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CAMA Working Paper 24/2023
May 2023

Yunjong Eo
Korea University
Centre for Applied Macroeconomic Analysis, ANU

James Morley
University of Sydney
Centre for Applied Macroeconomic Analysis, ANU

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JEL Classification

C22, C51, E32, E37

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

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Yunjong Eo†
Korea University and CAMA

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*We thank seminar participants at the Korea Development Institute and Sungkyunkwan University for comments and suggestions. Jaewon Lee provided invaluable research assistance.

†Yunjong Eo: Department of Economics, Korea University, Seoul 02841, South Korea; Tel: +82 2 3290 2212; Email: yunjongeo@korea.ac.kr

‡James Morley: School of Economics, University of Sydney, NSW 2006, Australia; Tel: +61 2 9351 3368; Email: james.morley@sydney.edu.au

1 Introduction

The COVID-19 recession was extremely deep but short lived, with a large recovery in economic activity making it appear more U shaped than L shaped. In this note, we consider the extent to which the shape of recessions such as the COVID-19 recession can be predicted in real time. To do this, we first revisit our Markov-switching model of U.S. real GDP from Eo and Morley (2022) that accommodates the two different types of recessions in terms of shape. Following Lenza and Primiceri (2022) for linear time series models, we find that it is important to account for extreme outliers during the pandemic when estimating model parameters, but a simple decay function for volatility from 2020Q2 leads to robust inferences compared to our original estimates. The model, which also allows for a gradual change in the long-run growth rate given the challenges of estimating a possible discrete structural break near the end of the sample period, clearly classifies the COVID-19 recession as being U shaped rather than L shaped. We then consider real-time data and find that our model could also be used in conjunction with Survey of Professional Forecasters (SPF) data to accurately predict the nature of recovery at the time of the trough of a recession. Our real-time analysis considers the last four recessions and we illustrate how plausible modeling choices which could have been made at the time would have correctly predicted the shape of each recession.

Our analysis builds off the large literature on real-time analysis of the output gap following the seminal paper by Orphanides and Norden (2002) and demonstrates that our Markov-switching model can be used for current analysis of the shape of a recession, in addition to *ex post* historical classification. We find that SPF data is useful for identifying the trough of a recession and the nature of recovery, even though the exact path of output is difficult to accurately predict. The results also provide an out-of-sample validation of our Markov-switching model of U.S. real GDP developed in Eo and Morley (2022) in terms of capturing and characterizing the COVID-19 recession.

The rest of this note is organized as follows: Section 2 presents our updated model, including the decay function used to address the extreme outliers during the pandemic, and reports parameter estimates and inferences about the shape of recessions. Section 3 considers real-time analysis for predicting the shape of the last four recessions. Section 4 concludes.

2 Updating the Model to Address COVID-19

We update our Markov-switching model from Eo and Morley (2022) to account for the extreme outliers due to the COVID-19 pandemic using a decay-function approach developed by Lenza and Primiceri (2022).[1] This model allows a given recession to either permanently alter the level of aggregate output (i.e., an L-shaped recession) or only have a temporary effect (i.e., a U-shaped recession). To also allow for the possibility of a change in the long-run growth rate near the end of the sample period, we consider a version of the model applied to "dynamically-demeaned" output growth, which was also considered in the robustness analysis in Eo and Morley (2022).[2] In particular, following Kamber, Morley and Wong (2018), dynamic demeaning involves calculating deviations from a slowly-moving time-varying unconditional mean as follows: $\Delta\tilde{y}_t \equiv \Delta y_t - \frac{1}{40}\sum_{j=0}^{39}\Delta y_{t-j}$. Then, our model for dynamically-demeaned output growth, $\Delta\tilde{y}_t$, has the following time-varying conditional mean based on three regimes:

