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The Role of Economic Policy Uncertainty in Predicting U.S. Recessions: A Mixed-frequency Markov-switching Vector Autoregressive Approach

Mehmet Balcilar, Rangan Gupta, and Mawuli Segnon

Abstract

This paper analyzes the performance of the monthly economic policy uncertainty (EPU) index in predicting recessionary regimes of the (quarterly) U.S. GDP. In this regard, the authors apply a mixed-frequency Markov-switching vector autoregressive (MF-MSVAR) model, and compare its in-sample and out-of-sample forecasting performances to those of a Markov-switching vector autoregressive model (MS-VAR, where the EPU is averaged over the months to produce quarterly values) and a Markov-switching autoregressive (MS-AR) model. The results show that the MF-MS-VAR fits the different recession regimes, and provides out-of-sample forecasts of recession probabilities which are more accurate than those derived from the MS-VAR and MS-AR models. The results highlight the importance of using high-frequency values of the EPU, and not averaging them to obtain quarterly values, when forecasting recessionary regimes for the U.S. economy.

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Keywords Business cycles; economic policy uncertainty; mixed frequency; Markov-switching VAR models

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1 Introduction

Theoretical explanations as to why uncertainty negatively affects economic activity can be traced back to the early works of [Bernanke \(1983\)](#) and [Dixit and Pindyck \(1994\)](#), and more recently in that of [Bloom \(2009\)](#). In the aftermath of the “Great Recession”, the emphasis seems to have shifted to developing quantifiable measures of uncertainty, either based on structural structural vector autoregressive (SVAR) models ([Mumtaz and Zanetti, 2013](#); [Alessandri and Mumtaz, 2014](#); [Theodoridis and Mumtaz, 2016](#); [Jurado et al., 2015](#)), or based on newspaper articles ([Baker et al., 2013](#)). Irrespective of what is the source of the measure of uncertainty used, it is then, in general, incorporated into SVAR models, to analyze its impact on the economy ([Aastveit et al., 2013](#); [Colombo, 2013](#); [Mumtaz and Zanetti, 2013](#); [Alessandri and Mumtaz, 2014](#); [Theodoridis and Mumtaz, 2016](#); [Jurado et al., 2015](#)). However, the news-based measures of uncertainty seems to have gained tremendous popularity in various applications in macroeconomics and finance (see [Redl, 2015](#), for a detailed review), most likely due to the fact that data on this measure (not only for the US, but also other European and emerging economies) is easily and freely available for use, and does not require any complicated estimation of a model to generate it in the first place. To construct the index, [Baker et al. \(2013\)](#) perform month-by-month searches of newspapers for terms related to economic and policy uncertainty.

While, it is true that the impact of economic policy uncertainty on macroeconomic and financial variables has been primarily based on SVARs (as discussed above), more recently, [Jones and Olson \(2013\)](#) studied time-varying correlation between industrial production (and inflation) with EPU using a multivariate DCC-GARCH model. Estimation results revealed that the sign of the correlation between EPU and output has been consistently negative.¹ [Karnizova and Li \(2014\)](#) took a different route, and used probit forecasting models to assess the ability of EPU to predict future US recessions. Based on both in-sample and out-of-sample analyses, their results suggested that policy uncertainty indexes are statistically and economically significant in forecasting recessions at the horizons beyond five quarters.

Our objective is to extend this line of research in analyzing the ability of the EPU in predicting US recessions probabilities using a mixed-frequency Markov-switching VAR model (MF-MS-VAR) model, with our two variables being real GDP (at quarterly frequency) and EPU (at monthly frequency). We also compare our results with MS-AR and MS-VAR models, where in the latter model, EPU is converted to quarterly frequency. It must be emphasized that, we not only predict recession probabilities in-sample, but also out-of-sample. The use of a MS framework in predicting turning points in GDP is quite well-established, ever since the initial work of [Hamilton \(1989\)](#), and hence, is an easily justifiable model to use (see [Chauvet and Hamilton, 2006](#); [Hamilton, 2008](#), for detailed reviews in this regard).² In addition, the MS framework also lends itself to modeling

¹The sign on inflation was found to have changed from negative to positive during the late 1990s.

