

# Long run inflation expectations

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$\pi$  process:

$$\pi_t = \bar{\pi}_t + \pi_t^{Stat}$$

- $\bar{\pi}_t$  is a random walk with RW stochastic volatility
- $\pi_t^{Stat}$  is a TV ARMA(1,1) also with stochastic volatility

## Forecaster $i$

- Information

$$s_t(i) = \begin{bmatrix} s_{1,t} = \pi_t = \bar{\pi}_t + \pi_t^{Stat} \\ s_{2,t}(i) = \bar{\pi}_t + \alpha(i)v_{c,t} \\ s_{3,t}(i) = \bar{\pi}_t + v_t(i) \end{bmatrix}$$

- Goal

$$\bar{\pi}_{t|t}(i) = E(\bar{\pi}_t | \{s_k(i)\}_{k=1}^t, \theta(i))$$

where  $\theta$  are the (time invariant) parameters indexing the stochastic process.

## Data:

$\pi_t, \bar{\pi}_{t|t}(i)$  for  $t = 1, \dots, T$  and  $i = 1, \dots, N$

## Interesting objects:

$$N^{-1} \sum_i \bar{\pi}_{t|t}(i) - E(\bar{\pi}_t | \{\pi_k\}_{k=1}^T)$$

$$\frac{\partial E(\bar{\pi}_t | \{s_k(i)\}_{k=0}^t)}{\partial(\text{shocks})} \quad (\text{'Impulse Responses'})$$

$$N^{-1} \sum_i \bar{\pi}_{t|t}(i) = f(\text{shocks}_{1:t}) \quad (\text{'Historical Decompositions'})$$

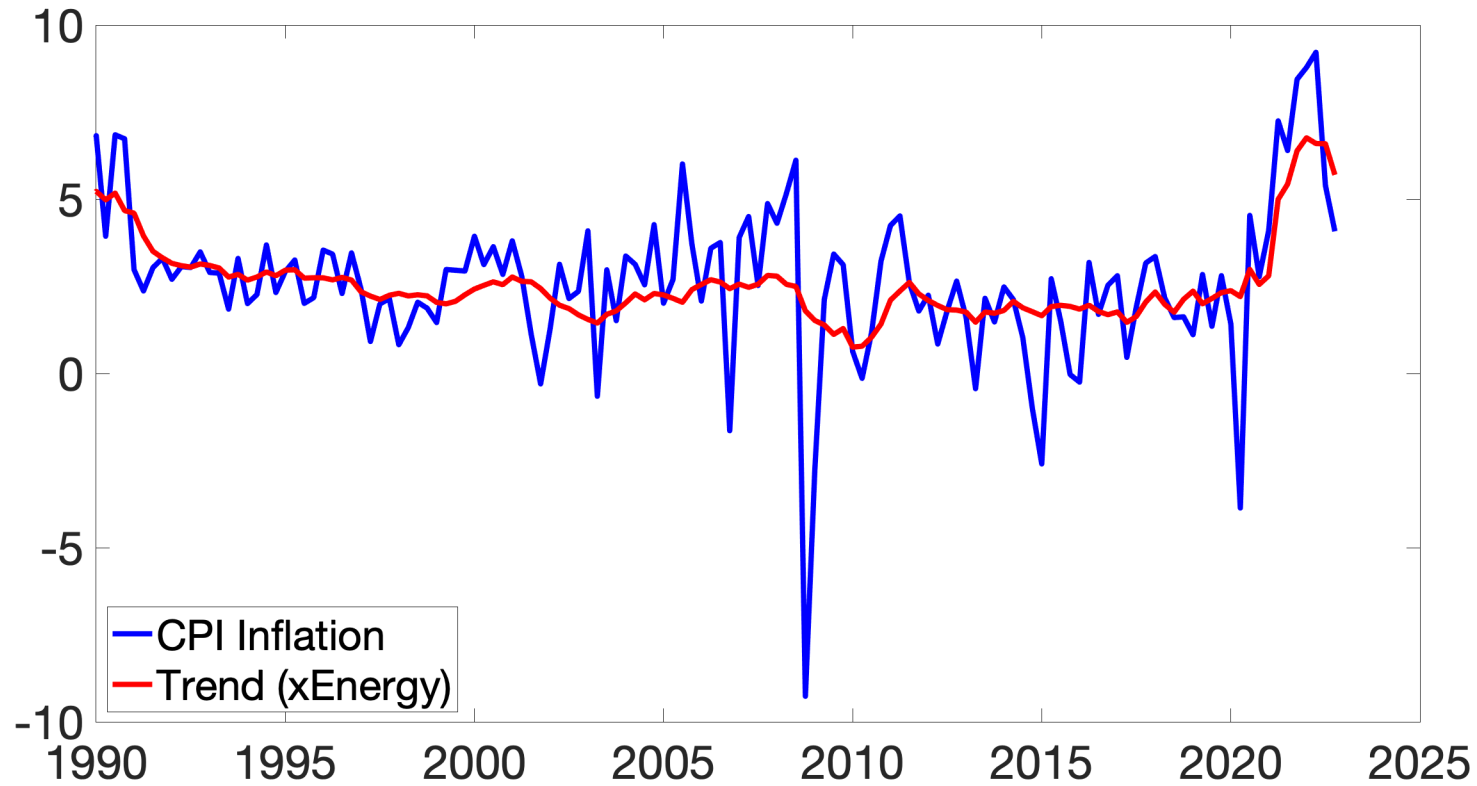
## Paper's Contributions:

1. Model
2. Sophisticated Implementation
3. Empirical Results

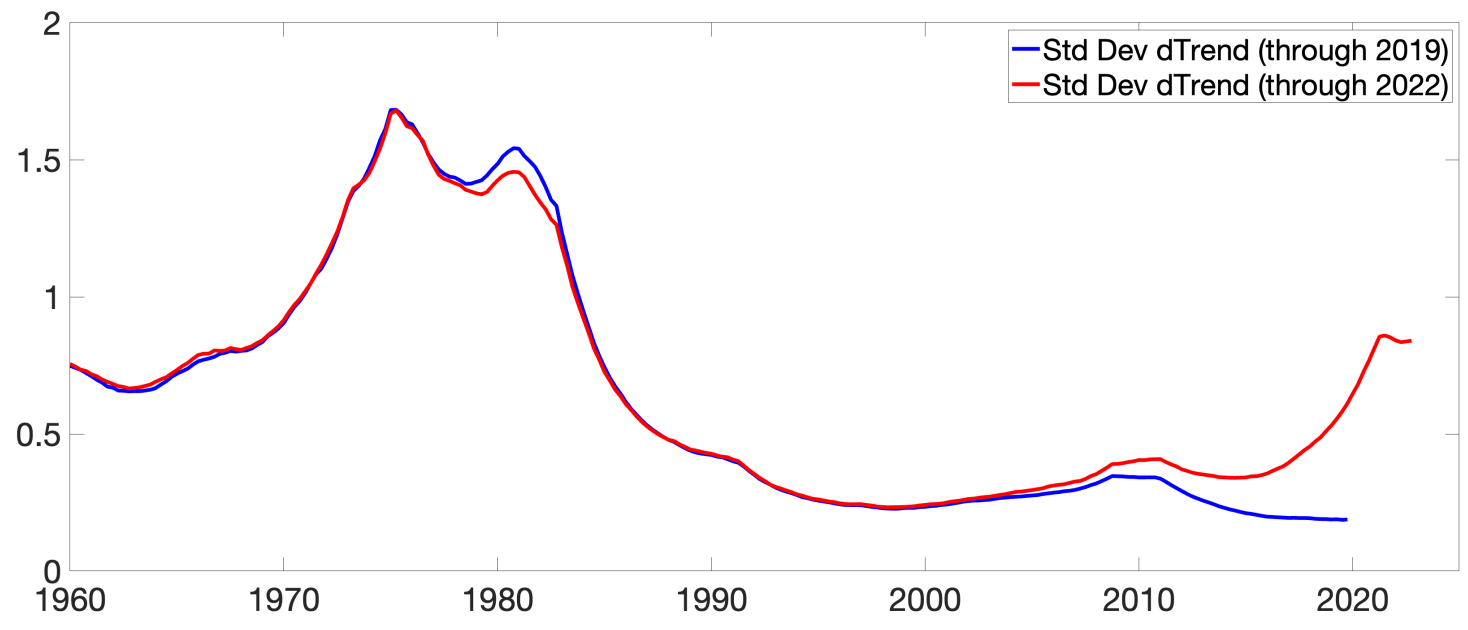
## Model:

$$\pi_t = \bar{\pi}_t + \pi_t^{Stat}$$

- $\bar{\pi}_t$  is a random walk with RW stochastic volatility;  $\pi_t^{Stat}$  is a TV **white noise** also with stochastic volatility



$$\pi_t = \bar{\pi}_t + \pi_t^{Stat}$$
$$StdDev(\Delta\bar{\pi}_t) = \sigma_{\Delta\bar{\pi}}$$