$$\begin{aligned}\Delta\tilde{y}_t = \mu_0 \;&+\; \chi_t\cdot\mu_1\cdot\mathbf{1}(S_t=1)\\ &+\; \chi_t\cdot\mu_2\cdot\mathbf{1}(S_t=2)+\sum_{k=1}^{m}\chi_{t-k}\cdot\lambda\cdot\mathbf{1}(S_{t-k}=2)+\chi_t e_t,\end{aligned} \tag{1}$$

where $\mathbf{1}(\cdot)$ is an indicator function, S_t is a latent Markov-switching state variable that takes on discrete values such that $S_t = 0$ for the expansionary regime, $S_t = 1$ for the L-shaped contractionary regime, and $S_t = 2$ for the U-shaped contractionary regime according to transition probabilities $Pr[S_t = j|S_{t-1} = i] = p_{ij}$ for $i, j = 0, 1, 2$, and $e_t \sim N(0, \sigma_t^2)$, with $\sigma_t^2 = \sigma_{v0}^2\cdot\mathbf{1}(t \leq \tau_v) + \sigma_{v1}^2\cdot\mathbf{1}(\tau_v < t)$ and τ_v = 1984Q2 based on the estimated breakdate in residual volatility reported in Eo and Morley (2022). The extreme observation of output growth in 2020Q2 due to the spread of COVID-19 is taken into account using a scaling factor χ_t, as proposed by Lenza and Primiceri (2022). Before the onset of the COVID-19 pandemic at time $t^* = 2020Q2$, we set $\chi_t = 1$ (i.e., $t < 2020Q2$). After that time period, $\chi_{t^*+j} = 1 + (c_0 - 1)\rho^j$, where j represents the time elapsed since the pandemic began. For

[1] The decay function was originally featured in a working paper version of Lenza and Primiceri (2020) that was released in August 2020 and so plausibly could have been considered in real time as early as 2020Q3 when data for the trough quarter 2020Q2 became available.

[2] See Eo and Kim (2016) to understand the significance of considering time-variation in long-run growth when identifying the contractionary regime.

output growth during contractionary regimes, we set $\mu_{1,t} = \mu_1$ and $\mu_{2,t} = \mu_2$ if $t < 2020Q2$ and $\mu_{1,t} = \chi_t \cdot \mu_1$ and $\mu_{2,t} = \chi_t \cdot \mu_2$ otherwise. Accordingly, if $S_t = 2$ during the pandemic, the bounceback effect based on the distributed lag term in (1) for the U-shaped recovery would be determined by $\lambda_{2,t-k} = -\mu_2/m$ if $t \leq 2020Q2$ and $\lambda_{2,t-k} = -\chi_{t-k} \cdot \mu_2/m$ otherwise, with the length of the post-recession bounceback effect set to $m = 5$ based on the estimate reported in Eo and Morley (2022). The scaling parameter c_0 is expected to be much larger than one given the extreme magnitude of the reduction in output growth in 2020Q2, but in practice we estimate it without any restriction on its value and, importantly, we do not impose which type of recession it is associated with *ex ante*. The decay parameter ρ is restricted to be between 0 and 1 in estimation.

Raw data for U.S. real GDP were obtained from FRED and converted to growth rates for the sample period of 1947Q2 to 2022Q4 by calculating 100 times the first differences of natural logarithms. For our real-time analysis in the next section, the real-time data for U.S. real GDP, including SPF nowcasts and forecasts, were obtained from the Philadelphia Fed's Survey of Professional Forecasters. We note that the real-time data, including the SPF responses corresponding to real GNP prior to 1992.

Table 1 presents the updated parameter estimates, which are very similar to those for the same parameters included in the original model in Eo and Morley (2022) (see Table 5 in the original paper). The additional parameters related to volatility during the COVID-19 pandemic are c_0 and ρ. The estimate of $\hat{c}_0 = 5.17$ suggests the shock in the pandemic was five times as large as a typical recessionary shock. Then, the estimate $\hat{\rho} = 0.83$ suggests that more than half of the extra volatility dies out within a year.

