Improved Recession Dating Using Stock Market Volatility

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Abstract

We offer improved dating of U.S. business cycle turning point both retrospectively and in real time. This improvement is made possible by augmenting existing Markov-switching dynamic factor models with additional information on stock return volatility. The model significantly improves prediction of the state of the economy using fully revised data. Real-time declarations can be made noticeably earlier than NBER announcements, beating both peak and trough announcements for recent recessions by several months.

Keywords: Business Cycle; Turning Point; Stock Return Volatility; Real Time; Recessions.

JEL codes: C32, C53, E32.

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1 Introduction

Dating turning points of business cycle is important for policy makers, financial market participants and firms. Using economic variables that are coincident with the business cycle, one can use a wide range of statistical models to make inferences about the current state of the economy, see Hamilton (2011). Markov-switching modeling is a popular choice because of its similarity with a traditional view of business cycle—alternating phases of expansion and recession. This paper offers an opportunity to improve dating of U.S. business cycle turning points both retrospectively and in real time within a framework of Markov-switching modeling.

The improvement is made possible by augmenting existing models with additional information on stock return volatility, which has long been found counter-cyclical (Schwert 1989, Hamilton and Lin 1996, Conrad and Loch 2015). Financial markets play an important role in recent business cycles. Ng and Wright (2013) point out that the recessions of 1990-1991 and 2001 had financial origins, with roots in the savings-and-loan crisis and the internet bubble, respectively. The Great Recession was driven by a housing market bubble, which led to a full-blown financial crisis. The association between these economic downturns and stock market turmoil gives us an opportunity to refine existing dating models.

Since the stock market is forward-looking, stock market volatility tends to rise prior to an economic downturn (Hamilton and Lin 1996). Therefore, the stock market entering a high volatility regime may imply that the economy is more likely to enter a recession. Inspired by this intuition, we use a Markov-switching dynamic factor model to represent the real economy, and estimate the regime of stock volatility based on a Markov-switching model of stock returns with
volatility feedback. The transition probability of the business cycle regime is allowed to vary with the regime of stock volatility. That is, the probability of transition between expansion and recession can be different in the high and low stock return volatility regimes.

Estimation is carried out via maximum likelihood. The likelihood ratio statistic strongly rejects the hypothesis that the transition probability of the business cycle regime is invariant across stock market regimes. Parameter estimates also show very different patterns in the regime of high and low volatility: when the economy was in an expansion and the stock market was calm last period, the economy is very likely, with probability 0.9955, to stay in the expansion. On the other hand, if the economy was in a recession associated with high stock market turbulence last period, the probability that the economy switches to an expansion is estimated to be indistinguishable from zero.

Our model expands on the work of Chauvet (1998), Chauvet and Hamilton (2006) and Chauvet and Piger (2008). Comparing our model to one that assumes no dependence between business cycle states and stock volatility states, our model significantly improves the accuracy of prediction of the state of the business cycle, measured by the area under the receiver operating characteristic curve. Our model also performs well in real time. We compare our real-time probabilities of recession with those constructed by Chauvet and Piger (2008), and use the declaration rule suggested by them, to establish U.S. business cycle turning point dates in real time. In general, both models identify business cycle turning points with a high level of accuracy. Our model would have beaten the NBER in calling the beginning of the past three recessions, with leads up to three months. Chauvet and Piger’s model also identifies business
cycle troughs much more quickly than the NBER, and our additional consideration of stock return volatility gives a further improvement of up to four months.

2 Model

In this section, we introduce the models used to examine the dynamic relationship between the regimes of business cycle and stock volatility. We do not focus on single indicator, e.g., real GDP, but extract useful information about the business cycle from multiple indicators. A standard model of excess stock returns is used to capture regime switches in volatility. Emphasis is placed on the relations between regime transitions for the business cycle and stock volatility.

