HRVATSKA NARODNA BANKA
EUROSUSTAV

31st DUBROVNIK ECONOMIC CONFERENCE

June 6 – 9, 2025, Dubrovnik, Croatia

Viral Acharya, Sebastian Hillenbrand and Venky Venkateswaran

Pandemic-era Inflation and Interest Rate Uncertainty in the US

Draft version

Please do not quote

Pandemic-era Inflation and Interest Rate Uncertainty in the US

Viral Acharya
NYU Stern

Sebastian Hillenbrand
HBS

Venky Venkateswaran
NYU Stern

June 2025

Table of Contents

Introduction

The post-Covid Recovery in the US

- Inflation surged to levels not seen for decades
- Delayed but sharp Fed response: rate hikes, quantitative tightening
- Rates remains high (and expected to be volatile)

What were the driving forces?

- Large shocks: supply (lockdowns, war) and demand (pent-up spending, fiscal stimulus) ?
- Loss of credibility: perceived dovish bias (New framework? "Team Transitory") ?
- Changes in the natural rate (r^*) ?

This paper: Evidence from financial markets + model-based inference

What we find

Empirical:

- Expected inflation rose sharply in 2021-22, but has since moderated significantly
- Interest rates rose with the hiking cycle and remain elevated
- Inflation uncertainty (σ_π) rose in 2021-22 and subsequently fell
- Interest rate uncertainty (σ_i) initially subdued, but rose sharply with the hiking cycle

$\Rightarrow$ *Relative* uncertainty (σ_i/σ_π) low in 2020-21, but spiked in 2022-23

Model:

- A stylized DSGE environment with learning about policy type

$\Rightarrow$ Loss of credibility $\rightarrow$ low relative uncertainty (σ_i/σ_π)

$\Rightarrow$ More volatile shocks $\rightarrow$ both σ_i and σ_π $\uparrow$ but relative uncertainty unaffected

Findings:

- Markets priced in a dovish Fed in 2020-2021, with a sharp reversal in 2022-23
- Shock volatility remains elevated

Related Literature

Determinants of post-Covid Inflation

- Ball, Leigh and Mishra (2022); Bernanke and Blanchard (2023); Giannone and Primiceri (2023); Gagliardone and Gertler (2024); di Giovanni, Kalemli-Özcan, Silva, Yildirim, and Yildirim (2023)....

This paper: Market-based evidence, Volatility vs credibility...

Expectations data to measure perceptions of Fed responsiveness

- Bauer, Pflueger and Sunderam (2024); Bocola, Dovis, Jorgensen and Kirpalani (2024) ...

This paper: Uncertainty, role of shock volatility...

Options-implied uncertainty measures

- Mertens and Williams (2021); Fleckenstein, Longstaff, and Lustig (2017); Wright (2017); Bahaj, Czech, Ding, and Reis (2023); Hilscher, Raviv, and Reis (2022)...

This paper: Structural interpretation, application to Covid...

Data: What do asset prices show?

Data Description

Expectations: Interest rate swaps, inflation swaps

- Forwards at 2y, 3y, 5y horizons

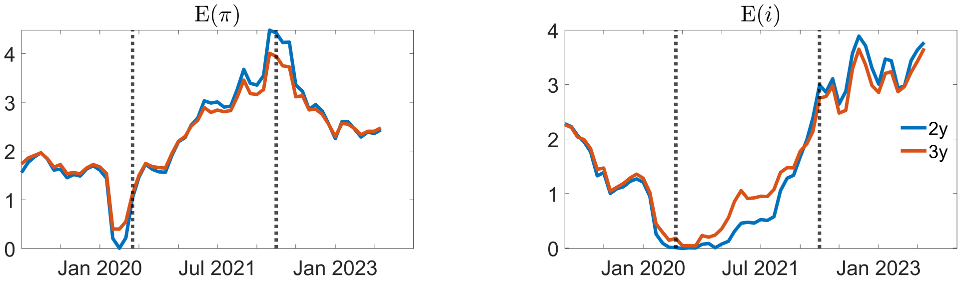
Rate uncertainty: Implied volatility from options on Treasury ETFs and TIPS ETFs

- Expiry: 6m, 1y, 2y
- Duration of underlying bonds: 7 (approx.)

