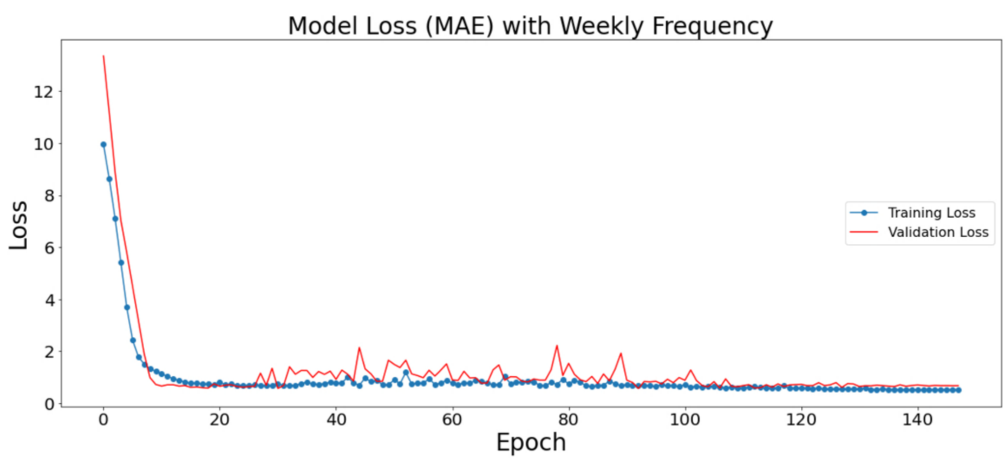
All three frequencies failed to reject the null hypotheses on the Augmented Dickey-Fuller and the Jarque – Bera tests. There is an effect in the 10-year dataset for instability and non–normality across decades of history as we accept the alternative hypotheses in the tests. The mean and variance are not stable as the first two moments in the distribution, so we cannot choose the classical ARIMA model and its model variants. Yet, there are periods of near normality as the third and fourth moments of the distribution, skew and kurtosis, are relatively close to zero.

Validation Metrics	Daily	Weekly	Monthly
Smooth L1 Loss	0.003	0.003	0.003
Mean Absolute Error (MAE)	0.673	0.660	0.596
Root Mean Squared Error (RMSE)	0.797	0.798	0.747

Table 6: Validation Metrics

The Neural Prophet Model has all validation metrics near zero, with the training and validation loss in a tight relationship as per below, yielding high accuracy.





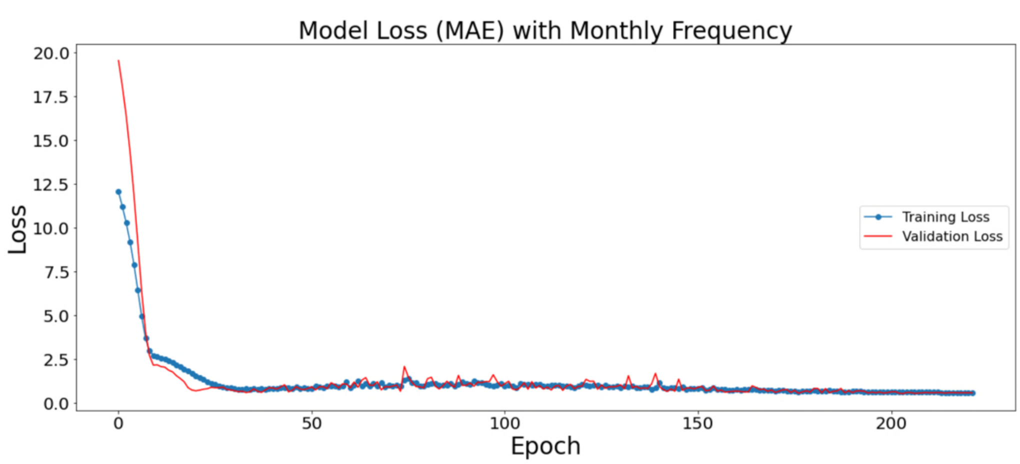
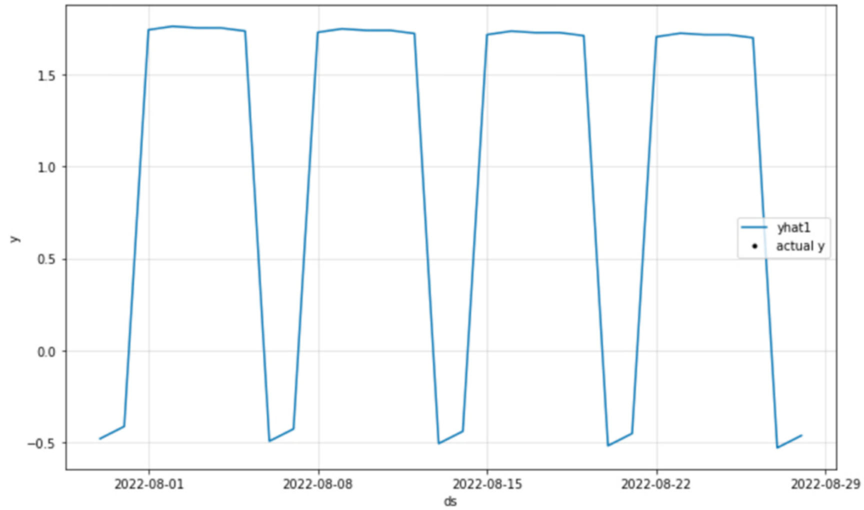