Figure 1 shows that the updated model captures the various NBER recessions well and classifies recessions as being U or L shaped in the same way as the original analysis in Eo and Morley (2022) (see panel (d) of Figure 6 in the original paper).[3] The additional COVID-19

[3]The finding that the 2007-09 recession was U shaped is arguably the most controversial finding with our model. Huang, Luo and Startz (2016) find it is L shaped using a similar model, but with regimes identified by the NBER instead of estimated using Markov-switching regimes. Likewise, Donayre and Panovska (2021) find it is L shaped when averaging across the Hamilton (1989) and the Kim, Morley and Piger (2005) models using Bayesian model averaging with weights based on the Schwarz information criterion. Eo and Morley (2022) show that it is crucial to allow for a slowdown in the long-run growth rate prior to the Great Recession, as we do when considering dynamic demeaning, in order to identify the Great Recession as being U shaped. That is, the slower growth in U.S. real GDP evident after the Great Recession appears to have started prior to the Great Recession, not because of it. See Eo and Morley (2022) for a full discussion of this timing of the trend growth slowdown.

recession is very short lived and is clearly classified as being more U shaped than L shaped.

3 Real-Time Analysis of the Last Four Recessions

In this section, we employ real-time analysis to examine the ability of our model to predict the shapes of recessions. We find that SPF data is helpful in determining the trough of a recession and also predicting the nature of recovery at the time of the trough, even though SPF predictions about the future level of output are not always particularly accurate or even unbiased.[4]

For our real-time analysis, we consider the last four recessions (1990-91, 2001, 2007-09, and 2020) for which enough data were available to have plausibly been able to estimate our model with different types of recessions at the time.[5] Given the real-time setting, we continue to consider dynamic demeaning to allow for possible gradual changes in the long-run growth rate.

First, we consider when SPF nowcasts and forecasts of real GDP predict the trough of a recession to have occurred. For the last four recessions, we find that median SPF predictions always correctly identify the trough as either a forecast or a nowcast (i.e., within the quarter following the trough). The real-time data and SPF predictions for both the quarter of the trough and the quarter following the trough are presented and compared with the final vintage data for the last four recessions in Figure 2.

Then using the SPF nowcasts and forecasts as augmented data for future observations of real GDP with which to estimate our model and classify a recession as being L or U shaped, we find that the implied nature of the recovery is correctly predicted for each recession.

[4]See Coibion and Gorodnichenko (2012, 2015) and Coibion, Gorodnichenko and Kamdar (2018) on information rigidity in SPF forecasts. In particular, Coibion and Gorodnichenko (2015) show that the degree of information rigidity significantly decreases one year after the start of a recession, making it unable to reject the null hypothesis of full-information rational expectations. This finding can potentially explain why SPF nowcasts and forecasts are effective in detecting the troughs of business cycles in our model. Also see Zanetti Chini (2023) on state-dependent biases related to recessions.

[5]While the Hamilton (1989) model had been around for a few years before the 1990-91 recession, models incorporating bounceback dynamics were only in the early stages of being developed, with the nonlinear model in Beaudry and Koop (1993) being a prominent early example, although it was not nested within a Markov-switching framework. See Kim and Nelson (1999) and Kim, Morley and Piger (2005) for Markov-switching models of U.S. real GDP that explicitly build off of Beaudry and Koop (1993). Also, see multivariate unobserved components models with Markov-switching in trends and cycles, such as Kim and Murray (2002), Kim and Piger (2002), and Kim, Piger and Startz (2007), that implicitly allowed for both L and U shaped recessions.

The results for this real-time analysis are presented in Figure 3. It is worth noting that our model augmented with SPF data does not always identify the end of a contractionary regime in real time even though the SPF is able to identify the trough. The issue is that the Markov-switching model can fit the SPF predicted data by suggesting a contractionary regime persists, as it is generally expected to with a conditional probability of around 70% according to the estimates in Table 1, with a sequence of positive forecast errors at least as well or slightly better than if a switch to an expansionary regime occurred and there were a sequence of negative forecast errors to capture the relatively weak initial recoveries implied by the SPF. Only with actual realized data do the contractionary probabilities settle down to what we find for the full-sample estimates.[6] But, importantly, the Markov-switching model combined with the SPF data does correctly predict the type of recession in real time when comparing to the final revised probabilities in Figure 1. Specifically, in Figure 3, we can see that the model identifies the 1990-91 and 2001 recessions as being L shaped and the 2007-09 and 2020 recessions as being U shaped at the time of the trough for each recession.