Inflation uncertainty: requires a correlation between real and nominal rates

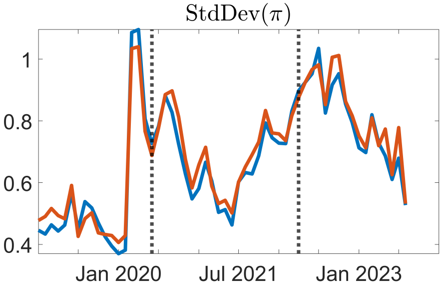
- Baseline assumption: rolling 3 month correlation
- Robustness: fixed correlation, comparison to other measures

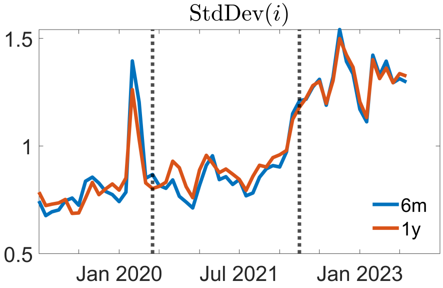
Data: Inflation and Rate Expectations



- Inflation expectations rose and fell, roughly tracking realized inflation
- Forward nominal rates started rising later and remain high

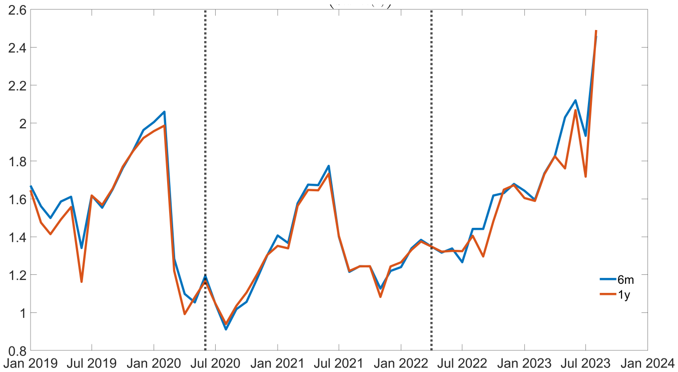
Data: Inflation and Rate Uncertainty





- Inflation uncertainty rose with the recovery and fell with the hiking cycle
- Interest rate uncertainty rose with a lag and remained high

Data: *Relative* Uncertainty, $\frac{\sigma(i)}{\sigma(\pi)}$



- Rel uncertainty low for most of 2020-21, but rose sharply in 2022-23

Model: What do these patterns say about Fed credibility?

Model: Overview

A stylized DSGE framework with learning

Key ingredients

- Current inflation depends on expected inflation, policy and an exogenous shock
- Policy follows a rule but type (responsiveness to inflation) unknown to agents
- Agents update beliefs by observing policy actions
- Exogenous process for the natural rate, r^*

Solution yields

- Expected interest rates and inflation at different horizons
- Standard deviations of rates and inflation at different horizons

Model: Equations

Natural real rate: sum of a random walk and a mean-reverting component

$$
\begin{aligned}
r_t^* &\equiv \hat{r}_t^* + \tilde{r}_t^* && \text{where} \\
\hat{r}_t^* &= \hat{r}_{t-1}^* + \hat{e}_t && \hat{e}_t \sim \mathcal{N}(0, \hat{\sigma}_e) \\
\tilde{r}_t^* &= \tilde{\rho}\tilde{r}_{t-1}^* + \tilde{e}_t && \tilde{e}_t \sim \mathcal{N}(0, \tilde{\sigma}_e)
\end{aligned}
$$

Inflation and nominal rates (in deviations from their natural levels):

$$
\begin{aligned}
\pi_t &\equiv \hat{\pi}_t - \pi_t^* \\
i_t &\equiv \hat{i}_t - r_t^* - \pi^*
\end{aligned}
$$

Deviations evolve according to

$$
\begin{aligned}
\pi_t &= \beta \mathbb{E}_t \pi_{t+1} - \kappa i_t + v_t \\
i_t &= \Phi_t \mathbb{E}_t \pi_{t+1} \\
v_t &= \rho v_{t-1} + u_t && u_t \sim \mathcal{N}(0, \sigma_u^2)
\end{aligned}
$$

where Φ_t : policy response coefficient. v_t : (exogenous) shock process

Model: Learning

Policy-maker can be of 2 types $j \in \{h, l\}$ and acts according to

$$\begin{aligned} \Phi_t &= \Phi_j \qquad \text{with prob} \quad 1-\epsilon \\ &= \Phi_{-j} \qquad \text{with prob} \quad \epsilon \end{aligned}$$

where $\Phi_h > \Phi_l$ and ϵ denotes noise (policy error).

