A FIR Filter to Date Post-WWII Recessions

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Abstract

A new FIR filter is designed to date U.S. recessions with the unemployment rate and the Conference Board employment trend index. Our approach is simple but one can see from the curve the dynamic process how the economy moves from one business cycle to the next. We also present a new use of the HP filter and uncover some useful information about the relationships among the yield curve, the Wu-Xia shadow rate, and the unemployment rate. We argue that an assessment of the labor market, based on the level of the unemployment rate, can be very wrong for the business cycle oriented monetary policy.

JEL classification numbers: E24, E37, E32.

Key words: Date recessions, the M-Coppock curve, the busniess cycle, the unemployment rate, the employment trend index

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1 Introduction

In the press release on December 16, 2015 for a rate hike, the Federal Open Market Committee (FOMC) made an assessment about the economy and the labor market in a support of its action: "A range of recent labor market indicators, including ongoing job gains and declining unemployment, shows further improvement and confirms that underutilization of labor resources has diminished appreciably since early this year."[1] In the same release, it added that "[t]he Committee currently expects that, with gradual adjustments in the stance of monetary policy, economic activity will continue to expand at a moderate pace and labor market indicators will continue to strengthen." At present there is a good reason for the FOMC to be optimistic about the U.S. labor market. The U.S. unemployment rate was at 5% in Novermber 2015 and the Novermber job creation index, monthly averages, from the Gallup, was at 31. Both indexes are at or near their best levels since 2009.[2] Nonetheless, our study of this paper documents evidence that the U.S. labor market has already been in a gradual process of losing its stenghth since October 2014. If the unemployment rate stays at projected 5% for the 2016, our model indicates that there will be a recession near the end of 2016. Because the central bank often uses the level of indicators such as the unemployment rate to make an assessment of the economy, such an approach can mislead. We will provide a reason why it misleads. One must see the weakness in an economy when it appears to be strong, and vice versa. We use a FIR filter to show how this can be done.

The Federal reserve banks use various probabilistic models to call if the peak or trough of economic activity has been reached in real time. We discuss three models here. The first model is from the Federal Reserve Bank of St. Louis, which poses the 0.92% smoothed U.S. recession probabilities in September 2015, indicating that there is no risk to have a recession near term. The bank credits the probability number to Jeremy Max Piger and Chauvet Marcelle (Chauvet 1998, Chauvet and Piger 2008). The Federal Reserve Bank of New York poses the probability charts of 12 month ahead recession based on the yield curve and the reading in Novermber 2015 for a recession in Novermber 2016 is at 2.96%. The bank credits the chart to Estrella and Trubin (2006) and Estrella and Mishkin

[1] Press release on December 16, 2015 by FOMC.

[2] See Gallup.com for the gallup job creation index.

(1996). The third chart is the GDP-based recession indicator index (Chauvet and Hamilton 2006) from the Federal Reserve Bank of Atlanta authorized by James D. Hamilton. The index stands at 13.3% in August 2015 with the lastest GDP figure, far away from the level 67%, suggested by James D. Hamilton, to call a recession.

The econometric models to forecast the probability of a recession in these figures are quite elegant and greatly enhance our understanding of the nature of the U.S. business cycle. However, these models and probability numbers are not without a problem. First, the probability near the peak or the trough of a cycle rises or falls too rapidly. This limits their applicability for conducting monetary policy because it leaves the central bank very little time to decide which action, 'the brake" or "the gas pedal", is right. Second, as we can see from the three figures, the locations of spikes of the probabilities vary, likely affected by various shocks. This causes a problem to tell when a recession begins or ends even after observing a spike. The uneven spikes also cause a problem in determining a proper uniform threshold value to call a recession. James Hamilton sets a uniform rule at 67% now to call a recession for his GDP-based model but a rule at 50%, based on our reading of his own chart, may work too.

In this paper we provide a new approach to date recessions in real time. Our model is very simple. More importantly, one can see the dynamic process how the economy approaches the peak or the trough. The original data we will use is either the unemployment rate from BLS or the employment trend index from the Conference Board. Our approach is to design a new filter[3], largely motivated by the Coppock curve that has been widely used in equity market.[4] Our filter, the M-Coppock curve, is the 12-period simple moving average of the sum of one period, three period and six period differences, a modified version of the original one. The M-Coppock curve is a causal FIR filter. Our main results are shown in Figures 3 and 4.

[3]The filter was privately communicated to a limited number of colleagues around 2012. It has been used in Ma and Tang (2012) to study sunspot cycles.

[4]There is a nice story about the way how Edwin S.C. Coppock came up with the idea. As an economist, he was asked by the Episcopalian Church to identify an investment initiation time for investors at long horizons. Mr. Coppock thought that the pain caused in the fall of stock market was like bereavements and required a period of mourning. He then asked the bishops how long it would normally take for people to get over the pain. The answer was 11 to 14 months, which was the reasons why he chose 11 and 14 in his design of the filter.

Different recessions may be caused by different shocks. That may be the main reason why it is still hard to predict recessions. Stock and Watson (2003a) in their conclusion of an analysis about the 2001 recession make a noted remark in this aspect: “Leo Tolstoy opened Anna Karenina by asserting, ‘Happy families are all alike; every unhappy family is unhappy in its own way.’ So too, it seems, with recessions.” Beyond shocks, the economy always evolves across time. A lesson learned from one particular recession may not apply to any future recessions. Despite the difficulties, one cannot exclude the possibility some common cyclical behavior of these recessions does exist (Lucas 1977). The cyclical behavior may be generated endogenously by the fundamental news, not purely by exogenous shocks (Cochrane 1994). It is, however, not easy to detect the flow of the fundamental news as pointed out by Cochrane (1994).

We document evidence that a uniform rule can be found to call a recession in real time by using the M-Coppock curves of the unemployment rate and the employment trend index, in a partial support to Cochrane (1994). The unemployment rate is known to be a leading indicator around the economic peak but lags substantially around the economic troughs. But we will show that the M-Coppock curve peaks near all of the economic troughs of post WWII recessions. The reason why this is the case is the fact that we consider the changes in the level of the indicator, not the level itself. The M-Coppock curve reaches its peak or trough earlier than the related peak or trough of the original series. This lead in time is the basic idea behind the capability of the M-Coppock curve to call a recession in real time, even for the unemployment rate. We will see that even if the current unemployment rate in levels continues to fall, our M-Coppock curve has started to trend higher since October 2014, which indicates that the strenghth of the current labor market becomes gradually weaker, not stronger. An assessment based on the level of the unemployment rate can be wrong.

There are many papers that have used various econometric models to forecast recession-related economic activity. Chauvet and Piger (2008), Chauvet and Potter (2005), Estrella and Hardouvelis (1991), Estrella and Mishkin (1996), Harvey (1988, 1989), and Stock and Waston (1989, 1991, 1993, 2003a) are just a few of good examples. See Hamilton (2010), Stock and Waston (2003b), and Wheelock and Wohar (2009) for a literature review. Berge (2014) and Fossati (2015) provide two latest studies, among many others. One important feature of the papers in the literature is to use financial variables or a combination of financial and macroeconomic factors to predict recessions. In particular, the yield curve and leading indicators are often used to forecast the probability of a recession. The Markovian switching model in Hamilton (1989) is very popular, among others. Some thresholds must be set priorly to determine if the economy is in a recession after a model has been estimated. These thresholds may be time-varying. Instability is always a concern because the economy may evolve structurally (see, e.g., Phelps 1999, Stock and Watson 2003b) and the shocks for a future recession may be totally different from todays'. For example, Stock and Watson (2003a, 2012) show that new shocks do often occur. Stock and Watson (2003b) provide a survey of a great number of papers regarding the predictability of outputs and inflation using interest rates, interest rate spread, returns, etc. A major problem in various models in the literature is that "[t]here is considerable instability in bivariate and trivariate predictive relations involving asset prices and other predictors" (Stock and Watson 2003b, p.823).

Our M-Coppock approach would alleviate the instability problem inherited in other studies. Because the M-Coppock curve just uses local information up to 18 periods, the underlying changes in the economic structures and the new shocks will be reflected in the curve but have no lasting memory beyond 18 periods. Thus, the monetary policy shock in the 1970s is not a part of the curve in the 2000s if the original series does not contain the shock in the 1970s. In a probabilistic model, as long as the estimated coefficients use the 1970s data, the shock will always be a part of the model in its forecasting even if the shocks that cause a later recession have nothing to do with the shocks in the 1970s.

Our M-Coppock curve may also provide a numerical measurement for the magnitude of a recession. As the spike of the M-Coppock curve reflects the effect of a shock - new or old, on the economy, we can use the height of the spike as a measure for the magnitude of a recession. Thus, based on the M-Coppock curve, it is possible to know if one recession is worse than another.

Finally, as a demonstration of the usefulness of filters in economic research, we apply the well-known HP filter to the yield curve in Estrella and Mishkin (1996) and Estrella and Trubin (2006), and the shadow rate in Wu and Xia (2015). We examine the relationships among the unemployment rate, the Wu-Xia shadow rate and the yield curve at the business cycle frequency (the results are provided in Figures 6a, 6b, 7-12, as well as Table 9). Further more, we explain why the yield curve has predictive power while the level of the unemployment rate may not.

There are many filters available in the literature. The popular HP filter (Hodrick and Prescott 1997) is a moving average filter with weights that depend on a parameter λ and the whole sample. The Baxter-King filter (Baxter and King 1995) is a bandpass filter using a finite period moving average with symmetric weights. There is no phase displacement of the Baxter and King filter. Christianno-Fitzgerald (1999) random walk bandpass filter, like the HP filter, uses the whole series. The Baxter-King filter loses K observations by each of the two ends. These filters are used to decompose a series into a trend and a cyclical component. The three part decomposition in King and Watson (1994) can be considered as a filter approach in the frequency domain. Our filter in this paper has a very different objective and it needs a phase displacement so that we can overcome the time lag in the unemployment rate. We use a moving average related to the latest 18 periods and lose 18 period obervations by the left end but do not lose any observations by the right.

The unemployment rate data is from BLS for the period 1948:01 to 2015:11, the employment trend index is from the Conference board for 1973:11 to 2015:10, the Wu-Xia shadow rate is from 1960:01 to 2015:11 downloaded from the Federal Reserve Bank of Atlanta, and the yield curve data is from the Federal Reserve Bank of New York for 1959:01 to 2015:11. Our VAR model in Section 5 uses these data from 1960:01 to 2015:11.

The rest paper is organized as follows. Section 2 introduces the M-Coppock curve filter. Section 3 presents the HP filter. Our presentation follows Emara and Ma (2014) and Ma, Tang, and Wang (2016). Section 4 presents our result about the unemployment rate. Section 4.1 is the result related to the Conference Board employment trend index. Section 5 discusses the relationship of the unemployment rate to the yield curve and the Wu-Xia shadow rate. Section 6 conlcudes.

2 M-Coppock Curve

Edwin S.C. Coppock created the original Coppock curve, named after him and published by the Barron's Magazine on October 15, 1962. It is an indicator to identify the turning point of a trend line of a monthly time series such as the monthly S&P 500 Index, using a 10-period weighted moving average (MA) of the sum of the 14-month rate of change and the 11-month rate of change. We modify this curve as a 12-period moving average of the sum of one-period, three-period and six-period differences.

Let $x(t) \in R^T$ be a time series and L be the lag operator defined such that for any series $x(t)$, $Lx_t = x_{t-1}$ and $L^0 = 1$, where T is the number of observations in a series. Then the M-Coppock curve $y(t)$ of a time series $x(t)$ is defined by, $n = 12$,

$$\begin{aligned} y_t &= \frac{1}{n}\sum_{j=0}^{n-1}\sum_{q=1,3,6}(x_{t-j} - x_{t-q-j}), \qquad t \geq n+6 \qquad (1) \\ &= \frac{1}{n}\sum_{j=0}^{n-1} L^j[(1-L)+(1-L^3)+(1-L^6)]x_t \\ &= \psi(L)x_t. \end{aligned}$$

The M-Coppock curve is just a causal FIR (finite impulse-response) filter, a moving-average operator with $\psi(L)$, a polynomial in the lag operator of the form with finite lags:

$$\begin{aligned} \psi(L) &= \frac{1}{12}\sum_{j=0}^{11} L^j[(1-L)+(1-L^3)+(1-L^6)] \qquad (2) \\ &= \frac{1}{12}(1-L^{12})(3+2L+2L^2+L^3+L^4+L^5), \\ &= \psi_0 + \psi_1 L + \cdots + \psi_{17}L^{17}, \end{aligned}$$

where

$$
\begin{aligned}
\psi_0 &= \frac{1}{4} \\
\psi_1 &= \psi_2 = \frac{1}{6} \\
\psi_3 &= \psi_4 = \psi_5 = \frac{1}{12} \\
\psi_{17} &= \psi_{16} = \psi_{15} = -\frac{1}{12} \\
\psi_{14} &= \psi_{13} = -\frac{1}{6} \\
\psi_{12} &= -\frac{1}{4}
\end{aligned}
$$

and $\psi_j = 0$ for $j = 6, 7, \cdots, 11$.

The success of our FIR filter to call recessions should leave the door open to design an "optimal" FIR that can forecast recessions with the smallest error, using the NBER recessions as the reference dates, a direction of interest that can be pursued in the future. In this paper we just focus on $\psi(L)$, with no intention for it to be optimal.