Image 9: Validation Metric Graphs from Neural Prophet Model of the Three Frequencies

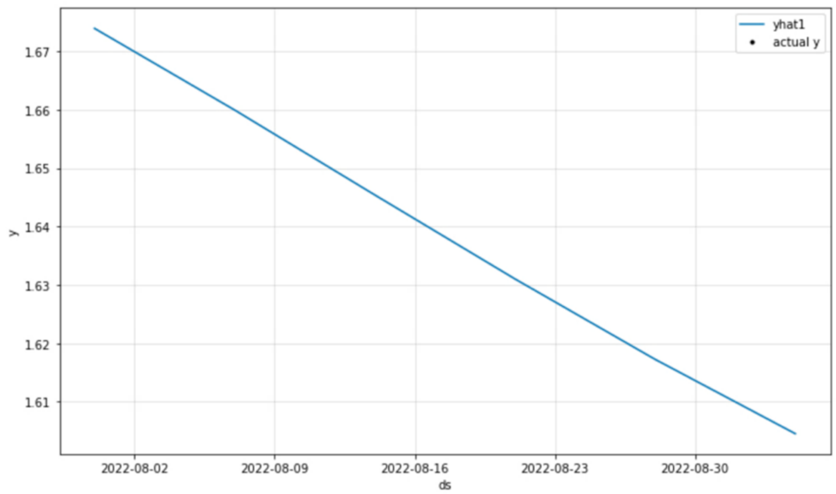
Analysis and Interpretation

As expected, there is more volatility in the daily forecasts than in weeks or months. The daily noise is smoothed out weekly only for a revisit of some swings in the forecasted monthly yield values in Image 10 below. The nature of deferred dollars drives this behavior as very little value is attached to daily yield values other than economic indicators. Private corporations, governments, and individuals look at weekly and monthly yield values as their pace of operations and budgeting are beyond daily views or actions. For example, buying a single-family residential house heavily influenced by the 10-year is a transaction that takes months, not days.

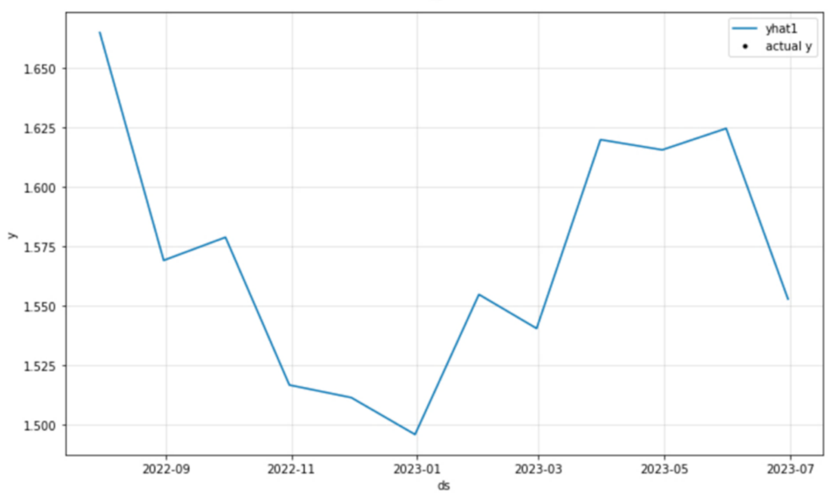
Moreover, in Image 11 below are the Seasonality Components of the Daily Forecasts showing yearly, weekly, and intra – day fluctuations as the daily seasonality parameter are enabled. There is less economic activity in the winter months starting from November to February, especially the 10-year influence on the US Real Estate market. Property buyers like to purchase when the weather is better when they take a physical look at the property. Financial Markets are closed on the weekend, so weekdays have higher yield values, and the uptick in the morning hours signals the opening of the financial markets until lunch. Afternoon yield values undulate as the rest of the hours of the day and night express non–US activity in different time zones than the U.S. Most importantly, the July 2022 end data implies an economic slowdown or recession in its forecast.



