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Econ 499

8 April 2018

Analysis of Model Selection When Predicting Business Cycle Turning Points

Abstract

Since the dawn of economy, people have sought after predicting its downturns. From the early ideas of Irving Fisher's present value model to advanced machine learning techniques. Investors and policy makers all around the world are interested in preparing for the absolute worst case scenario. This paper dives into analyzing two different models that attempt to predict recessionary periods in the United States. The first model is a Dynamic Factor Markov Switching model and the second is a Convoluted Neural Network. This paper seeks to shed light on the models currently in place at large institutions and see if one model performs better than the other.

Research Topic

Many people have a strong belief in the law of averages. Or rather, they believe that is is often the culmination of their actions that influence their future decisions. Nassim Nicholas Taleb, a prominent scholar and risk analyst, believes in quite the contrary. Most often it is the unexpected events that have the largest influence in shaping the trajectory of future outcomes. Taleb says,

> I don't particularly care about the usual. If you want to get an idea of a friend's temperament, ethics, and personal elegance, you need to look at him under the tests of severe circumstances, not under the regular rosy glow of daily life. Can you assess the danger a criminal poses by examining only what he does on an ordinary day? Can we

> understand health without considering wild diseases and epidemics? Indeed the normal is often irrelevant. Almost everything in social life is produced by rare but consequential shocks and jumps...(Taleb)

There is importance in studying the improbable. One major event that comes to mind when thinking about massive unexpected shifts is the state of the economy. Many economists over the years have attempted to learn about the nature of the economy. Some experts believe that it is possible to predict a recession in the economy, while others believe that the intricacies obfuscate the ability to tell the signal from the static.

This research paper will attempt to validate the former by building upon the previous models of Hamilton, Chauvet, and Piger. While many models have been constructed through research, we seek to add upon the class of dynamic-factor mixed-markov switching models (DF-MMS). In the past, ARIMA models have been shown to be restricted under the assumption of linearity (Hamilton). DF-MMS models allow for non-linear estimation which better suits the analysis of economic data.

Currently, the Federal Reserve employs a DF-MMS model when projecting probability of recession in real-time (FRED). This projection takes into account four different indices: non-farm payroll employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales. The DF-MMS model applied to these indices was developed by Chauvet in 1996 and is still currently used today. While these indices provide valuable insight, we intend to improve upon the model by adding in US Treasury Bond spreads and the Volatility Index (VIX) as possible indicators for economic regime switches.

Several other papers have improved upon the model of Chauvet by using Bayesian Estimation methods for the parameters (Chauvet and Piger, "A comparison of the real-time performance of business cycle dating methods."). These topics will be explored in throughout the research but at a given point in time a final method of estimation will be decided upon for the final model.It is also important to note that previous models continue to gain accuracy as they age given the new data further smooths out the probabilities of recession. The goal is to build a model that is accurate in the present as well as accurate into the future.

Another model this paper will look at is the Convoluted Neural Network which has been used primarily in the technology industry to provide spam filters and recommendation systems to consumers. This technology has also been implemented in the field of Natural Language Processing and has aided in building smarter artificial intelligence. Until recently, this technology has not been used in assessing the financial health of the markets. Later in the paper, we will detail how neural networks are currently being implemented in Economics. The paper will implement Chauvet's original model in the form of a neural network to see if any extra accuracy can be gained from its unique approach to classifying regime states.

As mentioned previously, it is the unlikely that has the most profound effect in society. By developing a better understanding of the elusive nature of the economy it is possible build an economy that is protected against the improbable. If the probability of recession can be estimated in real time then then it should be expected that the world would experience an extreme shift in paradigm and how companies approach risk in the market place. This is the ultimate problem we seek to solve by building upon the body of research.

Literature Review

The nature of the economy has been studied since the dawn of free market capitalism and for hundreds of years, it has surprised even the most well-read intellectuals in unique ways. In regards to the research on recession prediction, there have been several papers published in the field that have been highly regarded in moving forward the understanding of market structures and papers that have also been criticized. This section of the paper will detail out the summaries and methodologies used by these iconic papers and provide a discussion on how they apply to the research of this paper.