The gain $|\psi(\omega)|$ and phase displacement $\theta(\omega)$ of the M-Coppock curve are obtained by, respectively,

$$
|\psi(\omega)|^2 = \{\sum_{j=0}^{17} \psi_j cos(j\omega)\}^2 + \{\sum_{j=0}^{17} \psi_j sin(j\omega)\}^2,
$$

and

$$
\theta(\omega) = arctan\{\frac{\sum \psi_j sin(j\omega)}{\sum \psi_j cos(jw)}\},
$$

where ψ_j is given by (2) for $j = 0, 1, \cdots, 17$ and $\omega \in [0, \pi]$. Figure 1 is the gain and the phase of the M-Coppock curve. Figure 1 shows that the M-Coppock curve is a generalized linear phase FIR for the busisness cycle frequency band between 2 and 8 years per cycle. The M-Coppock curve is a new casual FIR filter, different from the three filters allured in the introduction. In particular, the bandpass Baxter-King filter uses a finite number of truncated symmetric coefficients of an infinite sequence and has no phase displacement. The HP filter and the Christianno-Fitzgerald random walk band pass filter use the whole series. Because the M-Coppock curve only uses 18-period data, structural breaks will not have a long lasting effect, unless the underlying economy follows a nonstationary random walk process with a very long lasting memory. Thus, if different recessions are caused by different transitory shocks or the same type of shocks with different magnitudes, our filter can be used as a measurement tool for isolated effects of these shocks. For example, the recession in 2008 has been called the Great Recession. Our M-Coppock curve in Figure 3 does show that the curve has reached the highest spike since 1948. That is, our curve can work as a measure for its "magnitude" of a recession.

Another important feature of the M-Coppock curve is that we can use $y(t)$ to forecast $x(t)$ by

$$x(t) = \psi^{-1}(L)y(t). \tag{3}$$

These operations in (1) and (3) can be easily implemented in Matlab using the function filter by setting $b = (\psi_0, \psi_1, \cdots, \psi_{17})$ and $a = 1$. To get $x(t)$ from $y(t)$, we just switch the positions of b and a.

3 The HP Filter

In this section we introduce the well-known HP filter (Hodrick and Prescott, 1997, and Kim et al., 2009). Given a series $x(t)$, the HP filter chooses the trend estimate $y(t)$ to minimize

$$\frac{1}{2}\sum_{t=1}^{T}(x_t - y_t)^2 + \lambda \sum_{t=2}^{T-1}[(y_{t+1} - y_t) - (y_t - y_{t-1})]^2. \tag{4}$$

As shown in Kim et al. (2009), the objective (4) can be written in a matrix form as

$$\frac{1}{2}|x - y|^2 + \lambda|Dy|^2, \tag{5}$$

where $x, y \in R^T$ and $|u|$ is the Euclidean norm, and $D \in R^{(T-2)\times T}$ is the second-order difference matrix given by

$$D = \begin{bmatrix} 1 & -2 & 1 & & & & \\ & 1 & -2 & 1 & & & \\ & & \ddots & \ddots & \ddots & & \\ & & & & 1 & -2 & 1 \end{bmatrix} \tag{6}$$

Entries in (6), not shown, are equal to zeros. Thus, $x = y + c$, where $y = (I + 2\lambda D'D)^{-1}x$ and $c = x - y$. y is a moving average of x with weights depending on λ and D in a subtle manner.

One problem associated with the use of the HP filter is that the cyclical component $(x - y)$ is weak dependence and contains both a "genuine" cyclical component of the economy and a noise component. Too much useful information about the state of the economy after the use of the filter has been put into the noise component. Indeed, powerful low frequency components have been passed the filter into the cyclical component (Figure 2). This is the part that has been thought to be driven by the Solow's residuals in the real business cycle literature. These low frequency components are often classified as the "spurious cycles". Because the filter only provides two part decompositions, the literature seems to suggest that these "spurious cycles" should be put into the secular trend in the vicinity of zero frequency. This suggestion is equally problematic because the low frequency components passing the filter have frequencies that appear to be too far away from the vicinity of the zero. Note that a small difference in the vicinity of the zero has a leap foreward effect. This two part decompostion poses a dilemma. King and Watson (1994) have provided a good solution to the dilemma by providing a three part decomposition using filters in the frequency domain, where the frequency band of each component follows more or less the business cycle bandpass suggested by Burns and Mitchell (1946). Motivated by King and Watson (1994), Emara and Ma (2014) provide a three part decomposition by a recursive use of the HP filter. The approach of this paper follows Emara and Ma (2014):

$$c(l-1) = y(l) + c(l), \;\; l = 1, 2, \cdots, k, \tag{7}$$

where, $c(0) = x$, and

$$y(l) = (I + 2\lambda D'D)^{-1} c(l-1), \tag{8}$$

$$c(l) = 2\lambda D'D(I + 2\lambda D'D)^{-1} c(l-1). \tag{9}$$

Then, we can decompose $\{x_t\}$ into three parts, for a given integer $k \geq 1$,

$$x = y + c + n,$$

where $y = y(1) = (I+2\lambda D'D)^{-1}x$, $c = \sum_{j=2}^{k} x(j) = c(1) - c(k)$, and $n = c(k)$. We call y, c and n the permanent trend, the cyclical trend and the noise component, respectively. The permanent trend represents the long run behavior of the series while the cyclical trend is in response to the movement of the series at the business cycle frequency. The noise component represents the movement at higher frequencies, not including in the permanent and cyclical trends. We find that this three part decomposition is very useful and has the potential to resolve the "spurious cycles" issue in the application of the HP filter. The name of "spurious cycles" is quite misleading as pointed out in Pollock (2013).

We choose $k = 11$ for the cyclical trends of Figures 6a and 6b in this paper[5] and $\lambda = 129,600$ for monthly data. The impact on the spectrum of the unemployment rate series in this recursive use of the HP filter can be seen from Figure 2. The HP filter is known to be less flexible than the Butterworth lowpass filter (Pollock 2013) but Figure 2 shows that our recursive use of the HP filter can perform equally well as the Butterworth filter, with a flexible choice of k, giving rise to a smoothier cyclical trend. If k goes to infinity, then our procedure goes back to the original HP filter because there is nothing left in n.

[5] See Emara and Ma (2014) for a study how k is rightly chosen for different indicators.

4 The Unemployment Rate

The unemployment rate is the percentage of people in the labor force without work and actively seeking work. It is a critical business cycle indicator that has been widely watched for the state of the economy. The following provides a summary of our best understanding about this indicator among economists:

> The unemployment rate is a trendless indicator that moves in the opposite direction from most other cyclical indicators. [...]. The NBER business-cycle chronology considers economic activity, which grows along an upward trend. As a result, the unemployment rate often rises before the peak of economic activity, when activity is still rising but below its normal trend rate of increase. Thus, the unemployment rate is often a leading indicator of the business-cycle peak. [...]. On the other hand, the unemployment rate often continues to rise after activity has reached its trough. In this respect, the unemployment rate is a lagging indicator. (NBER Q&A).

Figure 3 displays the recessions identified by NBER, the M-Coppock curve, and unemployment rates since 1948. The shaded bars in Figure 3 represent the recessions identified by NBER. There are altogether 11 recessions since 1948. The height of the bar has no particular meaning, but the width of the bar indicates the length of a recession. A recession can be as short as 7 months (the 1980 recession) and as long as 19 months (the 2007-2009 recession). As shown in Figure 3, the unemployment rate has a salient feature of asymmetry: it falls quite slowly and gradually during an expansion but rises sharply in a recession. Such a feature has been studied in detail in a seminal paper by Neftci (1984). Rothman (1991) provides an additional study of such an asymmetry, among many others.

The solid line in Figure 3 is the M-Coppock curve. For each of the 11 recessions, the M-Coppock curve crosses the zero horizontal axis (the zero line) and becomes positive around the same time as the beginning of the recession, and the M-Coppock curve forms a spike and reaches its local peak about the same time as the recession ends. For example, the 2007-2009 recession identified by

NBER starts in December 2007 and ends in June 2009. The M-Coppock curve becomes positive in October 2007 and reaches its local maximum in July 2009. It should be pointed out that the M-Coppock curve briefly crosses the zero horizontal line in 1963 and 1967. However, they are not necessarily leading to false recession calls. The economy did slow down sharply for a quarter during the two periods, which were caught by our filter. As a practical rule though, a recession call based on the M-Coppock curve may require the curve to cross the zero horizontal line with some strength and momentum; i.e., it may require the value of M-Coppock to be greater than certain value (0.2 for example). The dashed line represents the unemployment rates. As can be seen, the curve for the unemployment rate is much more volatile than the M-Coppock curve. Obviously, it is more difficult to directly use the unemployment rate without a filter to determine the beginning and ending of a recession.

There is also an asymmetry in the M-Coppock curve. The M-Coppock curve stays in the negative zone during an expansion and moves up and down within a narrow range. During a recession, it can climb up very quickly to form a sharp spike. These spikes are uneven, likely due to different shocks. Before it moves up sharply to the positive zone, it must make a turn in the negative zone, often far earlier than the time when a recession begins. In fact, we can see the dynamic process how the M-Coppock curve approaches the zero line from those critical turning points. This is why we say that the M-Coppock curve should be best used as an early warning system for monetary policy.

The time that the M-Coppock curve makes a turn cannot be easily seen from the level of the unemployment rate. For example, the unemployment rate in the U.S. economy continues to trend down at present but the M-Coppock curve has turned in October 2014 (Table 1). Thus, we can use some uniform rules to call a recession in real time, a practice that cannot be done from the level of the unemployment rate. Our prediction of the peaks and the troughs has been given in Table 2. The lead and lag discrepancies with respect to the NBER identified recessions are quite similar to what has been obtained by the probabilistic models in Hamilton (2010) and Chauvet and Piger (2008). But, our M-Coppock curve is much simpler, accessible to the pulic without any help from professionals.

The M-Coppock curve has some predictive power. For example, the M-Coppock curve stays in the negative zone right now but it has turned in October 2014 at -1.083 and been in an upward trend ever since then to reach the current reading at -0.625 (December 2015 in Table 2). This means that the labor market has gradually lost its strenghth since October 2014. Table 3 presents some projected scenarios about the unemployment rate and their M-Coppock curves. These projected cases do not mean to be accurate. They are used to show how the M-Coppock curve can be used to forecast recessions, given a forecasted unemployment rate. The five scenarios are based on the following assumptions:

- Scenario 1. Unemployment rate continues to decrease.
- Scenario 2. Unemployment rate starts to gradually increase to 5.10% by the end by the end of 2016 - the level experienced in August/September 2015.
- Scenario 3. Unemployment rate continues to decrease to the lowest level of 4.40% before the middle of 2016 and then increases 5.10% by the end of 2016.
- Scenario 4. Unemployment rate continues to decrease to the lowest level of 4.40% in the later part of 2016 and then increases gradually.
- Scenario 5. Unemployment rate continues to decrease to the lowest level of 4.40% in the later part of 2016 and then increases rapidly.

Scenario three is the only one where the M-Coppock dips slightly. But it immediately continues to move higher toward the zero line. In all other scenarios, the M-Coppock curve continues with its trend to approach the zero line. This indicates that the U.S. economy may be on its journal to the next recession at the moment.

It is of interest to ask a question if there is any gender differential in the labor market during a recession. Sahin et al. (2010) find that during the Great Recession women performed much better than men. In fact, the M-Coppock curve documents evidence women have performed better than men, not only in the Great Recession but also in every recession since 1969 recession. These results are present in Table 4. For the eleven recessions post WWII, men only performed better than women in two recessions in 1953 and 1960. It is a complicated issue why there is a gender differential in the labor market during recessions. Our curve can only provide a measure but not an explanation. It is still useful because it leads us to ask for the reason of such a difference. For example, the Korean and the Vietnam Wars may contribute somehow to the better performance of men in the labor market during 1953 and 1960 recessions.

4.1 The Employment Trend Index

The employment trend index from the Conference Board is a composite index that has incorporated eight labor market related indicators from different agencies. These indicators inlcude: Percentage of Respondents Who Say They Find Jobs Hard to Get (in The Conference Board Consumer Confidence Survey); Initial Claims for Unemployment Insurance (U.S. Department of Labor); Percentage of Firms With Positions Not Able to Fill Right Now (National Federation of Independent Business Research Foundation); Number of Employees Hired by the Temporary-Help Industry (U.S. Bureau of Labor Statistics); Ratio of Involuntarily Part-time to All Part-time Workers (BLS); Job Openings (BLS); Industrial Production (Federal Reserve Board); Real Manufacturing and Trade Sales (U.S. Bureau of Economic Analysis). Figure 4 provides the index and its M-Coppock curve. This time we observe that the M-Coppock curve penetrates the zero line each time from the positive to negative when the economy reaches its peak and then reaches its trough as the economic activity is also in the trough. This gives us the second method to call recessions in real time. Table 4 presents our recession calls in real time. Once again, the trough (or downward spike) in the M-Coppock curve can be used as a measure for the magnitude of a recession. In the Great Recession, the M-Coppock curve reaches -21.72 value, much worse than any others. It appears that our M-Coppock curve is the first filter that can provide a numerical measure for recessions. We also add the cyclical component of the index after using the HP filter once. As we can see from the graph, it is not easy to determine a uniform rule to call recessions based on the cyclical component of the HP filter.