The Daily Forecast for the next 30 days, starting every day in August 2022, shows volatility from negative 0.5 to about positive 1.6, as there is some overlap in yield values in the weekly forecast below.



From the first week in August 2022 onwards, the Weekly Forecast ranges from about 1.67 to about 1.60 as a straight linear downward trend for the next six weeks.



The Monthly Forecast for the next 12 months swings downward for the rest of 2022 from 1.66 to 1.50, then swings up to 1.625 and down to 1.550 for 2023.

Image 10: The Daily, Weekly, and Monthly Forecasts

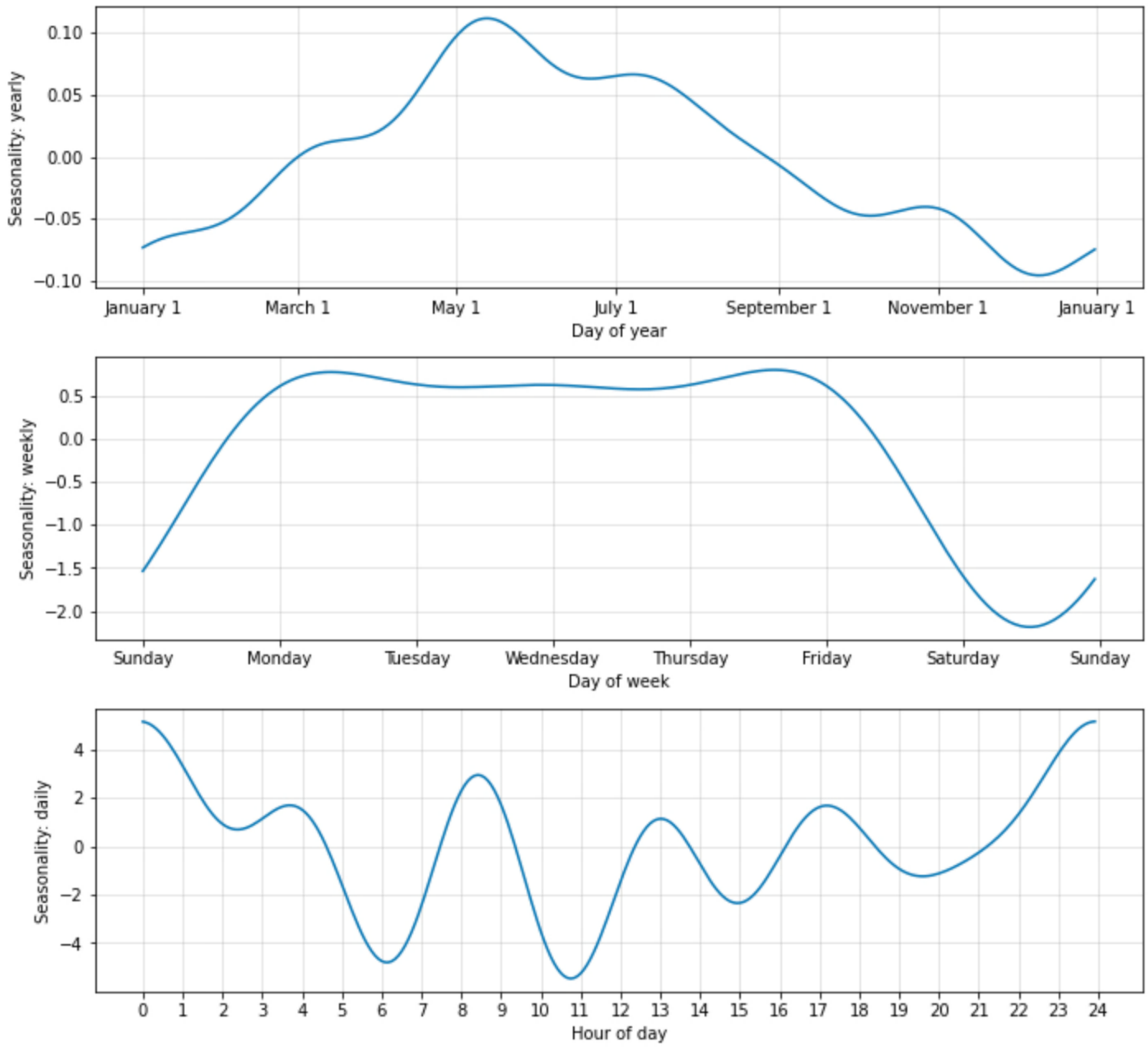


Image 11: The Daily Forecast Seasonality Components

The long term since 1982 shows deflationary money with a consistent downward trend for daily, weekly, and monthly. This raises the question for further analysis for future work regarding what is happening with the Global Reserve Currency and U.S. Dollar money. Image 12 below shows central regime switching in the dataset.