Two features of the business cycle are widely recognized: First, there tend to be parameter shifts across phases of the business cycle, motivating the use of the Markov-switching time series model (Hamilton (1989)). Second, many economic variables tend to comove over business cycles, and this feature can be formulated using the dynamic common factor model of Stock and Watson (1989). It has been shown that the Markov-switching dynamic factor (MSDF) model, capturing both regime shifts in the parameters and comovement among many economic variables, is able to detect the turning points of business cycle (Chauvet, Kim, and Nelson (1998), and Chauvet and Piger). We introduce our MSDF model in brief.

Let \( Y_{it} \) be the log level of the \( i \)th time series, and \( y_{it}' = \Delta Y_{it} - \Delta \bar{Y}_{it} \) be the demeaned first difference of \( Y_{it} \), the DFMS model has the form

\[
\begin{bmatrix}
y_{1t}' \\
y_{2t}' \\
\vdots \\
y_{It}'
\end{bmatrix} =
\begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_I
\end{bmatrix} c_t +
\begin{bmatrix}
e_{1t}' \\
e_{2t}' \\
\vdots \\
e_{It}'
\end{bmatrix}.
\]

(1)
We use for $y^*$ the four main economic indicators tracked by the NBER dating committee, i.e., industrial production, real income, employment, and real retail sales. Model (1) implies that each of these series consists of a component common to each series, $c_t$, and a idiosyncratic component, $e_{it}$. We assume the common component follows an autoregressive process with switching mean:

$$ (2) \phi(L)c_t = \mu_{S_{yt}} + \epsilon_t $$

where $S_{yt} = \{0,1\}$ is a two-state Markov switching variable, so the common component has a switching mean, i.e., $\mu_{S_{yt}} = \mu_0 + S_{yt}\mu_1$. $\epsilon_t$ is a normally distributed random variable with mean zero and variance set equal to unity for identification purposes, and $\phi(L)$ is a lag polynomial with all roots outside of the unit circle. We restrict $\mu_1 < 0$ so $S_{yt} = 1$ corresponds to the recession state, and the growth rate in a recession is lower than the normal rate $\mu_0$. Each idiosyncratic component is assumed to follow a stationary autoregressive process:

$$ (3) \rho_i(L)e^{*}_{it} = \omega_{it}, $$

where $\rho_i(L)$ is a lag polynomial with all roots outside of the unit circle, and $\omega_{it} \sim N(0, \nu_i^2)$. To capture switches in the stock market volatility, we use a Markov-switching model of stock returns, $r_t$, with volatility feedback:

$$ (4) r_t = \theta_1 E(\sigma_{S_{rt}}^2 | \Psi_{t-1}) + \theta_2 [E(\sigma_{S_{rt}}^2 | \Psi_{t-1})] + \sigma_{S_{rt}} u_t, $$

where $u_t \sim N(0,1)$ and $\Psi_t$ represents information set at time $t$. $S_{rt}$ is a second state variable following a two-state Markov switching process, and the volatility $\sigma_{S_{rt}} = (1 - S_{r,t})\sigma_0 + S_{r,t}\sigma_1$. We restrict $\sigma_0 < \sigma_1$, so $S_{r,t} = 1$ is the high volatility regime. Equation (4) is derived within a log-linear present value framework under the assumption of Markov-switching market volatility (see Turner, Startz, and Nelson (1989), Kim, Morley, and Nelson (2004), and Kim and Nelson
Equation (4) is motivated as follows. At the beginning of period $t$, the risk factor, $E(\sigma_{S_y,t}^2 | \psi_{t-1})$, is formed with information available at the end of period $t-1$, measured as $\sum_{j=0}^{1} \sigma_j Pr(S_r = j | \psi_{t-1})$. By the end of period $t$, additional information regarding volatility is observed and used to form a new expectation of $\sigma_{S_r,t}^2$, proxied by the actual value. If this new expectation is not equal to $E(\sigma_{S_r,t}^2 | \psi_{t-1})$, information about volatility revealed during the period has surprised agents. The coefficient $\theta_2$ captures the market price of the surprise.