Agents do not observe types, update beliefs $\boxed{p_t \equiv \text{Prob}_t(\text{type} = h)}$ according to

$$\begin{aligned} p_t|(\Phi_t = \Phi_h) &= \frac{p_{t-1}(1-\epsilon)}{p_{t-1}(1-\epsilon) + (1-p_{t-1})\epsilon} \\ p_t|(\Phi_t = \Phi_l) &= \frac{p_{t-1}\epsilon}{p_{t-1}\epsilon + (1-p_{t-1})(1-\epsilon)} \end{aligned}$$

Solution

Model: Connection to the New Keynesian Model

Key simplification: abstract from production/output gap

- Interest rates directly reduce inflation $\pi_t = \beta \mathbb{E}_t \pi_{t+1} - \kappa i_t + v_t$
- A single composite exogenous shock v_t (supply vs demand distinction less relevant)
- Policy sets rates based only on (expected) inflation $\mathbb{E}_t \pi_{t+1}$

Why?

- Lack of market-based measures for expected output gap (first or second moments)

$\Rightarrow$ Model estimates should be interpreted as composites

- E.g. policy dovishness could reflect larger role for supply shocks

Model-to-Data: Strategy

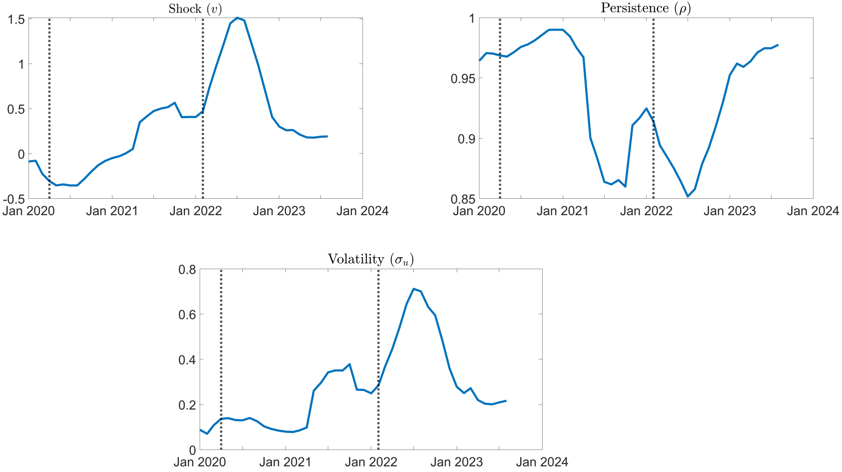
- Quarterly model
  - Treat data for each month as observations from independent economies
  - In progress: a regime-switching model
- Pre-assigned parameters, assumed constant over time (later: robustness)
  - $\beta = 0.99, \kappa = 1, \Phi_h = 1.5, \Phi_l = 0.5$
  - $\tilde{\rho} = 0.85 \;\; \hat{\sigma}_e^2 = \tilde{\sigma}_e^2 = 0$
- Random walk component $\hat{r}_t^*$: observed 5y5y fwd rate (real)
- Choose following to match expectations and uncertainty of i and π across horizons
  - v_t: Current shock
  - $p_t \in [0, 1]$: Current belief that policy is of type h
  - $\epsilon \in [0, 1]$: Likelihood of policy error, Prob(type-h chooses Φ_l or vice-versa)
  - $\rho \in [0, 1]$: Persistence of the shock
  - σ_u: Variance of the innovations to v
  - $\tilde{r}_t^*$: Current mean-reverting component of the natural rate

Solution Algorithm

Model: Fit

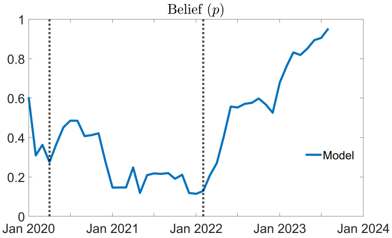
Note: Graphs show (6-month moving averages of) data moments and those implied by the model at estimated parameters .

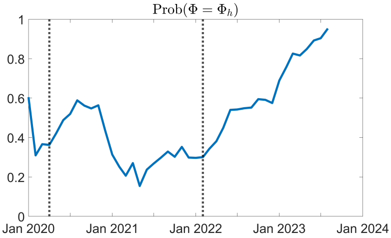
Model: Estimates



Note: Graphs show (6-month moving averages of) estimated parameters.

