INFLATION AND PROFESSIONAL FORECAST DYNAMICS: an evaluation of stickiness, persistence, and volatility

Elmar Mertens\textsuperscript{1}  James M. Nason\textsuperscript{2}

\textsuperscript{1}Federal Reserve Board

\textsuperscript{2}North Carolina State University

The results presented here do not necessarily represent the views of the Federal Reserve System or the Federal Open Market Committee

June 2016
**Research Question**

What is the relationship between survey forecasts and inflation?

**Inflation process is characterized by . . .**

- drifting mean / trend component
- time-varying volatility in shocks to trend and gap
- time-varying persistence

**Evidence about survey forecasts says . . .**

- surveys are good at forecasting inflation
- but there are also persistent forecast errors
- consistent with informational frictions in survey formation
Does “stickiness” vary over time?

How does “stickiness” interact with inflation?

Is “stickiness” related to monetary regimes?
1) **Stock-Watson-type UC model of inflation**

2) **Sticky/noisy information in survey forecasts**
1) Stock-Watson-type UC model of inflation

\[ \pi_t = \tau_t + \varepsilon_t \]
\[ \tau_t = \tau_{t-1} + \varsigma_{\eta,t-1} \eta_t \]
\[ \varepsilon_t = \varsigma_{\nu,t-1} \nu_t \]

\[ \log \varsigma^2_{l,t} = \log \varsigma^2_{l,t-1} + \sigma_l \zeta_{l,t} \quad \forall \ l = \eta, \ \nu \]

2) Sticky/noisy information in survey forecasts
STOCK-WATSON SV ESTIMATES $\zeta_{t\mid T}$
Trend SV (black), Gap SV (red)
STOCK-WATSON INFLATION PERSISTENCE

Long-run response $\partial \pi_{t+\infty} / \partial e_t = K_t$
1) Stock-Watson-type UC model of inflation

\[ \pi_t = \tau_t + \varepsilon_t \]
\[ \tau_t = \tau_{t-1} + \varsigma_{\eta,t-1} \eta_t \]
\[ \varepsilon_t = \varsigma_{\nu,t-1} \nu_t \]

\[ \log \varsigma^2_{l,t} = \log \varsigma^2_{l,t-1} + \sigma_l \zeta_{l,t} \quad \forall \ l = \eta, \ \nu \]

2) Sticky/noisy information in survey forecasts
1) Stock-Watson-type UC model of inflation

\[
\pi_t = \tau_t + \varepsilon_t
\]
\[
\tau_t = \tau_{t-1} + \varsigma_{\eta,t-1} \eta_t
\]
\[
\varepsilon_t = \theta_{t-1} \varepsilon_{t-1} + \varsigma_{\nu,t-1} \nu_t
\]
\[
\log \varsigma_{l,t}^2 = \log \varsigma_{l,t-1}^2 + \sigma_l \zeta_{l,t} \quad \forall \ l = \eta, \nu
\]

2) Sticky/noisy information in survey forecasts
1) Stock-Watson-type UC model of inflation

\[ \pi_t = \tau_t + \varepsilon_t \]
\[ \tau_t = \tau_{t-1} + \varsigma_{\eta,t-1} \eta_t \]
\[ \varepsilon_t = \theta_{t-1} \varepsilon_{t-1} + \varsigma_{\nu,t-1} \nu_t \]
\[ \log \varsigma_{l,t}^2 = \log \varsigma_{l,t-1}^2 + \sigma_l \zeta_{l,t} \quad \forall \ l = \eta, \nu \]

2) Sticky/noisy information in survey forecasts

\[ F_t \pi_{t+h} = (1 - \lambda) E_t \pi_{t+h} + \lambda F_{t-1} \pi_{t+h} \]
STICKY SURVEY FORECASTS
constant SI weight

SI Law of Motion

\[ F_t \pi_{t+h} = (1 - \lambda) E_t \pi_{t+h} + \lambda F_{t-1} \pi_{t+h} \]

\[ = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j} \pi_{t+h} \]
SI Law of Motion

\[ F_t \pi_{t+h} = (1 - \lambda) E_t \pi_{t+h} + \lambda F_{t-1} \pi_{t+h} \]

\[ = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j} \pi_{t+h} \]

Coibion & Gorodnichenko (2015, AER):

“SI” law of motion consistent with . . .