The two models can be linked through interactions between the two Markov-switching state variables $S_{y,t}$ and $S_{r,t}$, as in Hamilton and Lin (1996). Define a new state variable $D_t$ as follows:

$$D_t = 1 \text{ if } S_{y,t} = 0, S_{r,t} = 0$$
$$D_t = 2 \text{ if } S_{y,t} = 0, S_{r,t} = 1$$
$$D_t = 3 \text{ if } S_{y,t} = 1, S_{r,t} = 0$$
$$D_t = 4 \text{ if } S_{y,t} = 1, S_{r,t} = 1$$

Let the transition matrix of $D_t$ be $P$, a 4-by-4 matrix whose elements $p_{ij} = Pr(D_t = i | D_{t-1} = j)$. A necessary restriction is that $\sum_{i=1}^{4} p_{ij} = 1, \forall j$.

The formulation of $P$ reflects our assumption concerning $S_{y,t}$ and $S_{r,t}$. If we assume independence between $S_{y,t}$ and $S_{r,t}$, the transition probability matrix of $D_t$ is $P_y \otimes P_r$, where $P_y$ and $P_r$ are the transition probability matrices of state variable $S_{y,t}$ and $S_{r,t}$, respectively. In this case, estimating the model jointly is equivalent to estimating equation (1) and (4) separately.

However, in practice the return volatility regime correlates with the probability of the regime of business cycle. The counter-cyclicality of stock market volatility has previously been
incorporated into Markov-switching models by assuming that recession lags one period behind a high-volatility regime of the stock market (Hamilton and Lin 1996, and Kim and Nelson 2014). This assumption reflects the notion that stock market participants are usually forward-looking. However, unlike in our model Hamilton and Lin assume a single latent state variable. Specifically, they assume that the two state variables are identical except the time lag, i.e., \( S_{y,t} = S_{r,t-1} \).

We introduce a relatively flexible method to incorporate cyclicality of stock market volatility by assuming that the state of stock volatility will affect the probability of the state of the economy. Under the assumption of independent switching, the transition probability of \( D_t \) is

\[
\Pr(D_t = 1|D_{t-1} = 1) = \Pr(S_{y,t} = 0, S_{r,t} = 0|S_{y,t-1} = 0, S_{r,t-1} = 0)
\]

\[
= \Pr(S_{y,t} = 0|S_{r,t} = 0, S_{y,t-1} = 0, S_{r,t-1} = 0) \Pr(S_{r,t} = 0|S_{y,t-1} = 0, S_{r,t-1} = 0)
\]

\[
= \Pr(S_{y,t} = 0|S_{y,t-1} = 0) \Pr(S_{r,t} = 0|S_{r,t-1} = 0).
\]

The transitions of the two state variables only depend on their own lag. We extend the model to allow volatility to affect the business cycle by allowing the transition of \( S_{y,t} \) to depend on not only \( S_{y,t-1} \) but also \( S_{r,t-1} \). In this case, the state variable \( D_t \) has the transition probabilities as follows:

\[
\Pr(D_t = 1|D_{t-1} = 1) = \Pr(S_{y,t} = 0|S_{y,t-1} = 0, S_{r,t-1} = 0) \Pr(S_{r,t} = 0|S_{r,t-1} = 0) = P_{y,0}^{(1,1)} P_{r}^{(1,1)}
\]

where the superscript indicates the element of the transition matrix. Therefore, the independent switching is a special case in which \( \Pr(S_{y,t} = 0|S_{y,t-1} = 0, S_{r,t-1} = 0) = \Pr(S_{y,t} = 0|S_{y,t-1} = 0, S_{r,t-1} = 1). \) The other elements of the transition probability matrix \( P \) can be constructed similarly. Note that the transition matrix of \( S_{y,t} \) is dependent on the state of
stock volatility last period, so there are 6 free parameters (two in $P_{y,0}$, two in $P_{y,1}$, two in $P_r$) in the transition probability matrix.