²Multiple structural break tests developed by [Bai and Perron \(2003\)](#) indicated that there are breaks in

mixed frequency data. Our data covers the monthly period of 1947:01-2014:02, with the start date being determined by data availability of real GDP (first quarter of 1947), and the end date due to the same reasoning for EPU.³ Note that, our mixed-frequency approach also allows us to develop a monthly indicator for the quarterly GDP growth rate based on the EPU, which in turn, controls for the (unrealistic) assumption that the real-time data flow of the variables involved in the empirical analyses occurs at the same time. In this regard, we compare the performance of the MF-MS-VAR with a linear mixed-frequency VAR (MF-VAR) model as well, in terms of the movements of the monthly indicator of the quarterly GDP growth rates.

To the best of our knowledge, this is the first attempt to develop a MF-MS-VAR model for the quarterly U.S. GDP based on monthly EPU, and in turn, use it to predict, both in- and out-of-sample (1980:01-2014:02) recession probabilities. Our paper, can thus be considered to be an extension of the work of [Karnizova and Li \(2014\)](#), whereby, unlike these authors, when predicting recession probabilities, we do not average out the information over three months of the EPU to obtain its quarterly values, which in turn, could lead to possible loss of important information. In addition, unlike [Karnizova and Li \(2014\)](#), since we work with real GDP figures to predict the recession probabilities, our MF-MS-VAR approach also allows us to obtain a monthly indicator for the U.S. GDP contingent on the monthly information of the EPU. The remainder of the paper is organized as follows: Section 2 presents the data used in our analysis. In Section 3 we provide the basics of the econometric framework, while in Section 4 results of the empirical application is presented. Finally, Section 5 concludes.

2 Data

Our data set comprises of two variables: real GDP at quarterly frequency and the monthly EPU, and covers the period of 1947:01 to 2014:02, which matches the quarterly frequency of the former over 1947:Q1-2014:Q1. While the data on real GDP (in Billions of 2009 chained dollars and seasonally adjusted at an annual rate) is obtained from the FRED database of the Federal Reserve Bank of ST. Louis, the EPU is obtained from https://www.policyuncertainty.com/us_historical.html. Two overlapping sets of newspapers are used for the creation of this index. The first spans 1900-1985 and is comprised of the Wall Street Journal, the New York Times, the Washington Post, the

not only the growth rate of the real GDP, but also in the relationship between real GDP growth and EPU growth. In addition the [Brock et al. \(1996\)](#) test indicated evidence of uncaptured nonlinearity when applied to the residual of the AR and VAR models of growth rate of GDP, and real GDP growth and EPU growth, respectively. These two tests, thus, provide even more motivation to model the growth process of real GDP in a nonlinear fashion. Complete details of these results are available upon request from the authors.

³Though more recent data on EPU, starting in 1985:M1 (https://www.policyuncertainty.com/us_monthly.html), is available, we decided to use the historical version of EPU (which in fact starts in 1900:01), to allow us to cover all the post World War II recessions. This specifically why we also did not use daily data on EPU (https://www.policyuncertainty.com/us_daily.html) and equity market uncertainty (https://www.policyuncertainty.com/equity_uncert.html), both of which starts on January 1, 1985.

Chicago Tribune, the LA Times, and the Boston Globe. From 1985 onwards USA Today, the Miami Herald, the Dallas Morning Tribune, and the San Francisco Chronicle are added to the previously mentioned papers. To construct the index, month-by-month searches of each paper, starting in January 1900, is performed for articles containing the term “uncertainty” or “uncertain”, the terms “economic”, “economy”, “business”, “commerce”, “industry”, and “industrial” as well as one or more of the following terms: “congress”, “legislation”, “white house”, “regulation”, “federal reserve”, “deficit”, “tariff”, or “war”. In other words, for inclusion in the EPU, articles must include terms in all three categories pertaining to uncertainty, the economy and policy.⁴

To gain insights about the time series properties of our data sets, we first plot the logarithmic changes in real US GDP and EPU, cf. *Figure 1*. We observe a higher variability in EPU than in real GDP growth. As is standard practice in time series econometrics, we then tested for the unit root properties of the log-levels of real GDP and the EPU index. In this regard, we used the [Ng and Perron \(2001\)](#) unit root test, which has been shown to have very good size and power properties, relative to other standard unit root tests. Under the assumptions of a constant, and constant and trend in the test equation, the null of unit root cannot be rejected for the levels of the series. However, first-differencing ensures that the two variables of concern (growth rate of real GDP and growth rate of EPU), are stationary. These results along with the summary statistics of the growth rates of the two variables have been reported in *Table 1*.

