Reconstructing a Critical Interest Rate Spread from Macroeconomic Time Series Indicators

Grant Aarons
Undergraduate, Mechanical Engineering
The Cooper Union for the
Advancement of Science and Art
New York, New York 10003
Email: grant.m.aarons@gmail.com

This study sets out to build a model that predicts the spread between the 10 year treasury and the effective federal funds rate (F10FED). The F10FED spread is a time series that has gone negative in each recession since the end of WWII. Curve fitting many macroeconomic indicator time series to the F10FED series will reveal those macroeconomic variables that are most strongly correlated with the prescience of economic contraction. It is the time evolution of the curve fit coefficients that operate on the macroeconomics variables that this study truly longs to understand. The macroeconomic variable coefficients are a product of the dynamic model used in this study, and do not exist elsewhere. By attempting to understand the evolution of macroeconomic variable coefficients in dynamic model time, this study gains unique insight into the changing sector relationships within the economy.

1 Economic Cycles *

Economists have long been familiar with fairly regular cycles related to the structure of the economy. Since the founding of the National Bureau of Economic Research (NBER) in 1920, these business cycles have been extensively studied. [9] One of the original members of the NBER Simon Kuznets was given the task in 1934, by the Roosevelt Administration, of making the first official estimate of U.S. National Income. Since then the NBER has had the official role of dating U.S. recessions, as well as noting the peaks and troughs in economic activity.

1.1 Wholesale Price Inflation

Beyond the well-known business cycles,[1] there have been some well-defined patterns in inflation and interest rates over the last 150 years. Wars have certainly played a major role in inflation as Figure 1 shows. In a less-pronounced way, prices of key commodities have, at times, led to significant increases in the overall inflation rate. [5] The Great Inflation period, 1965-1981, super-imposed on moderately increasing wages a sharp rise in grain prices in 1972 and then added a 10-fold increase in crude-oil prices. [19] The overall inflation rate (PCU) went from about 2% in the 1960's to 14% in 1980.

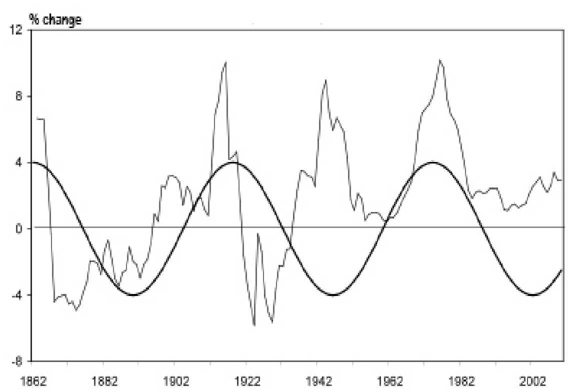

Fig. 1: Wholesale Price Inflation: 9 Year Centered Moving Average (1862-2006)

1.2 Long-Wave Theory

In the mid-1970's, policy-makers remembered the pain of the Great Depression either through their own direct experience as teenagers or through stories told by their parents. Consequently they went to great lengths to avoid a significant increase in the unemployment rate. [19] This point of view was particularly strong in the U.K. where pursuit of 4% unemployment rate led to an inflation rate of close to 25%.

[1] Economists have long been familiar with inventory cycles of 3-4 years duration (Kitchin cycles), capital equipment spending cycles of 7-10 years duration (Juglar cycles), and the commercial construction and heavy equipment cycle of 10-15 years duration (Kuznets cycles). These cycles have a certain regularity so that once a peak occurs, it is possible to have a rough idea of how the process will develop.

*Sections 1, 1.1, 1.2, and 1.3 are adapted from the paper by Professor Synnott "Economic Long-Wave Trends."

Even though long-term interest rates in the U.S. and the U.K. lagged behind inflation, they still went high enough to cause a breakdown in the long-term bond market. In both countries, this serious problem resulted in major political change.

The situation in Germany, at this time was governed by their policy-makers' memories of the post-World War I hyper-inflation which destroyed the German middle-class, paving the way for the rise of the Nazis. So, as soon as inflation began to pick up in the early 1970's, the Bundesbank raised interest rates aggressively, bringing about a slowdown in the economy and stopping inflation in its tracks.

These differing experiences illustrate the influence of monetary growth on inflation a point that Milton Friedman tirelessly expounded in the 1970's and 1980's. [7] The debate between monetarists and Keynesians (who favored more federal spending) was won in 1981 by the monetarists during the Reagan Administration. Federal Reserve Chairman Paul Volcker tamed inflation by keeping monetary growth below the rate of inflation. Interest rates rose and inflation dropped.

