Managing the Risks of Inflation Expectation De-anchoring

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European Central Bank and IMF

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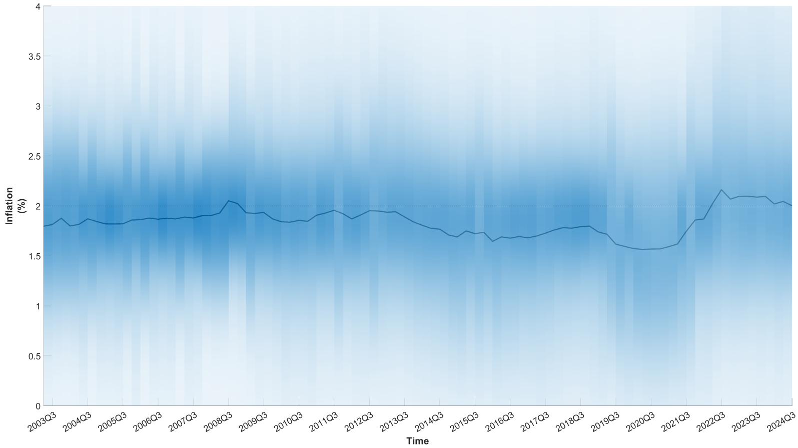
The views expressed are those of the authors and should not be attributed to the IMF, its Executive Board, or its management nor do they necessarily represent the view of ECB.

Aggregate probability distributions for longer-term inflation expectations

(annual percentage changes)

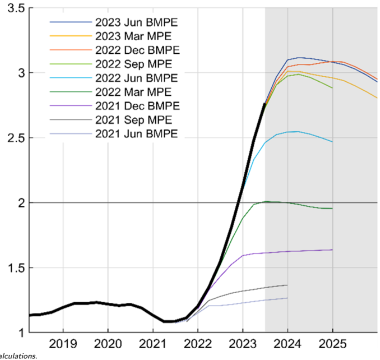


Sources: Authors' calculations, SPF.
Notes: The SPF asks respondents to report their point forecasts and to separately assign probabilities to different ranges of outcomes. This chart shows the bootstrapped pooled average probabilities assigned to different ranges of inflation outcomes in the longer term. Longer-term expectations refer to 5 years ahead responses.
Latest observations: 2024Q3.

Preview: Inflation De-Anchoring Risks Contained During Inflation Surge

Perceived inflation target in the projections from June 2021 to June 2023

(annual percentage changes)



Sources: Authors' calculations.

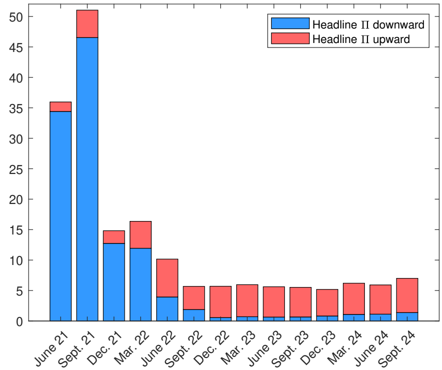
Notes: The charts show the perceived inflation target from June 2021 to June 2023. The perceived target is defined as:

$$\widehat{\pi^\star_t} = \rho\widehat{\pi^\star}_{t-1} + \varsigma(\pi_t - \widehat{\pi^\star}_{t-1}) + \varepsilon^{\pi^\star}_t$$

Latest observations: 2023Q2.

Risk of de-anchoring around the projections from June 2021 to June 2023

(percentages)



Sources: Authors' calculations.

Notes: The charts show the risk of de-anchoring for the projections from June 2021 to June 2023. The blue bars indicate downward, the yellow bars indicate upward de-anchoring. The model does not account for neither for the effective lower bound nor for non-standard measures.

Latest observations: 2023Q2.

Question

- **Current paradigm:** Inflation expectation targeting central banks promise that inflation will be at target in the medium-term on average.
- **Longer-term inflation expectations**: are time-varying [in surveys].
- **Policy concern:** Prolonged one sided deviations of inflation from target can threaten the credibility and may lead to a de-anchoring of inflation expectations.