In a paper titled, "A New Approach to the Economic Analysis of Non-Stationary Time Series and the Business Cycle" by James D. Hamilton is the leading paper that proposed econometricians move away from auto-regressive linear models into utilizing unobservable regime switching markov models. This concept has been popular among modern researchers and has been cited by over 8,742 authors [1]. This foundational paper has influenced the work of hundreds of researchers but is not without its flaws. Hamilton used a minimal model when writing the paper, citing only the current value of Real GNP as an independent variable. Also, Hamilton proposed making inferences about population parameters using maximum likelihood estimation. While this is an accepted method, other authors have gone on to later improve upon population parameter estimation using Bayesian Estimation techniques.

Another paper on, perhaps, the other end of the spectrum is a relatively recent paper published in 2010, titled "Neural Network Methods for Forecasting Turning Points in Economic Time Series" (Zhang et al.) goes into attempting to forecast changes in the business cycle using neural network models and 13 indicators of economic activity. While these methods are fairly new to the field of economics they have been well studied in fields such as statistics and computer science over since the early 1950s. Zhang's paper goes deeper into studying models that do not require as strenuous assumptions as linear models do. In this sense he is pushing forward Hamilton's idea of implementing non-orthodox statistical methods to make inference about a population. While this paper does not implement a neural network it is important to look at the less-accepted methods in the field to see what research might affect the current research in the future.

One last paper that was monumental in influencing the research done is this paper is titled,

[1] According to Google Scholar 2018

”A Comparison of the Real-Time Performance of Business Cycle Dating Methods” (Chauvet and Piger, “A comparison of the real-time performance of business cycle dating methods.”) in this paper Chauvet focuses not only on the appropriate statistical model but also finding factors that can deliver a quicker analysis that remains accurate. Many other research papers have documented rather accurate results but used factors that were only published once or twice a year. Chauvet was able to create a composite index on four different indices that are published roughly four times a year and still provides high accuracy using a hidden markov model. This model is paramount to the discussion and the model in this paper will be based off the work of Chauvet.

There are many more sources that could be cited and will be cited within this paper, but these are a few of the important works that should be explicitly discussed when referring to the research at hand. Ultimately, these papers provide historical context to the problem at hand, a forward looking technical perspective, and a robust accurate model. Our research can now be unfolded with these topics in mind so that a proper analysis can be done.

Data & Research Methods

All of the data used in this paper was obtained through official entities and has been checked for accuracy. The final data set is comprised of *Real Manufacturing & Trade Sales, Industrial Production, Nonfarm Payroll, Real Personal Income, 10 Year - 3 Month Treasury Spread* and the *VIX.*

Given the different starting times when these data have been collected, the final data set is considerably smaller than the most recent model posed by Piger. This will make comparison between the two models harder as the final model will have had less data to be trained. This was only a minor problem in the overall research of the topic. The final model captures three recessionary periods at differing lengths which provides confidence that the model will be able to pick up the distributed effects of each variable.

In order to account for continuously compounded returns, the log difference of first four variables mentioned above were used in the model. The treasury spread and VIX were not transformed due to the static nature of those variables.

There has been seven US recessions since 1967 and three US recessions since 1990. Appendix 1. details the points in time and duration of these recessionary events throughout history. Both models will attempt to determine what the current state of the economy is given the variables provided. This can be likened to trying to determine the weather outside in a windowless building. While it is nearly impossible to observe and verify such a macro-event, other variables can be used to determine said-event's current state.

Appendix 2. details the patterns that each variable has exhibited over time and throughout each recession. One important thing to note, each time the treasury spread has gone negative, implying a negatively sloping yield curve, the economy has entered into a recession shortly afterwards. This was a major fact when deciding to include the treasury spreads as an indicator variable for US recession.

It was also fortunate to have these data retrieved from reputable sources as there was no issue of missing data which would have posed large problems for the validity of the models. It should also be noted that it is a common prior assumption that financial data follow a Gaussian distribution. This was used as the prior for the DF-MMS. Further research could potentially look into using more informative priors rather than relying on the symmetric nature of the normal distribution. This juxtaposition makes the most sense when looking at the empirical distribution of these data. Appendix 3. shows the relative histogram and density of these data.

Model Analysis & Summary

Three models were then prepared and trained on the aforementioned data set. Each model produced interesting results. The next few subsection will be dedicated to describing the results of each model.