1.3 Generational Shifts

Today, this debate is far from over. Even with restraint on monetary growth (M2), enterprising lenders figure out ways to expand credit to riskier borrowers. Yield-hungry institutions eagerly accommodate this trend. Thus, in addition to commodity price cycles, which may last for 20-30 years,[2] we have even longer cycles based on the expansion or contraction of credit. [1]

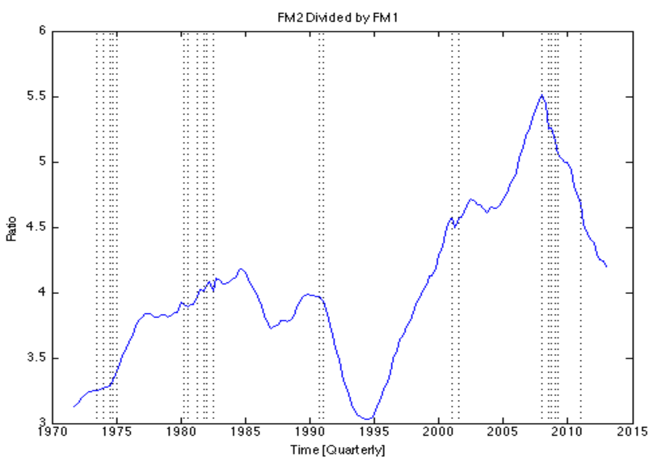

Fig. 2: FM2 Divided by FM1 [1]

At present, we appear to be in the contractionary phase of a long-term cycle in the usage of credit. The long-wave cycle in the usage of credit, and growth of illiquid assets, can be seen in Figure 2. The financial crisis of 2008-9 has led to financial losses for lenders and borrowers as well as tighter financial regulation. [6] [12] Down payment requirements have been increased to the point where home-building will continue its very slow recovery. We can think of this long-cycle in credit as a wave or as a tidal force that is now ebbing. It is an assumption of this study that the credit long-wave will influence shorter wave cycles and be influenced by them.

1.4 F10FED Indicator

The spread between the 10 year treasury note and the effective federal funds rate (F10FED) is a continuous time series data set available through Haver Analytics. [10] The F10FED spread is a time series that has gone negative[3] in each recession since the end of WWII. [9] Curve fitting many macroeconomic indicators to the F10FED series will reveal those macroeconomic variables that are most strongly correlated with the prescience of economic contraction.

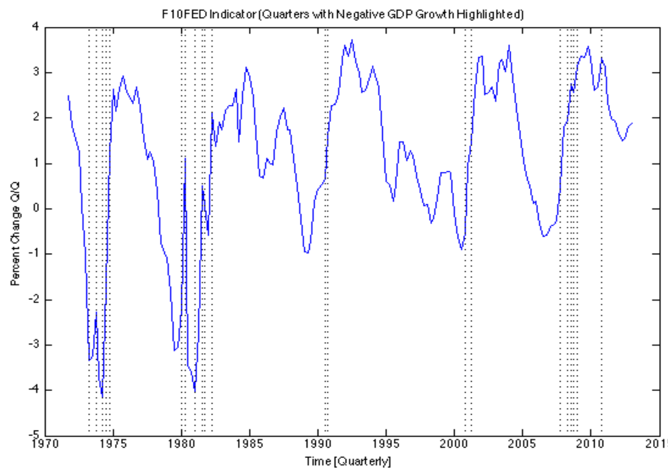

Fig. 3: F10FED Spread with Highlighted Quarters of Annualized Seasonally Adjusted Negative GDP Growth

When economists speak of yield curves they are typically speaking of how much additional interest a long-term bond or treasury will yield over the same bond or treasury of a shorter term. Long-term bonds typically yield a higher rate to protect investors from inflation and other volatility in the real rate of return over the life of the debt instrument. An Inverted Yield curve is the process by which long-term treasury notes bear an effective yield less than that of the short-term treasury notes.

The most commonly referenced Inverted Yield curve is the 10year-2year. [2] [3] [13] In this study, the historic time series of $F10FED$ was ultimately preferred for its continuity. Additionally, the inclusion of the effective Federal Funds Rate ($FFEDT$), in this critical interest rate spread, allows for analysis of monetary policy decisions prior to perceived economic recession. [4] [11]

[2]Typically a commodity price cycle begins with a sustained rise in price which leads first to exploration in new areas, and then to a multi-year development of the necessary infrastructure. A prime example is the oil trapped at Prudhoe Bay, Alaska and the construction of the Alaskan Pipeline.

[3]F10FED turns negative when the Federal Funds Rate is larger than the 10 Year Treasury note. This only occurs when the 10 Year note is driven down by a pessimistic economic outlook, or when the Federal Reserve makes a large contractionary monetary policy decision.

[4]The effective Federal Funds Rate is the result of target rates set by the Federal Reserve Open Market Committee, and to this day remains a primary monetary policy tool.

2 Macroeconomic Time Series Indicators

In this study the relationship between long-waves trends and shorter cycles is of primary interest; as was introduced in Section 1.2 on Long-Wave Theory. The indicators chosen for analysis in this study are presented in Table 1.

Table 1: Selected Macroeconomic Indicators in Study

Indicator Name	Indicator Abbreviation
Industrial Production	IP
$\frac{\text{Banking Consumer Credit}}{\text{Disposable Income}}$	$\frac{\text{FABW}}{\text{YPD}}$
Consumer Price Index	PCU
Investment Spending	FN
Standard and Poor's Index	SP500
$\frac{\text{Bank Credit}}{\text{Gross Domestic Product}}$	$\frac{\text{FAB}}{\text{GDP}}$
$\frac{\text{Standard and Poor's Index}}{\text{Disposable Income}}$	$\frac{\text{SP500}}{\text{YPD}}$
Effective Federal Funds Rate	FFEDT

The average quarterly percent change ($\overline{\%\Delta Q}$) is subtracted from each point in the time series of quarterly percent change ($\%\Delta Q$). The new time series that results for each macroeconomic indicator, has been made to fluctuate with greater frequency about the average that now stands as the new zero line. Increased fluctuation about the zero line creates a faster short term wave cycle, which it is hoped will increase interaction between the macroeconomic indicators being observed. These new wave like indicators still have units of quarterly percent change, but have been centered about the average value for the time series.

$$(\%\Delta Q)_{cycle} = (\%\Delta Q) - (\overline{\%\Delta Q}) \tag{1}$$

Autocorrelation errors arise from the quarterly percent change cyclic manipulation, but the benefits of percent fluctuations about a baseline average were deemed to far exceed the error introduced in point to point percent change within the time series. Cyclic transformation was necessary in the case of indicators that strictly trend in the positive direction, such as PCU, FAB, and GDP.