- Sticky information (Mankiw & Reis, 2002)
- Noisy information/Rational inattention (Woodford, 2002; Sims, 2003; Mackowiak & Wiederholt, 2009)
STICKY SURVEY FORECASTS
constant SI weight

SI Law of Motion

\[ F_t \pi_{t+h} = (1 - \lambda) E_t \pi_{t+h} + \lambda F_{t-1} \pi_{t+h} \]

\[ = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j} \pi_{t+h} \]

Coibion & Gorodnichenko (2015, AER):

“SI” law of motion consistent with . . .

- Sticky information (Mankiw & Reis, 2002)
- Noisy information/Rational inattention (Woodford, 2002; Sims, 2003; Mackowiak & Wiederholt, 2009)

Implication: Persistent forecast errors

\[ (E_t - F_t) \pi_{t+h} = \lambda (E_{t-1} - F_{t-1}) \pi_{t+h} + e_t \]
STICKY SURVEY FORECASTS
NEW: time-varying SI weight

**SI Law of Motion**

\[
F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h}
\]

\[
= \sum_{j=0}^{\infty} (1 - \lambda_{t-1-j}) \cdot \left( \prod_{l=0}^{j-1} \lambda_{t-1-l} \right) E_{t-j} \pi_{t+h}
\]

**Coibion & Gorodnichenko (2015, AER):**

“SI” law of motion consistent with ...

- Sticky information (Mankiw & Reis, 2002)
- Noisy information/Rational inattention (Woodford, 2002; Sims, 2003; Mackowiak & Wiederholt, 2009)

**Implication: Persistent forecast errors**

\[
(E_t - F_t) \pi_{t+h} = \lambda_{t-1}(E_{t-1} - F_{t-1}) \pi_{t+h} + e_t
\]
1) Stock-Watson-type UC model of inflation

\[ \pi_t = \tau_t + \epsilon_t \]
\[ \tau_t = \tau_{t-1} + \varsigma_{\eta,t-1} \eta_t \]
\[ \epsilon_t = \theta_{t-1} \epsilon_{t-1} + \varsigma_{\nu,t-1} \nu_t \]
\[ \log \varsigma_{l,t}^2 = \log \varsigma_{l,t-1}^2 + \sigma_l \zeta_{l,t} \quad \forall \ l = \eta, \nu \]

2) Sticky/noisy information in survey forecasts

\[ F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h} \]

...and add new time-varying parameters
1) Stock-Watson-type UC model of inflation

\[ \pi_t = \tau_t + \varepsilon_t \]
\[ \tau_t = \tau_{t-1} + s_{\eta,t-1} \eta_t \]
\[ \varepsilon_t = \theta_{t-1} \varepsilon_{t-1} + s_{\nu,t-1} \nu_t \]

\[ \log s_{l,t}^2 = \log s_{l,t-1}^2 + \sigma_l \zeta_{l,t} \quad \forall l = \eta, \nu \]

2) Sticky/noisy information in survey forecasts

\[ F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h} \]

...and add new time-varying parameters

\[ \lambda_t = \lambda_{t-1} + \sigma_\lambda \zeta_{\lambda,t} \quad 0 \leq \lambda_t \leq 1 \]
\[ \theta_t = \theta_{t-1} + \sigma_\theta \zeta_{\theta,t} \quad |\theta_t| \leq 1 \]
1. Does “stickiness” vary over time?