Model: Beliefs





2021: Market participants perceived

1. A policy rule that was less responsive to inflation (Loss of credibility?)
2. Larger, but less persistent shocks, relative to pre-Covid levels (Team transitory?)

2022-23: Credibility recovers but shock variance remains high

Note: Graphs show (6-month moving averages of) estimated parameters.

Model: Decomposing Uncertainty

Main idea: attribute changes in uncertainty to variation in

- Volatility: shock persistence or variance, (ρ, σ_u)
- Credibility: beliefs, (p_t)
- Policy variability: policy error, (ϵ)

Strategy: compute counterfactual uncertainty changing parameters one at a time

- Differences between these series isolate the role of each force
- Decompose change from a reference level: $\Phi_{t+s} = \Phi_h \;\; (\rho, \sigma_u)$ at pre-Covid levels

Model: Decomposing Uncertainty

For each month t and $x \in \{\pi, i\}$, compute variances under different assumptions

$$
\begin{aligned}
&\text{All parameters at estimated values} \quad \rightarrow \quad \sigma_t^2(x_{t+s}) \\
&\Pr(\Phi_{t+s} = \Phi_h) = \Pr(\Phi_t = \Phi_h)\ \forall s,\ \ (v_t, \rho, \sigma_u, r_t^*)\ \text{ at estim. values} \ \rightarrow\ \sigma_{t,III}^2(x_{t+s}) \\
&\Phi_{t+s} = \bar{\Phi}(p_t, \epsilon)\ \forall s,\ \ (v_t, \rho, \sigma_u, r_t^*)\ \text{ at estimated values} \ \rightarrow \quad \sigma_{t,II}^2(x_{t+s}) \\
&\Phi_{t+s} = \Phi_h\ \forall s,\ \ (v_t, \rho, \sigma_u, r_t^*)\ \text{ at estimated values} \quad \rightarrow \quad \sigma_{t,I}^2(x_{t+s}) \\
&\Phi_{t+s} = \Phi_h\ \forall s\ \ (\rho, \sigma_u)\ \text{at reference values,}\ (v_t, r_t^*)\ \text{ at estim. values} \ \rightarrow\ \sigma_{t,0}^2(x_{t+s})
\end{aligned}
$$

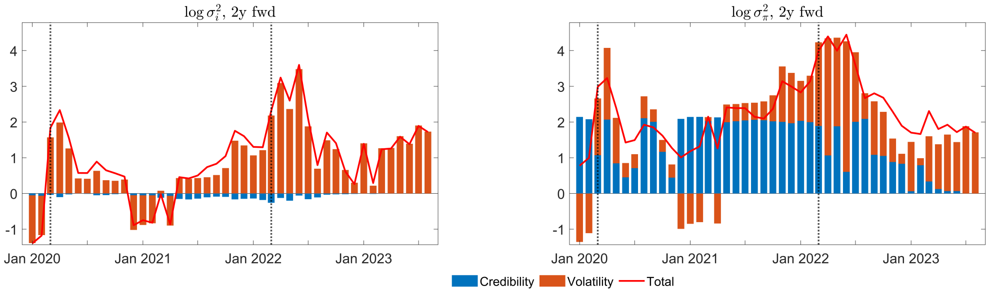
The overall change (w.r.t. the reference case)

$$
\text{Total} \quad \equiv \quad \log \sigma_t^2(x_{t+s}) - \log \sigma_{t,0}^2(x_{t+s})
$$

and the contributions of the various forces are:

$$
\begin{aligned}
\text{Volatility} \quad &\equiv \quad \log \sigma_{t,I}^2(x_{t+s}) - \log \sigma_{t,0}^2(x_{t+s}) \\
\text{Credibility} \quad &\equiv \quad \log \sigma_{t,II}^2(x_{t+s}) - \log \sigma_{t,I}^2(x_{t+s}) \\
\text{Policy randomness} \quad &\equiv \quad \log \sigma_{t,III}^2(x_{t+s}) - \log \sigma_{t,II}^2(x_{t+s})
\end{aligned}
$$

Model: Decomposing Changes in Uncertainty



- Low credibility, i.e. low p_t (yellow) $\Rightarrow$ higher σ_π and (slightly) lower σ_i
- High volatility (high ρ and/or σ_u) $\Rightarrow$ higher σ_π *and* σ_i

Note: Graphs show change in model-implied variance of forward rates (inflation and interest rates) relative to the reference case. Reference values for (ρ, σ_u) are averages for 2019.