The indicators in Table 1 were selected based on two criteria. First, every indicator listed is strongly associated with economic fluctuations in its own separate sector of the economy. Second, the indicators chosen have a wide range of cited cycle durations, which importantly allows for long-wave interplay between these different subsets of the economy. [8]

3 Optimizing Indicator Coefficients: Linear Program

Using linear programming to curve fit requires the total variance between two curves be computed over a specified time series. Linear programming requires that there be an established objective function returning real-valued scalar quantities, such as regression variance, as well as an established coefficient matrix that can be solved in a constrained or unconstrained manner.

3.1 Problem Definition

The model in this report attempts to use linear programming to curve fit the F10FED indicator. The objective function is set to the variance in curve fitting F10FED. In this linear programming problem, the search direction algorithm seeks coefficient values, defining the input indicator proportions, that optimizes the estimation curve to F10FED. The coefficient values are stored in the variable n-column matrix, $x\varepsilon\Re^{n\times 1}$, where n is the full number of considered macroeconomic input indicators for the estimated curve. The search for optimal coefficient values, x, takes into account the benefits and faults of certain coefficient proportions over the specified length of the time series. There is only one optimal set of coefficient values for a curve fit over a specified time series.

The time series data for the n macroeconomic indicators are stored in a data matrix $S\varepsilon\Re^{m\times n}$, where m is equal to the number of data points in the time series. Every indicator is permitted to have a lagged response in the linear superposition, and the actual output time series, F10FED, is cut short by the largest lag value[5]. $F10FED\varepsilon\Re^{m\times 1}$, where m is the number of quarterly data points in the time series.

Vector Formulation of Problem*:

$$\text{Problem 1} = \min_{x\varepsilon\Omega} x^\top S^\top S x - 2(x^\top S^\top) F10FED \tag{2}$$

Such that:

$$\Omega = \{x\varepsilon\Re^{n\times 1} : -\infty \leq x \leq \infty\}$$

Where:

S = m x n dimension matrix that has m times series points, corresponding to the n macroeconomic indicator time series; i = 1 ... m and j = 1 ... n
$F10FED$ = m-column vector that represents the actual time series of F10FED; trying to curve fit over j quarters of available data; i = 1 ... m
x = n-column vector representing the coefficients chosen for each indicator j being considered for use in the model; j = 1 ... n
m = number of quarters of data in the time series
n = number of indicators being considered

** Allow for the n indicators in S to be lagged by m quarters in the time series.*

Ω represents the unconstrained design space for this problem. There are no linear equality or inequality constraints

[5] If any input macroeconomic indicators require lags for an optimal curve fit to F10FED, then all time series must be cut short by this input indicator lag in order to retain equal length sets. In allowing for lags, the time series for curve fitting is cut short by the largest lag value

on x. The curve fit problem does not necessitate constraints on the coefficient n-column vector x. The n-column vector x represents the coefficients chosen for each of n indicator inputs to the estimation curve. There is only one set of optimal coefficients for every time series curve fit. An equality constraint is typically added to inequality constraints to bound x in either the positive or negative domain. In this curve fit problem the coefficient values of x may exist in both the positive and negative domains.

3.1.1 Solution Method

MATLAB has a general purpose solver, that can handle both linear and non-linear programming problems. The *fmincon* algorithm is implemented and accepts constrained as well as unconstrained problem types. The *fmincon* algorithm works well because it actively assess what type of "scaled" algorithm to apply to a particular problem, based on the parameter matrices. MATLAB is implementing the *Active-set* algorithm, which is outdated and slower than most other algorithms, but adequate for curve fitting optimization.

4 Building the Dynamic Model

The curve fit needs to operate on short intervals in order to retain the formulated cyclic quarterly percent change. The predictive model must implement curve fitting over subsets of time that correspond to generational prevalence of economic perspective. A dynamic model is proposed that gives weight to both historical retention of relationships and processing of short-term spikes in economic indicators.

4.1 Subset Breakdown

The dynamic model solves the linear program curve fit over subsets of the input indicators and actual output time series.[6] The coefficients determined on individual subset curve fits will vary based on how well time series inputs can estimate the actual output on that subset. A new cyclic transformation is applied on each subset curve fit. The average quarterly percent change slowly moves with the progression of the dynamic model. As the dynamic model steps forward the average quarterly percent change may creep upward or slide downward. The cyclic quarterly percent change time series varies at each dynamic model step because the subset average quarterly percent change will move. The cyclic transformation is applied over the subset region as follows:

$$(\%\Delta Q)_{cycle} = (\%\Delta Q) - (\overline{\%\Delta Q})\Big|_{i-SubsetSize-1}^{i} \qquad (3)$$

In this study, the time series data points are financial quarters of the year and a case that gets special attention later in this study is the 60 quarters (15 year) subset size. To transition nicely to later discussion we will use $SubsetSize = 60$ quarters (15 years). The first subset is called the training set, and the dynamic model will curve fit over this initial subset, from time index 1 to time index 60, as shown by the dotted blue line in Figure 4. The dynamic model then conducts the second subset curve fit by moving forward a single data point and the subset is then from time index 2 to time index 61 as shown by the solid green line in Figure 4. Finally, to demonstrate this repeatable process, the third subset curve fit is from time index 3 to time index 62 as shown by the solid red line in Figure 4.