The most general way to describe the correlation between the two state variables would be to estimate all parameters in $P$ without restriction, requiring 12 free parameters. Doing so will allow the model to capture other forms of correlation, e.g., the state of the economy leads the volatility regime. However, we argue that our specification is appropriate for two reasons. First, Ludvigson, et. al. (2015) find that heightened financial uncertainty is probably an exogenous impulse that causes recessions, and little evidence that negative shocks to real activity have adverse effects on financial uncertainty. Second, Hamilton and Lin (1996) compare the freely-estimated and restricted Markov-switching model and find their specification, i.e., $S_{y,t} = S_{r,t-1}$, a reasonable description of the comovement of stock returns and economic activity. We see these findings as empirical supports for our specification.

3 Estimation Results

In this section, we estimate the model using revised and real time data. The results from revised data tell us the dynamic relationship between the two states variables, while the results from real time data allow us to compare the speed with which turning points are identified.

3.1 Data and Estimation Method

We consider four coincident variables highlighted by the NBER in establishing turning point dates: (1) nonfarm payroll employment, (2) industrial production, (3) real manufacturing and trade sales, and (4) real personal income excluding transfer payments. Revised data is taken
from the website of the St. Louis Fed. The real-time data set is originally collected by Chauvet and Piger (2008). The excess return on stock market is measured by value-weight return of all CRSP firms minus the one-month Treasury bill rate.

The model is estimated via Kim’s (1994) approximate maximum likelihood algorithm. It is well known that maximum likelihood estimation of regime-switching models is plagued by complicated likelihood functions with numerous local maxima. In particular, starting values for these parameters far from “reasonable” values almost always resulted in a failure to converge. Therefore, we first estimate equations (1) and (4) separately with 20 different sets of randomly-generated starting values for the model parameters. Then the maximum likelihood estimates of equations (1) and (4) are used as the starting values for the parameters of the full model which allows correlation between regimes. The resulting estimates will be denoted by “MSDF-Vol” (MSDF with stock volatility).

3.2 Estimation Results Using Revised Data
The sample period is 1959m1 to 2018m12. We are interested in comparing the results from MSDF-Vol with those from a special case in which the transition probability matrix of $S_{y,t}$ does not depend on $S_{r,t}$. So we obtain a special case of our model by letting $P_y = P_{y,0} + P_{y,1}(1 - \tau)$ where $P_{y,i}$ is transition probability matrix of $S_{y,t}$ when $S_{r,t-1} = i$ and $\tau$ is the steady state probability of $S_{r,t} = 0$. We denote this case by “MSDF-Ind.” The log likelihood of the MSDF-Ind

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1 FRED variable codes are PAYEMS, INDPRO, CMRMTSPL, and W875RX1.
2 The data set is publicly available on Piger’s website https://pages.uoregon.edu/jpiger/research/published-papers/gp_ijof.zip
3 The excess return data can be found in the website of the Fama French Data Library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
4 The data of real manufacturing and trade sales before 1967 is not available before on FRED, but can be found in the data set provided by Mark Watson at http://www.princeton.edu/~mwatson/ddisk/bcdating.zip.
and the MSDF-Vol model is -5873.1 and -5438.0, which yields a likelihood ratio statistic of 807.3. Note that in the MSDF-Ind model we impose two additional restrictions on the parameters in the transition probability matrix, so 1% critical value of the likelihood ratio statistic is 9.2. It appears that the evidence against the hypothesis of independent switching is very strong.

![Figure 1](image)

**Figure 1**
Filtered probabilities that $S_{y,t} = 1$ from two models. Shades are NBER recession periods.

How does the stock volatility regime affect the probability of the business cycle phase?

Figure 1 shows the filtered probabilities of $S_{y,t} = 1$, given by $\Pr(S_{y,t} = 1, S_{r,t} = 0) + \Pr(S_{y,t} = 1, S_{r,t} = 1)$, together with the usual NBER recession shading, in two models. Both models provide timely assessment of the recession probability, but the MSDF-Vol performs better in most episodes.

