# Individual Trend Inflation

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# Outline

# Motivation

1. Trend Inflation
   - Trend inflation is one of the most important inputs for the conduct of monetary policy.
   - However, it is not observable and hence needs to be estimated, such as an Unobserved Components Model (UCM), which recently incorporates inflation expectations.
   - We will add an element of Noisy Information to this class of models (UCM+NI).
2. Trend Inflation of Individual Forecasters
   - The literature on information rigidity (such as sticky/noisy information) highlights the importance of heterogeneity, which creates disagreement among forecasters, etc.
   - Thus, it is natural to gauge the trend inflation of individual forecasters in addition to that of mean forecasts and see what we can learn from estimating individual trend inflation.

# Findings

1. The added noise term plays a crucial role.
2. There exists considerable heterogeneity among individual trend inflation forecasts. The forecasters can be divided into two groups, say Groups A (12 forecasters) and B (50 forecasters), by cluster analysis.
    - Group A forecasters enter the survey during the sample (relatively newcomers).
    - Group A forecasters are more flexible in adjusting their forecasts of trend inflation in response to new information (shifting trend believers vs shifting trend skeptics).
    - At the same time, Group A see less noise in the inflationary process and the impact of transitory inflationary shocks to wane more quickly.
3. Group A's forecasts account for the rise (and the fall) in the mean trend inflation and the larger disagreement in trend inflation.

# Related Literature

- UCM + Inflation Expectations: Kozicki and Tinsley (2012), Chan et al. (2018), Nason and Smith (2021), Patton and Timmermann (2010), Yoneyama (2021)
- Inflation Rigidity (esp. Noisy Information): Woodford (2003), Mankiw and Reis (2002), Mankiw et al. (2004), Coibion and Gorodnichenko (2012, 2015), Shintani and Ueda (2021)
- Individual trend inflation: Hattori and Yetman (2017), Shintani and Soma (2020)
- The effects of UMP and 2%IT: Hayashi and Koeda (2019), Christensen and Spiegel (2019), Miyao and Okimoto (2017), Ehrmann (2015), Honda et al. (2013), Ehrmann et al. (2012), Ueda (2012), Capistran and Ramos-Francia (2010), Hattori et al. (2021), de Mendonca and de Deus (2019), Hubert (2015), Pederson (2015).

# Outline

# Unobserved Components Model

$$\pi_t = \tau_t + c_t \tag{1}$$
$$\tau_t = \tau_{t-1} + \nu_t \tag{2}$$
$$c_t = \rho c_{t-1} + \omega_t \tag{3}$$

- $\pi_t$ is inflation rate, $\tau_t$ is a permanent component, and $c_t$ is a transitory component.
- This is known as the Beveridge-Nelson decomposition (Beveridge and Nelson, 1981). Very easy to implement (EViews, R, Matlab).
- Stock and Watson (2007, 2016) applies the UCM to an inflation dynamics. They call $\tau_t$ trend inflation. They also assume stochastic volatility for $\nu_t$ and $\omega_t$. Its estimation requires the Bayesian MCMC technique.

# UCM + Inflation Expectation

$$\pi_t = \tau_t + c_t \quad (1)$$

$$\tau_t = \tau_{t-1} + \nu_t \quad (2)$$

$$c_t = \rho c_{t-1} + \omega_t \quad (3)$$

$$\hat{\pi}_{t,+k} = \tau_t + \rho^k c_t + u_{t,+k} \quad (4)$$

- $\tau_t$ and $c_t$ are permanent and transitory components perceived by forecasters.
- $\hat{\pi}_{t,+k}$ is $k$ period ahead expected inflation (such as surveyed by Consensus Forecast).
- As long as $|\rho| < 1$, infinity long-run expected inflation converges to $\tau_t$ ($\hat{\pi}_{t,+\infty} = \tau_t$).
- Chan et al. (2018) and Nason and Smith (2021) estimate variants of this model.