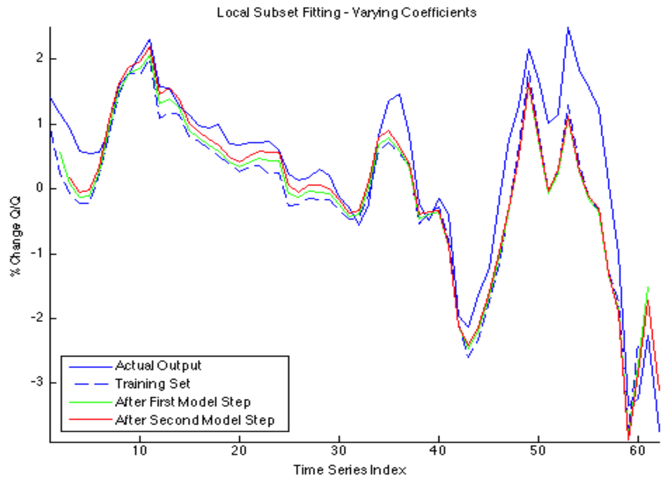

Fig. 4: Each Time Index takes part in many Curve Fits

Every subset curve fit has its own *unique coefficient values* for the linear program solution. Each subset curve fit is individually trying to match the actual F10FED output, represented by the solid blue line in Figure 4. There is no limit to how the coefficients can change, so long as the new coefficients produce a lower variance curve fit on the subset.

Although the coefficient solutions to the subset curve fits will be similar from one step to the next, they are not *identically* the same and we are confronted with the problem of stitching together these many sub problem results. Many subset curve fit results must be brought together algorithmically, hence the dynamic classification of this model.

4.2 Synthesis of Subset Results

The variance of many subset curve fits cannot simply be added together and then optimized. An optimization routine, such as our linear program, needs to be given an objective function that outputs a single real-valued scalar.[7]

To build the dynamic model algorithm, this study related each subset curve result to the period of time on which that result had been acquired. The optimal coefficient solutions ($C_1, C_2, \ldots C_n$; n indicators) for a subset were recorded at each time index on which that solution had been acquired. The time index of 1, in Figure 4, was used only once in the training set curve fit. However, the time index 2 was used in both the training set curve fit and the first dynamic model step made forward in time. The time index 2 would have seen two values for each of the optimal coefficient solutions

[6] Lags are temporarily suspended from the study while developing the dynamic model. Lags must be removed to avoid overlap in coefficient results from one subset curve fit to the next.

[7] All optimization routines need to operate on a single real-valued scalar. It is this requirement of the objective function that allows a search direction algorithm to find the optimum (typically minimum) in an optimization.

$(C_1, C_2, ...C_n)$. Additionally, the time index 3 was used in all three curve fits shown in Figure 4. The time index 3 would have seen three values for each of the optimal coefficient solutions $(C_1, C_2, ...C_n)$.

4.2.1 Running Average

In this study, the dynamic model takes a running average of optimal coefficient solutions at each time index. The equation governing the running average at each time index point immediately follows in equation 4.

Running Average

$$C(n)_i \underset{\forall T_i}{\mapsto} C(n)_t$$

$$\overline{C(n)_t} = \frac{\sum_1^{size(C_t)} C(n)_t}{size(C(n)_t)} \tag{4}$$

Where:

i = dynamic model steps forward in time

$C(n)_i$ = new coefficient values from model step i and corresponding subsets $T_{i=1,2,3}$

T_i = time index subset that receives the $C(n)_i$

$C(n)_t$ = array of coefficient values (All $C(n)$'s) that have been allocated to a particular time index t

$\overline{C(n)_t}$ = running average at time index t ($\frac{\sum_1^{size(C_t)} C(n)_t}{size(C(n)_t)}$)

The running average at each time index in the dynamic model acts to merge the many subset coefficient solutions a time index point will have taken part in. Once the solutions have been merged together, the decision remains on how to properly weight each of the time indices such that the best dynamic model in predicting future F10FED actual output values will result.

4.2.2 Moving Average

With simplicity in mind, the running average coefficients $\overline{C_t}$ at each time index i in the dynamic model, were pooled together as a moving average. As the dynamic model moves forward point by point, each new time index to join the subset curve fit will have its running average added to the moving average calculation. The equation governing the moving average, prediction coefficients in the dynamic model ($\widehat{C(n)_i}$), immediately follows in equation 5.