Our contributions:

- **Revisit optimal monetary policy** in presence of regime-switching expectations:
  - Exogenous switching: Similar to Clarida et al. (1999).
  - Endogenous switching: Trade-off of current welfare losses due to more reactive policy and welfare gains from increased credibility.
- **Propose a framework to model risk of inflation de-anchoring** derived from conditional stochastic simulations of a MS-DSGE around a baseline.

Literature Review

- **De-anchored inflation expectations:**
  - **European empirical evidence on de-anchoring:** Dovern et al. (2020); Corsello et al. (2021); Bahaj et al. (2023)
  - **Learning the inflation target:** Erceg and Levin (2003); Cogley and Sbordone (2008)
  - **Adaptive learning:** Marcet and Sargent (1989); Marcet and Nicolini (2003); Milani (2007, 2014); Slobodyan and Wouters (2012); Gáti (2023); Christiano et al. (2024)
  - **Adaptive learning of multiple models:** Carvalho et al. (2023)
- **Optimal monetary policy under learning and/or regime-switching:** Woodford (2010); Adam and Woodford (2012); Choi and Foerster (2021); Gasteiger (2021); Gobbi et al. (2019); Nakata and Schmidt (2022)
- **Regime-switching DSGE:** Hamilton (1990); Davig and Leeper (2007); Farmer et al. (2009); Bianchi (2012); Maih (2015); Foerster et al. (2016); Bianchi and Ilut (2017)

Outline

- Motivation & Question ✓
- Optimal Policy
- Model Overview
- Regime-Switching Kálmán Filter Learning
- Policy Applications & Conclusions

Optimal Policy - Notation

- The perceived inflation target follows a two-state Markov process. With two regimes: $i = h, \ell$. Where the **household's inflation target** is either $\pi^{*,h} = \pi^{*,CB}$ in the high credibility state, or $\pi^{*,\ell} \neq \pi^{*,CB}$ in the low credibility state.
- Constant probability case:

$$\text{Prob}(\pi_{t+1}^{*,h} = \pi^{*,h} | \pi_t^{*,h} = \pi^{*,h}) = p^h$$

$$\text{Prob}(\pi_{t+1}^{*,\ell} = \pi^{*,\ell} | \pi_t^{*,\ell} = \pi^{*,\ell}) = p^\ell$$

- We study optimal MP policy in the 3 equation NK model:

$$\widehat{\pi}_t = \kappa \widehat{y}_t + \beta E_t[\widehat{\pi}_{t+1}] + u_t$$

$$\widehat{y}_t = E_t[\widehat{y}_{t+1}] - \frac{1}{\sigma}(i_t - E_t[\widehat{\pi}_{t+1}] - r_t^n) + g_t$$

Optimal Policy - Constant Probability Case

- Discretion results in Clarida et al. (1999) for each regime:

$$i_t^h = \sigma E_t[\widehat{y}_{t+1}^h] + \left[1 + \frac{\kappa\beta\sigma}{\kappa^2+\lambda}\right] E[\widehat{\pi}_{t+1}^{CB}] + \frac{\sigma\kappa}{\kappa^2+\lambda} u_t + \sigma g_t$$

$$i_t^\ell = \sigma E_t[\widehat{y}_{t+1}^\ell] + \left[1 + \frac{\kappa\beta\sigma}{\kappa^2+\lambda}\right] E[\widehat{\pi}_{t+1}^{CB}] + \frac{\sigma\kappa}{\kappa^2+\lambda} u_t + \frac{(1-\beta)\sigma\kappa - 1}{\kappa^2+\lambda}(\pi^{*,\ell} - \pi^{*,CB}) + \sigma g_t$$

, where $\widehat{\pi}^{CB}$ is the inflation deviation from the CB's target.