# UCM + Noisy Information

$$
\begin{aligned}
\pi_t &= \tau_{i,t} + c_{i,t} + \epsilon_{i,t}, \ \ \epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon i,t}) & (1)\\
\tau_{i,t} &= \tau_{i,t-1} + \nu_{i,t}, \ \ \nu_{i,t} \sim N(0, \sigma^2_{\nu i}) & (2)\\
c_{i,t} &= \rho_i c_{i,t-1} + \omega_{i,t}, \ \ \omega_{i,t} \sim N(0, \sigma^2_{\omega i}) & (3)\\
\hat{\pi}_{i,t,+k} &= \tau_{i,t} + \rho_i^k c_{i,t} + u_{i,t,+k} \ \ u_{i,t,+k} \sim N(0, \sigma^2_{ui,+k}) & (4)
\end{aligned}
$$

1. $\pi_t$ is the latest actual inflation rate available when forecaster $i$ makes his inflation forecasts at time $t$. He decomposes the observed inflation into unobserved trend $\tau_{i,t}$ and transitory $c_{i,t}$ (UC) components subject to noise $\epsilon_{i,t}$ (NI). Eg. imputed rents, fees for package tours to abroad, etc.
2. $\epsilon_{i,t}$ can be justified by a noisy signal model of Woodford (2003). See Shintani and Ueda (2021) for two types of noisy models (Lucas vs. Woodford).
3. $\epsilon_{i,t}$ follows a stochastic volatility process.

$$
\sigma^2_{\epsilon i,t} = \gamma_i \exp(\lambda_{i,t}), \ \ \lambda_{i,t} = \theta_i \lambda_{i,t-1} + \eta_{i,t}, \ \ \eta_{i,t} \sim N(0, \sigma^2_{\eta i}) \qquad (5)
$$

# Outline

# Data: ESP Survey

- For inflation forecasts, we use the ESP Forecast Survey from 2004M4 to 2020M3. Each month, ESP collects predictions from about 40 professional forecasters on core CPI inflation (excluding fresh food).
- ESP asks for quarterly and annual (fiscal year) forecasts. We use 0- to 4-quarter and 1-year ahead forecasts.
- ESP asks for year-on-year CPI inflation. Cumbersome adjustments need to be made.
- Use “without the effects of consumption tax hikes” series, if available. Otherwise, the authors make adjustments.

How far?

# Data: Real-time CPI

- For the actual CPI ($\pi_t$), we use a month-to-month change in the seasonally adjusted core CPI.
- Every five years, the Statistics Bureau of Japan has changed base years for the CPI calculation. This involves changes in the weight and coverage of the CPI baskets, as well as compilation details such as quality adjustments. This sometimes caused significant revisions. For instance, the rebasement from the 2000 index to the 2005 index (taking place in 2006M8) lowered the reading of core inflation in the first half of 2006 by about 0.5% points. To mimic the information set of forecasters at the time, we will use real-time data to the extent possible.
- To exclude the effects of consumption tax hikes, 2% points are subtracted from $\pi_{2014M4}$, which is consistent with the adjustment made for the ESP forecasts mentioned above. Furthermore, 0.2% points are subtracted from $\pi_{2019M10}$, the effect of which was published by the Statistics Bureau of Japan.

# Transformation to Y/Y

$$\pi_t = \frac{P_t}{P_{t-1}} - 1 = p_t - p_{t-1} = \Delta p_t,$$

where $P_t$ is CPI at time $t$ and the lower letter denotes its logarithm. A year-on-year change in CPI, $\pi_t^m$ is

$$\pi_t^m = p_t - p_{t-12} = \Delta p_t + \cdots + \Delta p_{t-11} = \sum_{j=0}^{11} \pi_{t-j},$$

and hence its quarterly average $\pi_t^q$ is

$$\pi_t^q = \frac{1}{3}\sum_{j=0}^{2} \pi_{t-j}^m = \frac{1}{3}(\pi_t + 2\pi_{t-1} + 3\pi_{t-2} + \cdots + 3\pi_{t-11} + 2\pi_{t-12} + \pi_{t-13}),$$

or

$$\pi_t^q = \left[\frac{1}{3}, \frac{2}{3}, \frac{3}{3}, \ldots, \frac{3}{3}, \frac{2}{3}, \frac{1}{3}\right] \begin{bmatrix} \pi_{t-13} \\ \vdots \\ \pi_t \end{bmatrix} = \mathcal{S} \begin{bmatrix} \pi_{t-13} \\ \vdots \\ \pi_t \end{bmatrix}.$$