5 The Yield Curve and Shadow Rate

The yield curve has predictive power for economic activity. Indeed, the yield curve and the related term structures have been extensively studied in the literature. Estrella and Hardouvelis (1991) and Estrella and Mishkin (1996) provide probabilitic models to forecast real economic activity. The Federal Reserve Bank of New York uses their approach to forecast the probability of a recession one year ahead. Harvey (1988, 1989) make two seminal contributions in the use of the term structure to forecast growth in consumption and real economic activity. An important lesson from Harveys is that the term structure contains more reliable information about the underlying economy than the equity market, which is often thought to be a leading indicator. Wikipedia.org under the term "yield curve" discusses the relationship between the yield curve and the business cycle by stating that "[t]he slope of the yield curve is one of the most powerful predictors of future economic growth, inflation, and recessions[.]" with a citation to the work in Estrella and Mishkin (1996). More detailed discussions of the yield curve and its predictive power can be also found in Estrella and Trubin (2006).

Even though the unemployment rate is an equally important indicator for the business cycle, it receives much less attention than the yield curve. In particular, few economists would feel comfortable to use it as a leading indicator (Stock and Watson 1989) and it has been excluded in the leading indicator index from the Conference Board. People often see it as a lagging indicator. That may be the reason why Hamilton (2010) felt it is not a reliable indicator to date recessions even if his model using the unemployment rate predicted the Great Recession. Therefore, it is of interest to know how the yield curve, the short-term rate, and the unemployment rate are actually related.

To understand these relationships better, we put the unemployment rate, the Wu-Xia shadow rate (Wu and Xia 2015), and the yield curve together in Figure 5. The Wu-Xia shadow rate is in particular important at present when the federal fund rate is near zero. From Figure 5, we can see that the Wu-Xia shadow rate (in upside down), the yield curve and the unemployment rate all form a downward spike near the beginning of a recession and they tend to fall during economic expansions. Beyond these spikes, the Wu-Xia shadow rate and the yield curve turn to be much more volatile than the unemployment rate. It is hard to figure out how the three are related during the economic peaks and troughs from the levels of these rates.

We use the HP filter technique introduced in Section 3 and get out their cyclical trends into Figures 6a and 6b. Now the relationships among the three become quite transparent. Note that these curves are just a part of the data because they are one part of three part decompositions. No data can be generated or created by the HP filter. We can see from Figures 6a and 6b that the cyclical trends in the yield curve and the unemployment rate move together. Note that the Wu-Xia shadow rate has been drawn upside down for comparison purpose. Thus, it moves in the opposite direction to the yield curve and the unemployment rate.

The yield curve crosses the zero line during an expansion, which explains when the yield curve starts its flattening process. For example, the whole process of flattening yield curve for the Great Recession started in 2005. The yield curve crosses the zero line from the negative zone during recessions or near the end of recessions. This is the steepening process of the yield curve. Because the steepening process starts in the economic trough while the flattening process starts during an expansion, this explains why the yield curve is considered as a leading indicator. Figures 6a and 6b document evidence that the unemployment rate and the Wu-Xia shadow rate have equal predictive power as the yield curve, as two leading indicators.

The major reason why economists recognize the predictive power of the yield curve, but not of the unemloyment rate or even of the Wu-Xia shadow rate, is that the unemployment rate and the Wu-Xia shadow rate are nonstationary (Table 6), where their long run trends have contaminated their predictive power at the business cycle frequency. The yield curve, on the other hand, is a stationary process (Tables 6 and 7). What we have done is to remove the long run trends in these series and uncover the genuine information they have at the business cycle frequency (Table 7). Our M-Coppock curve has predictive power because it uses the 12-period moving average of three differences in the unemployment rate so that the long run trend in the unemployment rate has been removed, which can be seen from (2) in Section 2.

The idea behind the design of the HP filter is to remove the trend from an I(1) series so that the series can be analyzed at the business cycle frequency, especially in the literature of the real business cycle. This idea, starting with Burns and Mitchell (1946), is fundamental to the study of macroeconomic fluctuations. King and Watson (1994) decompose the series of the unemployment rate and the inflation rate into three parts and establish the Phillips curve by using the cyclical component. To find the close relationships among the three, we follow the lead of the literature. We use the following procedure: A). We use the HP filter to remove the long run trends of the three series; b). We use various criteria for model specification as given in Table 8, which shows that the optimal number of lags is four; C). Then we run the VAR model as follows

$$y_t = \beta_1 y_{t-1} + \cdots \beta_q y_{t-q} + \epsilon_t; \tag{10}$$

where $y_t = [u_t, v_t, w_t]'$. Here u, v and w denote the unemployment rate, the Wu-Xia shadow rate and the yield curve (or spread), respectively. D). We eliminate those lags that have multicollinearity with others; E). However, the model obtained in D) has a serial correlation. Thus, we use the Cochrane-Orcutt iterated procedure to estimate the coefficents again as follows

$$y_t = X_t \beta + u_t \tag{11}$$

where X_t has been identified in D), and

$$u_t = \varphi_1 u_{t-1} + \cdots + \varphi_{12} u_{t-12} + \nu_t, \tag{12}$$

where ν_t is Gaussian noise $N(0, \sigma^2)$ of mean zero and constant variance.

Figures 7 and 8 report the results for the unemployment rate. Figures 9 to 12 display the results of the model for the Wu-Xia shadow rate and the yield curve. As can be seen from these figures, the model fits the data well (see Table 9 for detail). The residuals are shown in Figures 8, 10 and 12. We want to use this model to show that the levels of the unemployment rate and the Wu-Xia shadow rate should not be used as a good assessment of the U.S. economy, especially for the business cycle oriented monetary policy. The three equations in Figures 7, 9 and 11 are given by, respectively,

$$\begin{array}{rcccc} \hat{u} & = & 0.0002 & + & 0.9608\ u, \qquad R^2 = 0.96 \\ & & (-0.011, 0.011) & & (0.946, 0.976) \\ \hat{v} & = & -0.0005 & + & 0.9325\ v, \qquad R^2 = 0.93 \\ & & (-0.032, 0.031) & & (0.913, 0.952) \\ \hat{w} & = & 0.0002 & + & 0.8964\ w, \qquad R^2 = 0.90 \\ & & (-0.022, 0.023) & & (0.873, 0.920) \end{array}$$

the 95% confidence bands are given in parentheses. Symbols with hat are the model predictions.

The relationships among the three may not be that surprise. Phelps (1999), Fitoussi et al. (2000), and Phelps and Zoega (2001) find that some positive relationship between the employment and stock prices exist. For example, Phelps (1999) documents evidence that the lagged ratio of stock capitalization over corporate capital can explain the employment growth in the US for the period from 1970 to 1998. Fitoussi et al. (2000) and Phelps and Zoega (2001) identify the productivity and the profitability as two main drivers for the relationship. Farmer (2012, 2015) use VECM to establsih a remarkably stable relation between the unemployment rate and the stock price for data that spans over seventy years. Farmer (2012) finds that there is a nonstationary in the unemployment rate and cointegrated relationship between the logarithm of the real S&P 500 index (in units of nominal wage) and the logarithm of a logistic transformation of the percentage unemployment rate. His estimates indicate that countercyclical movements in the unemployment rate are Granger caused by cyclical movements in the stock prices, also see Farmer (2015). Ma et al. (2016) use the unemployment rate and the capacity utilization rate to identify profitable hedging strategies by reducing recessionary risks. Hall (2015) uses the noted Diamond-Mortensen-Pissarides search-matching model and ties the unemployment with the economy-wide discount factor, which is clearly related to both the shadow rate and the yield curve. These papers suggest that the employment or unemployment related indicators may contain far more information than what has been thought before in the literature.

But, the way to look at them must be changed because their long run trends can mud the true value of these series for the study of the business cycle. Monetary policy that is based on these assessments can be very wrong.

6 Conclusions

This paper presents a simple M-Coppock curve to date recessions in real time. Our approach is simple. More importantly, one can directly watch the dynamic process how the economy moves from one business cycle to another by watching the time when the M-Coppock curve turns. These turns indicate the underlying forces in the economy are about to make a turn. Our curve as a filter is less volatile than the unemployment rate and removes the long run trend so that its predictive power at the business cycle frequency is uncovered. Our study indicates that the U.S. economy at the moment is in a process of losing its strenghth, an assessment that is not easy to obtain from the level of the unemployment rate. Our M-Coppock curve and the HP filter with a recursive use provide some new tools to uncover some important information behind the unemployment rate. A future study is to investigate how to use them in the study of productivity, profitability and other indicators. The scope of this paper is limited to the U.S. economy. We hope this filter is useful too for other economies.

7 Acknowledgement

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Figure 1. Gain and Phase of M−Coppock Curve

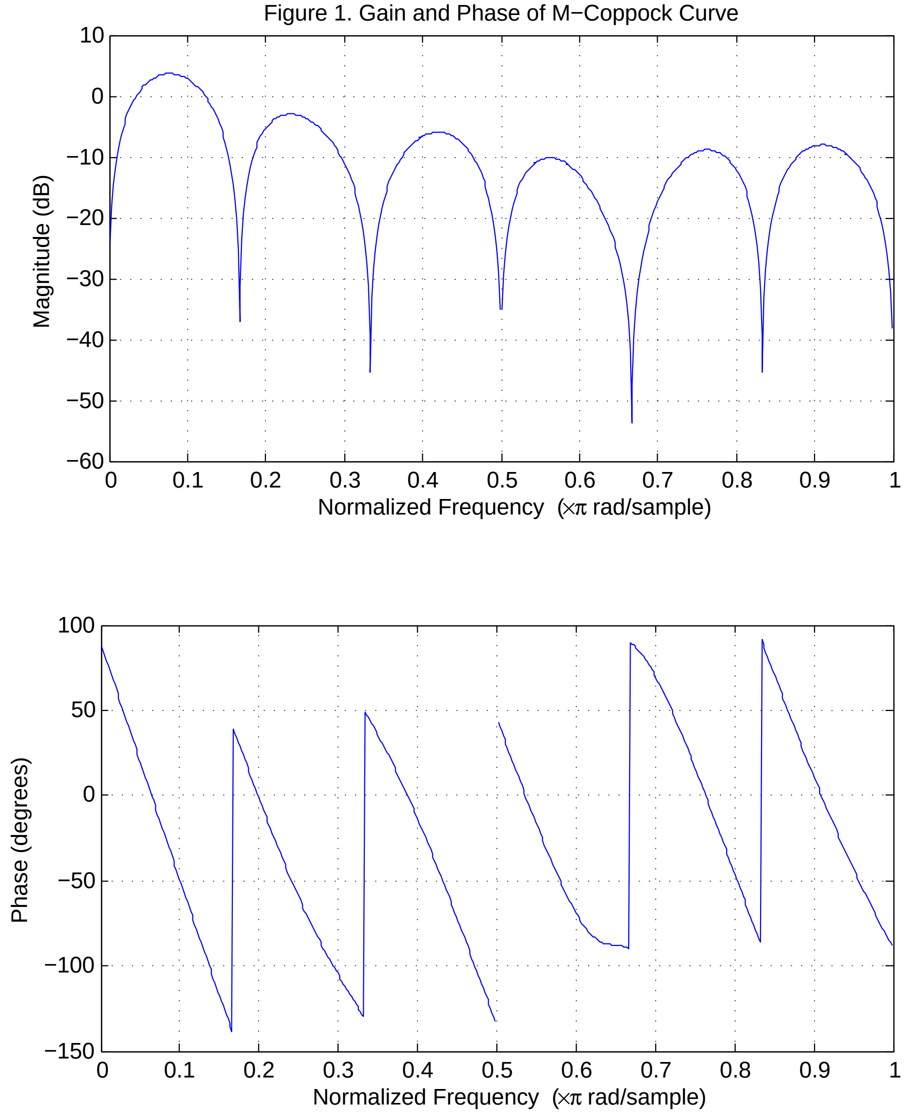


Figure 2. Single−sided Magnitude spectrum (rads/sample) of the noise components of the unemployment rate after using the HP filter