- Commitment results in a smoothing rule that considers future switching:

$$\begin{aligned} i_t^h = {} & r_t^n + \pi^{*,CB} + (1-p^h)(\pi^{*,\ell} - \pi^{*,CB}) \\ & + \left[p^h - \frac{\beta\kappa\sigma}{\lambda} A\right] E_t\left[\widehat{\pi}_{t+1}^h\right] + \left[(1-p^h) - \frac{\beta\kappa\sigma}{\lambda} B\right] E_t\left[\widehat{\pi}_{t+1}^\ell\right] \\ & + \frac{\beta\kappa\sigma}{\lambda}\left\{ p^h\left(E_t\left[\widehat{\pi}_{t+2}^h\right] - E_t\left[\widehat{\pi}_{t+1}^h\right]\right) + (1-p^h)\left(E_t\left[\widehat{\pi}_{t+2}^\ell\right] - E_t\left[\widehat{\pi}_{t+1}^\ell\right]\right)\right. \\ & \left. + C\left(E_t\left[\widehat{\pi}_{t+1}^h\right] - E_t\left[\widehat{\pi}_t^h\right]\right) + D\left(E_t\left[\widehat{\pi}_{t+1}^\ell\right] - E_t\left[\widehat{\pi}_t^\ell\right]\right)\right\} + \sigma g_t \end{aligned}$$

Optimal Monetary Policy Summary

The optimal policy in the case of constant switching probabilities, leads to higher rates and a bias in due to the inflation target gap, the endogenous switching introduces a more aggressive response to surprises in inflation.

- Optimal policy under **constant regime switching probabilities**
  $\rightarrow$ Similar to Clarida et al. (1999), using formulation of Nakata and Schmidt (2022): Forceful leaning against de-anchoring.
- Optimal policy under **endogenous switching probabilities**
  $\rightarrow$ As in Woodford (2010); Adam and Woodford (2012) a more aggressive response to realized inflation.

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Definition of De-Anchoring - Based on Filtering of Regimes

Long-term inflation expectations are time-varying.

Our framework:

- Household form regime-switching expectations about the inflation target.
- Taylor rule is defined and communicated with constant target:
  - **Anchored Regime:** Agents base their decisions on a constant inflation target.

$$\pi^* = 2.0\%$$

  - **De-Anchored Regime:** Agents base their decisions on a time varying inflation target.

$$\pi^* \longrightarrow \pi^* + \widehat{\pi^*}_t$$
$$\widehat{\pi_t^\star} = \rho \widehat{\pi^\star}_{t-1} + \varsigma(\pi_t - \widehat{\pi^\star}_{t-1}) + \varepsilon_t^{\pi^\star}$$

Once the probability of the de-anchored regime is higher we call expectations to be de-anchored.

Model - Regime-Switching NAWM

- The empirical exercise is based on the NAWM (Christoffel et al. ,2009) a workhorse macroeconomic DSGE model (Smets/Wouters plus open economy)
- Price and wage setting in the NAWM: Calvo with partial indexation scheme (Coenen, 2009)

$$P_{H,f,t} = \Pi_{H,t-1}^{\chi_H} \bar{\Pi}_t^{1-\chi_H} P_{H,f,t-1} \tag{1}$$

with $\chi_H = 0.42$ for domestic prices and $\chi_W = 0.63$ for wages.

$$\begin{aligned} \left(\widehat{\pi}_{H,t} - \widehat{\pi^*}_t\right) \quad = \quad & \frac{\beta}{1+\beta\chi_H} E_t\left[\widehat{\pi}_{H,t+1} - \widehat{\pi^*}_{t+1}\right] + \frac{\chi_H}{1+\beta\chi_H}\left(\widehat{\pi}_{t-1} - \widehat{\pi^*}_t\right) \\ & \frac{\beta\chi_H}{1+\beta\chi_H} E_t\left[\widehat{\pi^*}_{t+1} - \widehat{\pi^*}_t\right] + \frac{(1-\beta\xi_H)(1-\xi_H)}{\xi_H(1+\beta\chi_H)}\left(\widehat{mc}_t^H + \widehat{\varphi}_t^H\right) \end{aligned}$$