With the eventual NBER chronology serving as the standard for accuracy, one way to measure the accuracy of the filtered probabilities is the area under the receiver operating
characteristic curve (AUROC), following Berge and Jordà (2011) and Liu and Moench (2016). When comparing the performance of model m to that of model c, model m is preferred to model c if $AUROC_m > AUROC_c$. Aastveit et al. (2018) show how to compute the standard error of the difference between AUROC of two models and test formally whether model m is preferred to model c. The AUROC of the MSDF-Ind and MSDF-Vol model is 0.9213 and 0.9807, respectively. The standard error of the difference is 0.0132. Since the difference between two AUROC values divided by the standard error follows a standard normal, the p-value of null hypothesis of no difference is very small, suggesting that MSDF-Vol has superior classification ability.

A perfect model has AUROC = 1, while a completely uninformative model has AUROC = 0.5.

![Figure 2](image)

**Figure 2**
Filtered probabilities that $S_{yt} = 1$ in calm (left) and volatile state (left) from the MSDF-Vol model. Shades are NBER recession periods.

We turn now to an examination of the dynamic relationship between switches in the business cycle and stock volatility. Figure 2 shows the filtered probabilities of recession in the calm regime ($S_{yt} = 1$ and $S_{rt} = 0$, left panel) and in the volatile regime ($S_{yt} = 1$ and $S_{rt} = 1$, right panel), along with shading indicating NBER recession phases. From the figure, $Pr(S_{yt} = 1, S_{rt} = 1)$.
1, $S_{r,t} = 1$) is close to one during every NBER recession, but it is not the case for $Pr(S_{y,t} = 1, S_{r,t} = 0)$. The evidence suggests that economic recessions are usually associated with financial market turmoil.

The matrices of transition probabilities were estimated for MSDF-Vol model to be:

$$P_{y,0} = \begin{bmatrix} 0.9955 & 0.0045 \\ 0.0045 & 0.5765 \end{bmatrix}, P_{y,1} = \begin{bmatrix} 0.9187 & 0.0813 \\ 0.0813 & 0.1 \end{bmatrix}, P_r = \begin{bmatrix} 0.9561 & 0.0439 \\ 0.0439 & 0.9015 \end{bmatrix}$$

$P_{y,j}$ is the estimated transition probability matrix of $S_{y,t}$, conditional on the lagged volatility regime to be $j$, and $P_r$ is the transition probabilities for $S_{r,t}$. These estimates suggest that when the economy was in an expansion and the stock market was calm last period, that is, $S_{y,t-1} = 0$ and $S_{r,t-1} = 0$, the economy is very likely to stay in the expansion: $S_{y,t} = 0$ with probability 0.9955. On the other hand, if the economy was in recession associated with the stock market turbulence last period, the probability that the economy switches to an expansion is estimated to be indistinguishable from zero.

### 3.3 Real-time Analysis of Turning Points

Estimates based on the most recent data revisions suggest that the regime switch in stock volatility is tightly associated with the recession regime. Taking account of this dynamic relationship can enhance model’s classification ability. Now we examine how these findings could be useful for detecting business cycle turning points in real time.

To reflect the information available for forecasters, we recursively estimate the model at each point of time using the data up-to-date. We follow Chauvet and Piger (2008) (CP hereinafter) and conduct a real-time simulation exercise briefly described as follows. For each monthly vintage $R$, we create a monthly data set of the four coincident variables that would have been available at the end of month $R$. Because of reporting lags, the final data point is
month $R - 2$. For each vintage $R$, the MSDF-Vol model is applied to the data set, and a chronology of turning point dates determined. We use monthly data from February 1967 to July 2013, collected by Giusto and Piger (2017).