Full Model

This model is the full model because not only does it incorporate the original variables proposed by Chauvet but also includes the variables of interest, treasury spreads and the volatility index of the United States stock market. As mentioned previously, a simple normal distribution was used as a conjugate prior for each variable in the model and despite this obvious flaw, still produced desirable results. Looking at Appendix 4., in contrast with the gray bars showing true recessionary periods, the model predicts with high accuracy contractionary periods. While there is some noise through out the probabilities, this can be expected. Piger commented on this phenomena on his website saying,

> Historically, three consecutive months of smoothed probabilities above 80% has been a reliable signal of the start of a new recession, while three consecutive months of smoothed probabilities below 20% has been a reliable signal of the start of a new expansion. (Jeremy Piger)

So as it appears, the small blips that are under three months are false positives. It could be reasoned that further research into developing a strong prior distribution for some of the more skewed data could normalize the sensitivity of the model.

Reduced Model

The second model was a re-implementation of the model put forth by Chauvet. This was done to contrast the full model's accuracy with a previously published model. In Appendix 5. it is possible to see the extended time line of data the accuracy this model displays. When looking at the AIC and BIC for both the Full and Reduced Model,

	Full Model	**Reduced Model**
AIC:	-5120.499	-19480.16
BIC:	-5029.618	-19396.24

it appears that the full model seems to be a better choice in terms of model selection. Another interesting output of full model is the transition matrix showing that the probability of transitioning from an expansionary state to a recessionary state for any given time period is only 7.1%, while the probability of remaining in an expansionary state is 92.9%. In comparison, the transition matrix

$$X = \begin{bmatrix} 0.763 & 0.237 \\ 0.071 & 0.929 \end{bmatrix}$$

Figure 1: Full Model Transition Matrix

for the reduced model shows that the probability of recession is around 21.6% while the probability of continuing into expansion are only 78.4% It appears that the full model adds accuracy and

$$Y = \begin{bmatrix} 0.946 & 0.054 \\ 0.216 & 0.784 \end{bmatrix}$$

Figure 2: Reduced Model Transition Matrix

validity to the previously published model which is a good sign. If further research can be done into establishing proper prior distributions, as mentioned previously, this model could be successful in predicting recession probabilities.

Neural Network

Finally, this section will cover the details behind the neural network model and discuss the proponents and possible shortcomings of the model. A neural network is modeled primarily after how the human brain operates. There are several nodes that are fed information and experience transformation through what is called an *activation function*. The output is then compared with what is already known, and then error is slowly "trained" away through back-propagation. Over time, it's possible to train a neural network to classify images, and even detect market anomalies. In this model, each variable is passed in as an input node. While this neural networks are relatively