Model: Decomposing Changes in Uncertainty

Goal: show decomposition of the relative volatility of forward interest rates and inflation

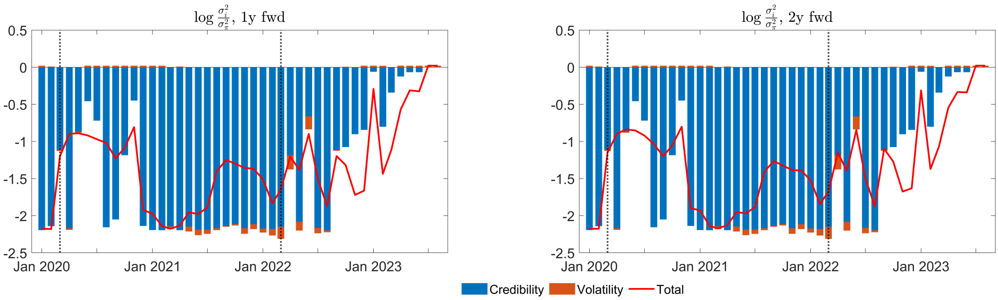
- Focus on $Var(i_{t+s})$ and $Var(\pi_{t+s})$ for $s = 4, 8$ quarters forward
- Results broadly similar for other horizons/maturities

Strategy:

- Use estimated model parameters to compute the contributions of volatility and credibility
- Reference case: (ρ, σ_u) set to averages for 2019 and $\Phi_{t+s} = \Phi_h \ \forall s$

Object of interest: Contribution to $Var(i_{t+s})$ less contribution to $Var(\pi_{t+s})$

Model: Decomposing Relative Uncertainty



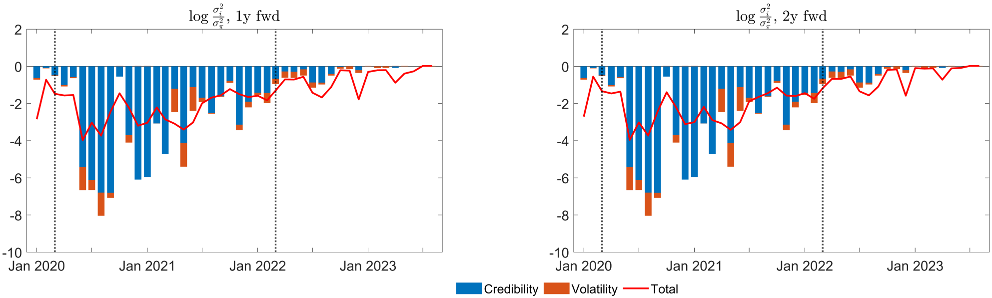
- Low relative uncertainty in 2021 almost entirely due to loss of credibility
- Lower shock persistence also contributed though only marginally

Note: Graphs show change in model-implied relative uncertainty relative to the reference case. Reference values for (ρ, σ_u) are averages for 2019.

Robustness

- Policy coefficients: $(\Phi_h, \Phi_l) = (1.50, 0.05)$ (baseline: $(\Phi_h, \Phi_l) = (1.5, 0.5)$)
- Elasticity of inflation to policy: $\kappa = 0.75$ (baseline: $\kappa = 1$)
- Target 2y ETF options (baseline: 1y)

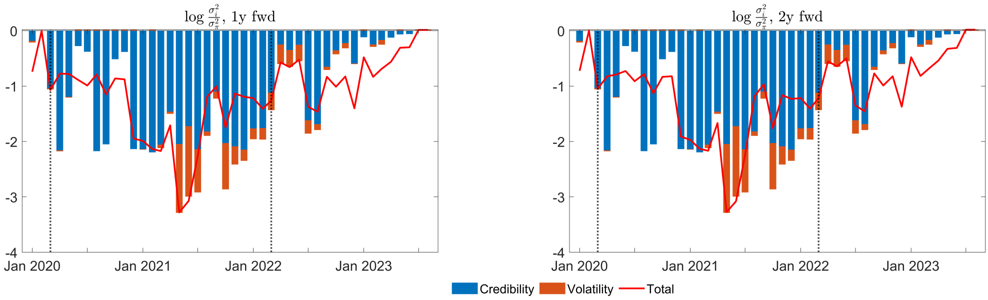
Robustness: $(\Phi_h, \Phi_l) = (1.5, 0.05)$



- Low relative uncertainty in 2021 almost entirely due to loss of credibility
- Lower shock persistence also contributed though only marginally

Note: Graphs show change in model-implied relative uncertainty of forward rates relative to the reference case. Reference values for (ρ, σ_u) are averages for 2019.

