Handout for "Inflation and Professional Forecast Dynamics: An Evaluation of Stickiness, Persistence, and Volatility"

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Inflation expectations are extremely relevant for central banks because they contain information about whether the monetary policy makers will be able to stabilize inflation or not. However, obtaining information about inflation expectations may be a daunting task. This paper studies the joint dynamics of realized inflation and inflation predictions of professional forecasters, obtained from the Survey of Professional Forecasters (SPF). The main purpose of this study is to extract the beliefs of the average respondent of the SPF about stability, persistence, volatility and stickiness of inflation.

This article combines two nonlinear models to study the joint dynamics of realized inflation and average SPF inflation. The first model corresponds to the unobserved components (UC) model of inflation of Stock and Watson (2007) and the second one to a nonlinear version of the sticky information (SI) model of Mankiw and Reis (2002). The UC model decomposes inflation (π_t) into trend (τ_t) and gap (ε_t), where $\pi_t = \tau_t + \varepsilon_t$. This model becomes nonlinear when stochastic volatility (SV) is introduced, by allowing variances the error terms of the trend and the gap to follow log random walks (as it is done in this article). The adapted SI model produces a h-step ahead inflation prediction of a SI forecaster, given by $F_t\pi_{t+h}$. This prediction is a weighted average of the previous period's SI forecast, $F_{t-1}\pi_{t+h}$, and a rational expectations (RE) inflation forecast, $\mathbb{E}_t\pi_{t+h}$. The authors allow for time-varying weights, in order to permit inflation stickiness to vary. The result is a nonlinear law of motion of the form $F_t\pi_{t+h} = \lambda_{t-1}F_{t-1}\pi_{t+h} + (1-\lambda_{t-1})\mathbb{E}_t\pi_{t+h}$.

The state space system that describes the UC component of the model is described by the following equations:

$$
\begin{aligned}
\pi_t &= \tau_t + \varepsilon_t \\
\tau_{t+1} &= \tau_t + \varsigma_{\eta,t}\eta_{t+1}, \quad \eta_{t+1} \sim N(0,1) \\
\varepsilon_{t+1} &= \sum_{j=0}^{k-1} \theta_{j,t} + \varepsilon_{t-j} + \varsigma_{\nu,t}\nu_{t+1}, \quad \nu_{t+1} \sim N(0,1) \\
\ln \varsigma_{l,t+1}^2 &= \ln \varsigma_{l,t}^2 + \sigma_l \xi_{l,t+1}, \quad \xi_{l,t+1} \sim N(0,1), l = \eta, \nu \\
\theta_{j,t+1} &= \theta_{j,t} + \sigma_{\phi,j}\phi_{j,t+1}, \quad \phi_{j,t+1} \sim N(0,1), j = 1, \ldots, k
\end{aligned}
$$

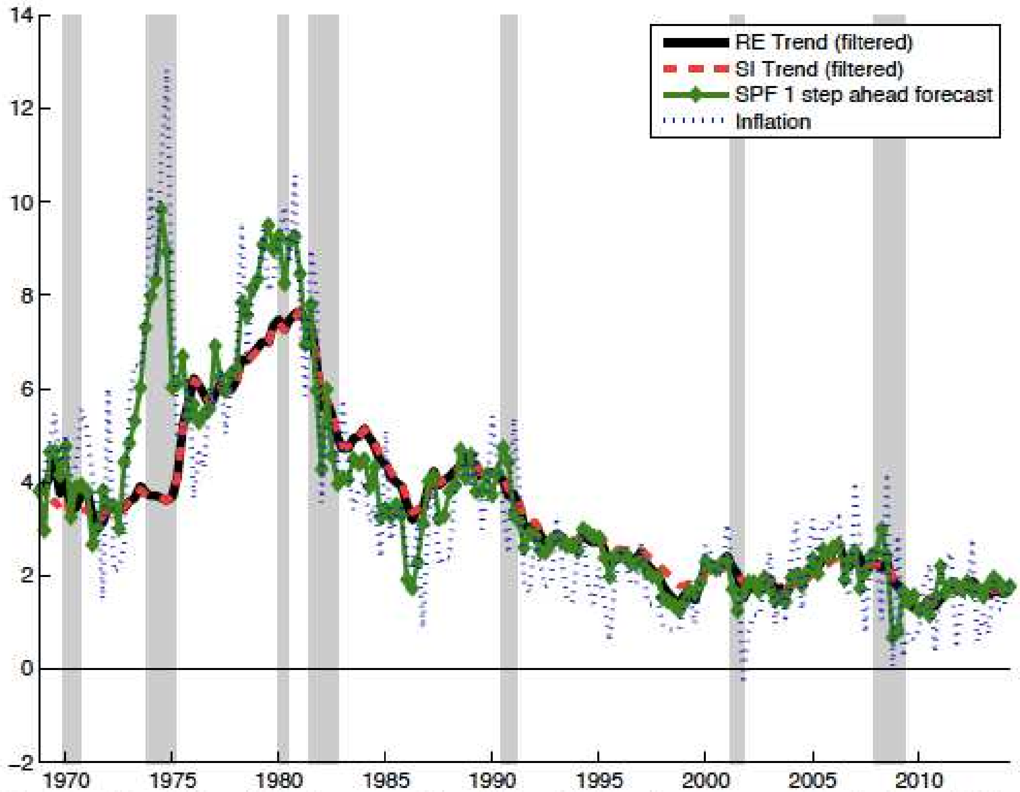
The following system of equations describes the SI component of the model:

$$
\begin{aligned}
\pi_{t,t+h}^{SPF} &= F_t \pi_{t+h} + \varsigma_{t,t+h} \\
F_t \pi_{t+h} &= \lambda_{t-1} F_{t-1} \pi_{t+h} + (1 - \lambda_{t-1}) \mathbb{E}_t \pi_{t+h} \\
\lambda_t &= \lambda_{t-1} + \sigma_\kappa \kappa_t
\end{aligned}
$$