## $\sigma_{\Delta\bar{\pi}}$ and Long-Run Expectations (Beveridge-Nelson Arithmetic in time-invariant linear models)

- $\Delta\pi_t$ : Change in inflation
- $z_t$  vector of other variables that might be informative about future values of  $\pi$
- Suppose

$$\begin{bmatrix} \Delta\pi_t \\ z_t \end{bmatrix} = C(L)\varepsilon_t$$

- Let

$$\pi_t^{LR} = \pi_t^{BN} = \lim_{k \rightarrow \infty} \pi_{t+k|t}$$

Then

- $\pi_t^{BN}$  is a martingale

$$\Delta\pi_t^{LR} = e_1' C(1)\varepsilon_t$$

where  $e_1 = [1, 0, 0, \dots, 0]'$ .

- And

$$\text{var}(\Delta\pi_t^{LR}) = e_1' C(1) \Sigma_\varepsilon C(1)' e_1 = \text{var}^{LR}(\Delta\pi_t) \stackrel{\text{model}}{=} \text{var}(\Delta\bar{\pi}_t)$$

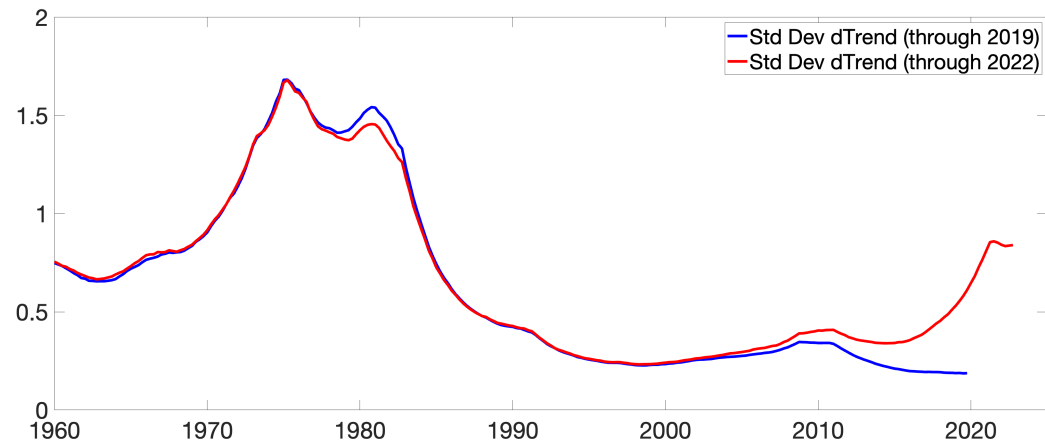
- Thus: Forecasters with different  $z$ 's will have different long-run forecasts ( $\pi_t^{LR} = \lim_{k \rightarrow \infty} \pi_{t+k|t}$ )  
... but the variances of the change in forecasts will be identical.

## 2 Implications:

1. We can learn about  $\text{var}^{LR}(\Delta\pi_t) \stackrel{model}{=} \text{var}(\Delta\bar{\pi}_t)$  from  $\text{var}(\Delta\pi_t^{LR})$
2. Differences across time or forecaster in  $\text{var}(\Delta\pi_t^{LR})$  are associated with differences in  $\text{var}^{LR}(\Delta\pi_t) \stackrel{model}{=} \text{var}(\Delta\bar{\pi}_t)$ .