Comparison of Regimes

	Credible Regime	De-Anchored Regime
Inflation target	Fixed - Parameter	Time-varying - Endogenous state
Model parameters	Estimated	Estimated
# of endogenous states	$115 + 1$	$115 + 2$
# of shocks	21	$21 + 1$
# of observables	18	18
Steady state	Calibrated and estimated	Same as in the credible regime
Shock variance	Estimated	Estimated + calibrated

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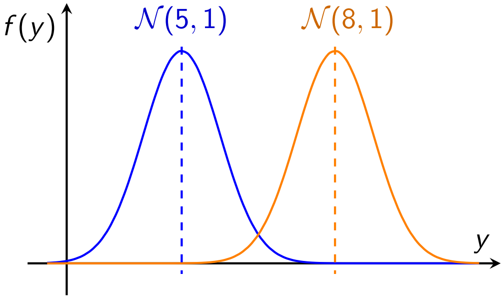
Intuition - Regime-Switching Kálmán Filter Learning

1. Agents **form expectations** given each regime
2. They have *a priori* beliefs about the regime probability - giving rise to a **mixture of normals**
3. **Structural shocks** and **data** realizes
4. Beliefs about the regime probabilities are updated - resulting in a *posterior* of regime probabilities.

Additional details on Regime-Switching Kálmán Filter.



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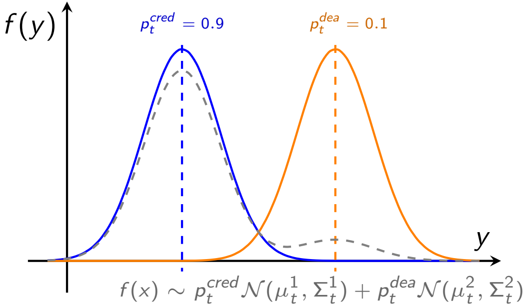

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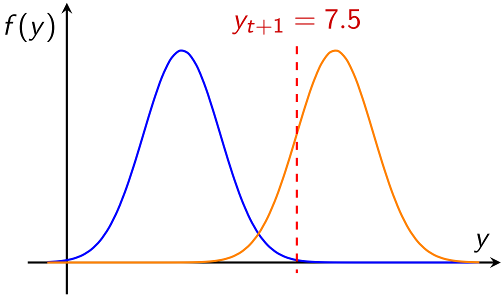

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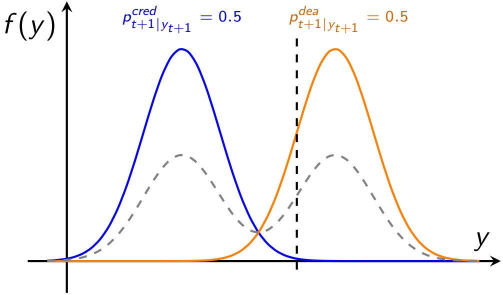
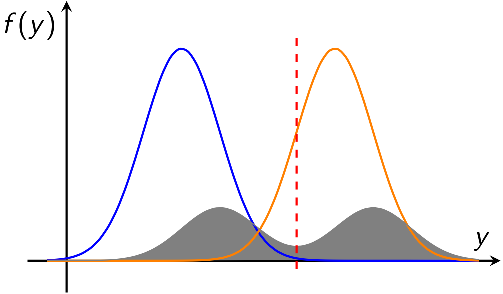


Additional details on Regime-Switching Kálmán Filter.