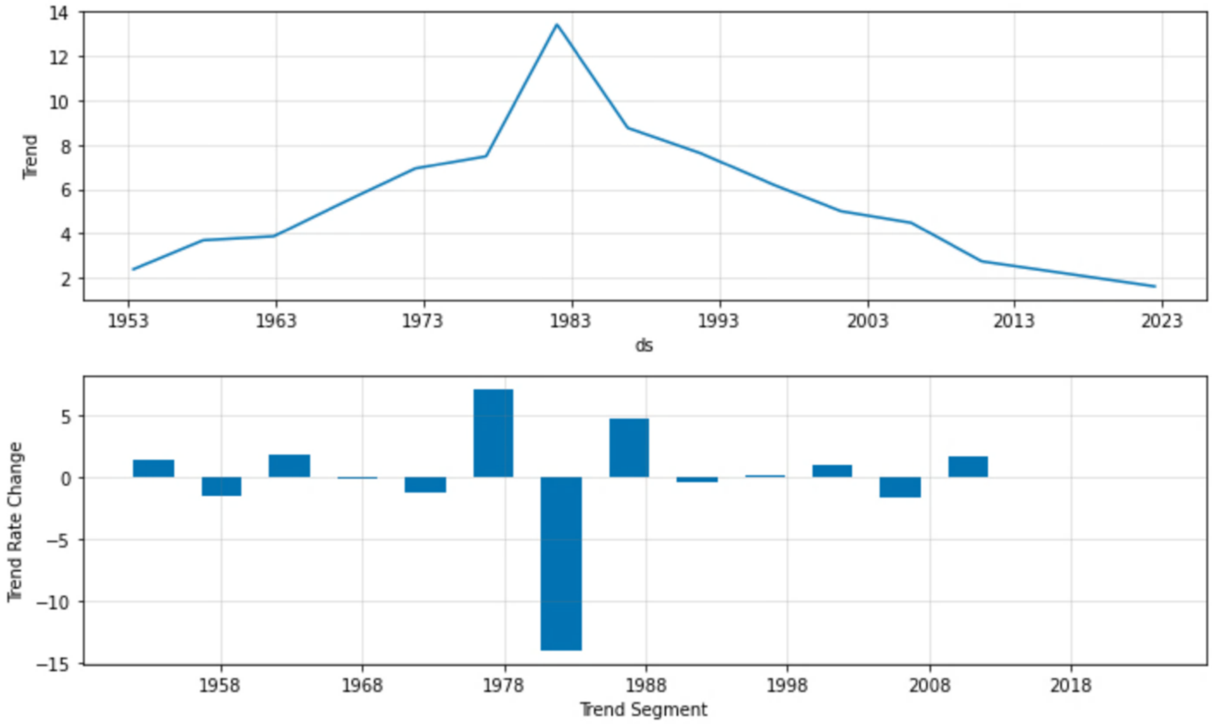
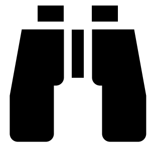


Image 12: Monthly Parameter Plot

Conclusions

The first overall takeaway is that the high accuracy across three different frequencies is impressive. The complex domestic, international, individual, and institutional influences for a single dataset representing a Global Reserve Currency have an essential takeaway. The long-term trend implies a perpetual U.S. Dollar Shortage since, for forty years, albeit with some short upswings. If the US and the rest of the world keep pushing prices up in an economic shortage and showing the yields falling consistently, then we need a new Global Monetary Policy to create more U.S. Dollars. Since the Global Reserve Currency is loaned into existence overseas, regardless of the U.S. Banking System actions, the quantity of U.S. Dollars fails to fill the need for capital raising for governments and private enterprises in dozens of countries. The Global Reserve Currency has been, and will constantly be challenged, but until another government-issued paper is valued more like when the U.S. Dollar took over the British Pound Sterling after World War II, then the U.S. Dollar is here to stay. We need international cooperation to modify, not replace, the U.S. Dollar system of money to resolve the issues of entity and identity resolution with more transparency to inform all human beings on earth to make better money decisions.

Directions for Future Work



The 10 – year Bond Note is only a start, but another similar entity and a chain of entities would be directions for future work. For example, the US Treasury 30-year bond, like the 10-year, can also be looked into, but more importantly, the overall yield curve below with its various maturity points may add value. Aside from a single data array, we could look at a series of data arrays on the U.S. dollar money shortage. The 12 points below and their shape would describe economic conditions in the US and the rest of the world. Moreover, there is also the Eurodollar Futures Curve and the spreads of various curves that can also be used as a dataset with Neural Prophet.

1 Month	2 Month	3 Month	6 Month	1 Year	2 Year	3 Year	5 Year	7 Year	10 Year	20 Year	30 Year

Table 7: The U.S. Treasury Yield Curve Maturity Points

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