The ability to identify the shape of recession in real time also means that we are able to obtain a reasonably reliable estimate of the output gap in real time. Morley and Panovska (2020) show that the output gap based a set of linear and nonlinear models that includes the Hamilton (1989) model and the Kim, Morley and Piger (2005) model is substantially more reliable than the Hodrick and Prescott (1997) and Hamilton (2018) filters when using the standard metrics for real-time evaluation from Orphanides and Norden (2002). Figure 4 shows that the estimated output gap based on the trend/cycle decomposition approach in Morley and Piger (2008), which was also considered in Eo and Morley (2022), is quite reliable in real-time when calculated using real-time real GDP data augmented with SPF predictions and that it is very similar to the estimated model-averaged output gap reported in Morley and Panovska (2020).[7] Specifically, by identifying the 1990-91 and 2001 recessions as being L shaped in real-time, our model also implies little or no output gap for the 1990-91 and 2001 recessions. By contrast, it implies large, negative output gaps for the 2007-09 and 2020

[6]Data revisions also play some role in different real-time probabilities. For example, the finding of a high probability of a contractionary regime in 1986Q2 given the 1990Q1 vintage of data considered in panel (b) of Figure 3 reflects an implied negative growth rate for the quarter of -0.44% based on real GNP data at the time that was revised away in later vintages with the switch to real GDP in 1992, for which the corresponding final-vintage growth rate in 1986Q2 is 0.45%.

[7]See Eo (2022) for the estimation of the output gap using SPF forecasts based on unobserved components models.

recessions, consistent with their identification as U-shaped recessions in real-time and the *ex post* estimated output gap based on the final vintage data.

4 Conclusion

We have shown that a Markov-switching model of U.S. real GDP with two different types of recessions from Eo and Morley (2022) clearly identifies the COVID-19 recession as being U shaped and was able to do so in a real-time setting when including a decay function for shock volatility during the pandemic in the model and augmenting real-time real GDP data with observations based on predictions from the SPF. Indeed, the Markov-switching model would have successfully predicted the shape of the last four recessions in real time at the time of the trough identified by the SPF. This analysis shows that SPF data can be useful in making qualitative predictions about the nature of a recession even if the quantitative predictions about the path of real GDP are not always very accurate. We also find that estimates of the implied highly-asymmetric output gap are also quite reliable in the real-time setting. As our focus is on predicting the shape of a recession, we leave analysis about why a particular recession is L or U shaped to future research, although we note that a very recent paper by Huang, Luo and Startz (2023) provides a promising extension of our model to incorporate time-varying transition probabilities that allows consideration of what variables might drive or predict different types of recessions.

References

Beaudry, Paul, and Gary Koop. 1993. "Do Recessions Permanently Change Output?" *Journal of Monetary Economics*, 31(2): 149–163.

Coibion, Olivier, and Yuriy Gorodnichenko. 2012. "What Can Survey Forecasts Tell Us about Information Rigidities?" *Journal of Political Economy*, 120(1): 116–159.

Coibion, Olivier, and Yuriy Gorodnichenko. 2015. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." *American Economic Review*, 105(8): 2644–2678.

Coibion, Olivier, Yuriy Gorodnichenko, and Rupal Kamdar. 2018. "The Formation of Expectations, Inflation, and the Phillips Curve." *Journal of Economic Literature*, 56(4): 1447–1491.

Donayre, Luiggi, and Irina Panovska. 2021. "Recession-Specific Recoveries: L's, U's and Everything in between." *Economics Letters*, 209: 110145.

Eo, Yunjong. 2022. "Estimating the Output Gap Using Survey Expectations." *manuscript*.