The combination of the two nonlinear models yields a nonlinear state space representation (for space reasons it is not exposed in this document). In this case a particle filter algorithm adapted from Creal (2012) and Herbst and Schorfheide (2014) is used. The steps of the particle filter algorithm are the following: (i) Initialize the filter by drawing M particles from a prior distribution; (ii) for every $t = 1, \ldots, T$ draw a new particle conditional on the previous particles and the prior, compute objects of interest using the Kalman filter, compute particle weights and resample particles using the new weights; (iii) approximate the filtered distribution of particles by using the results obtained in (ii); (iv) compute the date t data density for every step. There is another algorithm to compute a smoothed version but it is not presented here.

The results show that the model that best fits the data is a version of the model that includes stochastic volatility, a time varying adjustment parameter and an AR(1) process for inflation gap. When analyzing the filtered and smoothed inflation trend and gap, the authors find that changes in these variables have occurred in different magnitudes between 1968 and 2014. Figure 1 shows the case in which a 1-step ahead inflation forecast is considered. We observe that, for example, the inflation spike of 1974 was explained mostly by gap inflation while the inflation peak of the early 1980s by trend inflation.

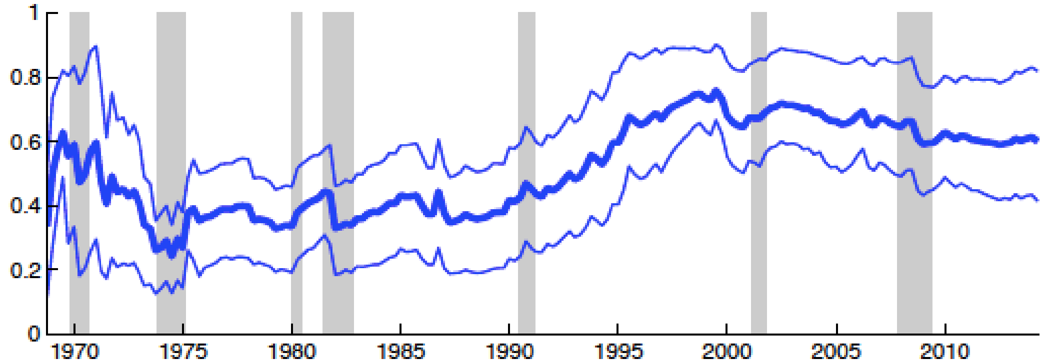
Figure 1: Filtered RE, $\tau_{t|t}$, and SI, $F_{t|t}\tau_t$, Trend Inflation $\pi^{S}_{t,t+1}PF$, and Realized Real Time Inflation π_t

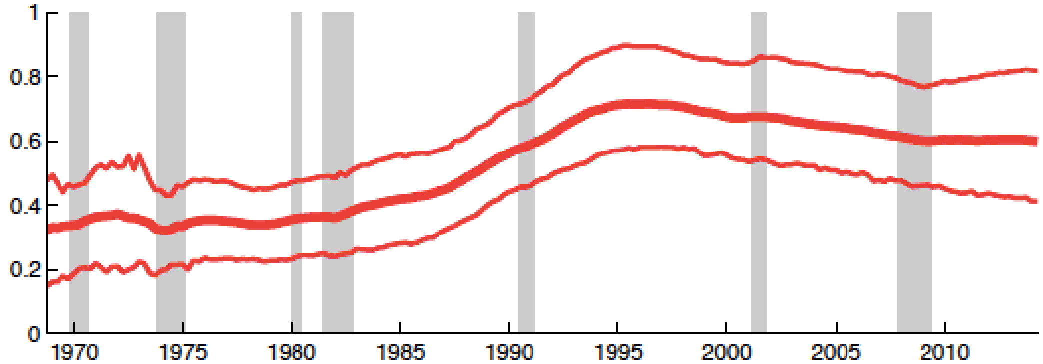


The plots of filtered RE trend inflation, $\tau_{t|t}$, and filtered SI trend inflation, $F_{t|t}\tau_t$, are generated using the particle filter estimates of the TVP-SI law of motion and the SW-UC-SV-TVP-AR(1) model. The average SPF inflation nowcast prediction corresponds to $\pi^{SPF}_{t,t+1}$.

The authors also find that the volatility components of the UC representation increase in periods of crises and that the inflation gap's persistence has changed over time. Finally, they also find that the weights of the SI representation have varied substantially over time, as Figure 2 shows.

Figure 2: Filtered and Smoothed $\lambda_{t|t}$





The plots of the filtered, $\lambda_{t|t}$, and smoothed, $\lambda_{t|T}$, TVP-AR1 coefficient are generated using the particle filter estimates of the TVP-SI law of motion and SW-UC-SV-TVP-AR(1) model. The thick and thin blue (red) plots are the filtered (smoothed) estimates and interquartile range coverage bands of $\lambda_{t|t}$ ($\lambda_{t|T}$), respectively.