Figure 3 shows the real-time probabilities during the five most recent recessions produced by MSDF-Vol model and the original CP’s estimates. That is, these figures show a sequence of $\Pr(S_{y,t} = 1|\Psi_{t+2})$, where $\Psi_{t+2}$ corresponds to the information available in month $t + 2$. The information set starts at $t + 2$ because we could observe realization of the four coincident variables at time $t$ with a two month reporting lag. The vertical lines represent the NBER announcement dates of determination of a peak in economic activity. We find that the MSDF-Vol model provides pretty timely, even early, assessments of business cycle turning points.

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6 We thank Jeremy Piger for providing the complete history of real time probabilities of recession. The recession probability series produced for each release back to the August 1, 2006 release is available on his website http://pages.uoregon.edu/jpiger/us_recession_probs.htm/.
Figure 3

Real-time filtered probabilities based on the MSDF-Vol model and Chauvet and Piger’s estimates. Shades are NBER recession periods. The vertical lines represent the NBER announcement dates of determination of a peak.
Figure 4 Business cycle turning points obtained in real time based on decision rule suggested by Chauvet and Piger.

Table 1 Business cycle peak dates announced in real time

<table>
<thead>
<tr>
<th>Peak date announced:</th>
<th>Days ahead of NBER announcement: CP</th>
<th>Days ahead of NBER announcement: MSDF-Vol</th>
</tr>
</thead>
<tbody>
<tr>
<td>NBER</td>
<td>1980/6/3</td>
<td>-58</td>
</tr>
<tr>
<td></td>
<td>1982/1/6</td>
<td>-53</td>
</tr>
<tr>
<td></td>
<td>1991/4/25</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>2001/11/26</td>
<td>-66</td>
</tr>
<tr>
<td></td>
<td>2008/12/1</td>
<td>-89</td>
</tr>
</tbody>
</table>
To obtain specific turning point dates, we must convert the regime predictions for individual months into predictions about a new turning point. Here, we follow CP and consider a decision rule of declaring a peak and a trough as follows:

- Declare a recession as soon as $\Pr(S_{y,t-k} = 1 | y_t, y_{t-1}, ..., y_1; \hat{\theta}_t) \geq 0.8$ for $k = 0, 1, 2$ and $\Pr(S_{y,t-3} = 1 | y_t, y_{t-1}, ..., y_1; \hat{\theta}_t) < 0.8$, where $\theta_t$ is the vector of model parameters estimated using information up to time. Then date the start of the recession as the earliest $k$ for which this probability was above 50%. An analogous procedure, with the 80% threshold replaced by 20% and inequality symbols reversed, is used to establish business cycle troughs.

Figure 4 compares NBER news releases with the performance of the CP and MSDF-Vol model in dating business cycle chronology. The five plots correspond to five US recessions after 1980. The grey bars represent recession period identified by each approach according to the CP’s decision rule. In general, both MSDF-Vol and CP model identify business cycle turning points with a high level of accuracy. Every NBER turning point date is matched by a similar date produced by both models. Also, the MSDF-Vol model never produces a turning point date that

<table>
<thead>
<tr>
<th>Trough date announced: NBER</th>
<th>Days ahead of NBER announcement: CP</th>
<th>Days ahead of NBER announcement: MSDF-Vol</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981/7/8</td>
<td>189</td>
<td>250</td>
</tr>
<tr>
<td>1983/7/8</td>
<td>38</td>
<td>99</td>
</tr>
<tr>
<td>1992/12/22</td>
<td>449</td>
<td>479</td>
</tr>
<tr>
<td>2003/7/17</td>
<td>320</td>
<td>443</td>
</tr>
<tr>
<td>2010/9/20</td>
<td>263</td>
<td>294</td>
</tr>
</tbody>
</table>
does not match an NBER date. Nor does the CP model. That is, both models produce no false positives and no false negatives.