# Estimation

Observation Equation

$$\begin{bmatrix} \pi_t \\ \hat{\pi}^q_{i,t} \\ \vdots \\ \hat{\pi}^q_{i,t,+4} \\ \hat{\pi}^a_{i,t,+1} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathcal{B} \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ \mathcal{Z}_\tau & \mathcal{Z}_c \end{bmatrix} \begin{bmatrix} \tau_{i,t} \\ c_{i,t} \end{bmatrix} + \begin{bmatrix} \epsilon_{i,t} \\ u^q_{i,t} \\ \vdots \\ u^q_{i,t,+4} \\ u^a_{i,t,+1} \end{bmatrix}$$

Transition Equation

$$\begin{bmatrix} \tau_{i,t} \\ c_{i,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho_i \end{bmatrix} \begin{bmatrix} \tau_{i,t-1} \\ c_{i,t-1} \end{bmatrix} + \begin{bmatrix} \nu_{i,t} \\ \omega_{i,t} \end{bmatrix}$$

where $\mathcal{B}, \mathcal{Z}_\tau$ and $\mathcal{Z}_c$ are selection matrices for y/y transformation and quarterly/annually average.

- Estimated by Bayesian Markov Chain Monte Carlo (MCMC) with an efficient Gaussian smoother of De Jong and Shephard (1995) and a multi-move sampler of Shephard and Pitt (1997) and Watanabe and Omori (2004) for stochastic volatility.
- Gibbs sampler for 21,000 replications, with 1,000 burn-in replications discarded and 20,000 replications retained.

# Outline

# Log Marginal Likelihood Estimates

| | |
|---|---|
| Baseline Model | -28.491 |
| Alternative Models: | |
| Drop a noise term $\epsilon_{i,t}$ | -66.506 |
| Use only $\hat{\pi}^q_{i,t,+0}$ | -33.165 |
| Assume stochastic volatility of $\nu_{i,t}$ and $\omega_{i,t}$ | -33.971 |

$$\begin{aligned}
\pi_t &= \tau_{*,t} + c_{*,t} + \epsilon_{*,t}, \;\; \epsilon_{*,t} \sim N(0, \sigma^2_{\epsilon *,t}) \\
\tau_{*,t} &= \tau_{*,t-1} + \nu_{*,t}, \;\; \nu_{*,t} \sim N(0, \sigma^2_{\nu *}) \\
c_{*,t} &= \rho_* c_{*,t-1} + \omega_{*,t}, \;\; \omega_{*,t} \sim N(0, \sigma^2_{\omega *}) \\
\hat{\pi}_{*,t,+k} &= \tau_{*,t} + \rho_i^k c_{*,t} + u_{*,t,+k} \;\; u_{*,t,+k} \sim N(0, \sigma^2_{u*,+k})
\end{aligned}$$

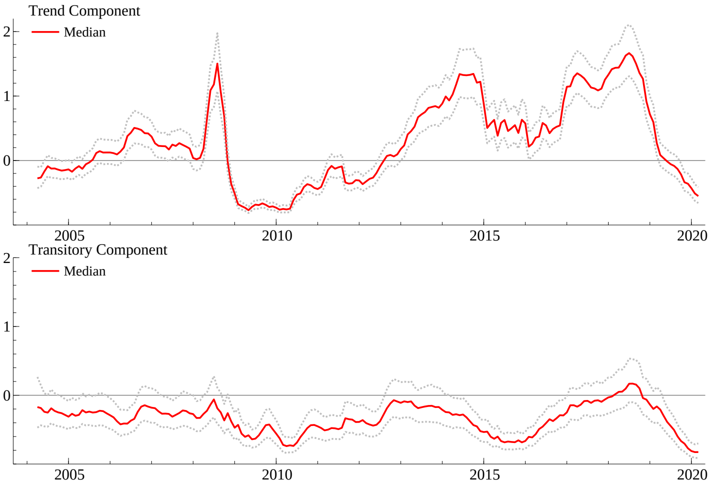
- * denotes mean forecaster.
- In the Bayesian context, model comparison should be based on marginal likelihood (not on simple criteria like AIC, BIC, etc.). The smaller negative values indicate a better fit.
- Marginal likelihood is based on predictive likelihood of $\pi_t$ over 2017M4-2020M3 (Chan et al., 2018). Technically speaking, this is the most complicated part.