2. How does “stickiness” interact with inflation?

3. Is “stickiness” related to monetary regimes?
## RELATED LITERATURE

### Surveys and fundamentals
- Coibion & Gorodnichenko (2015), Nason & Smith (2014)
- Ang, Bekaert, & Wei (2007), Faust & Wright (2013)

### Inflation models
- Cogley & Sargent (2005), Cogley, Primiceri, & Sargent (2010)

### Particle filtering / learning / smoothing
OUR CONTRIBUTIONS AND MAIN RESULT

Our contributions

- Joint state space for inflation and surveys that nests RE and SI
- Multivariate trend cycle decomposition for inflation with time-varying gap persistence
- Particle learning and smoothing combined with Rao-Blackwellization
- Expand on univariate regression results of Coibion and Gorodnichenko (2015, AER)

Main result

Striking comovement between inflation persistence and stickiness of surveys
AGENDA

1. Nonlinear State Space
2. Estimation Strategy
3. Results
Nonlinear State Space
- recursive law of motion for SI
- state vector
- measurement vector

Estimation Strategy

Results
AGENDA

1 Nonlinear State Space
   - recursive law of motion for SI
     - state vector
     - measurement vector

2 Estimation Strategy

3 Results
RECURSIVE SI LAW OF MOTION
consider the case of a constant-parameter AR for the inflation gap . . .

**UC model of inflation**

\[
x_t = [\tau_t \ \varepsilon_t]' \\
\pi_t = \delta_x \ x_t \\
x_t = \Theta \ x_{t-1} + \Xi_{t-1} \omega_t
\]
RECURSIVE SI LAW OF MOTION

consider the case of a constant-parameter AR for the inflation gap . . .

**UC model of inflation**

\[ x_t = [\tau_t \ \varepsilon_t]' \]

\[ \pi_t = \delta_x \ x_t \]

\[ x_t = \Theta \ x_{t-1} + \Xi_{t-1} \omega_t \]

**SI forecasts**

\[ F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h} \]
RECURSIVE SI LAW OF MOTION
consider the case of a constant-parameter AR for the inflation gap . . .

UC model of inflation

\[ \pi_t = \delta_x x_t \]
\[ x_t = \Theta x_{t-1} + \Xi_{t-1} \omega_t \]
\[ x_t = [\pi_t \varepsilon_t]' \]

\[ E_t \pi_{t+h} = \delta_x E_t x_{t+h} \]

SI forecasts

\[ F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h} \]
\[ F_t \pi_{t+h} = \delta_x F_t x_{t+h} \]
RECURSIVE SI LAW OF MOTION
consider the case of a constant-parameter AR for the inflation gap . . .

<table>
<thead>
<tr>
<th>UC model of inflation</th>
<th>( x_t = [\tau_t \ \varepsilon_t]' )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \pi_t = \delta_x x_t )</td>
<td>( \Rightarrow E_t \pi_{t+h} = \delta_x E_t x_{t+h} )</td>
</tr>
<tr>
<td>( x_t = \Theta x_{t-1} + \Xi_{t-1} \omega_t )</td>
<td>( \Rightarrow E_t x_{t+h} = \Theta^h x_t )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SI forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td>( F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h} )</td>
</tr>
<tr>
<td>( \Rightarrow F_t \pi_{t+h} = \delta_x F_t x_{t+h} )</td>
</tr>
<tr>
<td>( \Rightarrow F_t x_{t+h} = \Theta^h F_t x_t )</td>
</tr>
</tbody>
</table>
RECURSIVE SI LAW OF MOTION
consider the case of a constant-parameter AR for the inflation gap . . .

<table>
<thead>
<tr>
<th>UC model of inflation</th>
<th>$x_t = [\tau_t \ \varepsilon_t]'$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_t = \delta_x x_t$</td>
<td>$\Rightarrow E_t \pi_{t+h} = \delta_x E_t x_{t+h}$</td>
</tr>
<tr>
<td>$x_t = \Theta x_{t-1} + \Xi_{t-1} \omega_t$</td>
<td>$\Rightarrow E_t x_{t+h} = \Theta^h x_t$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SI forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_t \pi_{t+h} = (1 - \lambda_{t-1}) E_t \pi_{t+h} + \lambda_{t-1} F_{t-1} \pi_{t+h}$</td>
</tr>
<tr>
<td>$\Rightarrow F_t \pi_{t+h} = \delta_x F_t x_{t+h}$</td>
</tr>
<tr>
<td>$\Rightarrow F_t x_{t+h} = \Theta^h F_t x_t$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Recursive SI representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_t x_t = (1 - \lambda_{t-1}) x_t + \lambda_{t-1} \Theta F_{t-1} x_{t-1}$</td>
</tr>
</tbody>
</table>
TVP-GAP PERSISTENCE AND ANTICIPATED UTILITY