So we work with percentage changes, C , of real GDP or EPU, computed as:

$$C_t = 100 * [\ln(data_t) - \ln(data_{t-1})], \quad (1)$$

where $data_t$ denotes the real US GDP or EPU at period t .

Since we work with growth rates of the two variables to ensure stationarity, we loose one observation from the beginning of the sample period.

3 Methodology

The recently developed MF-MS-VAR model by [Camacho \(2013\)](#) in state space representation can be formalized as:

$$Z_t = \Omega_{\delta_t} \theta_t + \epsilon_t, \quad t = 1, 2, \dots, T, \quad (2)$$

where $Z_t = (Z_{t,1}^q, Z_{t,2}^m)'$ is a vector that contains quarter-on-quarter and month-on-month growth rates of the economic indicators, $\theta_t = (Z_t^m, Z_{t-1}^m, Z_{t-2}^m, Z_{t-3}^m, Z_{t-4}^m)'$ is a vector of lagged month-on-month growth rates, $\Omega_{\delta_t} = (A_1, A_2, A_3, A_4, A_5)$ is a Block matrix whose elements are given by:

⁴To deal with changing volumes of new articles for a given paper over time, [Baker et al. \(2013\)](#) divide the raw counts of policy uncertainty articles by the total number of news articles containing terms regarding the economy or business in the paper. The authors then normalize each paper's series to unit standard deviation prior to December 2009 and sum each paper's series.

$$A_1 = \begin{pmatrix} \frac{1}{3}I_{N_1} & 0 \\ 0 & I_{N_2} \end{pmatrix}, \quad A_2 = \begin{pmatrix} \frac{2}{3}I_{N_1} & 0 \\ 0 & I_{N_2} \end{pmatrix}, \quad A_3 = \begin{pmatrix} I_{N_1} & 0 \\ 0 & I_{N_2} \end{pmatrix},$$

$$A_4 = \begin{pmatrix} \frac{2}{3}I_{N_1} & 0 \\ 0 & I_{N_2} \end{pmatrix}, \quad A_5 = \begin{pmatrix} \frac{1}{3}I_{N_1} & 0 \\ 0 & I_{N_2} \end{pmatrix},$$

and $\epsilon_t \sim N(0, R)$. Note that N_1 is the number of quarterly indicators and N_2 denotes the same at monthly frequency. As stressed in [Mariano and Murasawa \(2003\)](#) the quarter-on-quarter growth rate of quarterly indicators calculated at each month of the sample can be obtained as the average sum of previous month-on-month growth rates as follows:

$$Z_{t,1}^q = \frac{1}{3}Z_{t,1}^m + \frac{2}{3}Z_{t-1,1}^m + Z_{t-2,1}^m + \frac{2}{3}Z_{t-3,1}^m + \frac{1}{3}Z_{t-4,1}^m. \quad (3)$$

[Camacho \(2013\)](#) assumed that the monthly growth rates of the economic indicators follow a Markov switching VAR(p) process, which is governed by a state variable δ_t , that is assumed to evolve according to a first-order Markov chain with transition probability:

$$\Pr(\delta_t = j | \delta_{t-1} = i, \delta_{t-2} = h, \dots, \mathfrak{I}_{t-1}) = \Pr(\delta_t = j | \delta_{t-1} = i) = p_{ij}, \quad (4)$$

where $i, j = 0, 1$ and \mathfrak{I}_t is the information set available at the time t . Using the Kalman filter, the MF-MS-VAR model can be easily estimated via maximum likelihood method, with easily computable filtered probabilities: $\Pr(\delta_t = j | \mathfrak{I}_t)$, and smoothed probabilities: $\Pr(\delta_t = j | \mathfrak{I}_T)$. We refer the reader to [Camacho \(2013\)](#) for more details on the estimation procedure.

4 Empirical Results

We use a lag-length (p) of one, as justified by the Bayesian Information Criterion (BIC), and following [Camacho \(2013\)](#), we allow only the drifts of the models to switch, since shifts do not depend on the dynamics of the autoregressive process or the covariance matrices ([Hamilton, 1989](#)). Panel (a) of [Figure 2](#) compares the monthly estimates of the U.S. quarterly GDP growth rates that are obtained from the linear MF-VAR and the MF-MS-VAR models. Both indicators are in accordance with the NBER-referenced business cycles (indicated by the shaded areas in [Figure 2](#)). The positive growth rates are interrupted by large changes in the direction, which in turn, align quite well with the U.S. recessions.