# Posteriors for Mean Forecaster

| | Mean | Standard Deviation | Geweke's CD |
|---|---|---|---|
| $\rho_*$ (AR of $c_{*,t}$) | 0.887 | 0.039 | 0.37 |
| $\sigma_{u*,+0q}$ $(\hat{\pi}^q_{*,t,+0})$ | 0.205 | 0.011 | 0.43 |
| $\sigma_{u*,+1q}$ $(\hat{\pi}^q_{*,t,+1})$ | 0.204 | 0.011 | -0.03 |
| $\sigma_{u*,+2q}$ $(\hat{\pi}^q_{*,t,+2})$ | 0.159 | 0.009 | -0.55 |
| $\sigma_{u*,+3q}$ $(\hat{\pi}^q_{*,t,+3})$ | 0.112 | 0.007 | 0.34 |
| $\sigma_{u*,+4q}$ $(\hat{\pi}^q_{*,t,+4})$ | 0.116 | 0.008 | -0.60 |
| $\sigma_{u*,+1a}$ $(\hat{\pi}^a_{*,t,+1})$ | 0.110 | 0.007 | 0.49 |
| $\sigma_{\nu,*}$ $(\tau_{*,t})$ | 0.015 | 0.001 | -0.62 |
| $\sigma_{\omega,*}$ $(c_{*,t})$ | 0.018 | 0.002 | -0.32 |
| $\theta_*$ (AR of $\lambda*,_t$) | 0.933 | 0.046 | 0.48 |
| $\sigma_{\eta*}$ (SV) | 0.274 | 0.108 | 0.12 |
| $\gamma_*$ (SV) | 0.018 | 0.008 | -1.09 |

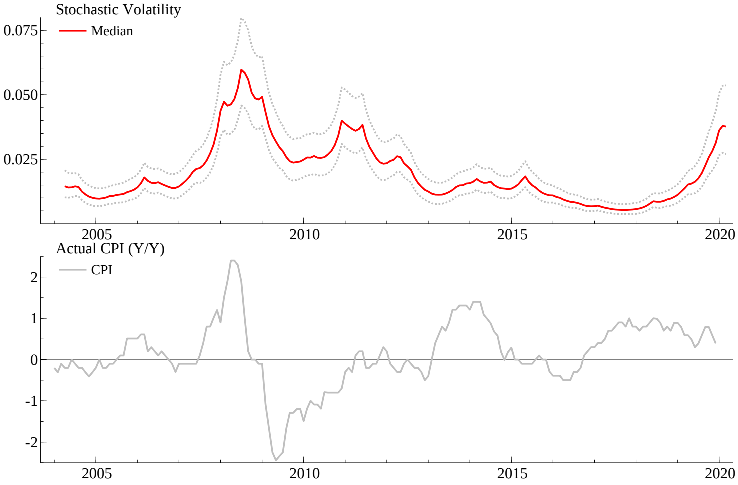
- Standard deviation of the HP filtered $\pi_t$ is 0.030%, which is comparable with 0.015 of $\sigma_{\nu,*}$. Gamma prior for this is 0.1%, which is slightly lower than the actual standard deviation of $\pi_t$ (0.14%).

# Estimates from Mean Forecaster (1)




- $\tau_{*,t}$ increased markedly after 2% IT (2013M1) and QQE (2013M4). It rose again after YCC (2016M9).
- $c_{*,t}$ hoovered small negative. The inflation forecasts tend to become the higher for the longer horizon (upward sloping).

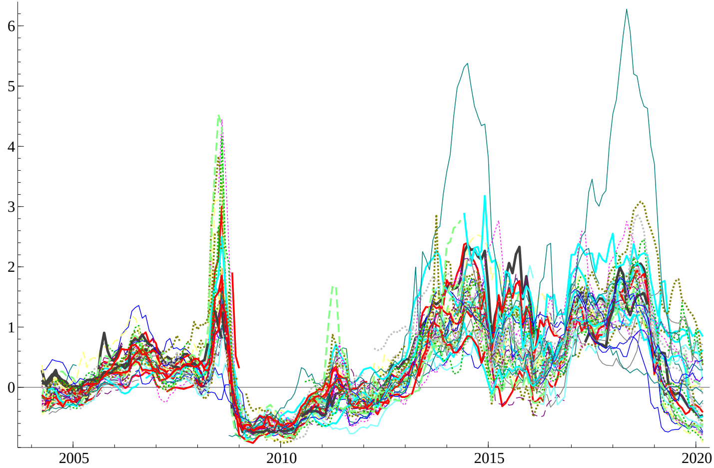
# Estimates from Mean Forecaster (2)




- Volatility is significant. It wad not high during 2013-2018. The end-of-period problem?