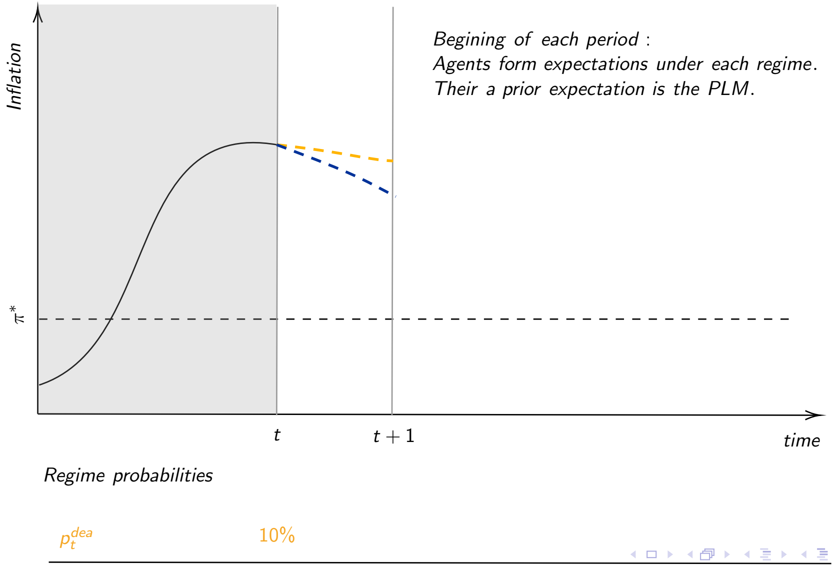
Intuition - Regime-Switching Kálmán Filter Learning

Time advances...

- Agents form expectations
- Shocks and data realizes
- Regime probabilities are updated



Intuition - Stochastic Simulation with Regime-Switching Kálmán Filter Learning



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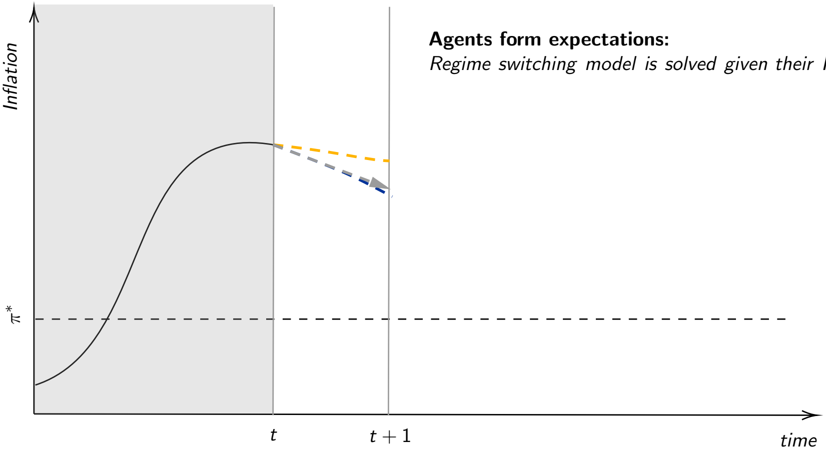

Agents form expectations:
Regime switching model is solved given their PLM.

Regime probabilities

p_t^{dea} 10%

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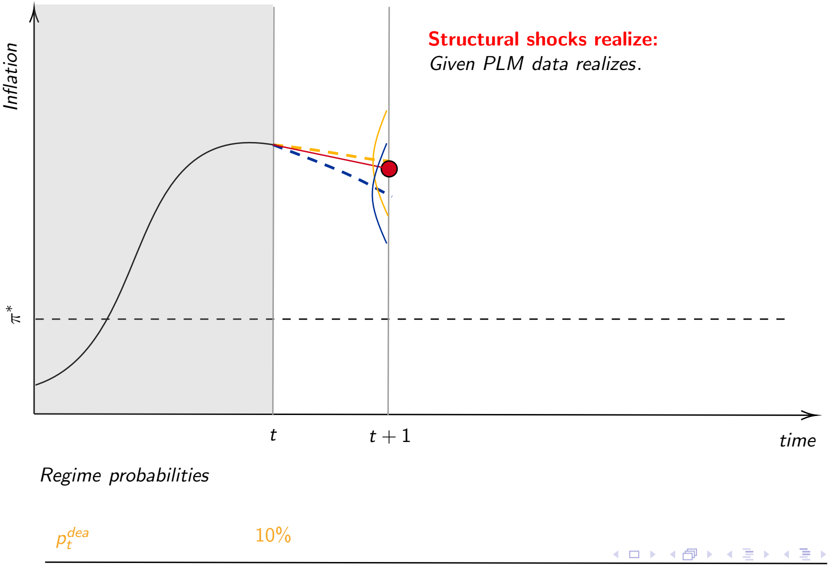