**UC model with TVP transition**

\[ \pi_t = \delta_x x_t \]
\[ x_t = \Theta_{t-1} x_{t-1} + \Xi_{t-1} w_t \]

**Anticipated utility approximations**

\[ E_t x_{t+h} \approx \Theta_t^h x_t \]
\[ F_t x_{t+h} \approx \Theta_t^h F_t x_t \]
\[ F_t x_t \approx (1 - \lambda_{t-1}) x_t + \lambda_{t-1} \Theta_{t-1} F_{t-1} x_{t-1} \]

**Inflation expectations and forecasts**

\[ E_t \pi_{t+h} = \delta_x E_t x_{t+h} \]
\[ F_t \pi_{t+h} = \delta_x F_t x_{t+h} \]
AGENDA

1 Nonlinear State Space
   - recursive law of motion for SI
   - state vector
   - measurement vector

2 Estimation Strategy

3 Results
“Linear” States $S_t$

$$\begin{bmatrix} x_t \\ F_t x_t \end{bmatrix} = S_t = \begin{bmatrix} \Theta & 0 \\ (1 - \lambda_{t-1}) \Theta & \lambda_{t-1} \Theta \end{bmatrix} S_{t-1} + \begin{bmatrix} B_{t-1} \\ (1 - \lambda_{t-1}) B_{t-1} \end{bmatrix} w_t$$

“Non-Linear” States $V_t$

$$V_t = \begin{bmatrix} \lambda_t \\ \log \varsigma_{\eta,t}^2 \\ \log \varsigma_{\nu,t}^2 \end{bmatrix} \sim p(V_t|V_{t-1})$$
“Linear” States $S_t$

\[
\begin{bmatrix}
    x_t \\
    F_t x_t
\end{bmatrix}
= S_t =
\begin{bmatrix}
    \Theta_{t-1} & 0 \\
    (1 - \lambda_{t-1})\Theta_{t-1} & \lambda_{t-1}\Theta_{t-1}
\end{bmatrix}
S_{t-1}
\]

\[
+ \begin{bmatrix}
    B_{t-1} \\
    (1 - \lambda_{t-1})B_{t-1}
\end{bmatrix} w_t
\]

“Non-Linear” States $V_t$

\[
V_t = \begin{bmatrix}
    \lambda_t \\
    \log \zeta^{2,\eta,t} \\
    \log \zeta^{2,\nu,t} \\
    \theta_t
\end{bmatrix}
\sim p(V_t|V_{t-1})
\]
"Linear" States $S_t$

\[
\begin{bmatrix}
  x_t \\
  F_t x_t
\end{bmatrix} = S_t = \begin{bmatrix}
  \Theta_{t-1} & 0 \\
  (1 - \lambda_{t-1})\Theta_{t-1} & \lambda_{t-1}\Theta_{t-1}
\end{bmatrix} S_{t-1} + \begin{bmatrix}
  B_{t-1} \\
  (1 - \lambda_{t-1})B_{t-1}
\end{bmatrix} \omega_t
\]

TVP-transition and interaction between $\lambda_t$ and $(B_t, \Theta_t)$!

"Non-Linear" States $\mathcal{V}_t$

\[
\mathcal{V}_t = \begin{bmatrix}
  \lambda_t \\
  \log \zeta_{\eta,t}^2 \\
  \log \zeta_{\nu,t}^2 \\
  \theta_t
\end{bmatrix} \sim p (\mathcal{V}_t | \mathcal{V}_{t-1})
\]
AGENDA