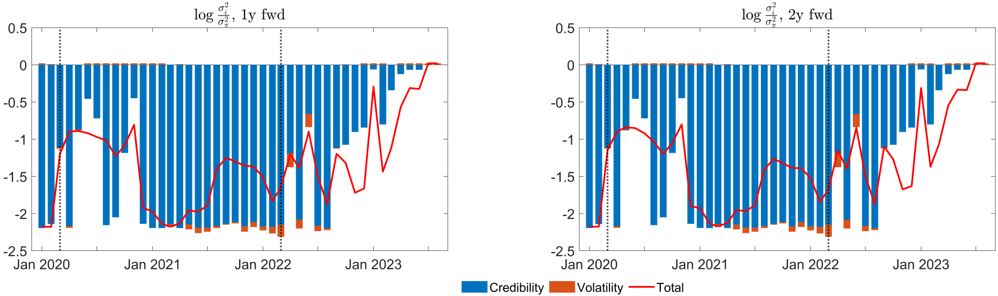
Robustness: $\kappa = 0.75$



- Low relative uncertainty in 2021 almost entirely due to loss of credibility
- Lower shock persistence also contributed though only marginally

Note: Graphs show change in model-implied relative uncertainty relative to the reference case. Reference values for (ρ, σ_u) are averages for 2019.

Robustness: Target 2y ETF Options



- Low relative uncertainty in 2021 almost entirely due to loss of credibility
- Lower shock persistence also contributed though only marginally

Note: Graphs show change in model-implied relative uncertainty relative to the reference case. Reference values for (ρ, σ_u) are averages for 2019.

Model: Solution

Conjecture that the solution takes the (recursive) form

$$\pi(v,p,\Phi_j) = (a_j p + b_j)v$$
$$i(v,p,\Phi_j) = \Phi_j \mathbb{E}\pi(v',p',\Phi_j') = \Phi_j \rho v \mathbb{E}(a_{j'}\ p' + b_{j'}|p)$$

To solve for (a_j, b_j), substitute conjecture into the equation for π

$$\pi(v,p,\Phi_j) = (\beta - \kappa\Phi_j)\rho v \mathbb{E}(a_{j'}\ p' + b_{j'}|p)$$

Evaluating the expectation and matching coefficients,

$$a_j = \frac{\rho\left(\beta - \kappa\Phi_j\right)}{1-\rho\left(\beta-\kappa\tilde{\Phi}_h\right)}\frac{\rho\left(\kappa\Phi_h - \kappa\Phi_l\right)}{1-\rho\left(\beta-\kappa\tilde{\Phi}_l\right)}\left(2\epsilon-1\right)$$

$$b_j = \frac{\rho\left(\kappa\tilde{\Phi}_l - \kappa\Phi_j\right)+1}{1-\rho\left(\beta-\kappa\tilde{\Phi}_l\right)} \qquad \text{where}$$

$$\tilde{\Phi}_h = (1-\epsilon)\Phi_h + \epsilon\Phi_l \qquad\qquad \tilde{\Phi}_l = (1-\epsilon)\Phi_l + \epsilon\Phi_h$$

Numerical Algorithm

For each t and a given $(v_t, p_t, \epsilon, \rho, \sigma_u, \tilde{r}_t^*)$, simulate a large number of paths

Compute

- Average $\mathbb{E}(i_{t+s}), \mathbb{E}(\pi_{t+s})$ for $s = 8, 12, 20$ (quarters)
- Std(i_{t+s}^{ETF}), Std(π_{t+s}^{ETF}) for $s = 2, 4$ (quarters)
- Sum of squared deviations from data moments

Search over $(v_t, p_t, \epsilon, \rho, \sigma_u, \tilde{r}_t^*)$ to minimize sum of squared deviations

- Non-linear optimizer: Particle swarm (initial swarm size = 500)

Back