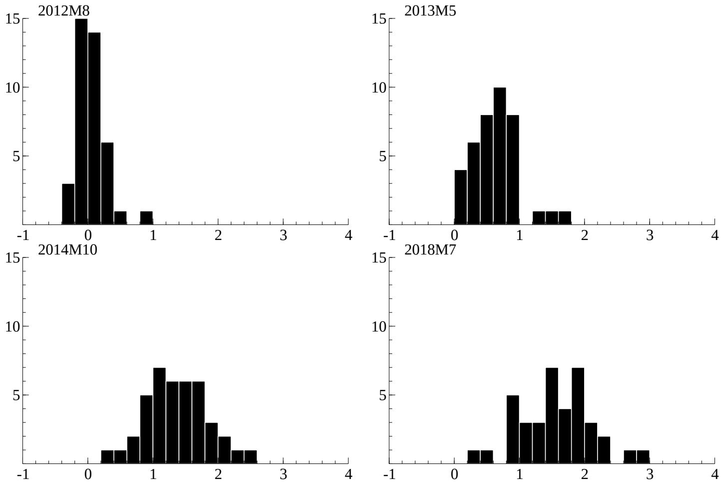
# Outline

# Individual Trend Inflation



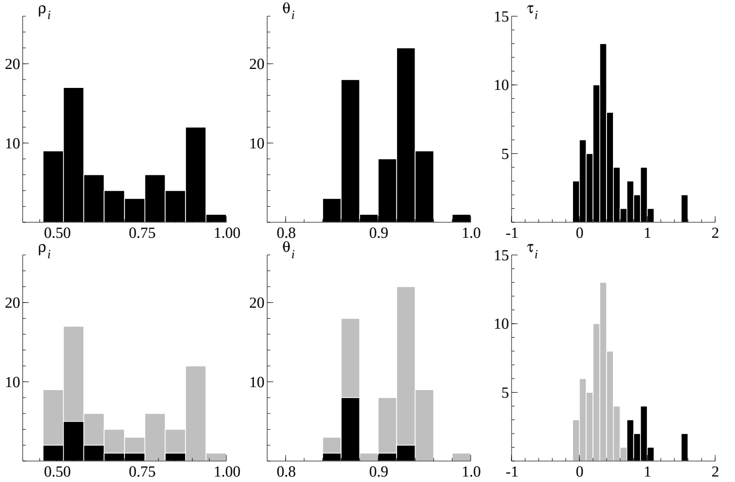

- Move together in a very broad view, but considerable heterogeneity.

# Histogram of Individual Trend Inflation



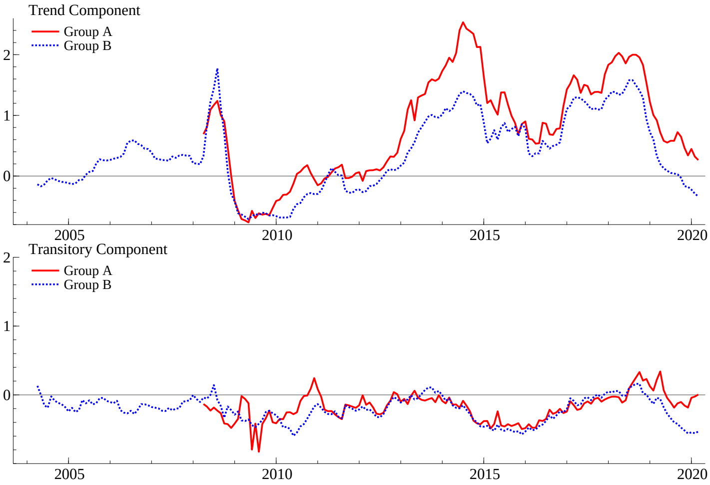

- Right shift
- Wider dispersion

# Histogram of Estimated Parameters




- Two types of forecasters?
- Applying K-mean cluster algorithm identifies two groups: Group A (12 forecasters) and Group B (50 forecasters).