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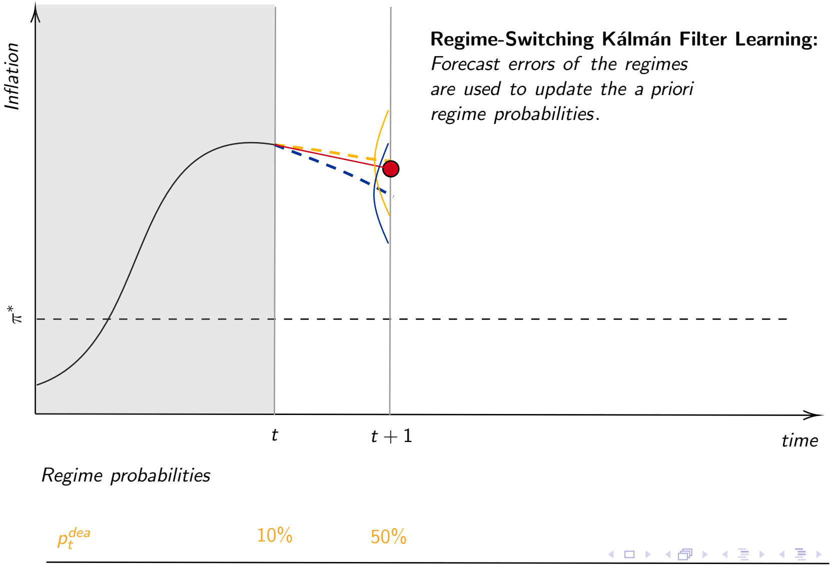
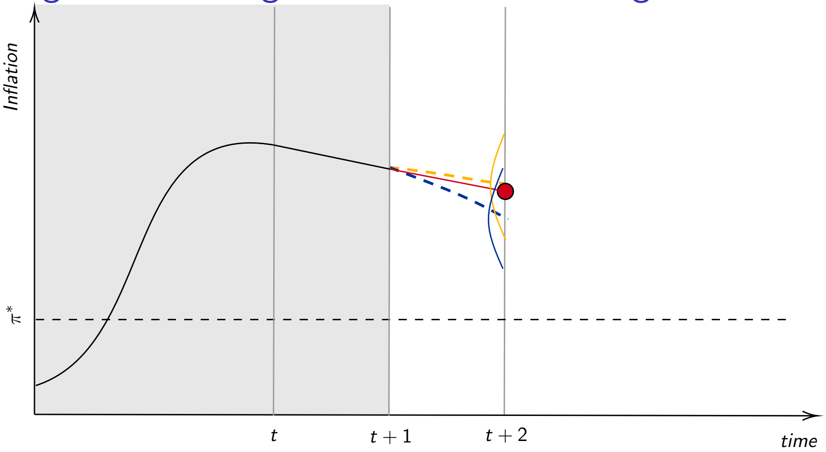


Regime-Switching Kálmán Filter Learning:
Forecast errors of the regimes are used to update the a priori regime probabilities.

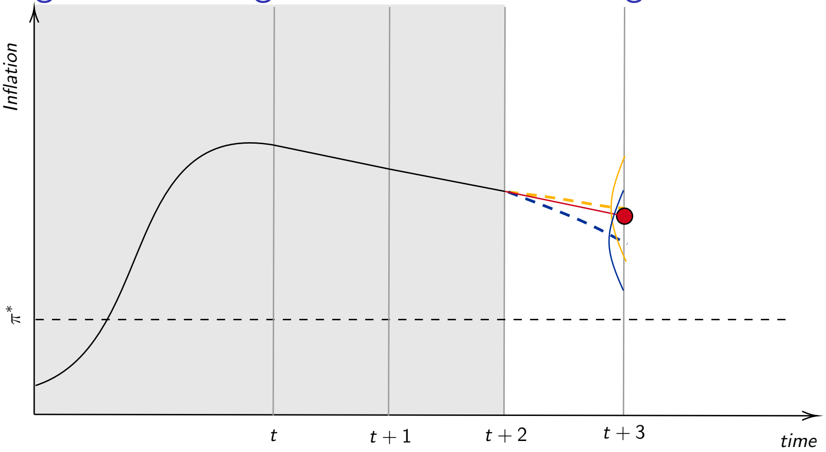
Intuition - Regime-Switching Kálmán Filter Learning: De-Anchoring