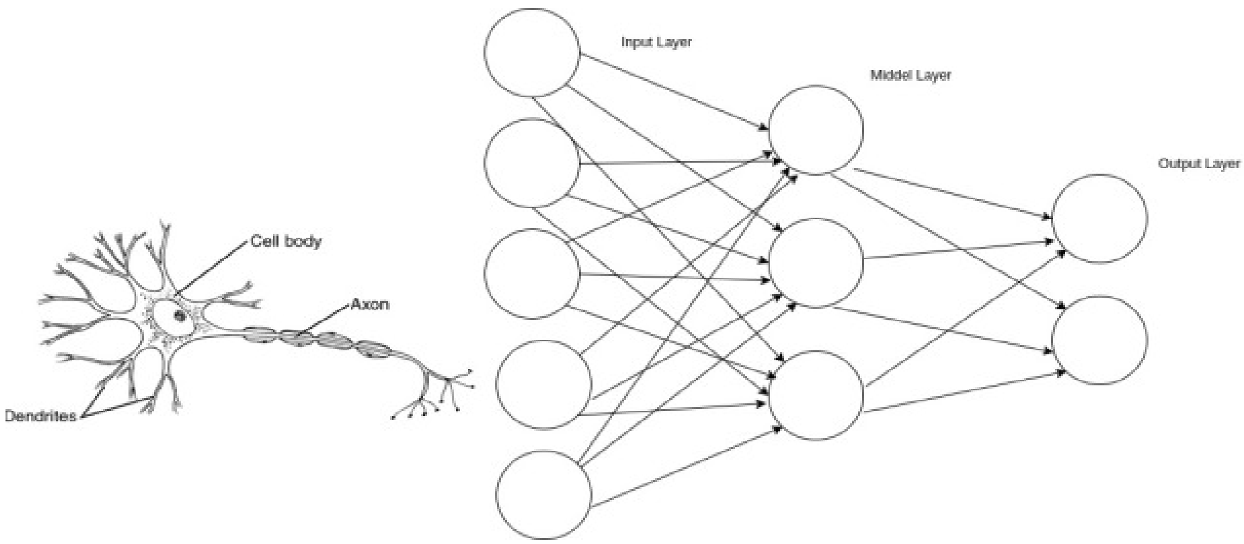


Figure 3: Neural Networks & the Brain (Nielsen)

new, the underlying mathematics is just matrix algebra. The model is then cross validated across 30 different batches, randomly sampling the testing data set each time in order to get a well mixed model. Appendix 6. displays the training data with each epoch. The accuracy, over time, converges to 88.52% which is means that the model was able to accurately predict that it was in a recessionary state 88.52% of the time. These results are excellent but could use improvements. Typically, it's better to see accuracy up near 93-95%.

One major issue with neural networks is the fact that its output is uninterpretable. Meaning, neural networks are what's called a black-box model. A user from stackoverflow.com described the nature of a black-box neural network:

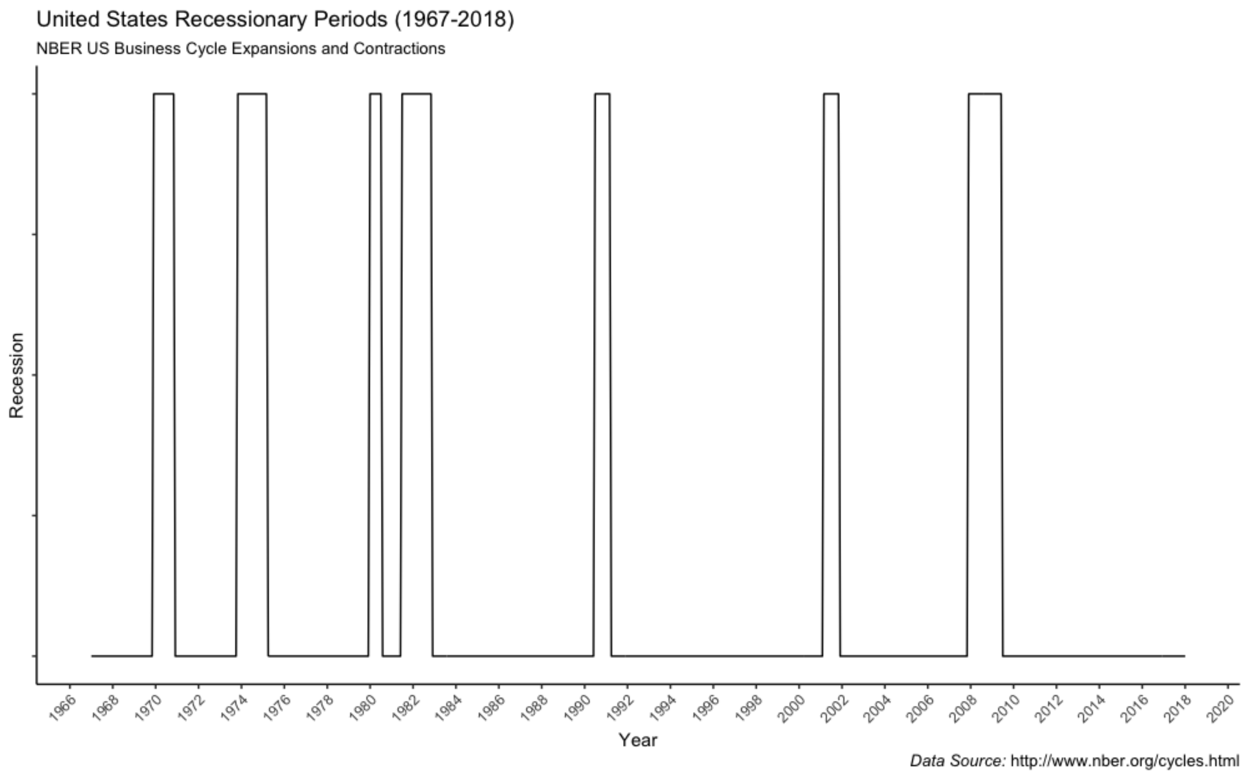
> A neural network is a black box in the sense that while it can approximate any function, studying its structure won't give you any insights on the structure of the function being approximated. (Lucas Gallindo)