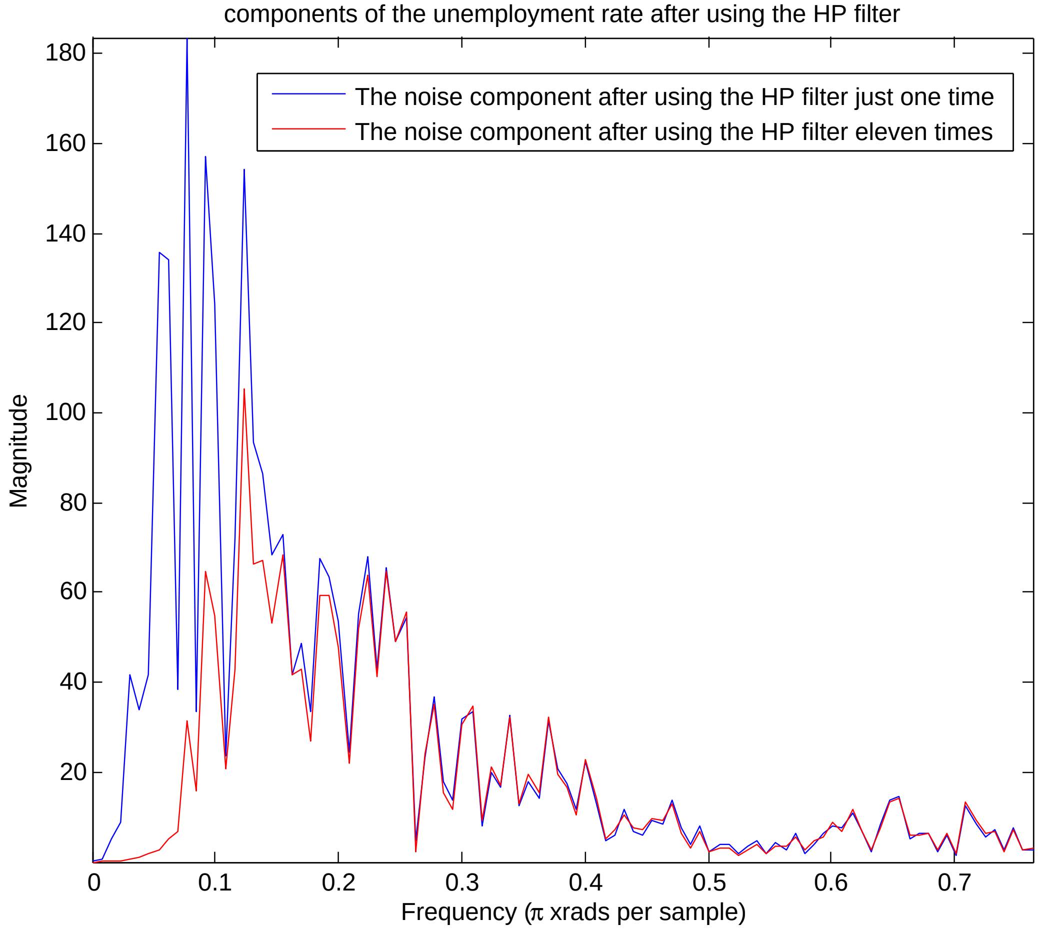


Figure 3. The Unemployment Rate and its M−Coppock Curve

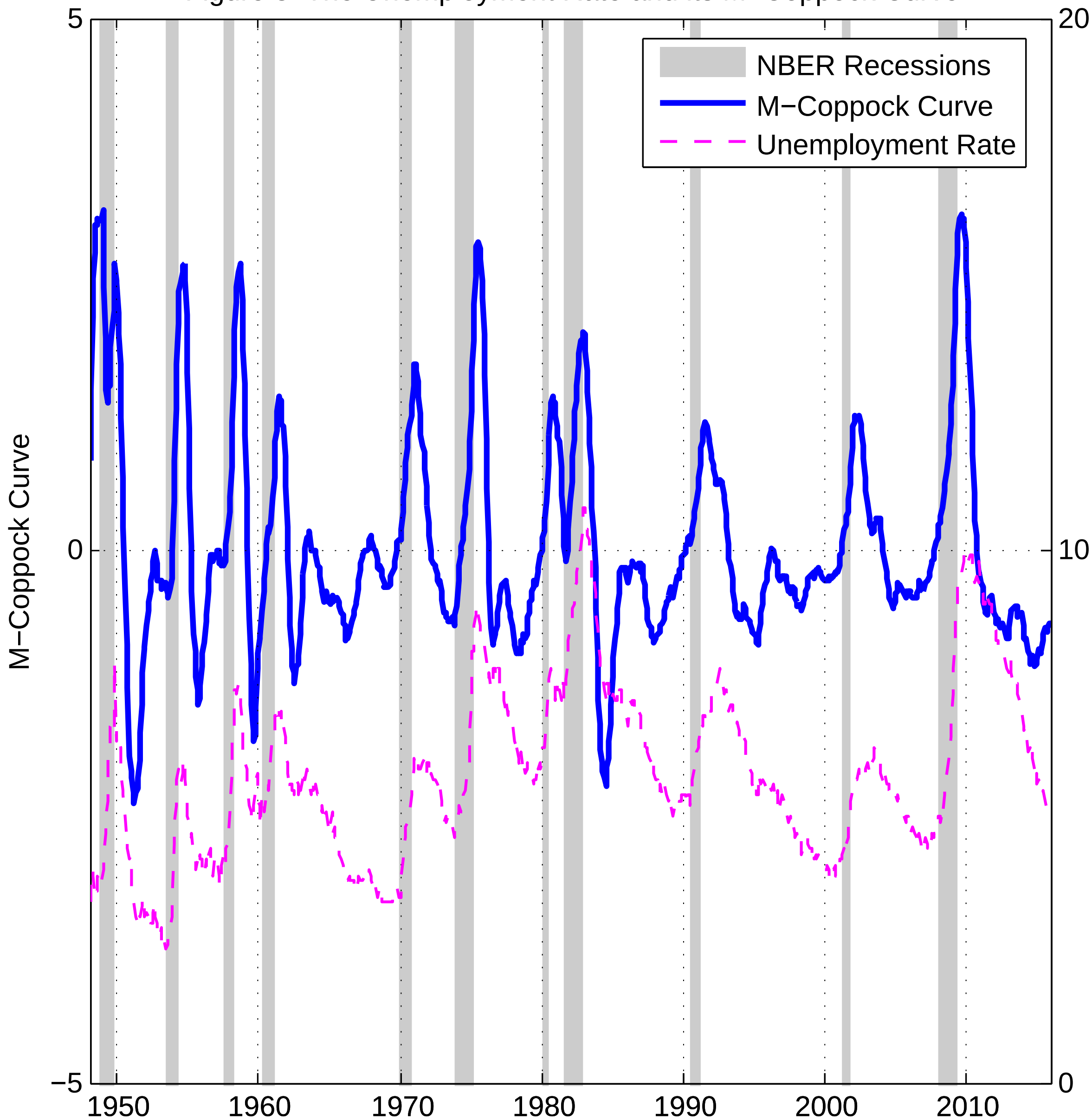


Figure 4. M−Coppock Curve Versus Cyclical Component of Employment Trend Index

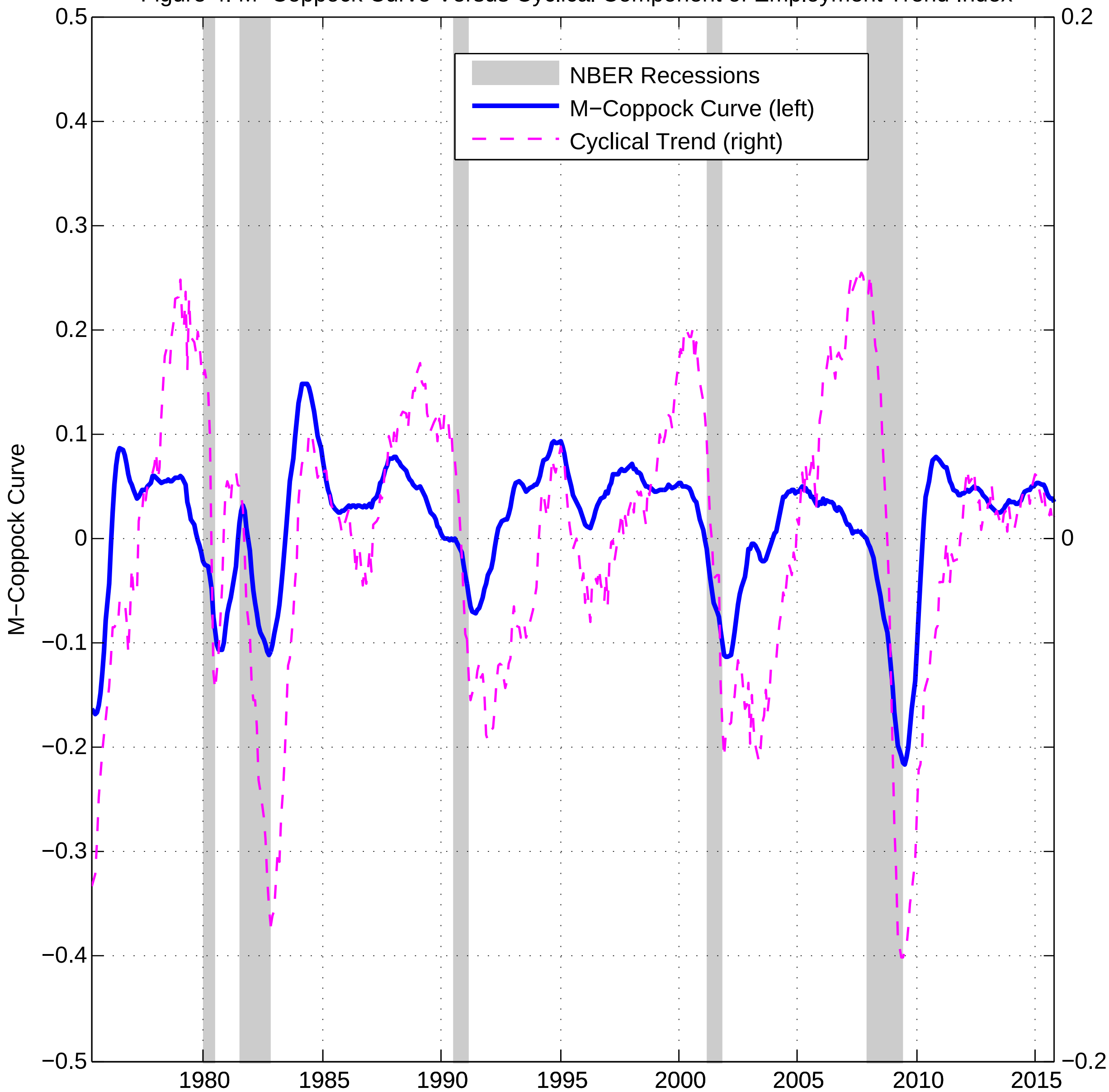


Figure 5. Unemployment, Yield Curve and Shadow Rate(−)

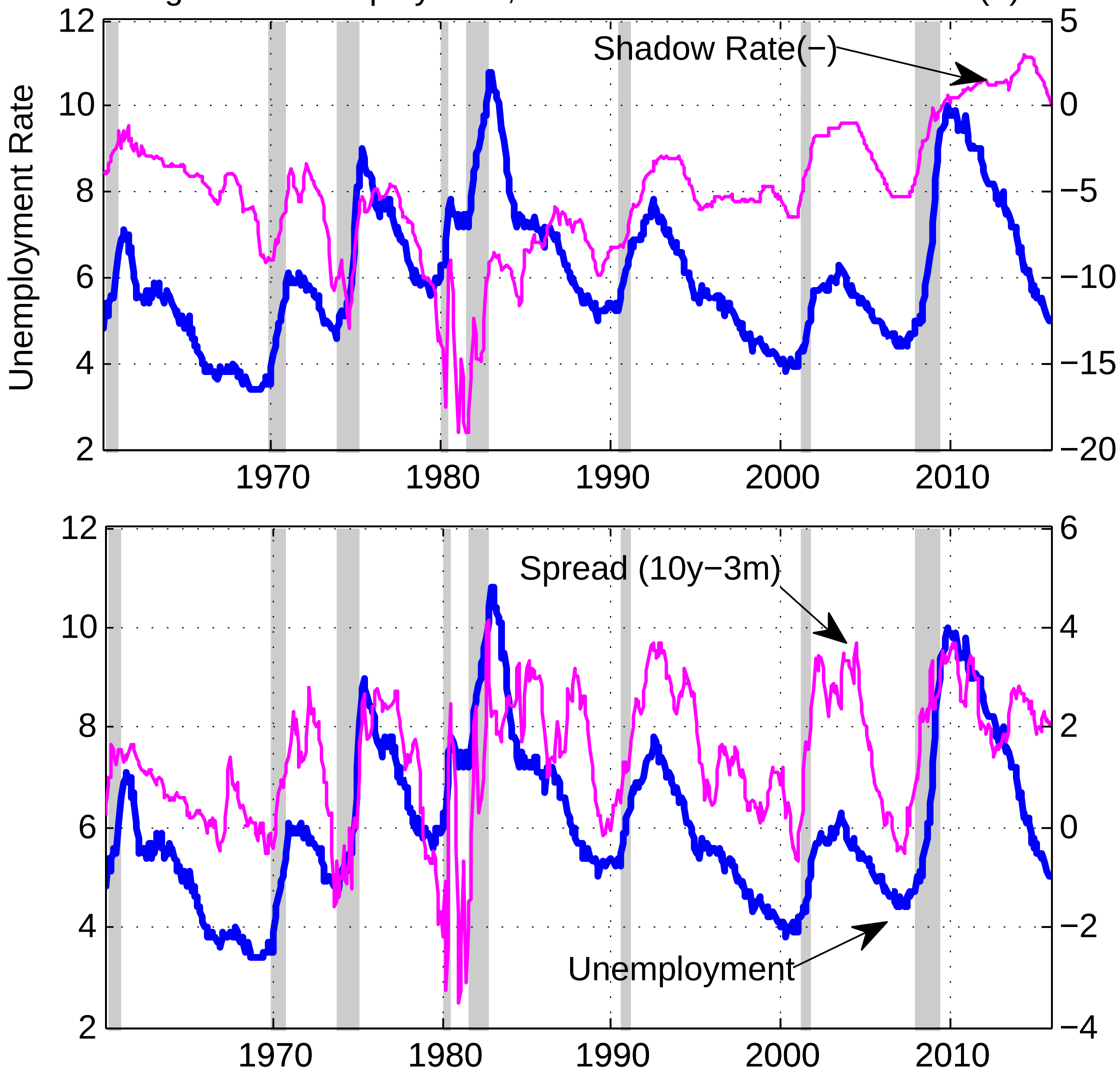


Figure 6a. Cyclical Trends of Unemployment Rate and Shadow Rate(−)