Table 5 and 6 give the amount of time before the NBER date that the turning point from both models would have been available. The MSDF-Vol model would have beaten the NBER in calling the beginning of the past three recessions, with leads up to 92 days, while the CP model does not show any systematic improvement over the NBER in the speed at which it identifies peak dates. Furthermore, the CP model would have identified business cycle troughs much more quickly than the NBER, but the MSDF-Vol model would have called troughs even more quickly than the CP model—up to 123 days.

The real-time simulations indicate that incorporating information contained in stock volatility could enhance the timeliness of the MSDF-Vol model for detecting business cycle turning points. However, for detecting beginning of recessions without financial origins, e.g., those in the early 1980s, the MSDF-Vol model performs just equally well as the CP model. Therefore, the usefulness of the MSDF-Vol model hinges on the origin of recession.
Table 3  Real-time smoothed probabilities around October 2008 from Chauvet and Piger’s estimates.

<table>
<thead>
<tr>
<th></th>
<th>Probability observed on</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>2008/11/30</td>
<td>2008/12/31</td>
<td>2009/1/31</td>
<td>2009/2/28</td>
</tr>
<tr>
<td></td>
<td>CP</td>
<td>MSDF-Vol</td>
<td>CP</td>
<td>MSDF-Vol</td>
<td>CP</td>
</tr>
<tr>
<td>Jul-08</td>
<td>66.0</td>
<td>97.7</td>
<td>88.3</td>
<td>98.5</td>
<td>89.8</td>
</tr>
<tr>
<td>Aug-08</td>
<td>96.2</td>
<td>99.9</td>
<td>97.7</td>
<td>99.9</td>
<td>96.9</td>
</tr>
<tr>
<td>Sep-08</td>
<td>99.2</td>
<td>1</td>
<td>98.0</td>
<td>99.9</td>
<td>97.6</td>
</tr>
<tr>
<td>Oct-08</td>
<td></td>
<td>16.1</td>
<td>99.9</td>
<td>68.5</td>
<td>99.9</td>
</tr>
<tr>
<td>Nov-08</td>
<td></td>
<td></td>
<td>75.4</td>
<td>1</td>
<td>98.5</td>
</tr>
<tr>
<td>Dec-08</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>98.2</td>
</tr>
</tbody>
</table>

With specific regard to identification of the Great Recession, one of the reasons that the CP model would not have called the beginning of the recession earlier is the peculiar dive in the recession probability in the middle of 2008, see Table 4. The probability moved to 99.2% when the September data became available but fell back to 16.1% with the next month’s data, which showed industrial production and real personal income less transfers to be growing again in October. Therefore, the Chauvet-Piger rule would not call the beginning of a recession even though we found three consecutive over-80% probabilities. It took two more months to smooth the peculiar dive, so the Chauvet-Piger rule would announce peak date in February 2009.

Because the MSDF-Vol model does not generate the peculiar dive in the recession probability, given that 2008 was a year of financial turmoil, and it generates high recession probabilities earlier than the CP model, the MSDF-Vol model would have beaten the NBER in identifying the Great Recession.
The 80% threshold set by Chauvet and Piger plays an important role in identifying recessions. A lower threshold increases the chance of identifying a recession but at the cost of more false positives. Table 4 reports the recession announcement dates based on thresholds from 50% to 90%. Both models perform pretty well using a 70% or 80% threshold. However, the CP model generates more false positives (denoted by *) than the MSDF-Vol model does as the threshold lowers to 50%. On the other hand, if we use a 90% threshold, both models generate one false negative. Based on these results, a 70% or 80% threshold is useful for identifying US recessions.

Table 4  Recession announcement dates using different thresholds (* indicates a false positive)

<table>
<thead>
<tr>
<th>Criteria=</th>
<th>50%</th>
<th>60%</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSDF-Vol model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CP model</td>
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4. **Conclusion**

Dating recessions when they happen is of interest for obvious reasons. The use of Markov-switching models has proved to be of considerable value in this endeavor. The addition of correlated switches in stock return volatility could improve timeliness of models for detecting business cycle turning points both in real time and retrospectively.

**References**