# Trend and Transitory Components of Two Groups



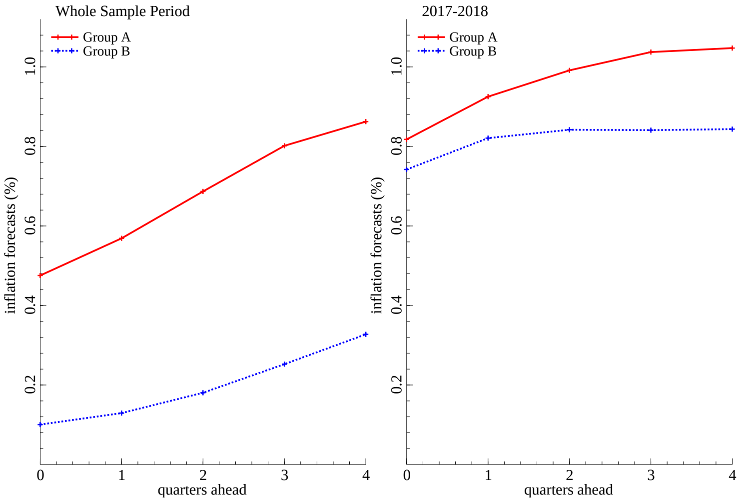

- Trend inflation is higher for Group A (but not for transitory components).
- Group A entered the survey during the sample period.

# Posteriors for Groups A and B

| | Group A | Group B | t-value | q-value |
|---|---|---|---|---|
| $\rho_i$ | 0.589 | 0.708 | -2.821 | 0.003 |
| $\sigma_{u,i,+0q}$ | 0.294 | 0.285 | 0.379 | 0.353 |
| $\sigma_{u,i,+1q}$ | 0.289 | 0.283 | 0.252 | 0.401 |
| $\sigma_{u,i,+2q}$ | 0.247 | 0.236 | 0.606 | 0.273 |
| $\sigma_{u,i,+3q}$ | 0.217 | 0.187 | 1.371 | 0.088 |
| $\sigma_{u,i,+4q}$ | 0.249 | 0.220 | 1.301 | 0.099 |
| $\sigma_{u,i,+a}$ | 0.207 | 0.181 | 1.339 | 0.093 |
| $\sigma_{\nu,i}$ | 0.025 | 0.023 | 0.668 | 0.253 |
| $\sigma_{\omega,i}$ | 0.026 | 0.026 | -0.114 | 0.455 |
| $\theta_i$ | 0.882 | 0.916 | -3.182 | 0.001 |
| $\sigma_{\eta,i}$ | 0.145 | 0.251 | -5.429 | 0.000 |
| $\gamma_i$ | 0.010 | 0.015 | -3.180 | 0.001 |

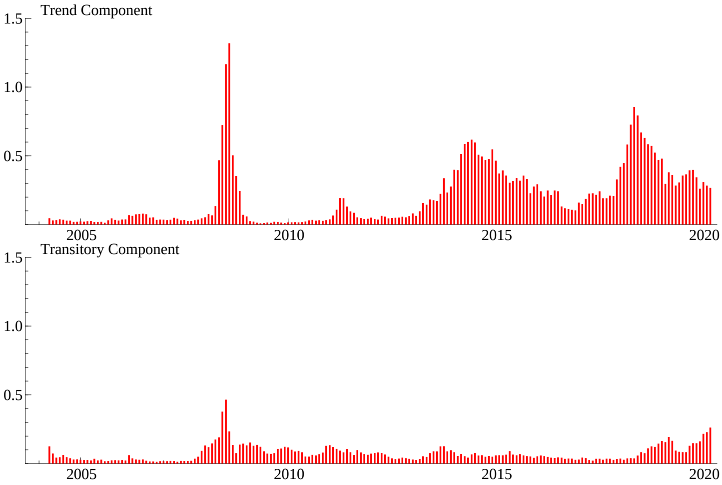
- The difference is significant at the 5% level for $\rho_i$, $\theta_i$, $\sigma_{\eta,i}$ and $\gamma_i$.
- Group A sees less noise in the inflationary process, expects the impact of transitory inflationary shocks to wane more quickly.

# Quarterly Inflation Forecasts ($\hat{\pi}^{q}_{i,t,+k}$)




- Inflation forecast curve of Group A is higher (because of higher $\tau_{i,t}$).
- Its curvature is steeper (because of smaller $\rho_i$).

# Disagreement




- Three hikes in disagreement of trend inflation.
- Most disagreement comes from trend inflation.

# Outline

# Source of Heterogeneous Responses

Group A enter the survey during the sample (relatively newcomers). They are more flexible in adjusting their forecasts of trend inflation in response to new information (shifting trend believers). At the same time, they see less noise in the inflationary process and the impact of transitory inflationary shocks to wane more quickly.