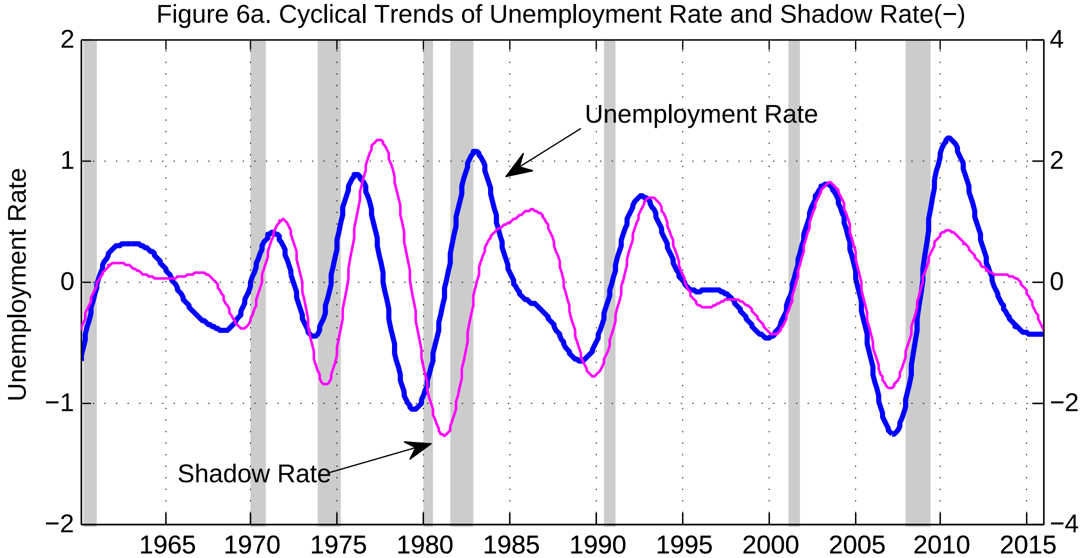


Figure 6b. Cyclical Trends of Unemployment Rate and Yield Curve

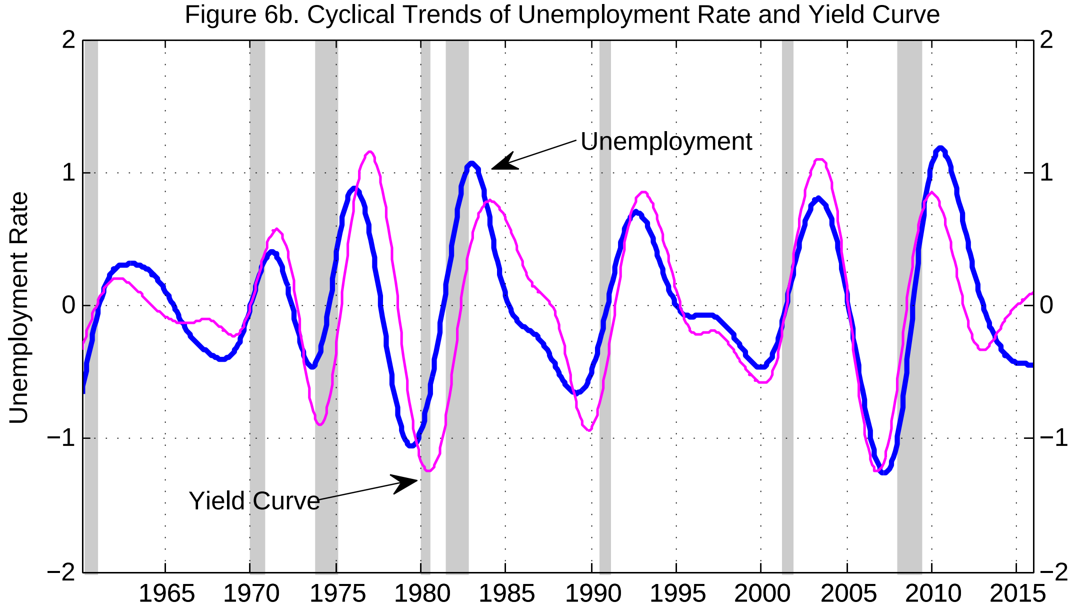


Figure 7. Unemployment Rate and Model Prediction

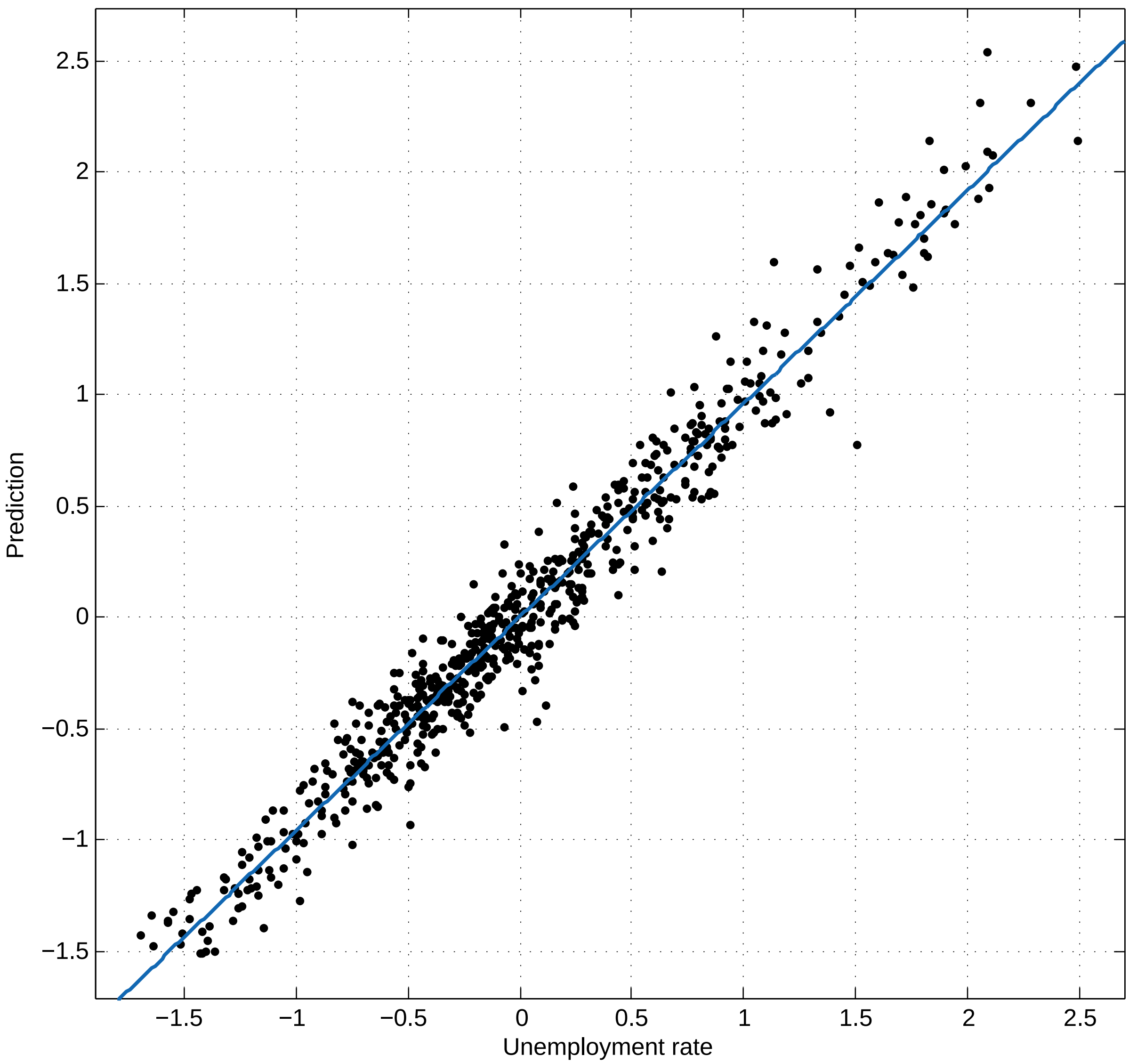


Figure 8. Unemployment Rate: Actual (blue) versus Predicted (red)