Even though the MF-VAR and MF-MS-VAR performs similarly in terms of the construction of monthly indicators of the U.S. economic activity, the latter model can, in addition, be used to convert the business cycle signals provided by the economic indicators into recession probabilities. In order to determine the accuracy of the MF-MS-VAR model to account for the business cycles, Panel (b) of [Figure 2](#) plots the values of the smoothed recession probabilities of state $\delta_t = 1$. The fact that the probability of state 1

corresponds to recessions is due to the reasonable match between the quarters of high probabilities of this state and the NBER recessions. The MF-MS-VAR model is observed to capture the recessions quite well.

Even though we observe a high correlation between the probabilities of recession and the NBER referenced recessions, the question is whether or not the MF-MS-VAR model outperforms other possible competitors used for business cycles dating. In this regard, we look at a MS-VAR model – where the monthly EPU are averaged over three-months to produce quarterly values of the same, and a MS-AR model, as two possible competitors. We start off with in-sample accuracy, and compute the quadratic probability score (QPS) in this regard, as proposed by [Brier \(1950\)](#). Formally,

$$\text{QPS} = \frac{1}{T} \sum_{t=1}^T (p_t - r_t)^2, \quad (5)$$

where p_t is the forecast probability made at the time t , r_t is the realization of the event at the time t , and T denotes the total number of the observations. We note that QPS ranges between 0 and 1, with a score of 0 indicating a perfect accuracy. The computed values of QPS for our models are near zero and reported in [Table 2](#). The MF-MS-VAR model provides the smallest score, followed by the MS-VAR and MS-AR models for the in-sample. In addition to the QPS, we also apply the equal forecast accuracy test of [Diebold and Mariano \(1995\)](#). When we compare the MF-MS-VAR with the MS-VAR (MS-AR), the null of equal predictive accuracy is rejected at 5% (10%) levels of significance. So results from the QPS and the [Diebold and Mariano \(1995\)](#) tests highlights the superiority of the MF-MS-VAR models relative to the MS-VAR and MS-AR models, based on an in-sample analysis.

However, the in-sample analysis does not account for the effect of the non-synchronous releases that characterizes the real-time flow of macroeconomic information. To provide a more realistic assessment of the reliability of MF-MS-VAR results, we also look at a pseudo real-time analysis as proposed by [Camacho \(2013\)](#). Towards this end, we evaluate the ability of the MF-MS-VAR model, relative to the MS-VAR and MS-AR models, in predicting recession probabilities (based on recursive estimation of the models) over the out-of-sample period of 1980:01-2014:02, using an in-sample period of 1947:1-1979:12. The decision to start our out-of-sample forecasting exercise in 1980:01, which also gives us more or less a 50 percent split of the in- and out-of-samples, is in line with a major breakpoint due to changes in US monetary and fiscal policies (see [Bekiros and Paccagnini \(2013\)](#) for a detailed discussion in this regard). As can be seen from [Table 2](#), the MF-MS-VAR is still the best model, but the MS-AR model performs slightly better than the MS-VAR model, based on the QPS statistic. In addition, the [Diebold and Mariano \(1995\)](#) rejects the null of equal forecast accuracy of the MF-MS-VAR model relative to both the MS-VAR and MS-AR models at 1% level of significance. So, as with the in-sample, the MF-MS-VAR model outperforms its two competitors in a pseudo real-time forecasting exercise as well. Our results, hence, provides convincing

evidence in favor of the MF-MS-VAR model in predicting U.S. recession probabilities for both within and out-of-sample exercises.

5 Conclusion

This paper applies a mixed-frequency Markov-switching VAR (MF-MS-VAR) model for quarterly U.S. GDP to predict in-sample and out-of-sample US recession probabilities using the monthly index of news-based economic policy uncertainty (EPU) as a predictor. The MF-MS-VAR model yields a monthly indicator for the quarterly growth rates of real GDP based on the monthly EPU. But more importantly, our empirical results show that the MF-MS-VAR fits the different recession regimes and provides out-of-sample forecasts which are more accurate than those from a MS-VAR (where the EPU is averaged over the months to produce quarterly values) and MS-AR models. Our results not only highlight the importance of the monthly EPU in predicting the movements of the quarterly GDP growth rates and the associated recessionary regimes, but also shows that important information emanating from the EPU will be compromised if one averages its monthly values into quarterly ones.