- Young individuals with less history update their expectation more strongly (Malmendier and Nagel, 2016)?
- Strategic behavior to make some forecasters differentiate themselves (Laster et al., 1999; Ottaviani and Sørensen, 2006)?
- Affiliations?

| | Group A | Group B |
|---|---|---|
| Banks and Insurance Companies | 3 (0.25) | 15 (0.30) |
| Security Firms | 6 (0.50) | 23 (0.46) |
| Others (non-financial) | 3 (0.25) | 12 (0.24) |
| Total | 12 (1.00) | 50 (1.00) |

# Effectiveness of the 2% Inflation Target and UMP

If, accompanied by the series of new measures, the new inflation target had been viewed as perfectly credible, there shouldn't be an increase in disagreement on trend inflation.

- The introduction of inflation targeting tends to reduce the dispersion of inflation forecasts (Crowe, 2010; Ehrmann et al., 2012), but the opposite happened in 2013 in Japan.
- The difficulty in targeting inflation from below, where under persistently low inflation below the central bank target, expectations tend to be unanchored, and forecasters disagree more (Ehrmann, 2015).

Some forecasters (Group A) lifted their trend inflation to 2% and this was a cause of rising disagreement. Though other forecasters (Group B) also raised their assessment of trend inflation, it was by much less.

- The glass is half full and half empty for the BOJ. The adoption of the inflation target and subsequent unconventional monetary policy measures succeeded in raising the trend inflation estimates of some forecasters but not all.

# Conclusion

- We propose a noisy information model to extract trend inflation of individual forecasters.
- We find that:
  1. The added noise term plays a crucial role.
  2. There exists considerable heterogeneity among individual trend inflation forecasts that drives the dynamics of the mean trend inflation forecasts.
- It is straightforward to apply our model to inflation forecasts made by professional forecasters in other countries. In principle, our model can also be applied to extract individual trend inflation of other agents such as households or corporations.

# How far do they forecast?

Responses of ID731 in [2019]

| | Quarters ahead | | | | | | | | | Years ahead | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | -1 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 0 | 1 | 2 |
| M1 Survey | 0.7 | 0.6 | 0.6 | 0.6 | 0.3 | 0.3 | 0.4 | 0.4 | 0.3 | 0.6 | 0.4 | 0.3 |
| M2 Survey | #N/A | 0.6 | 0.6 | 0.6 | 0.3 | 0.3 | 0.4 | 0.4 | 0.3 | 0.6 | 0.4 | 0.3 |
| M3 Survey | 0.4 | 0.3 | 0.1 | 0.3 | 0.2 | 0.4 | 0.4 | 0.3 | 0.3 | 0.5 | 0.2 | 0.3 |
| M4 Survey | 0.5 | 0.2 | 0.2 | -0.1 | 0 | 0 | 0.1 | 0.4 | 0.4 | 0.6 | 0.1 | 0.2 |
| M5 Survey | #N/A | 0.7 | 0.5 | 0.3 | 0 | 0 | 0.1 | 0.4 | 0.4 | #N/A | 0.4 | 0.2 |
| M6 Survey | 0.7 | 0.5 | 0.8 | 0.5 | 0.5 | 0.6 | 0.9 | 0.9 | #N/A | 0.6 | 0.7 | 0 |
| M7 Survey | 0.7 | 0.5 | 0.8 | 0.5 | 0.5 | 0.6 | 0.9 | 0.9 | #N/A | 0.6 | 0.7 | 0.2 |
| M8 Survey | #N/A | 0.5 | 0.8 | 0.5 | 0.5 | 0.6 | 0.9 | 0.9 | #N/A | 0.6 | 0.7 | 0.2 |
| M9 Survey | 0.5 | 0.8 | 0.5 | 0.5 | 0.6 | 0.9 | 0.9 | #N/A | #N/A | 0.6 | 0.7 | 0.2 |
| M10 Survey | 0.5 | 0.8 | 0.5 | 0.5 | 0.6 | 0.9 | 0.9 | #N/A | #N/A | 0.6 | 0.7 | 0.2 |
| M11 Survey | #N/A | 0.7 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | #N/A | #N/A | 0.6 | 0.5 | 0 |
| M12 Survey | 0.7 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | #N/A | #N/A | #N/A | 0.6 | 0.5 | 0 |

Note: 2-year ahead forecasts are available on a continuous basis only from the 2012M10 survey.

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