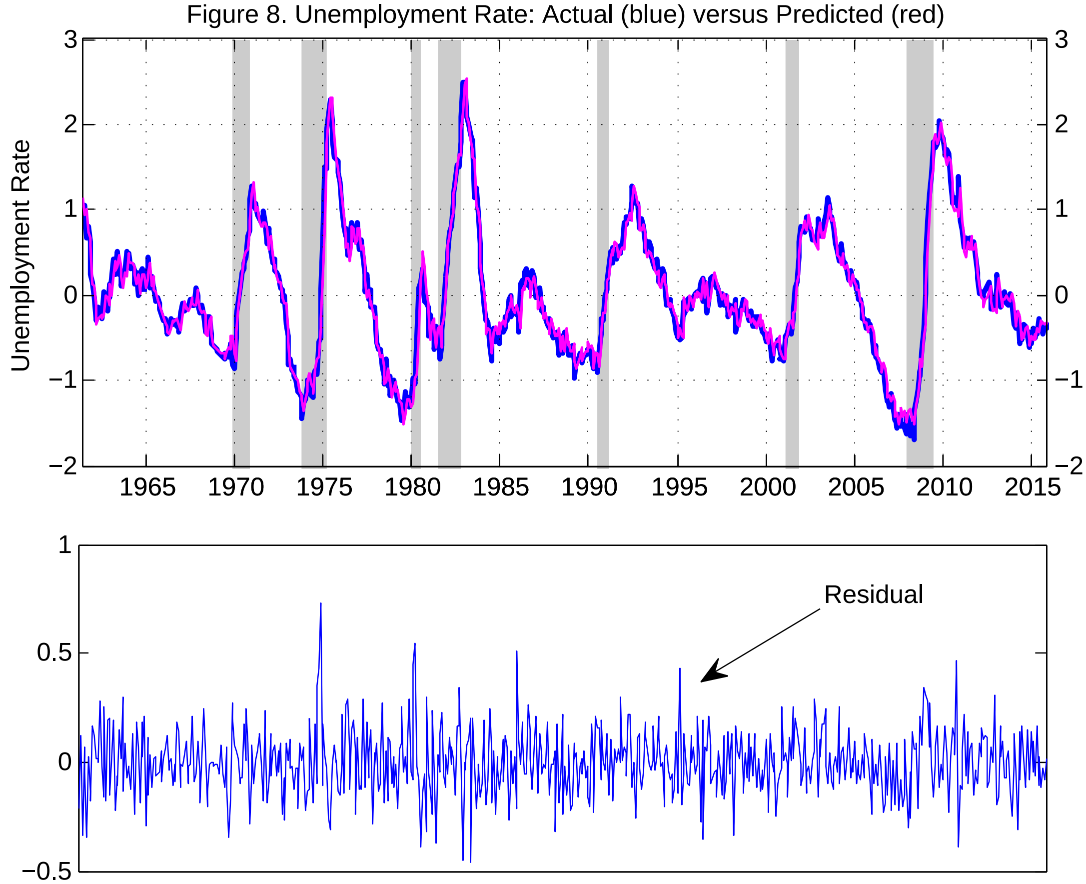


Figure 9. Wu−Xia Shadow Rate and Model Prediction

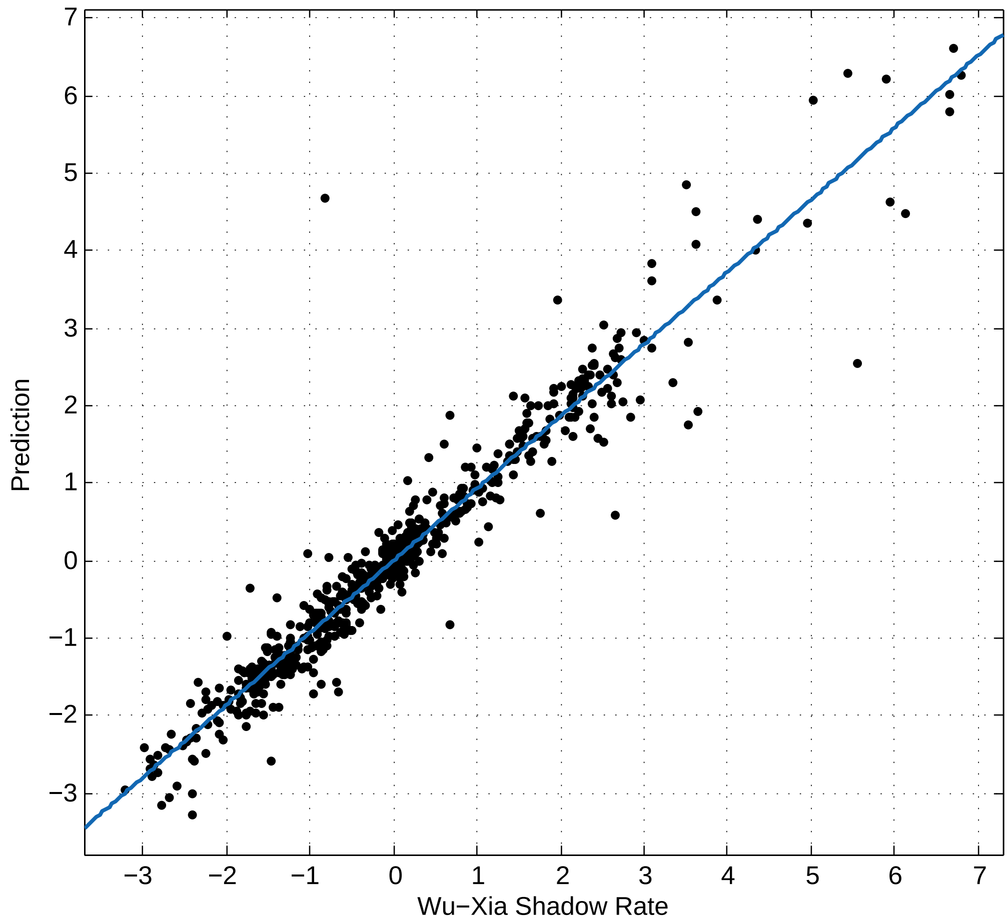


Figure 10. Wu−Xia Shadow Rate: Actual (blue) versus Predicted

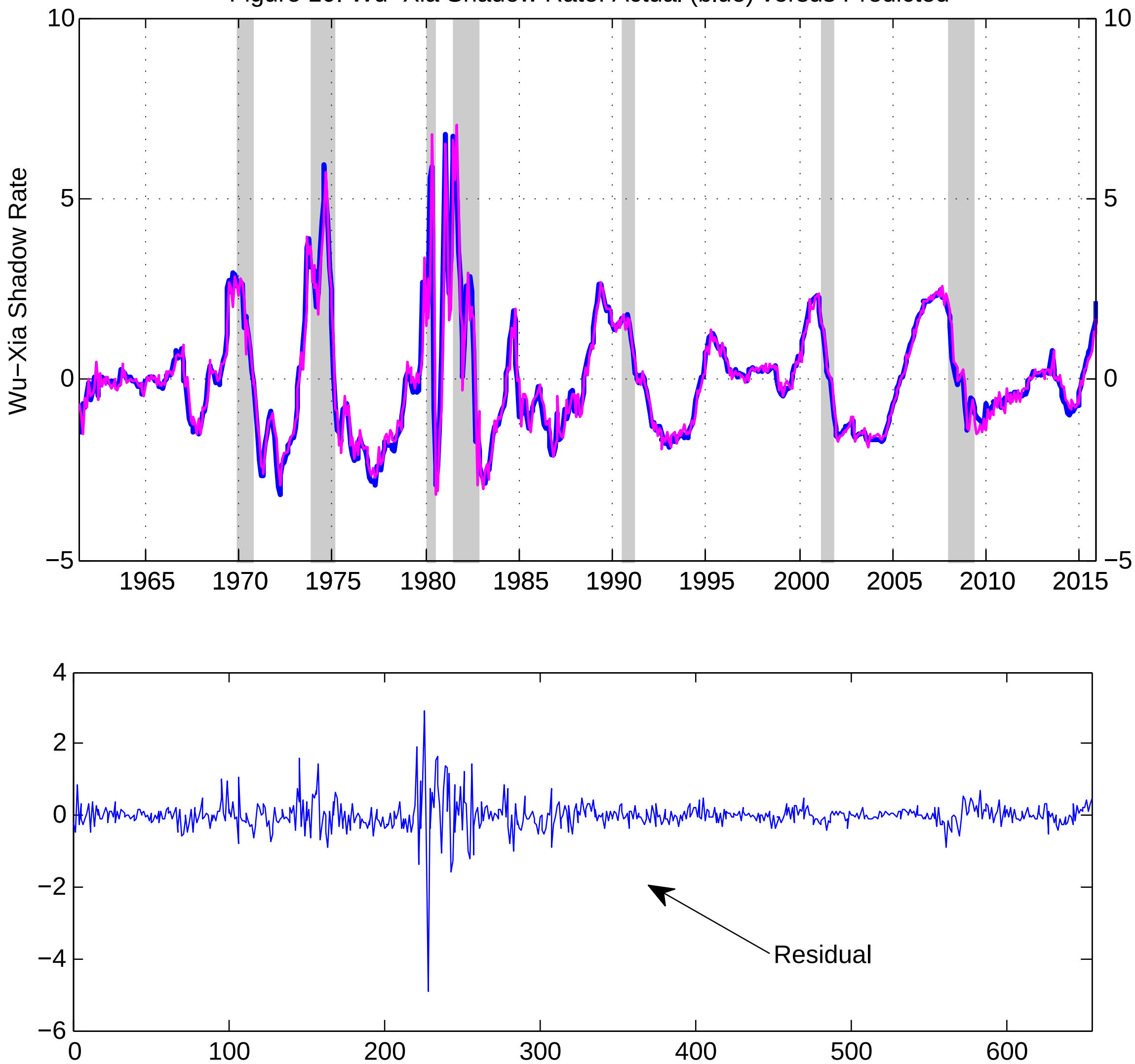


Figure 11. Yield Curve and Model Prediction

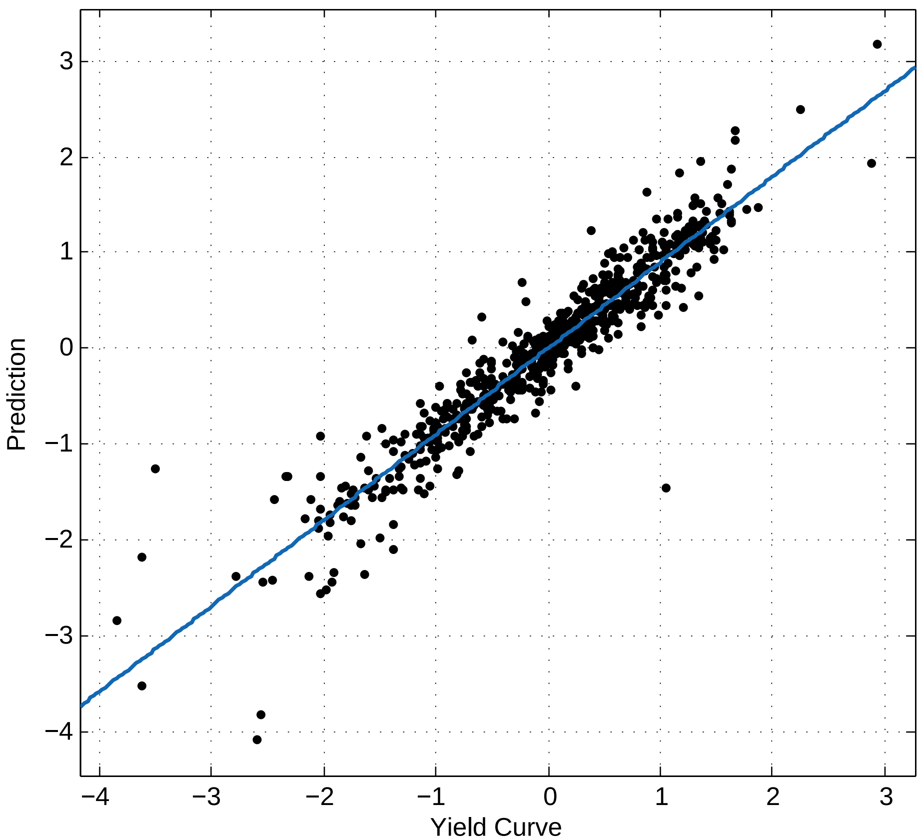


Figure 12. Yield Curve: Actual (blue) versus Predicted

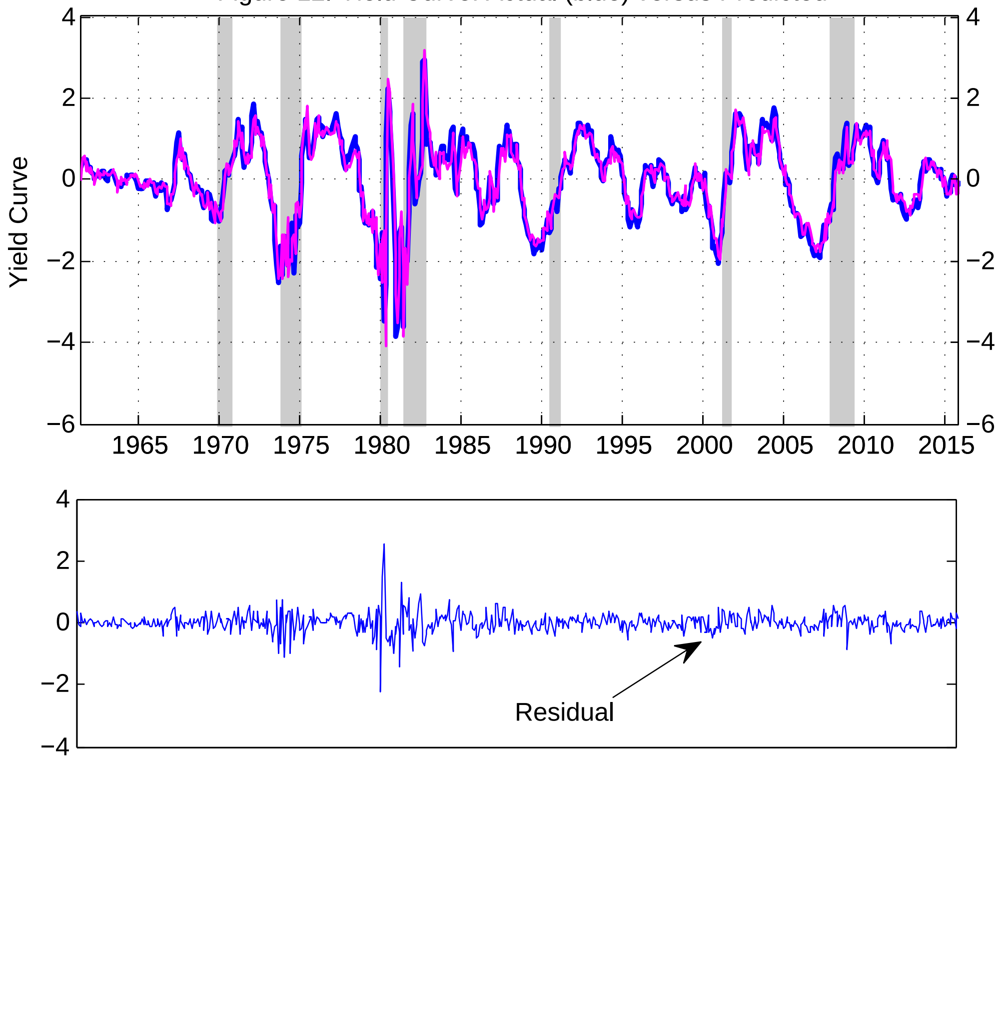


Table 1: This table reports the M-Coppock curve from Oct-14 to Nov-15. The M-Coppock curve reached the local lowest point at -1.083 and climbs up since then to the current reading at -0.675. We call a recession when the M-Coppock curve crosses the zero line from the negative zone to the positive zone at three levels: 0.0, 0.1, and 0.2 (see Table 2).

Date	Unemployment Rate	M-Coppock Curve
Oct-14	5.7	-1.083
Nov-14	5.8	-1.067
Dec-14	5.6	-1.017
Jan-15	5.7	-0.933
Feb-15	5.5	-0.967
Mar-15	5.5	-0.942
Apr-15	5.4	-0.850
May-15	5.5	-0.783
Jun-15	5.3	-0.733
Jul-15	5,3	-0.750
Aug-15	5.1	-0.758
Sep-15	5.1	-0.717
Oct-15	5.0	-0.683
Nov-15	5.0	-0.675

Table 2: Recession Forecast Using Unemployment Rates 1948:01-2015:11. This panel reports the M-Coppock curve and its forecasting ability of the NBER recessions. The original data are from the CPS downloaded from the BLS (ID: LNS14000000). The unemployment rate is the seasonal-adjusted monthly unemployment rate for civilian labor with age 16 years and over for period from 1948:01 to 2015:11. The M-Copock value in period k is the 12-month simple moving average of the sum of one month, three month and six month differences. Figure 3 is the M-Coppock curve and the original unemployment rate. A recession starts when the M-Coppock crosses the zero line from below by three levels, 0, 0.1, or 0.2. A recession ends when the M-Coppock reaches a local peak. Lead(+) and lag(-) discrepancies are measured by the number of lags(-) and leads (+) over the the NBER recessions in months underneath the calling dates.