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Table 1: Descriptive statistics and unit root tests

| | min | max | mean | std.dev | skewness | kurtosis |
|----------|---------|--------|-------|---------|----------|----------|
| Real GDP | -2.623 | 3.908 | 0.784 | 0.958 | -0.102 | 4.380 |
| EPU | -92.494 | 86.309 | 0.049 | 24.215 | 0.007 | 4.029 |

| | NP (Level: Constant) | NP (Level: Constant+Trend) | NP (First-Difference: Constant) | NP (First-Difference: Constant+Trend) |
|-----------|----------------------|----------------------------|---------------------------------|---------------------------------------|
| Real GDP | 1.305 | -3.189 | -51.700*** | -70.926*** |
| hline EPU | -2.459 | -2.816 | -10.829** | -18.011** |

Note: NP: [Ng and Perron \(2001\)](#) unit root test; *** (**) indicates rejection of the null of unit root at 1% (5%) level of significance.

Table 2: Relative performance metrics and equal forecast accuracy tests

| | In-sample 1947.01-2014.02 | Pseudo real-time 1980.01-2014.02 |
|-----------------------------|------------------------------|-------------------------------------|
| Quadratic probability score | | |
| MF-MS-VAR | 0.194 | 0.210 |
| MS-VAR | 0.206 | 0.294 |
| MS-AR | 0.209 | 0.292 |
| Equal accuracy test | | |
| MF-MS-VAR vs. MS-VAR | 2.005** | 4.091*** |
| MF-MS-VAR vs. MS-AR | 1.771* | 3.936*** |

Note: The table reports the QPS and [Diebold and Mariano \(1995\)](#) equal test for mixed-frequency Markov-switching vector autoregression (MF-MS-VAR), Markov-switching vector autoregression (MS-VAR), and Markov-switching autoregression (MS-AR) models. ***, **, and * denote significance at 1%, 5% and 10%, respectively.