Eo, Yunjong, and Chang-Jin Kim. 2016. "Markov-Switching Models with Evolving Regime-Specific Parameters: Are Postwar Booms or Recessions All Alike?" *Review of Economics and Statistics*, 98(5): 940–949.

Eo, Yunjong, and James Morley. 2022. "Why Has the U.S. Economy Stagnated since the Great Recession?" *Review of Economics and Statistics*, 104: 246–258.

Hamilton, James D. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica*, 57(2): 357–84.

Hamilton, James D. 2018. "Why You Should Never Use the Hodrick-Prescott Filter." *Review of Economics and Statistics*, 100(5): 831–843.

Hodrick, Robert J, and Edward C Prescott. 1997. "Postwar US Business Cycles: An Empirical Investigation." *Journal of Money, Credit, and Banking*, 1–16.

Huang, Yu-Fan, Sui Luo, and Richard Startz. 2016. "Are Recoveries All the Same: GDP and TFP?" *Oxford Bulletin of Economics and Statistics*.

Huang, Yu-Fan, Sui Luo, and Richard Startz. 2023. "Recessions, Recoveries, and Leverage." *Available at SSRN 4419734*.

Kamber, Güneş, James Morley, and Benjamin Wong. 2018. "Intuitive and Reliable Estimates of the Output Gap from a Beveridge-Nelson Filter." *Review of Economics and Statistics*, 100(3): 550–566.

Kim, Chang-Jin, and Charles R Nelson. 1999. "Friedman's Plucking Model of Business Fluctuations: Tests and Estimates of Permanent and Transitory Components." *Journal of Money, Credit and Banking*, 317–334.

Kim, Chang-Jin, and Christian J Murray. 2002. "Permanent and Transitory Components of Recessions." *Empirical Economics*, 27(2): 163–183.

Kim, Chang-Jin, and Jeremy Piger. 2002. "Common Stochastic Trends, Common Cycles, and Asymmetry in Economic Fluctuations." *Journal of Monetary Economics*, 49(6): 1189–1211.

Kim, Chang-Jin, James Morley, and Jeremy Piger. 2005. "Nonlinearity and the Permanent Effects of Recessions." *Journal of Applied Econometrics*, 20(2): 291–309.

Kim, Chang-Jin, Jeremy M Piger, and Richard Startz. 2007. "The Dynamic Relationship between Permanent and Transitory Components of US Business Cycles." *Journal of Money, Credit and Banking*, 39(1): 187–204.

Lenza, Michele, and Giorgio E. Primiceri. 2020. "How to Estimate a VAR after March 2020." European Central Bank Working Paper Series 2461.

Lenza, Michele, and Giorgio E. Primiceri. 2022. "How to Estimate a Vector Autoregression after March 2020." *Journal of Applied Econometrics*, 37: 688–699.

Morley, James, and Irina B Panovska. 2020. "Is Business Cycle Asymmetry Intrinsic in Industrialized Economies?" *Macroeconomic Dynamics*, 24(6): 1403–1436.

Morley, James, and Jeremy Piger. 2008. "Trend/Cycle Decomposition of Regime-Switching Processes." *Journal of Econometrics*, 146(2): 220–226.

Orphanides, Athanasios, and Simon van Norden. 2002. "The Unreliability of Output-Gap Estimates in Real Time." *Review of Economics and Statistics*, 84(4): 569–583.

Zanetti Chini, Emilio. 2023. "Can We Estimate Macroforecasters' Mis-Behavior?" *Journal of Economic Dynamics and Control*, 149: 104632.