NBER		Rule 0.0		Rule 0.1		Rule 0.2	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
53M07	54M05	53M11	54M09	53M12	54M09	53M12	54M09
		-4	-5	-5	-5	-5	-5
57M08	58M04	57M09	58M08	57M10	58M08	57M10	58M08
		-1	-4	-2	-4	-2	-4
60M04	61M02	60M07	61M05	60M08	61M05	60M08	61M05
		-3	-3	-4	-3	-4	-3
69M12	70M11	69M10	71M01	69M12	71M01	70M01	71M01
		+2	-2	0	-2	-1	-2
73M11	75M03	74M04	75M06	74M05	75M06	74M06	75M06
		-5	-3	-6	-3	-7	-3
80M01	80M07	80M01	80M09	80M01	80M09	80M03	80M09
		0	-2	0	-2	-2	-2
81M07	82M12	81M10	82M11	81M11	82M11	81M11	82M11
		-3	0	-4	0	-4	0
90M07	91M03	90M02	91M06	90M04	91M06	90M08	91M06
		+5	-3	+3	-3	-1	-3
01M03	01M11	01M03	02M02	01M04	02M02	01M04	02M02
		0	-3	-1	-3	-1	-3
07M12	09M06	07M10	09M07	07M11	09M07	07M12	09M07
		+2	-1	+1	-1	0	-1
False		63M04	63M03	63M05	63M07		
False		67M06	67M11	67M11	67M11		

Note: The NBER mean delay for calling the peak equals 8.2 months with 1.11 Std and its mean delay for call the trough equals 15.20 with std 2.43 (since 1980). Our largest discrepancy is from 1973. Let us see the quarterly GDP growth rates (%) from 1973Q4 to 1975Q3: 0.92, -0.73, 0.18, -0.92, -0.37,-1.31, 0.76, 1.69. The NBER 73 recession may start 74M01, not 73M11. There is a good reason for the two false alarms. Annual growth rates in real GDP from 1963Q3 to 1964Q1 were 8.0%, 2.9%, and 8.9%, respectively. Annual growth rates from 1967Q1 to 1967Q3 were 3.7%, 0.3%, and 3.5% (Data source: BEA). The unemployment rate in the two periods both climbed higher (Figure 2). Such one quarter slowdown had been caught by our M-Coppock curve. The 1987 market crash and the 1997 asian financial crisis have also been reflected in the M-Coppock curve. It is our impression that there were always some shocks in the near future when the M-Coppock curve made a turn. The M-Coppock curve made a turn in October 2014 for the current economy, which may contribute to the current turmoil in the equity market.

Table 3: This table provides a number of projected scenarios about the forward unemployment rate in 2016 and the calculated M-Coppock curve of these projected rates. As we can see from the table, the M-Coppock curve continues to climb up and the upward trend is much harder to deter, even if the unemployment rate continues to move lower in scenario two.

UR=Uemployment rate. Coppock=the M-Coppock curve.

	UR	Coppock	UR	Coppock	UR	Coppock	UR	Coppock	UR	Coppock
2015M08	5.1	-0.758	5.1	-0.758	5.1	-0.758	5.10	-0.758	5.10	-0.758
2015M09	5.1	-0.717	5.1	-0.717	5.1	-0.717	5.10	-0.717	5.10	-0.717
2015M10	5.0	-0.683	5.0	-0.683	5.0	-0.683	5.00	-0.683	5.00	-0.683
2015M11	5.0	-0.675	5.0	-0.675	5.0	-0.675	5.00	-0.675	5.00	-0.675
2015M12	5.0	-0.625	5.0	-0.625	4.9	-0.650	4.90	-0.650	4.90	-0.650
2016M01	5.0	-0.617	5.0	-0.617	4.8	-0.683	4.90	-0.658	4.90	-0.658
2016M02	5.0	-0.533	5.0	-0.533	4.7	-0.658	4.80	-0.617	4.80	-0.617
2016M03	5.0	-0.500	5.0	-0.500	4.6	-0.692	4.80	-0.608	4.80	-0.608
2016M04	5.0	-0.442	5.0	-0.442	4.5	-0.708	4.70	-0.600	4.70	-0.600
2016M05	5.0	-0.425	5.0	-0.425	4.4	-0.775	4.60	-0.642	4.60	-0.642
2016M06	5.0	-0.367	5.0	-0.367	4.5	-0.750	4.60	-0.625	4.60	-0.625
2016M07	5.0	-0.325	5.0	-0.325	4.6	-0.708	4.50	-0.642	4.50	-0.642
2016M08	5.0	-0.242	5.0	-0.242	4.7	-0.592	4.50	-0.592	4.50	-0.592
2016M09	5.0	-0.192	5.0	-0.192	4.8	-0.492	4.40	-0.600	4.40	-0.600
2016M10	4.9	-0.150	5.1	-0.100	4.9	-0.358	4.50	-0.542	4.70	-0.492
2016M11	4.9	-0.117	5.1	-0.033	5.0	-0.225	4.60	-0.475	5.00	-0.342
2016M12	4.9	-0.100	5.1	0.017	5.1	-0.083	4.70	-0.375	5.30	-0.125
2017M01	4.9	-0.083	5.1	0.050	5.2	0.067	4.80	-0.275	5.60	0.108
2017M02	4.9	-0.083	5.1	0.067	5.3	0.217	4.90	-0.158	5.90	0.375
2017M03	4.9	-0.083	5.1	0.083	5.4	0.375	5.00	-0.042	6.20	0.658

Table 4: Recession Differentials and the Gender Differentials in the Labor Market during Recessions. We use the spike of the M-Coppock curve as a measure for the magnitude of that recession. We apply the same measure for the M-Coppock curves for men and women. A recession is ranked number one if its spike value is the highest and so on. Women did much better than men in the job market in nine out of eleven recessions. In particular, men suffered the worst in the 1974-1975 and 2007-2009 recessions while women suffered the worst in the 1953-1954 and 1974-1975 recessions. The 2007-2009 and 1974-1975 recessions were the worst for overall labor force.

NBER Recessions	All Sex Spike Value	Rank	Men Spike Value	Rank	Women Spike Value	Rank	Women Better
1948-1949	2.69	3	2.93	4	2.15	4	Y
1953-1954	2.69	3	2.68	5	2.81	1	N
1957-1958	2.69	3	2.96	3	2.13	5	Y
1960-1961	1.45	6	1.39	10	1.56	7	N
1969-1970	1.76	5	1.71	8	1.61	6	Y
1974-1975	2.90	2	2.98	2	2.73	2	Y
1980-1980	1.44	7	2.04	7	0.69	11	Y
1981-1982	2.05	4	2.57	6	1.44	8	Y
1990-1991	1.22	9	1.48	9	0.88	10	Y
2001-2002	1.27	8	1.34	11	1.25	9	Y
2007-2009	3.15	1	3.89	1	2.34	3	Y
Mean	2.12	-	2.36	-	1.78	-	-
Std. Errors	0.22	-	0.25	-	0.21	-	-

Table 5: Recession Forecast Using Employment Trend Index 1973:11-2015:11. A recession starts when the M-Coppock penetrates the zero line from above by -0.5 and a recession ends when the M-Coppock reaches a local trough (see Figure 4). Lead or lag discrepancies are in months.

				$\Rightarrow$	$Rule - 0.5$			
NBER	Call	NBER	Delay	Model	Call	Discrepancy		Spike
Start	End	Start	End	Start	End	Start	End	Value
1973:11	1975:03	-	-	-	1975:05	-	2	-9.58
1980:01	1980:07	6	12	1979:11	1980:08	2	1	-6.58
1981:07	1982:12	6	8	1981:11	1982:08	4	3	-6.17
1990:07	1991:03	9	21	1990:09	1991:05	2	2	-5.75
2001:03	2001:11	8	20	2001:01	2001:12	2	1	-13.39
2007:12	2009:06	12	15	2007:12	2009:04	0	0	-21.72
Mean	-	8.20	15.20	-	-	2.00	1.50	-
Std.	Errors	1.11	2.43	-	-	0.63	0.42	-

Table 6: The Augmented Dickey-Fuller unit-root test.
u=Unemployment, v=Shadow Rate, w=yield Curve

Variables	ADF Test Statistic	P-Value	PP rho Test Statistic	PP t Test Statistic	P-Value
u	-1.441	0.5625	-9.514	-2.172	0.2165
v	-1.541	0.5132	-8.197	-1.932	0.3172
w	-3.839	0.0025	-34.663	-4.209	0.0006

Note: Yield curve appears to be stationary while the other two are not.

Table 7: The Augmented Dickey-Fuller unit-root test of cyclical components (HP).

Variables	ADF Test Statistic	P-Value	PP rho Test Statistic	PP t Test Statistic	P-Value
u	-3.086	0.0276	-32.844	-4.113	0.0009
v	-4.297	0.0004	-50.989	-5.069	0.0000
w	-5.241	0.0000	-62.555	-5.713	0.0000

Note: The three series are stationary in the cyclical components (use the HP filter once).

Table 8: VAR model specifications. The VAR orders, p, are selected according to the LR, FPE, AIC, HQIC, and SBIC criteria.

	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2397.77				0.268	7.199	7.21	7.22
1	-309.39	4176.80	9	0	0.000	0.964	1.00	1.04
2	-227.75	163.29	9	0	0.000	0.746	0.80	0.89
3	-194.68	66.13	9	0	0.000	0.677	0.75	0.88*
4	-167.65	54.06*	9	0	0.000*	0.620*	0.72*	0.88

Note: The optimal lag-order is four with the asterisk in the table.

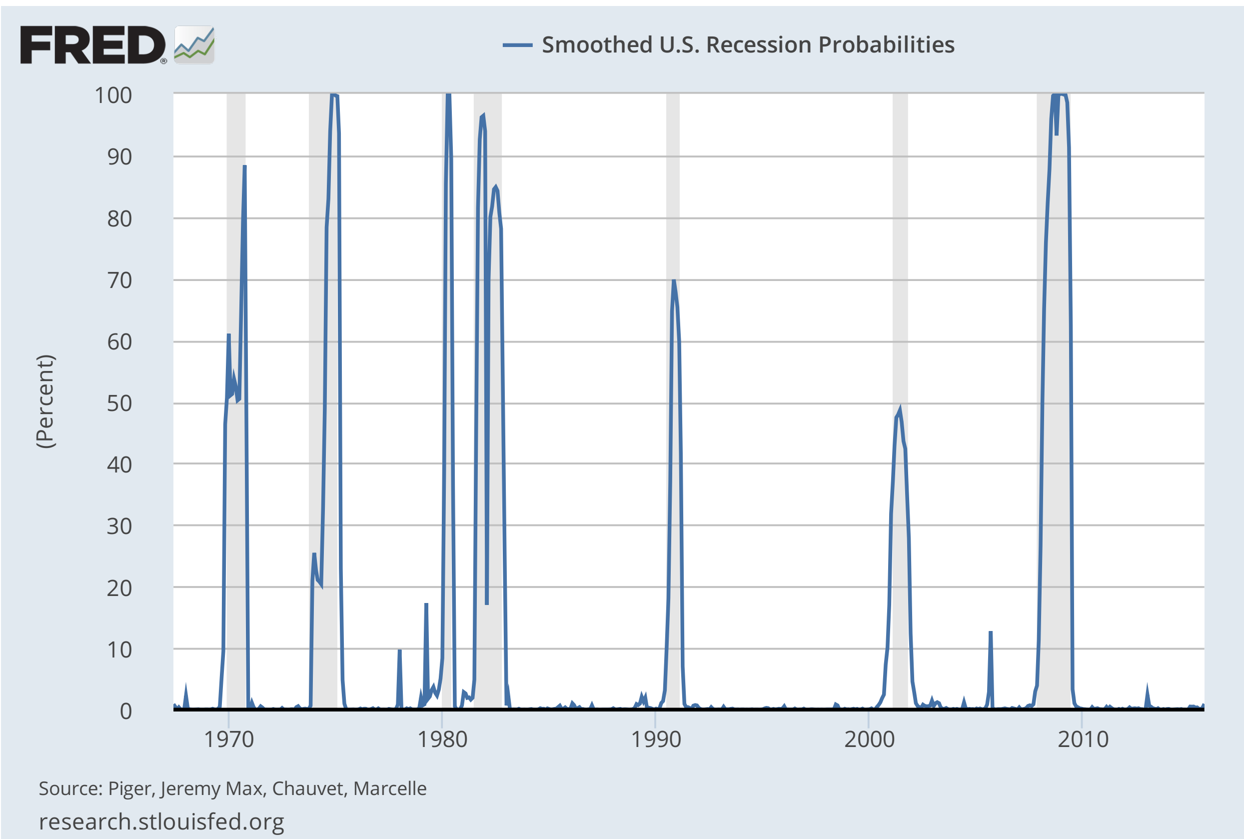
Table 9: Cochrane-Orcutt-GLS: u=unemployment rate, v=shadow rate, w=spread