Moving Average

$$\widehat{C(n)_i} = \frac{\sum_{t=i}^{t=i+SubsetSize-1} \overline{C(n)_t}}{SubsetSize} \tag{5}$$

Where:

$\widehat{C(n)_i}$ = moving average and predictive coefficient

Predictive coefficients $\widehat{C(n)_i}$ are calculated for all n indicators in the dynamic model and the predictive coefficients change after each i^{th} predicted model point. With every new subset, after a model step, a new curve fit will have taken place changing not only the time indices included in the moving average, but also the running average at each time index. The moving average coefficient ($\widehat{C(n)_i}$) is deemed the predictive coefficient because it is this coefficient that is multiplied by the $(i + SubsetSize + 1)^{th}$ row of the S matrix, the $(i + SubsetSize + 1)^{th}$ quarter in the time series, to give the next predicted value of the output F10FED. The study has indicator knowledge at the $(i + SubsetSize + 1)^{th}$ time series point, but no knowledge of the actual output F10FED.

Model Prediction of $F10FED$

$$F10\widehat{FED_{t=i+SubsetSize}} = S_{t=i+SubsetSize-1} \widehat{C_{i+SubsetSize}} \tag{6}$$

The dynamic model does not in any way use quarter to quarter accuracy of its own predictions, against actual output F10FED, to fine tune its own dynamic processes. The model simply predicts the next value of the output by using the prediction coefficients at model time i to wager a guess at the actual output value of F10FED at step i.

4.2.3 Prediction Strengths

The dynamic model is concurrently grounded by the number of coefficients contributing to the running average and free to interpret short-term cycles through use of the moving average. The running average acts to anchor the prediction coefficients by equally weighting all dynamic model subset coefficients acquired with use of that time index point. The furtherest time index from the dynamic model prediction, most historic, will have seen $SubsetSize$ (60) different subset coefficients; the running average value making it on to the moving average calculation is indeed indicative of memory over the entire $SubsetSize$ (60 Quarters). The time index just prior to the predicted F10FED point, the newest time index to enter model, will have only seen 1 subset coefficient value and is therefore less pinned down to the history it has seen. An analogy can be made to a tree blowing in the wind. The young top branches may sway a great distance, but the oldest portion of the tree, its trunk, will hardly budge.

The moving average was intended solely to combine the differing effects of low count running averages with high count running averages, such that a prediction coefficient could be synthesized. The moving average accomplishes this goal, while preserving the intention of the running average. When a new time index enters the dynamic model, the running average coefficient value is equal to the most recent subset curve fit that was performed; the new time index has only taken part in a single subset curve fit and that fit is given additional weight when carried into the moving average calculation.

$$\widehat{C(n)_i} = \frac{\sum_{t=i-SubsetSize}^{t=i-1} \left[\frac{\sum_{t=i-SubsetSize}^{t=(i+t)-1} [C(n)_{(i=t)}]}{i-t}\right]}{SubsetSize} \tag{7}$$

**relationship explicitly defined for i* $\geq$ *SubsetSize*

The use of two separate types of averaging, moving and running, makes for an interesting evolution of the indicator prediction coefficients. The moving average simulates a quickly adapting irrational perspective, while the running average simulates a rational generation's knowledge of historical long-wave trends.

4.3 Local Subset Sizing Limits

The *SubsetSize* is of pivotal parameter in this study. The *SubsetSize* changes the interaction that takes place between the running average and the moving average. The *SubsetSize* alters how long a generational viewpoint will weigh on the predictions of the future. Stated another way, the predictive coefficient ($\widehat{C(n)}_i$) completes one full generation cycle every *SubsetSize* quantity of quarters. The *SubsetSize* determines how the entire string of running average coefficients will ground the prediction, before a new single data point enters the subset and is no longer a prediction.

In order to address the combined effects of varying *SubsetSize*, the study looked at how well the dynamic model predictions fit the actual output F10FED. The variance for each *SubsetSize* trial was then divided by the number of prediction points because *SubsetSize* alters the number of prediction points in the model. Revised variance to account for varying number of model prediction points is given below.

$$\frac{\text{Variance}}{\text{\# Predictions}} = \frac{\sum_{i=SubsetSize+1}^{i=length(F10FED)} (\text{F10FED}_i - \widehat{F10FED_i})^2}{length(series) - SubsetSize} \tag{8}$$

A fundamental focus of this study was model simplicity. [16] The dynamic model aimed to reduce complexity by admitting only a few indicators, and finding those indicator's subset curve coefficients. The few indicators used in the dynamic model were given lag options of $0-8$ quarters. The use of lags and only a few indicator coefficients helps to eliminate potential over-fitting of the data.

Permutations were conducted on all sets of 2,3,&4 indicators from our macroeconomic indicator set from Section 2 - Macroeconomic Indicators. For every quantity of indicators modeled (2,3,&4) and for all indicator compositions the dynamic model $\frac{Variance}{\#Predictions}$ was found. Results for the lowest prediction variance for each level of model complexity (2,3,&4 indicators used) were found and the lowest dynamic model variance uses only three indicators $\frac{FABW}{YPD}$, $SP500$, and $FFEDT$. The model is not complex in the sense that it has a limited number of input time series being used to curve fit the output time series. Many models today are far too complex, manipulating many indicators and losing all recognizable relevance to the economics field, as a lens for better understanding. [14]

Keeping model complexity in mind, it was decided that the few indicators chosen would be allowed a modest set of lag options. Lags do not add to model complexity in the same way as going from a 3 indicator model to a 100 indicator model. Each of the indicators ($\frac{FABW}{YPD}$, $SP500$, and $FFEDT$) were lagged anywhere from $0-8$ quarters and the options were run through a permutation such that all possible input time series lag interactions were observed. The results in Table 2 show a drop in the $\frac{Variance}{\#Prediction}$ to 1.547 from a previous low of 1.666.