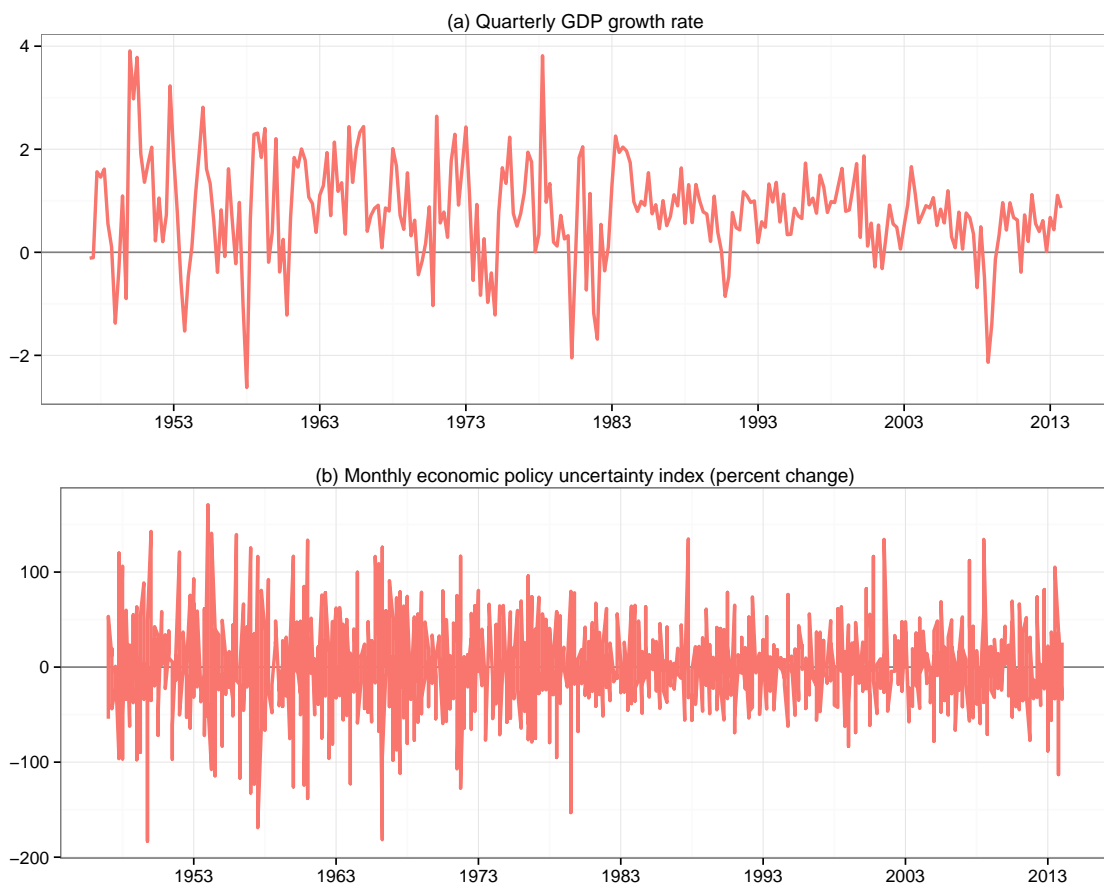


Figure 1: Plots of growth rates of U.S. real GDP and EPU.

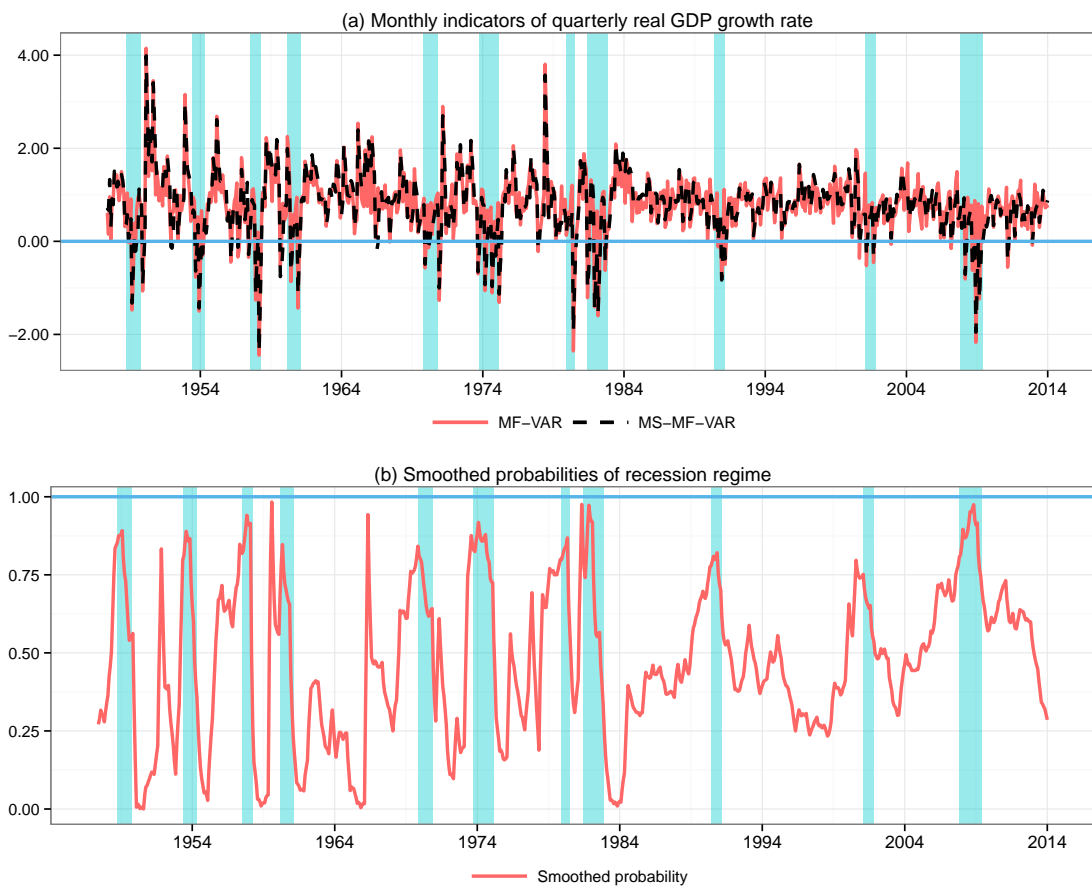


Figure 2: Monthly indicator of quarterly real GDP growth rate, and smoothed recession probabilities. Note: Shaded areas in panels (a) and (b) represent the recessions as documented by the NBER.

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