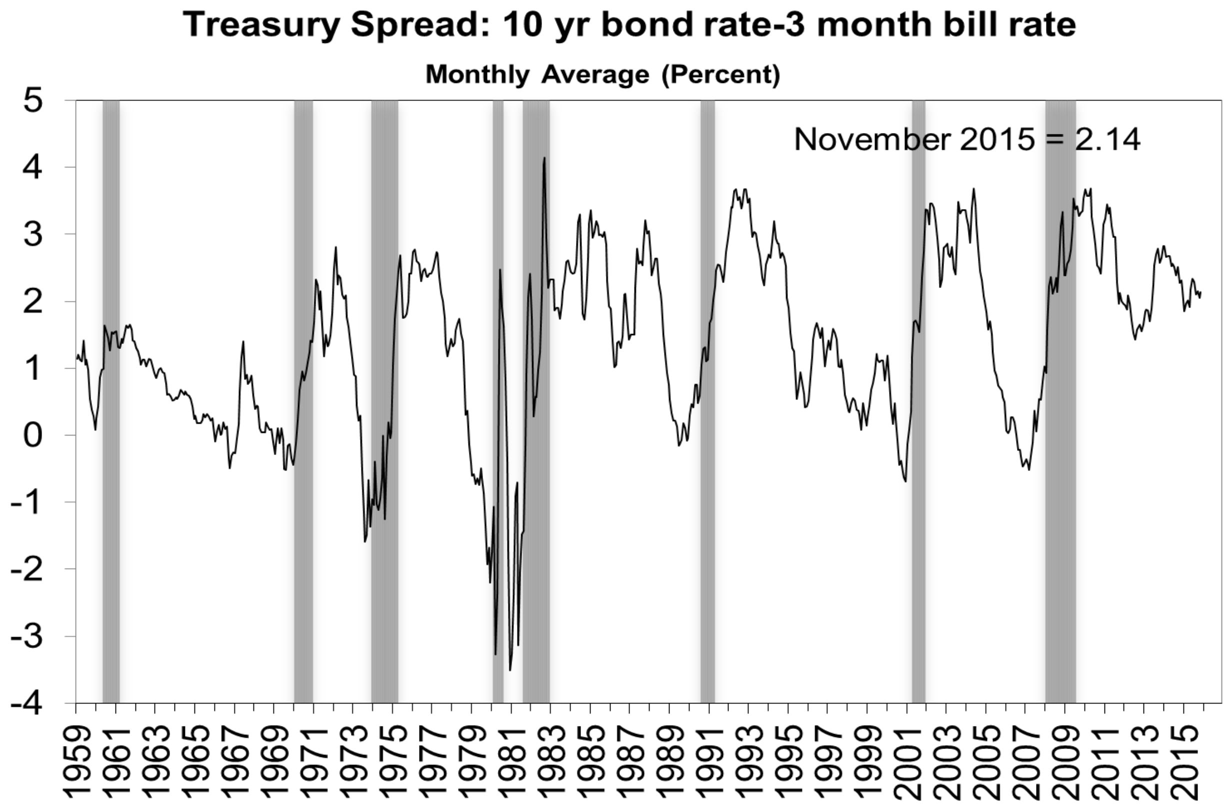
u(t)	Model			v(t)	Model			w(t)	Model		
	Coeffient	SE	t-statistic		Coefficient	SE	t-statistic		Coefficient	SE	t-statisric
Const.	-0.0004	0.0044	-0.094	Const.	0.0013	0.0101	0.129	Const.	0.0032	0.0605	0.053
u(t-1)	0.7617	0.0349	21.833	u(t-1)	-0.5177	0.0960	-5.391	u(t-1)	0.3174	0.0648	4.896
u(t-2)	0.4490	0.0430	10.433	u(t-2)	0.4402	0.0969	4.543	u(t-3)	0.2012	0.0749	2.687
u(t-5)	-0.2484	0.0204	-12.152	v(t-1)	1.5110	0.0445	33.966	u(t-4)	0.1164	0.0729	1.596
v(t-2)	0.0180	0.0098	1.840	v(t-2)	-0.5080	0.0753	-6.749	v(t-1)	-0.2278	0.0326	-6.989
v(t-4)	0.0180	0.0085	2.110	v(t-3)	-0.1809	0.0573	-3.157	v(t-2)	0.1447	0.0288	5.031
w(t-2)	0.0444	0.0102	4.368	v(t-5)	0.1283	0.0227	5.661	v(t-4)	-0.0510	0.0282	-1.806
				w(t-1)	-0.2055	0.0579	-3.549	w(t-1)	0.5155	0.0452	11.413
				w(t-2)	0.4232	0.0888	4.768	w(t-2)	-0.2777	0.0482	-5.758
				w(t-3)	-0.4263	0.0901	-4.733	w(t-3)	-0.1638	0.0460	-3.559
				w(t-4)	0.1939	0.0578	3.353	w(t-4)	-0.1757	0.0450	-3.904
AR(12)	Coefficient	SE	t-Statistic		Coefficent	SE	t-Statistic		Coefficient	SE	t-Statistic
φ_1	0.1402	0.0388	3.617	φ_1	-0.2404	0.0387	-6.216	φ_1	0.5049	0.0377	13.401
φ_2	-0.1792	0.0390	-4.595	φ_2	-0.2916	0.0398	-7.327	φ_2	0.1789	0.0423	4.229
φ_3	-0.1001	0.0396	-2.529	φ_3	-0.1107	0.0413	-2.678	φ_3	0.5075	0.0428	11.845
φ_4	-0.1121	0.0398	-2.819	φ_4	-0.0525	0.0413	-1.273	φ_4	0.0644	0.0458	1.405
φ_5	0.0392	0.0400	0.980	φ_5	-0.0066	0.0412	-0.161	φ_5	-0.1190	0.0458	-2.597
φ_6	-0.0466	0.0399	-1.166	φ_6	0.0820	0.0409	2.003	φ_6	-0.3576	0.0452	-7.917
φ_7	-0.0575	0.0398	-1.444	φ_7	-0.1309	0.0410	-3.196	φ_7	-0.2300	0.0452	-5.092
φ_8	0.0507	0.0398	1.271	φ_8	0.0793	0.0413	1.921	φ_8	0.0552	0.0458	1.205
φ_9	0.0027	0.0396	0.068	φ_9	0.1432	0.0413	3.467	φ_9	0.2968	0.0458	6.481
φ_{10}	-0.0132	0.0393	-0.337	φ_{10}	0.0562	0.0412	1.363	φ_{10}	0.0474	0.0428	1.108
φ_{11}	0.0774	0.0387	1.998	φ_{11}	-0.0029	0.0396	-0.074	φ_{11}	0.1183	0.0422	2.800
φ_{12}	-0.1304	0.0384	-3.399	φ_{12}	-0.1479	0.0384	-3.852	φ_{12}	-0.2680	0.0376	-7.118

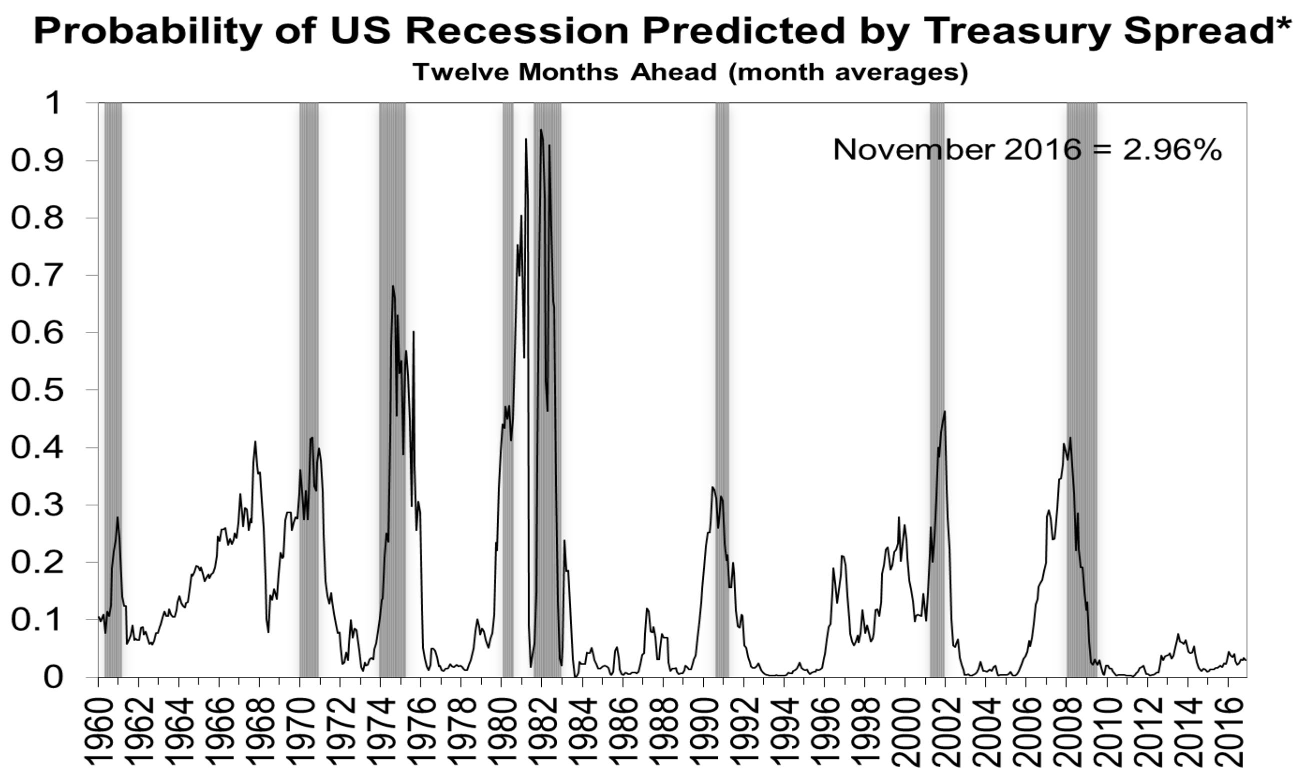
Note: First, the HP filter is used to remove the trends as in Table 7. Second, we use model specification in Table 8 to identify lags. Third, we run VA(5) first and then eliminate those lags that have multicollinearity. Finally, we run the Cochrane-Orcutt iterated procedure with 12 lags.

Appendix: Selected FOMC Predictations (for referees, not for publication)

The first figure was downloaded from the Federal reserve at St. Louis. The graph was created by the method developed in Chauvet (1998) and Chauvet and Piger (2008). The second one was downloaded from the Fegeral reserve bank at the New York. The graph was created by the method in Estrella and Trubin (2006) and Estrella and Mishkin (1996). The third one was downloaded from the Federal reserve bank in Atlanta. The figure was created by James Hamilton, using the method in Chauvet and Hamilton (2006).







*Parameters estimated using data from January 1959 to December 2009, recession probabilities predicted using data through November 2015. The parameter estimates are α=-0.5333, β=-0.6330.

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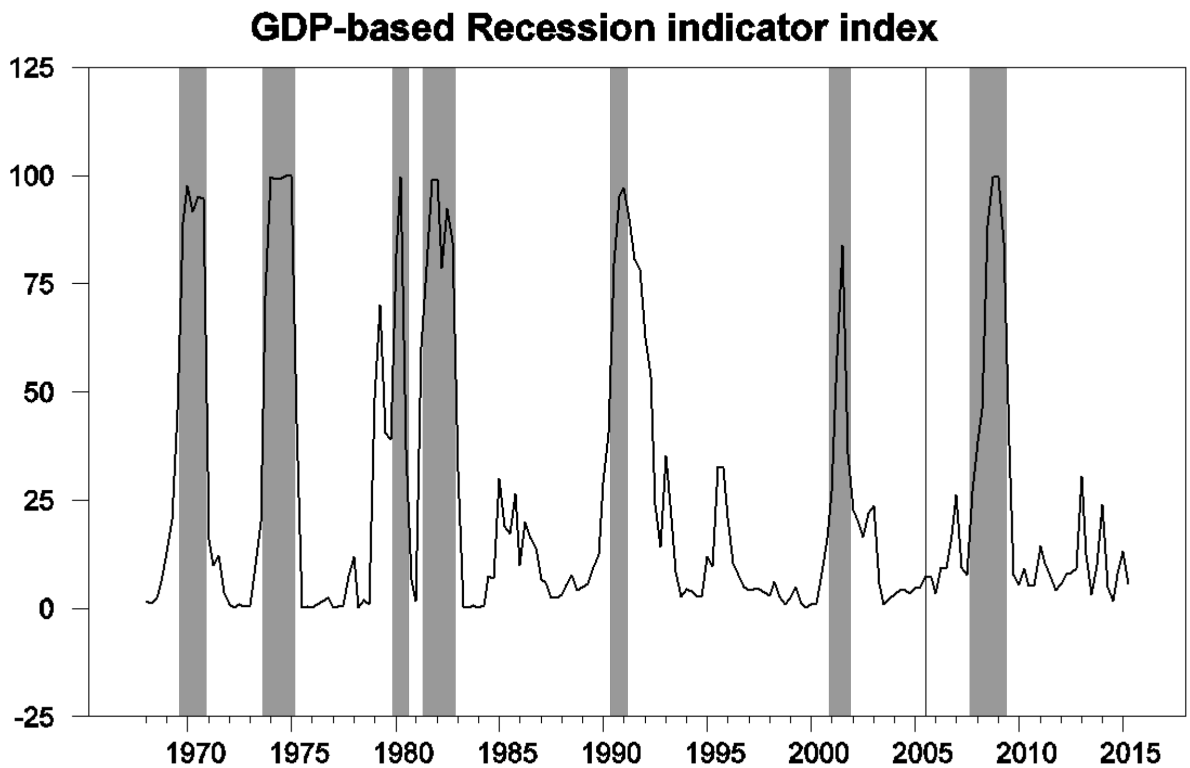
GDP-based Recession indicator index
125
100
75
50
25
0
-25
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015