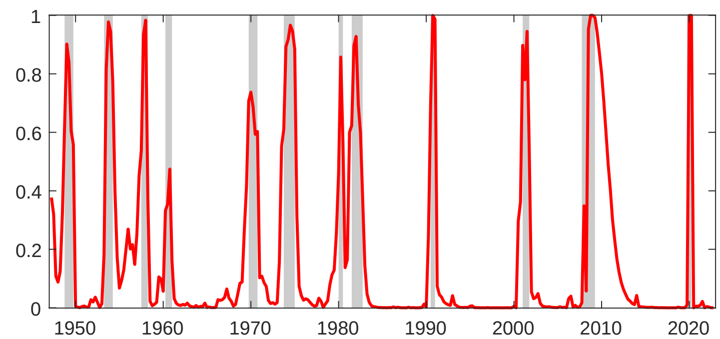
Table and Figures

Table 1: Parameter estimates for the updated model

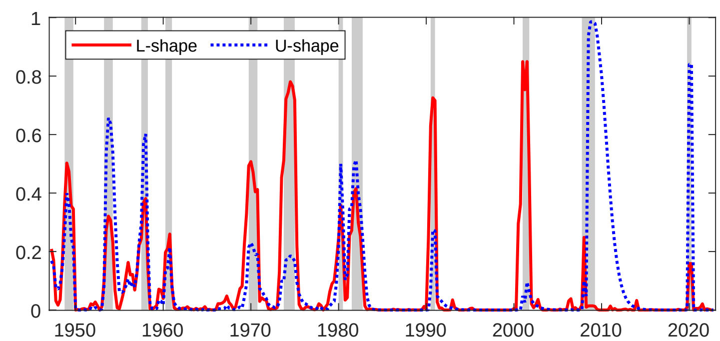
Parameter	Estimate	Standard Error
p_{01}	0.03	0.01
p_{02}	0.02	0.01
p_{11}	0.74	0.11
p_{22}	0.71	0.11
μ_0	0.07	0.04
μ_1	-1.19	0.18
μ_2	-1.89	0.22
λ_2	0.38	0.04
σ_{v0}	0.87	0.06
σ_{v1}	0.43	0.03
c_0	5.17	1.09
ρ	0.83	0.07
log-lik	-347.92	

Note: The model in (1) is estimated using the full sample of realized data from 1947Q2 to 2022Q4 with parameters τ_v = 1984Q2 and $m = 5$ based on Eo and Morley (2022). Estimates are reported for both μ_2 and λ_2 even though they are jointly estimated using the restriction $\lambda_{2,t-k} = -\mu_2/m$ if $t \leq 2020Q2$ and $\lambda_{2,t-k} = -\chi_{t-k} \cdot \mu_2/m$ otherwise.

Figure 1: Recession probabilities for the updated model



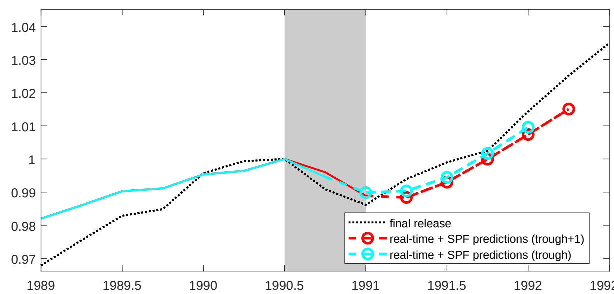
(a) Probability of Recession



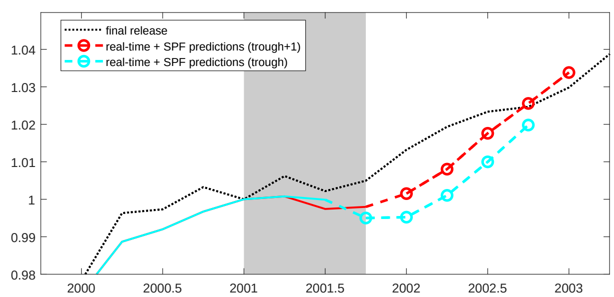
(b) Probabilities of Type of Recession

Note: The shaded areas denote NBER recession dates.