1. Nonlinear State Space
   - recursive law of motion for SI
   - state vector
   - measurement vector

2. Estimation Strategy

3. Results
### DATA AND MEASUREMENT VECTOR

#### Measurement Vector

\[
y_t = \begin{bmatrix}
p_{t}^* \\
p_{SPF,t+1\rightarrow t+1} \\
\vdots \\
p_{SPF,t+1\rightarrow t+5}
\end{bmatrix}
= \begin{bmatrix}
p_{t} \\
F_t p_{t+1} \\
\vdots \\
F_t p_{t+5}
\end{bmatrix}
+ \begin{bmatrix}
\xi_{t,p} \\
\xi_{t,t+1} \\
\vdots \\
\xi_{t,t+5}
\end{bmatrix}
= C_t S_t + \xi_t
\]

#### Data

- Real-time measure of realized inflation \( p_t^* \)
- SPF surveys for GDP/GNP deflator 1968:Q4 – 2016:Q1
- Forecast horizons up to one year out
- Surveys collected mid-quarter \( t \), treated as \( F_{t-1}(\cdot) \)
**DATA AND MEASUREMENT VECTOR**

**Measurement Vector**

\[
y_t = \begin{bmatrix}
\pi_t^* \\
\pi_{SPF}^{t+1 \rightarrow t+1} \\
\vdots \\
\pi_{SPF}^{t+1 \rightarrow t+5}
\end{bmatrix} = \begin{bmatrix}
\pi_t \\
F_t\pi^{t+1} \\
\vdots \\
F_t\pi^{t+5}
\end{bmatrix} + \begin{bmatrix}
\xi_{t,\pi} \\
\xi_{t,t+1} \\
\vdots \\
\xi_{t,t+5}
\end{bmatrix} = c_t s_t + \xi_t
\]

**Data**

- Real-time measure of realized inflation \( \pi_t^* \)
- SPF surveys for GDP/GNP deflator 1968:Q4 – 2016:Q1
- Forecast horizons up to one year out
- **Surveys collected mid-quarter \( t \), treated as \( F_{t-1}(\cdot) \)**
AGENDA

1. Nonlinear State Space
2. Estimation Strategy
3. Results
Nonlinear state space with conditional linearity

Data: \( Y_t \sim p(Y_t|S_t, V_t; \Psi) \)

States: \( S_t \sim p(S_t|S_{t-1}, V_{t-1}; \Psi) \)  
\( V_t \sim p(V_t|V_{t-1}; \Psi) \)

\( S_t|(Y^t, V^t; \Psi) \sim N(S_{t|t}, \Sigma_{t|t}) \)
### Nonlinear state space with conditional linearity

**Data:** \( \mathcal{Y}_t \sim p (\mathcal{Y}_t | S_t, \mathcal{V}_t; \Psi) \)

**States:**
- \( S_t \sim p (S_t | S_{t-1}, \mathcal{V}_{t-1}; \Psi) \)
- \( \mathcal{V}_t \sim p (\mathcal{V}_t | \mathcal{V}_{t-1}; \Psi) \)

\( S_t | (\mathcal{Y}^t, \mathcal{V}^t; \Psi) \sim N (S_{t|t}, \Sigma_{t|t}) \)

### Previous draft of the paper:

Particle filtering and smoothing conditional on calibrated \( \Psi \)

### Revised draft: “Particle Learning”

Online estimation of \( \Psi \) embedded in particle filter and smoother
(see Storvik, 2002; Carvalho et al, 2010)
**Storvik’s (2002) idea: track swarm of posteriors**

\[ \Psi^{(i)} \sim p(\Psi | Y^t, V^{t,(i)}) \]

- Characterize posteriors by sufficient statistics \( s_t^{(i)} \)
- Embedded into ”particle learning” by Carvalho et al.

Requires analytic posteriors, available in our case

**Consider the prior for** \( \sigma^2_\lambda = \text{Var} (\lambda_t - \lambda_{t-1}) \)

\[
\begin{align*}
(\sigma^2_\lambda)^{(i)} | V_t^{(i)} & \sim IG \left( s_{t-1}^{(i)} \right) \\
\end{align*}
\]

\[
\begin{align*}
s_{t-1}^{(i)} &= \left[ \alpha_{t-1}^{(i)}, \beta_{t-1}^{(i)}, \ldots \right]
\end{align*}
\]
Storvik’s (2002) idea: track swarm of posteriors

\[ \Psi^{(i)} \sim p(\Psi | \mathcal{Y}^t, \mathcal{V}^{t,(i)}) \]

- Characterize posteriors by sufficient statistics \( s_t^{(i)} \)
- Embedded into ”particle learning” by Carvalho et al.