Overall, the model is quite successful in determining the current state of the economy and as technology uncovers more about the neural network, it would seem that economic modeling might see more machine learning techniques become prominent. It's only drawback is that the nature of the output cannot be dissected or understood. It is merely a tool for prediction.

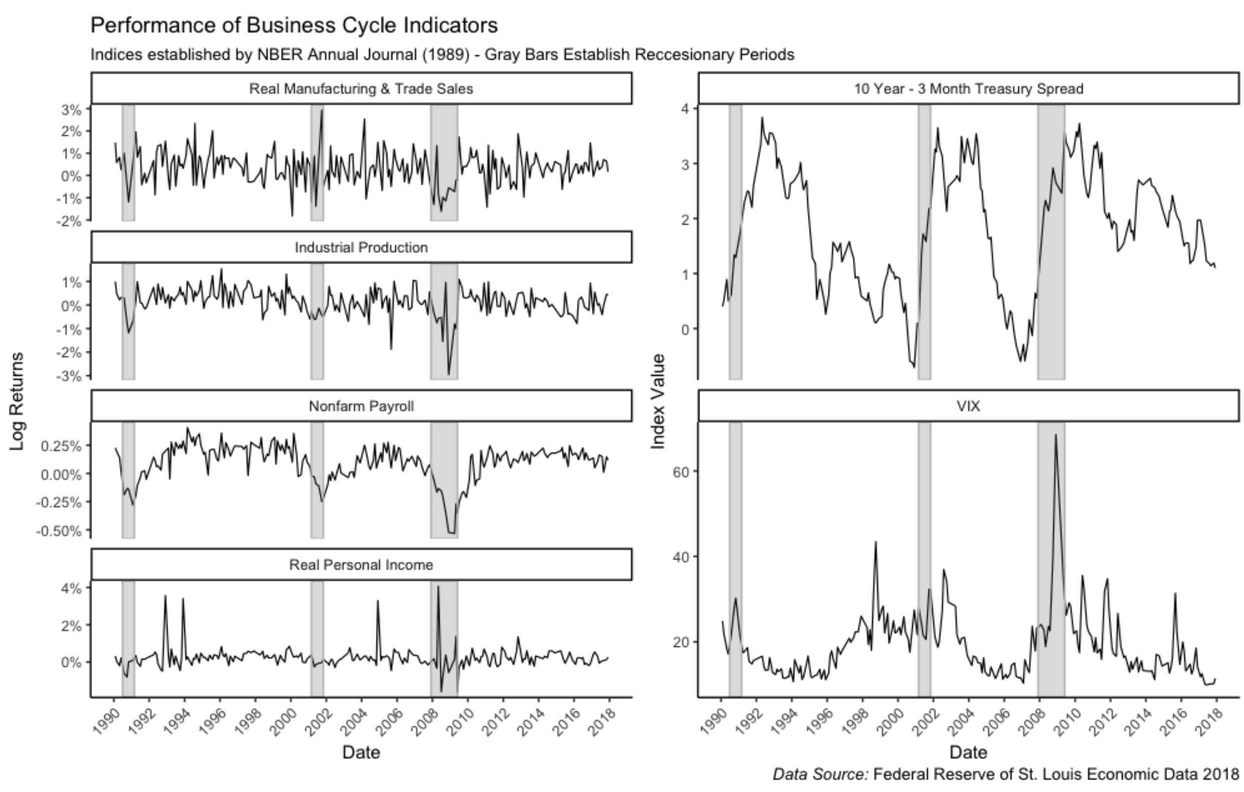
Conclusion

In conclusion, these models are important to the future of economic forecasting. As the economy becomes ever more complicated and vast, simple linear models will reach their limitations and new models will need to pick up the slack. The Dynamic Factor Markov Switching Model is nearly 20 years old but can still be built upon. The neural network is sleek and fast but has obvious shortcomings when it comes to the statistical weighting other models have. The code used to generate the models and plots can found at: https://github.com/dylanjm/senior_thesis