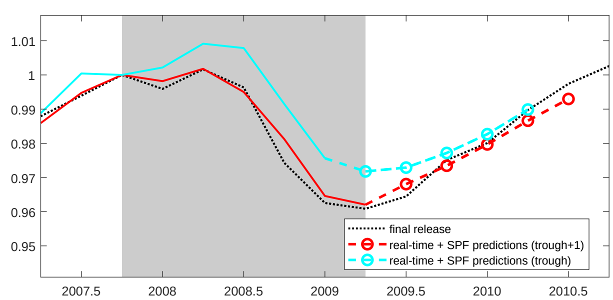
Figure 2: Log real GDP for final vintage versus real-time data plus SPF predictions



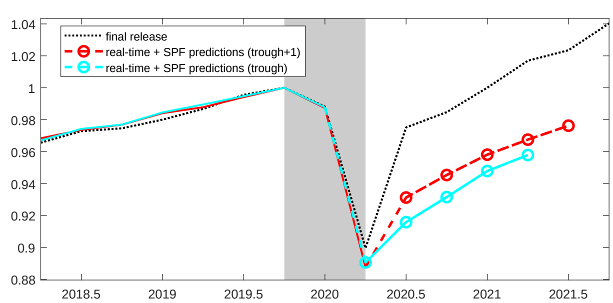
(a) 1990-91 Recession



(b) 2001 recession



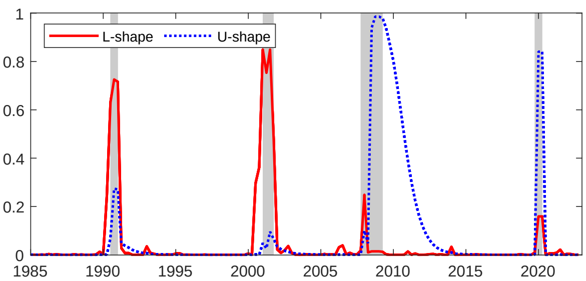
(c) 2007-09 recession



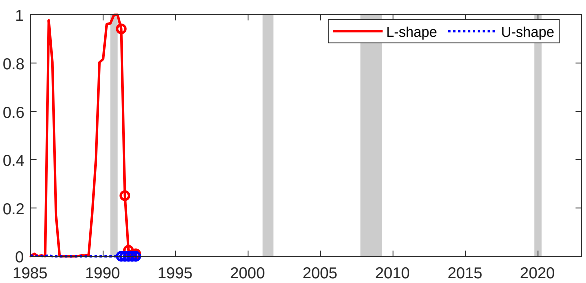
(d) 2020 Recession

Note: Log real GDP is normalized to one at the peak of each recession. Data from SPF predictions are indicated by the circle markers. The shaded areas denote NBER recession dates.

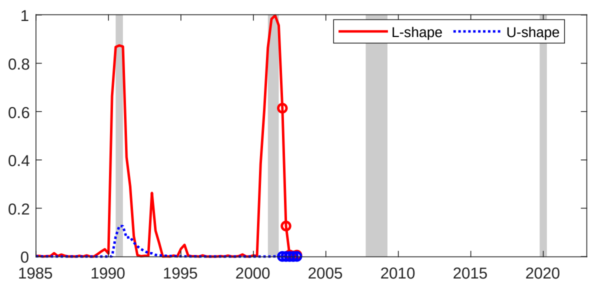
Figure 3: Recession probabilities for full sample estimation versus real-time predictions