Requires analytic posteriors, available in our case

Consider the posterior for \( \sigma_{\lambda}^2 = \text{Var} (\lambda_t - \lambda_{t-1}) \)

\[ (\sigma_{\lambda}^2)^{(i)} \mid (\mathcal{V}_t^{(i)}, \mathcal{V}_{t-1}^{(i)}) \sim IG \left( s_t^{(i)} \right) \]

\[ s_t^{(i)} = \left[ \alpha_{t-1}^{(i)} + \frac{1}{2}, \beta_{t-1}^{(i)} + \frac{1}{2} \cdot \left( \lambda_t^{(i)} - \lambda_{t-1}^{(i)} \right)^2, \ldots \right] \]
1. Nonlinear State Space
2. Estimation Strategy
3. Results
• Joint UC-SI state space
• TVP-AR(1) in inflation gap
• GDP/GNP deflator, real time 1968:Q3 – 2015:Q4
• SPF for $h = 1, \ldots, 5$
• Estimated with particle learning
AGENDA

1 Nonlinear State Space

2 Estimation Strategy

3 Results
   • Nowcast: RE vs SI
   • Inflation trend and gap
   • Signal embedded in the SPF
   • Non-linear inflation states
   • SI weight $\lambda_t$
   • [Scale Parameters]
AGENDA

1. Nonlinear State Space

2. Estimation Strategy

3. Results
   - Nowcast: RE vs SI
   - Inflation trend and gap
   - Signal embedded in the SPF
   - Non-linear inflation states
   - SI weight \( \lambda_t \)
   - [Scale Parameters]
SI NOWCAST

$F_t \pi_t$ (red), inflation $\pi_t$ (black)

\[
F_t \pi_t = (1 - \lambda_{t-1})\pi_t + \lambda_{t-1} F_{t-1} \pi_t
\]
SPF NOWCAST AND DATA

\( \pi_{t,t}^{SPF} \) (blue), inflation \( \pi_t^* \) (black)
$F_t \pi_t = (1 - \lambda_{t-1}) \pi_t + \lambda_{t-1} F_{t-1} \pi_t$
Local-level trend is EWMA of $\pi_t$  

$\tau_{t|t} = (1 - K_t)\tau_{t-1|t-1} + K_t\pi_t$  

where $K_t$ is the Kalman gain for the trend

SI trend is EWMA of $\tau_t$  

$F_t\tau_t = (1 - \lambda_{t-1})\tau_t + \lambda_{t-1}F_{t-1}\tau_{t-1}$

SI nowcast is nearly an EWMA of $\pi_t$  

$F_t\pi_t = (1 - \lambda_{t-1})\pi_t + \lambda_{t-1}F_{t-1}\pi_t$
AGENDA

1. Nonlinear State Space
2. Estimation Strategy
3. Results
   - Nowcast: RE vs SI
   - Inflation trend and gap
   - Signal embedded in the SPF
   - Non-linear inflation states
   - SI weight $\lambda_t$
   - [Scale Parameters]
TREND INFLATION
RE (black), SI (red), filtered estimates
TREND INFLATION: UC-SI VS UC
RE Trends, UC-SI model (black), UC model (blue)
AGENDA

1. Nonlinear State Space
2. Estimation Strategy
3. Results
   - Nowcast: RE vs SI
   - Inflation trend and gap
   - Signal embedded in the SPF
   - Non-linear inflation states
   - SI weight $\lambda_t$
   - [Scale Parameters]
SPF AND TREND INFLATION
One-step ahead forecast (red), inflation (blue), SI trend (black)
SPF AND TREND INFLATION
Three-steps ahead forecast (red), inflation (blue), SI trend (black)
SPF AND TREND INFLATION
Four-steps ahead forecast (red), inflation (blue), SI trend (black)
SPF AND TREND INFLATION
Five-steps ahead forecast (red), inflation (blue), SI trend (black)
AGENDA