Table 2: With a 15 Year Window and Lags

Composition:	$\frac{\text{FABW}}{\text{YPD}}$,SP500,FFEDT
Best Fit Lags	$3-8-0$
$\frac{Variance}{\#Predictions}$	1.547

It is justifiable that $FFEDT$ with a lag of zero would yield the lowest prediction variance by point. $FFEDT$ is directly related to the output we are trying to curve fit, and the connection between $FFEDT$ & $F10FED$ exhibits an immediate response. When the effective federal funds rate is raised, there is an immediate decrease in the spread between the 10 year treasury and the federal funds rate. The funds rate changes almost instantaneously while the 10 year treasury is typically much slower to respond. Therefore the spread between the two is going to be immediately related to the change in the effective federal funds rate in a negative way (spreads will decrease as the $FFEDT$ rate increases and 10 year remains relatively constant). The adjustment of the 10 year treasury is fast when the economy is frightened about impending recession, and the adjustment is slow when the economy is comfortable with the current economic growth environment.

With the chosen input indicators aided by lagging as detailed in Table 2, the accuracy of the model was finally ready for comparison to the actual output $F10FED$. The negative quarters of annualized seasonally adjusted GDP growth are detailed as dotted black lines in Figure 5. The dynamic model fit can be assessed over the entire prediction time frame (1972Q1-2013Q2).

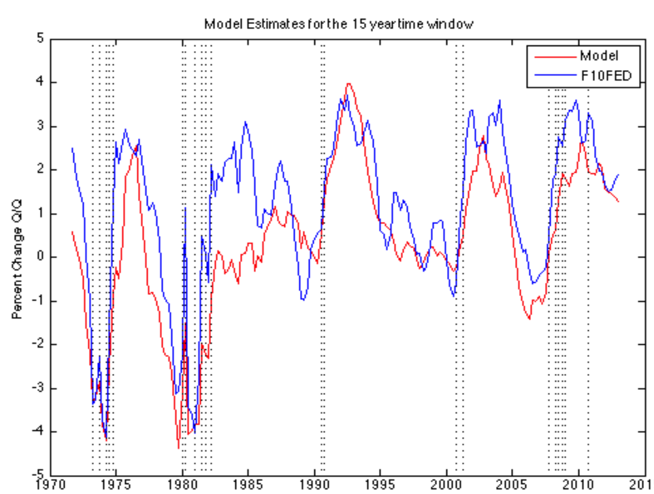

Fig. 5: Accuracy Testing Final Model

The $F10FED$ spread is predictive of recessions because it has a drop in value without any omniscient knowledge of what real GDP growth numbers will look like in the future. All in all the dynamic model provides close to, if not the same predictive capacity as the $F10FED$ spread. With the prediction capacity nearly matched, the study can now look at the components of the dynamic model prior to economic contraction. Where the $F10FED$ spread is finished giving economic predictions, the dynamic model will now help in better understanding the background indicator relationships prior to economic contraction.

5 Indicator's Coefficient Evolution in Model Time

As the dynamic model takes steps forward the predictive coefficients are subject to change under the constraints set by the running average at each time index point and the moving average over which the dynamic model is currently situated. The predictive coefficients for each of the three indicators used are shown below as they change in time. These predictive coefficients act on their corresponding indicator time series to yield the dynamic model in the previous section (Figure 5).

5.1 Shifts in Indicator Relationships

It is the time evolution of predictive coefficients that this study truly longs to understand. The predictive coefficients are a product of the dynamic model used in this study, and do not exist elsewhere. The predictive coefficients are values thought to be at the root of F10FED movements. By attempting to understand the motion of predictive coefficients the study gains unique insight as to how the economy shifts in function and how sector relationships evolve in a macroeconomy.

Table 3: Coefficients Evolving in Model Time*

Summary	min	$-\sigma$	mean	$+\sigma$	max
$\widehat{C}(\frac{\text{FABW}}{\text{YPD}})_i$	-0.03	0.07	0.12	0.16	**0.21**
$\widehat{C}(\text{SP500})_i$	-0.02	-0.01	0.00	0.01	0.03
$\widehat{C}(\text{FFEDT})_i$	**-0.62**	-0.53	-0.44	-0.35	-0.18

*Largest magnitude coefficients of $\frac{\text{FABW}}{\text{YPD}}$ & $FFEDT$ bolded

The predictive coefficient of $SP500$ ($\widehat{C}(SP500)_i$) oscillates almost perfectly about zero. The $SP500$ time series is needed as a positive coefficient just as often as it is needed as a negative coefficient in the curve fit of $F10FED$. The prediction of $F10FED$ does not depend on the $SP500$ coefficient in any one discernible direction. The $SP500$ series was most likely selected as one of the best fitting 3 indicators, because of its volatile tendency prior to economic contraction. The $SP500$ is a primary location where short-term economic information first hits the market, and the $SP500$ indicator helps the dynamic model to better address short-term fluctuation. This result agrees with intuition and can be argued for much more easily than the predictive coefficient case for $FFEDT$ and $\frac{\text{FABW}}{\text{YPD}}$.