Regime probabilities

p_t^{dea}	10%	50%	75%
p_t^{cred}	90%	50%	25%

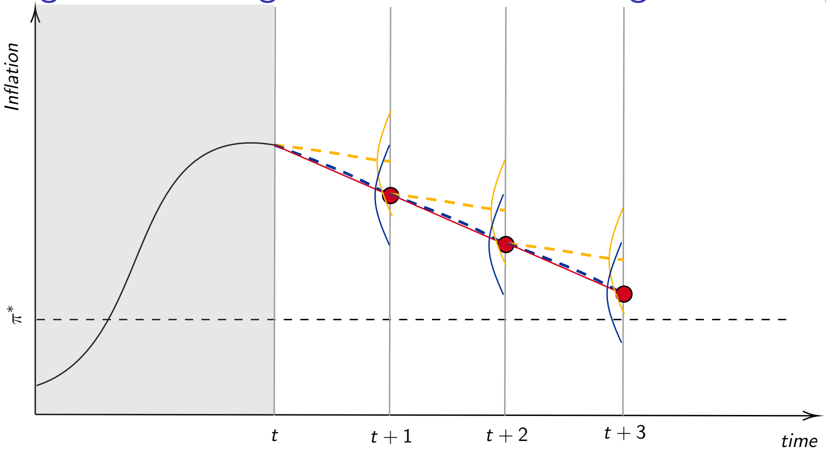
Intuition - Regime-Switching Kálmán Filter Learning: De-Anchoring



Regime probabilities

	t	$t+1$	$t+2$	$t+3$
p_t^{dea}	10%	50%	75%	90%
p_t^{cred}	90%	50%	25%	10%

Intuition - Regime-Switching Kálmán Filter Learning - Credibility



Regime probabilities

p_t^{dea}	10%	5%	3%	1%
p_t^{cred}	90%	95%	97%	99%

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Real-Time Exercises on Euro Area Projections

Definition of exercise:

- Each quarter: take real-time database and projection.
- Filter the data plus forecast with RS-NAWM
- Conduct stochastic simulations around the baseline and filter for regime probabilities.
- Calculate de-anchoring risks.

Definition of de-anchoring:

- Filtered regime probability of de-anchored regime exceeds 50%.

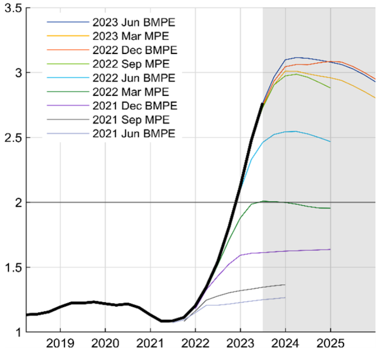
Definition of the risk of de-anchoring:

- The share de-anchored simulation paths around a projection.

Real-Time Exercises on Euro Area Projections

Perceived inflation target in the projections from June 2021 to June 2023

(annual percentage changes)



Sources: Authors' calculations.