1 Nonlinear State Space

2 Estimation Strategy

3 Results
   • Nowcast: RE vs SI
   • Inflation trend and gap
   • Signal embedded in the SPF
   • Non-linear inflation states
   • SI weight $\lambda_t$
   • [Scale Parameters]
STOCHASTIC VOLATILITY IN TREND SHOCKS

Top: filtered, bottom: smoothed
STOCHASTIC VOLATILITY IN GAP SHOCKS

Top: filtered, bottom: smoothed
GAP AR COEFFICIENT $\theta_t$

Top: filtered, bottom: smoothed
AGENDA

1. Nonlinear State Space
2. Estimation Strategy
3. Results
   - Nowcast: RE vs SI
   - Inflation trend and gap
   - Signal embedded in the SPF
   - Non-linear inflation states
   - SI weight $\lambda_t$
   - [Scale Parameters]
SI WEIGHT $\lambda_t$

top: filtered, bottom: smoothed
SI WEIGHT AND MODEL SPECIFICATION

$\lambda_t$: TVP-AR(1) in red
SI WEIGHT AND MODEL SPECIFICATION

\( \lambda_t: \text{TVP-AR(1) in red, Const-AR with } \theta = 0 \text{ in black} \)
SI WEIGHT AND (ONE MINUS) INFLATION PERSISTENCE
Blue: IMA coefficient $\psi_t$ from $\Delta \pi_t = (1 - \psi_t L) e_t$
AGENDA

1 Nonlinear State Space

2 Estimation Strategy

3 Results
   - Nowcast: RE vs SI
   - Inflation trend and gap
   - Signal embedded in the SPF
   - Non-linear inflation states
   - SI weight $\lambda_t$
   - [Scale Parameters]
VOLATILITY OF $\lambda_t$ SHOCKS
Estimates of time-invariant parameter, updated with particle learning
VOLATILITY OF $\theta_t$ SHOCKS
Estimates of time-invariant parameter, updated with particle learning
VOLATILITY OF SHOCKS TO TREND LOG-VARIANCE
Estimates of time-invariant parameter, updated with particle learning
MEASUREMENT ERROR VARIANCE: INFLATION
Estimates of time-invariant parameter, updated with particle learning
MEASUREMENT ERROR VARIANCE: SPF-NOWCAST
Estimates of time-invariant parameter, updated with particle learning

![Graph showing measurement error variance over time with particle learning updates.](image-url)
MEASUREMENT ERROR VARIANCE: SPF-Q1
Estimates of time-invariant parameter, updated with particle learning
MEASUREMENT ERROR VARIANCE: SPF-Q2
Estimates of time-invariant parameter, updated with particle learning
MEASUREMENT ERROR VARIANCE: SPF-Q3
Estimates of time-invariant parameter, updated with particle learning
MEASUREMENT ERROR VARIANCE: SPF-Q4
Estimates of time-invariant parameter, updated with particle learning
Surveys have been sticky over the last couple of decades.

Sticky surveys should not be discarded: they are (at least) informative about the trend.

Still, trend inflation should lead the survey trend (which could be ominous given inflation data seen in recent years).

For future work: Sequencing of transition of persistence and stickiness from one ”regime” to another.
1. Does “stickiness” vary over time?
   Yes! Surveys have been quite sticky over the last couple of decades, but they were much less sticky before the mid-1980s.

2. How does “stickiness” interact with inflation?
   Stickiness seems to rise with falling inflation persistence and decreasing trend volatility.

3. Is “stickiness” related to monetary regimes?
   For future research: Stickiness seems to coincide with “well anchored” inflation expectations.
OUR CONTRIBUTIONS AND MAIN RESULT

Our contributions

- Joint state space for inflation and surveys that nests RE and SI
- Multivariate trend cycle decomposition for inflation with time-varying gap persistence
- Particle learning and smoothing combined with Rao-Blackwellization
- Expand on univariate regression results of Coibion and Gorodnichenko (2015, AER)

Main result

Striking comovement between inflation persistence and stickiness of surveys