The inverse relationship between $FFEDT$ and $F10FED$ is apparent. When $FFEDT$ has an increase in quarterly percent change the spread between $FFEDT$ and the 10 year treasury must contract, therefore the $FFEDT$ predictive coefficient ($\widehat{C}(FFEDT)_i$) should always be negative. The inverse relationship between $FFEDT$ and $F10FED$ is always present, but surprisingly the magnitude of this inverse relationship fluctuates quite wildly. Looking at $FFEDT$ in row 3 of Table 3, the ± 1 Standard Deviation of the coefficient gaussian distribution has a spread of 0.18. $FFEDT$'s role in predicting $F10FED$ has greater coefficient magnitude variability than any other indicator used in this study. The strong relationship between $FFEDT$ and $F10FED$ was expected, but the intense variability in magnitude was unexpected requiring further examination.

The $\frac{\text{FABW}}{\text{YPD}}$ predictive coefficient ($\widehat{C}(\frac{\text{FABW}}{\text{YPD}})_i$) is strictly positive across almost the entire dynamic model prediction space. It is not until 2012 that this coefficient turns negative in the dynamic model. There must be some larger trend, a long-wave perhaps, at work in this scenario. The credit in consumer banking or disposable income must have been drastically effected near the years 1992-95 and the years 2008-13; both periods where the coefficient moved from an average value of 0.1164 to intelligibly low points.

6 Discussion

The results of the dynamic model cannot stand by themselves. The evolution of indicator coefficients in time may appear correct or seem to tell a story, but in order to validate a model the results of that model must be compared to an empirical data set that tells the same story. Of particular interest in the dynamic model results was the $\frac{\text{FABW}}{\text{YPD}}$ predictive coefficient drop into a negative value after 2012. The predictive coefficient drop from 2008-13 is similar to model results in the period from 1992-95. The economic prosperity during these two time periods could not be any different from each other. From 1992-195 the Clinton Administration presided over what would become one of the most prosperous economic periods in recent United States history. Conversely, from 2008-13 the United States economy has experienced one of the most painful and strenuous recoveries with unemployment stagnant in the 7-10% range for most of the 5 year period.

These two snapshots of the United States economy are very different from each other, and the $\frac{\text{FABW}}{\text{YPD}}$ coefficient does not propose that these two periods are identical. Rather the $\frac{\text{FABW}}{\text{YPD}}$ coefficient tells us that there must be some common underlying long-wave trend in these two periods. An empirical dataset must be observed in conjunction with the $\frac{\text{FABW}}{\text{YPD}}$ coefficient evolution in order to truly understand the long-wave trend at work. The plot of $\frac{\text{M2}}{\text{M1}}$ is superimposed on the evolving $\frac{\text{FABW}}{\text{YPD}}$ coefficient, and the two plots are provided below in Figure 6.

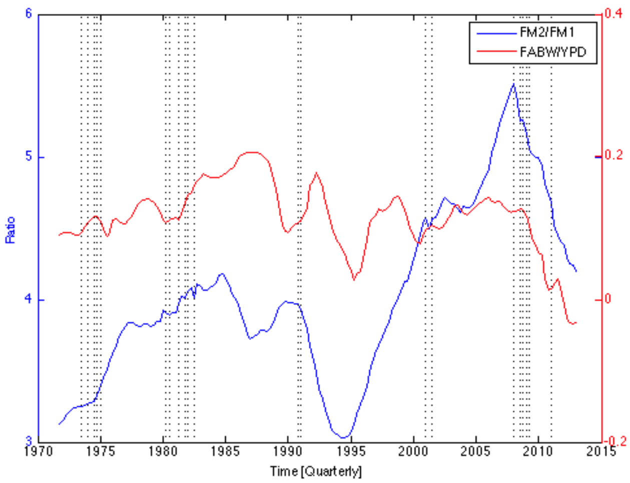

Fig. 6: Comparison of $\frac{\text{FABW}}{\text{YPD}}$ Predictive Coefficient from Dynamic Model to the Monetary Supply Ratio $\frac{FM2}{FM1}$

The money stock M1 measures currency in circulation as well as certificates of deposit. The money stock M2 contains all of M1's measures, but additionally measures the quantity of some basic time sensitive securities, such as savings deposits, money market mutual funds and other time deposits. The ratio of M2 to M1 gives a broad synopsis of credit growth in the United States economy. [1] The correlation between these two plots, $\frac{\text{M2}}{\text{M1}}$ and $\frac{\text{FABW}}{\text{YPD}}$, does not need explicit calculation to help validate the results of the dynamic model in this study. The two plots move in tandem with each other in the 1992-95 period and also in the 2008-13 period.

The choice of $\frac{\text{FABW}}{\text{YPD}}$ as an input macroeconomic indicator was intended to showcase Credit in Consumer Banking ($FABW$) and also scale those credit changes by Disposable Income (YPD). The ratio is believed to scale up the effects of Consumer Credit when disposable income declines, and scale down the effects of Consumer Credit when disposable income increases. The thought was that if consumers have an increasing quantity of disposable income, they do not rely on the credit markets to achieve capital goals.