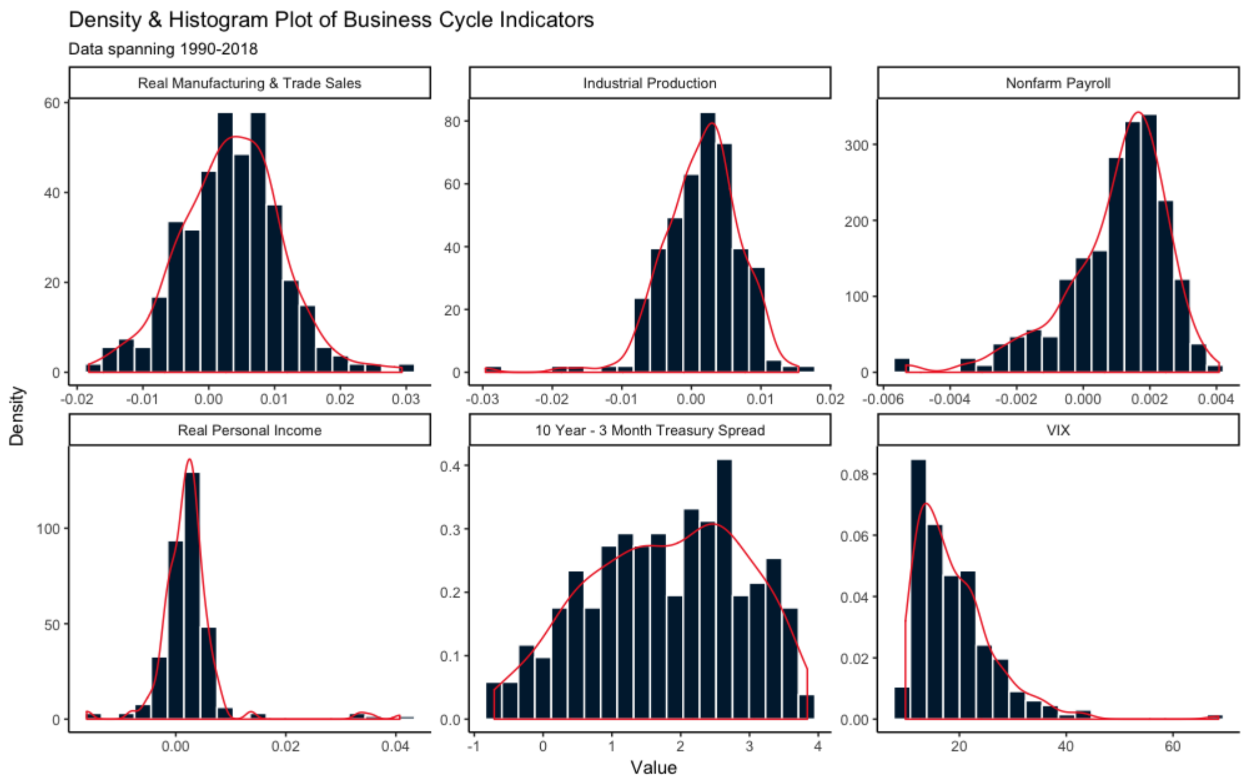
1. Appendix: U.S. Recessions



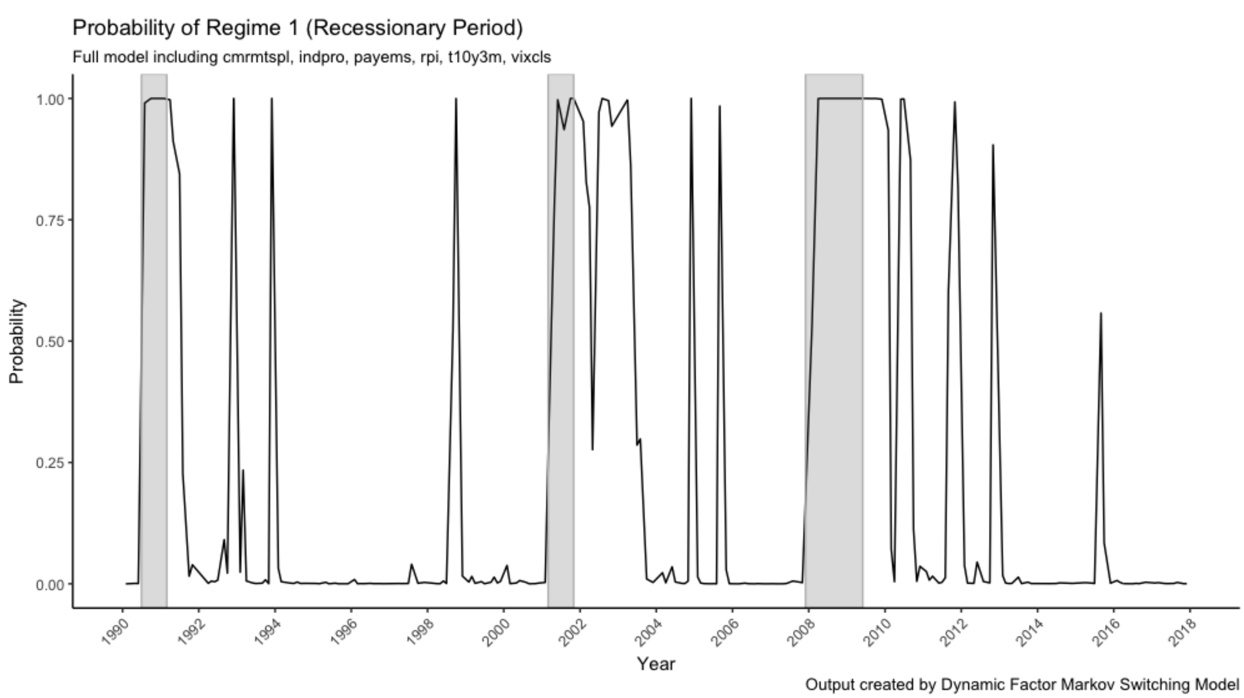
2. Appendix: Time Series Summary of Variables