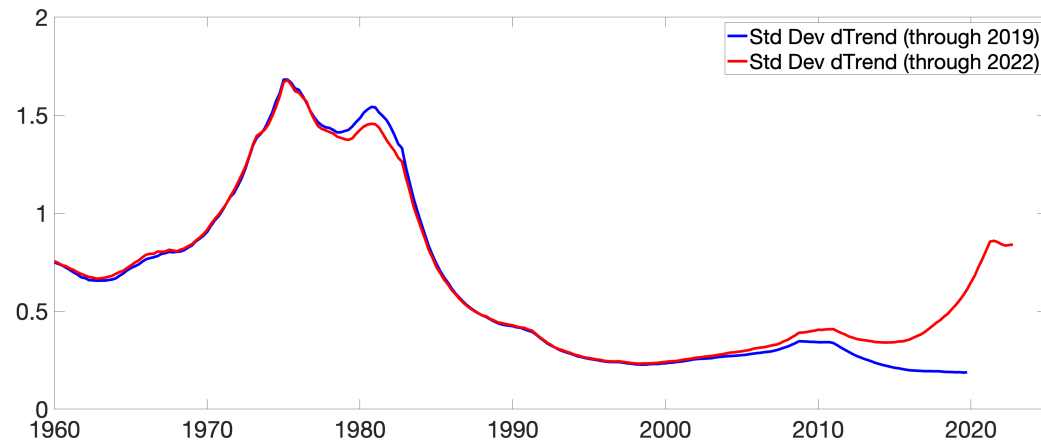
We can we learn about  $var^{LR}(\Delta\pi_t) \stackrel{model}{=} var(\Delta\bar{\pi}_t)$  from  $var(\Delta\pi_t^{LR})$



Standard Deviation of  $\Delta\pi_{it}^{LR}$  (pooled over forecasters)

Time Period	number of obs	$\hat{\sigma}_{\Delta\pi^{LR}}$
<b>1991-2010</b>	<b>1714</b>	<b>0.27</b>
<b>2011-2019</b>	<b>1028</b>	<b>0.32</b>
<b>2020-2022</b>		
<b>2021-2022</b>		

We can we learn about  $var^{LR}(\Delta\pi_t) \stackrel{model}{=} var(\Delta\bar{\pi}_t)$  from  $var(\Delta\pi_t^{LR})$



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<b>2011-2019</b>	<b>1028</b>	<b>0.32</b>
<b>2020-2022</b>	<b>219</b>	<b>0.30</b>
<b>2021-2022</b>	<b>134</b>	<b>0.32</b>

Differences across time and forecaster in  $var(\Delta\pi_t^{LR})$

### Forecaster $i$

- Information

$$s_t(i) = \begin{bmatrix} s_{1,t} = \pi_t = \bar{\pi}_t + \pi_t^{Stat} \\ s_{2,t}(i) = \bar{\pi}_t + \alpha(i)v_{c,t} \\ s_{3,t}(i) = \bar{\pi}_t + v_t(i) \end{bmatrix}$$

- Stochastic volatility with different information:

$$\sigma_{\Delta\bar{\pi}}^2(t) = [var(\Delta\bar{\pi}_t)]$$

$$\text{Forecaster } i: [\sigma_{\Delta\bar{\pi}}^2(t) | s_t(i), s_{t-1}(i), \dots]$$