The $\frac{\text{FABW}}{\text{YPD}}$ coefficient is a measure of consumer credit growth scaled by consumer necessity, and the $\frac{\text{M2}}{\text{M1}}$ time series curve is a similar measure of credit's role in the economy. When credit markets are contracting the dynamic model would assume a low value for the $\frac{\text{FABW}}{\text{YPD}}$ coefficient because this sector of the economy is clearly not participating to the rise or fall of the F10FED indicator. When credit is contracting, the $\frac{\text{FABW}}{\text{YPD}}$ coefficient should be less important to economic health. The $\frac{\text{M2}}{\text{M1}}$ time series only aids the description of what is occurring in the dynamic model $\frac{\text{FABW}}{\text{YPD}}$ coefficient.

6.1 Credit Growth: Monetary Policy Effect

The dynamic model was not built to forecast recessions, although it could potentially be used to that end. The dynamic model was constructed to better understand key economic indicators. The indicators of interest in this study have been shown to vary in amplitude with the peaks and troughs of the credit long-wave. A potential application of this dynamic model had always been to observe the role of the effective federal funds rate on the $F10FED$ spread. The large variation of the predictive $FFEDT$ coefficient looked promising and after inspection of the $\frac{\text{FABW}}{\text{YPD}}$ coefficient superimposed on the same graph as $\frac{\text{M2}}{\text{M1}}$, the logical conclusion was to look at $FFEDT$ and $\frac{\text{M2}}{\text{M1}}$ on the same plot.

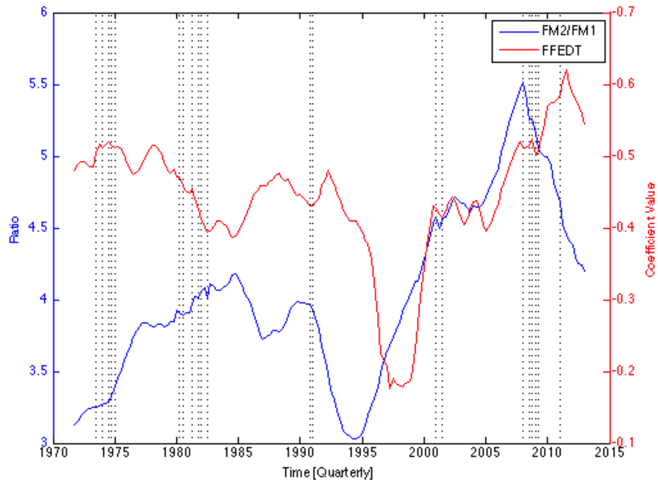

Fig. 7: Comparison of $FFEDT$ Predictive Coefficient from Dynamic Model to the Monetary Supply Ratio $\frac{FM2}{FM1}$

Again it is incredible how well the dynamic model prediction coefficient lines up with the $\frac{\text{M2}}{\text{M1}}$ time series. In the region from 1970-90 the two plots seem to be out of phase with each other. Surprisingly, in the next period from 1990-2013 the two plots have a completely different interaction, a visual coherence with each other. The dynamic model over the last 20 years shows an increasing $FFEDT$ coefficient magnitude, and the effects of monetary policy (federal funds rate) on economic prosperity increase with the growth of credit. The $FFEDT$ cyclically transformed time series is given a prediction coefficient of near -0.15 in the year 1997, and by 2011 this indicator specific prediction coefficient has nearly quadrupled to -0.6 in magnitude when curve fitting to the prescient time series $F10FED$.

The peaks and troughs show that $FFEDT$ lags the credit long-wave by about a year. The effective federal funds rate had been a monetary policy tool with little bearing on the $F10FED$ prosperity spread (1992-99), but is currently a very powerful tool in moving the $F10FED$ spread (2000-13). These conclusions help to verify cautious claims made by the Federal Reserve Chairwoman and supporting Federal Open Market Committee members. Agreement of this predictive coefficient evolution in the model, with Federal Reserve current comments on the state of the economy, can only be used to validate the dynamic model developed.

The two plots move in phase with one another and remain that way following the 1984-90 period. This can be attributed to increased TBTF presence of central banking in credit growth affairs [1], and potentially be related to the beginning of the Alan Greenspan tenure as Federal Reserve Chairman (1987-2006).

Credit growth renders monetary policy tools increasingly powerful, and hinders the capacity of the Federal Reserve to make corrective moves. Pulling the punch bowl away just as the party is getting good, would certainly not apply in this $FFEDT$ sensitive economic environment. The $FFEDT$ coefficient in this dynamic model should be watched more carefully by the Federal Reserve to ensure policy moves do not directly lead to and cause recessionary periods.

7 Running-Moving Average Subset Curve Fit Model

The results of this dynamic model have helped in understanding the effects of a long-wave credit cycle on $\frac{\text{FABW}}{\text{YPD}}$ and $FFEDT$. In the present economy it appears that the growth of credit is accompanied by increased consumer credit and increased effective federal funds rate contributions to economic contraction.

The running average and moving average techniques of this study could be implemented with other macroeconomic indicators given there exists a prescient continuous indicator time series on which to curve fit. The confidence in the dynamic model predictions are high, and to promote widespread adoption of this technique a separate dynamic model should be established on a more refined sector's prescient indicator (separate study on commodities or currency markets).

The results are promising, the method is simple, and the error in over-fitting seems to have been avoided. The time series is broken into subsets and a curve fit is applied on each subset. The subset curve fit results are linked through use of a running-moving average combination. The evolution of macroeconomic variable coefficients is saved for later analysis. Trends in the macroeconomic variable relations are observed and compared with non-model time series dataset for reference as well as validation.

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