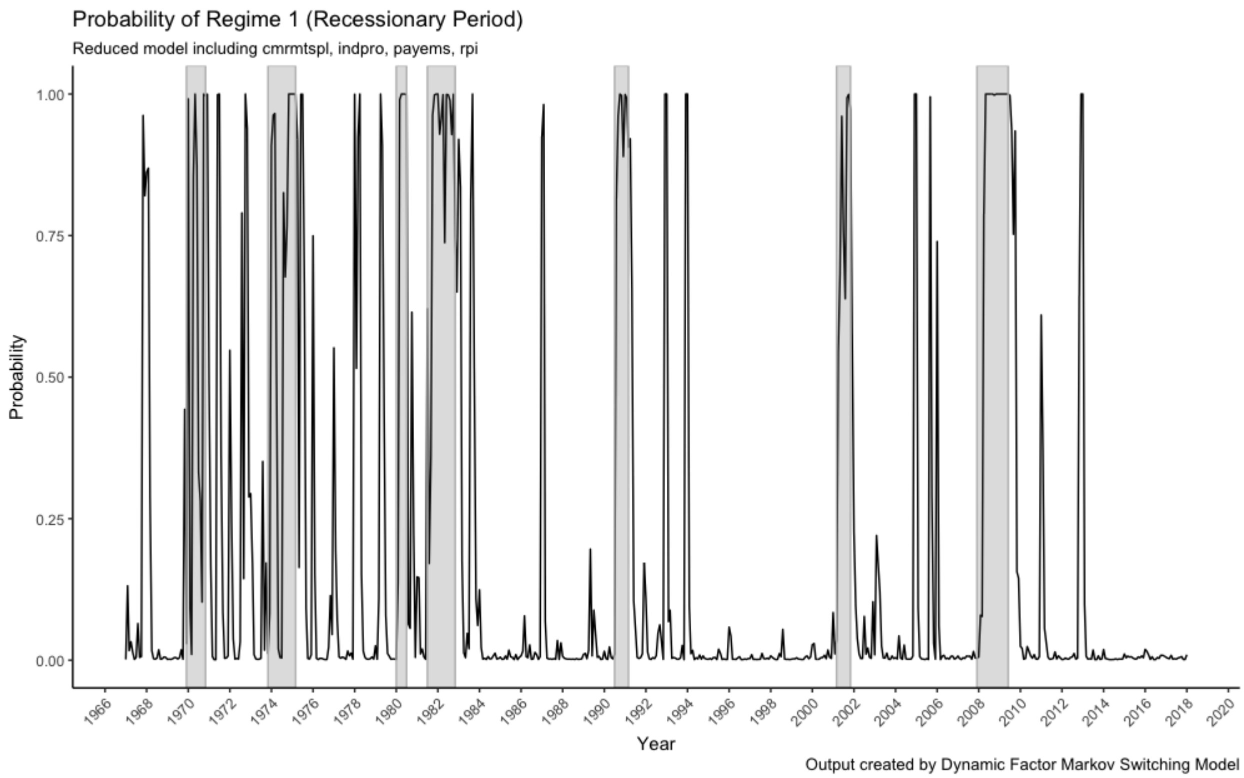
3. Appendix: Distribution of Data



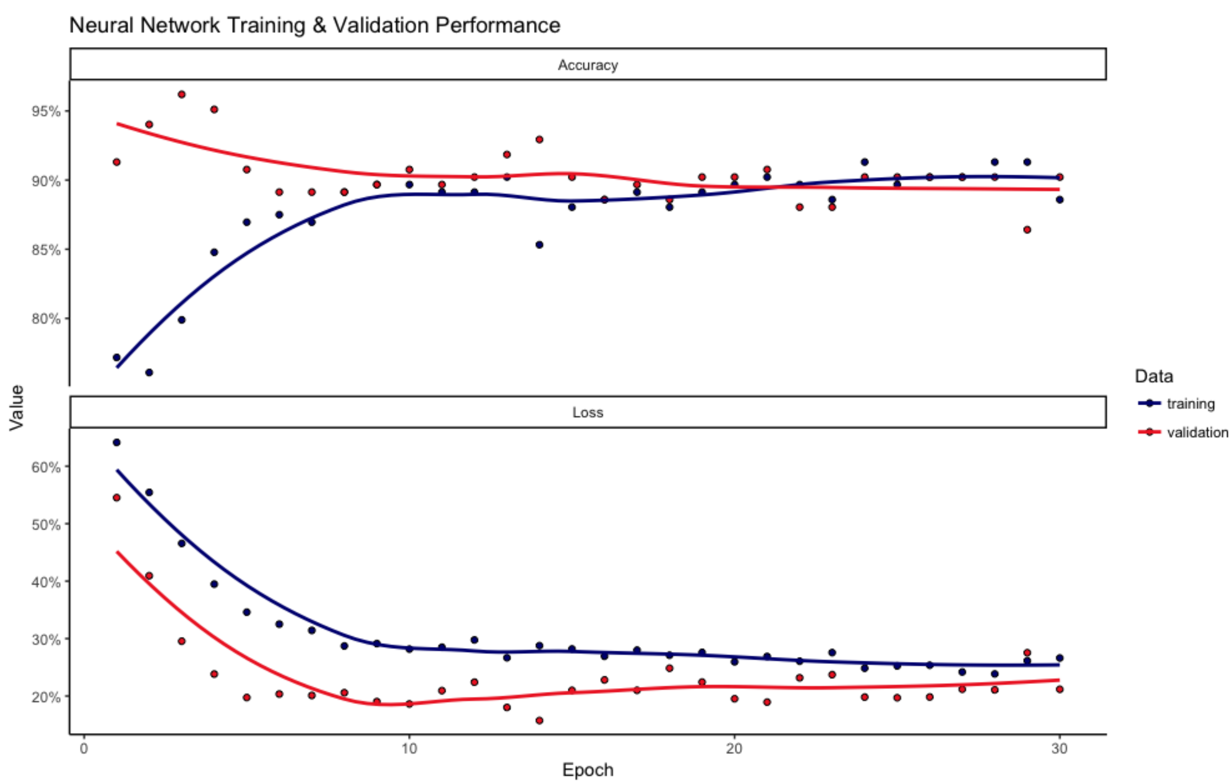
4. Appendix: Full Model Probability Output



5. Appendix: Reduced Model Probability Output



6. Appendix: Neural Network Training Data



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