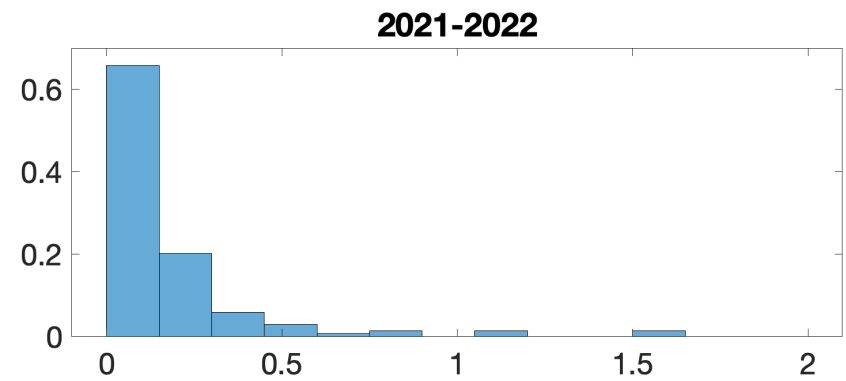
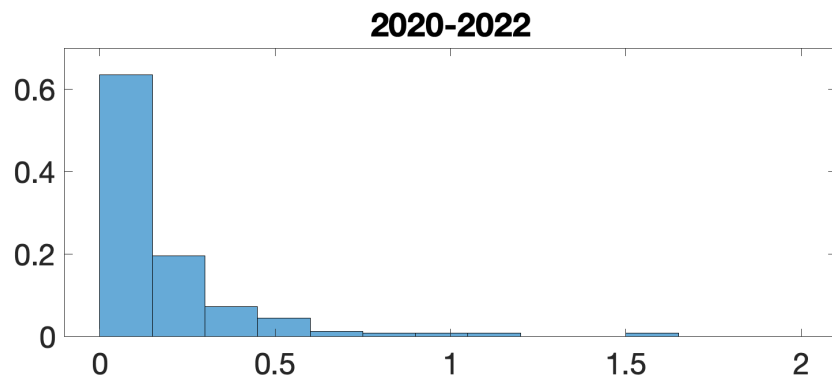
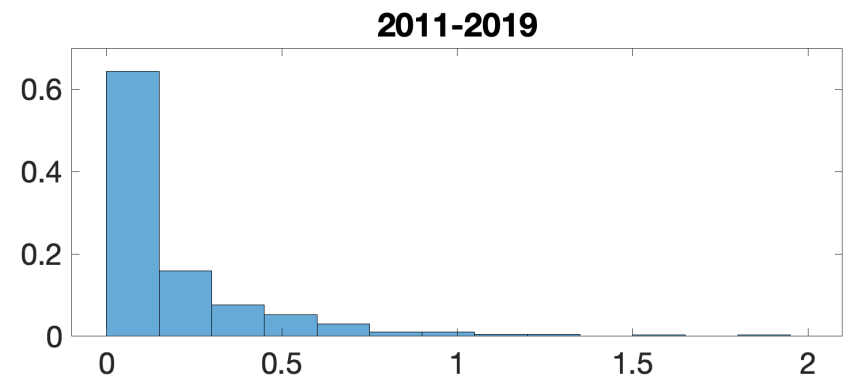
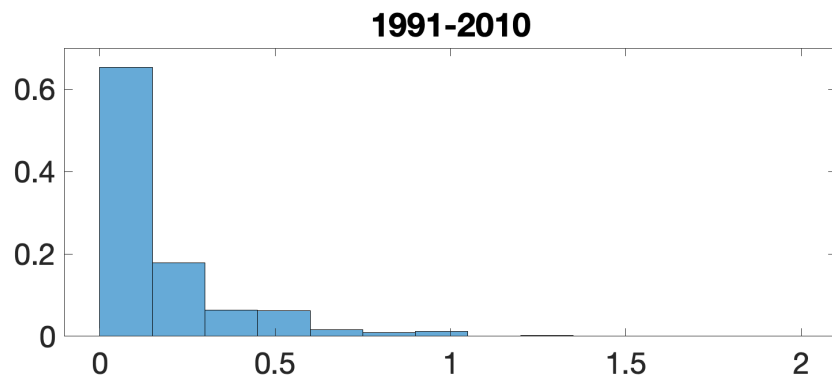
- These differences will be reflected in

$$\text{Var}(\Delta\pi_{it}^{LR})$$

- Are there differences across  $i$  in  $\text{Var}(\Delta\pi_{it}^{LR})$ ?
- Have these differences increased recently?
- Problem .. limited data for each forecaster ... observations not independent over  $i$ , etc.

One look at data: Histogram of  $|\Delta\pi_{it}^{LR}|$  over different time periods. (Disagreement .. fat tails?)

Histograms of  $|\Delta\pi_{it}^{LR}|$



Wrapping up:

FMR Inflation model

$$\begin{aligned}\pi_t &= \bar{\pi}_t + \pi_t^{Stat} \\ \bar{\pi}_t &= \bar{\pi}_{t-1} + \sigma_{\bar{\pi},t} \nu_t \\ \ln(\sigma_{\bar{\pi},t}) &= \ln(\sigma_{\bar{\pi},t}) + e_t\end{aligned}$$

Data

- Inflation Data: significant recent increase in  $\sigma_{\bar{\pi},t}$
- Long-run Expectations Data: little change in  $\sigma_{\bar{\pi},t}$