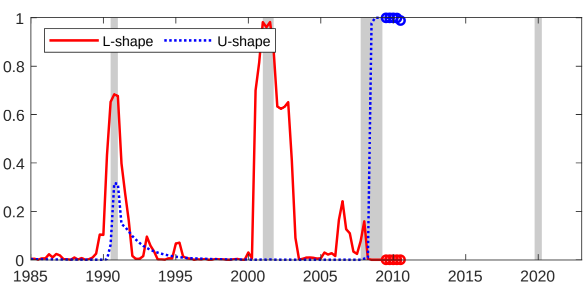
(a) full sample



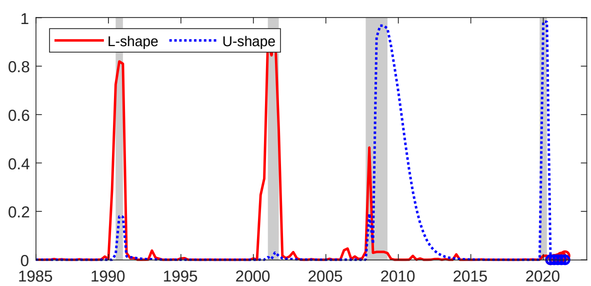
(b) 1990-91 Recession



(c) 2001 recession



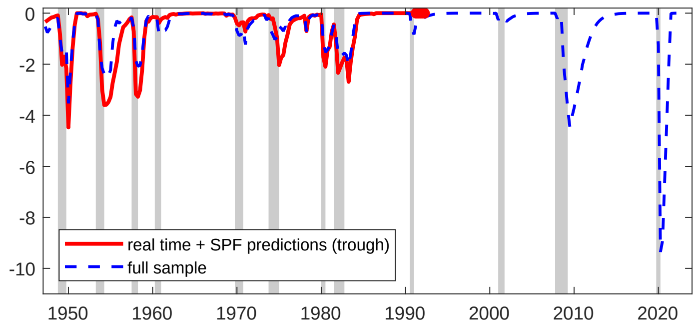
(d) 2007-09 recession



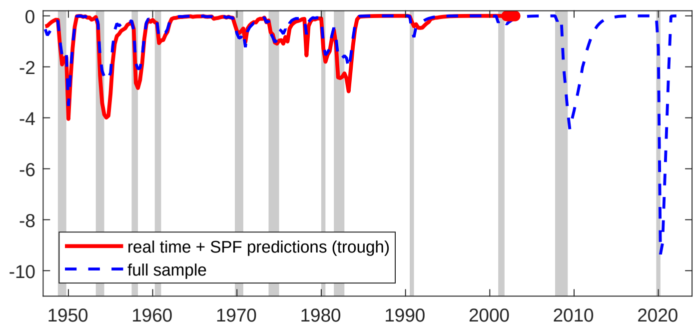
(e) 2020 Recession

Notes: The dates for SPF predictions are indicated by the circle markers in the real-time estimations shown in panels (b)-(e). The shaded areas denote NBER recession dates.

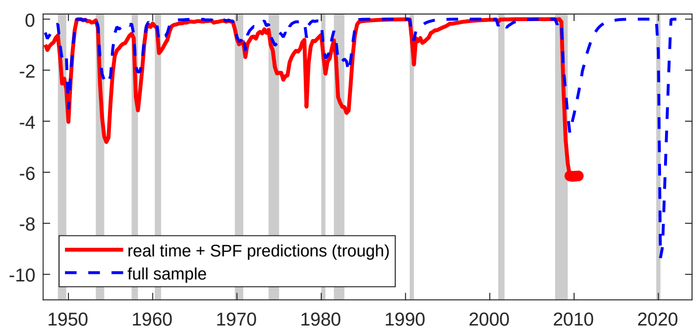
Figure 4: Estimates of output gap in real time and full sample for the last four recessions



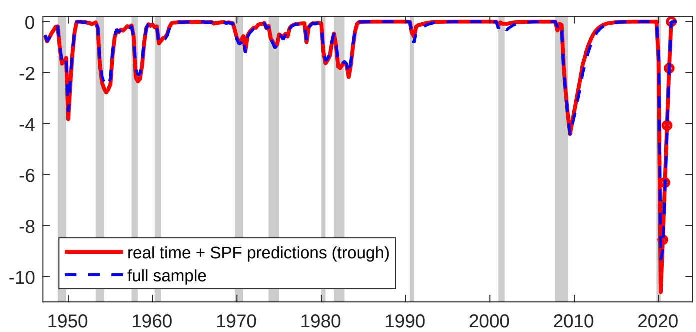
(a) 1990-91 Recession



(b) 2001 recession



(c) 2007-09 recession



(d) 2020 Recession

Note: The dates for SPF predictions are indicated by the circle markers. The shaded areas denote NBER recession dates.