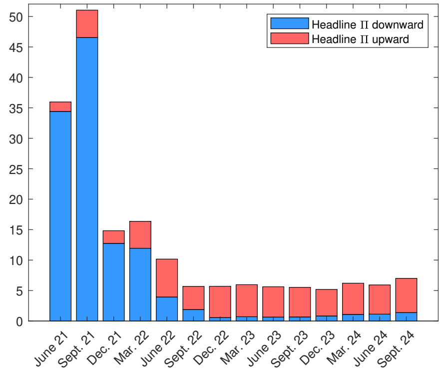
Notes: The charts show the perceived inflation target from June 2021 to June 2023. The perceived target is defined as:

$$\widehat{\pi^\star_t} = \rho\widehat{\pi^\star}_{t-1} + \varsigma(\pi_t - \widehat{\pi^\star}_{t-1}) + \varepsilon_t^{\pi^\star}$$

Latest observations: 2023Q2.

Risk of de-anchoring around the projections from June 2021 to June 2023

(percentages)

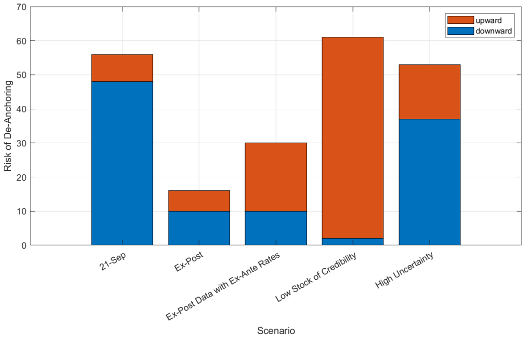


Sources: Authors' calculations.

Notes: The charts show the risk of de-anchoring for the projections from June 2021 to June 2023. The blue bars indicate downward, the yellow bars indicate upward de-anchoring. The model does not account for neither for the effective lower bound nor for non-standard measures.

Latest observations: 2023Q2.

Drivers of De-anchoring



- **Sep 21:** 'before the inflation surge': very flat expected inflation, low inflation period implied low perceived target.
- **Ex-post:** Re-evaluating the Sept 21 exercise with the ex-post realization of data.
- **Rate-setting:** ex-post data realization, but expected policy path from original Sep 21 exercise.
- **Stock of credibility:** assuming that the inflation surge had been preceded by a high inflation period (average inflation 2.9)
- **High uncertainty:** revisit the ex-post analysis, but assuming a higher shock variance.

Conclusions

- Introduction of a model based measure of de-anchoring and risks of de-anchoring.
- optimal policy implications call for leaning against de-anchoring risks and even stronger response to inflation is warranted if the CB can affect de-anchoring risks.
- complementary to survey based and capital market based measures, also allowing to evaluate de-anchoring risks on policy counterfactuals and scenarios.

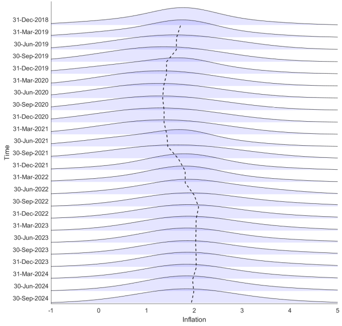
Thank you for your attention!

BACKGROUND SLIDES

Longer-term Inflation Expectations in the Euro Area

Aggregate probability distributions for longer-term inflation expectations

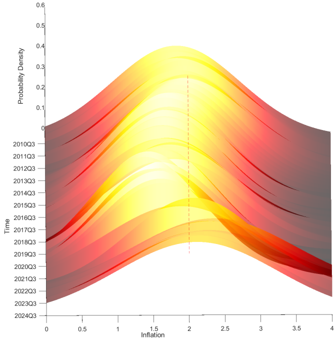
(annual percentage changes)



Sources: Authors' calculations, SPF.
Notes: The SPF asks respondents to report their point forecasts and to separately assign probabilities to different ranges of outcomes. This chart shows the bootstrapped pooled average probabilities assigned to different ranges of inflation outcomes in the longer term. Longer-term expectations refer to 5 years ahead responses.
Latest observations: 2024Q3.

De-anchored component of longer-term inflation expectations

(annual percentage changes)



Sources: Authors' calculations.
Notes: The charts show the de-anchored component of the Gaussian Mixture Model fitted to the long-term inflation expectations according to the ECB's SPF. The blue bars indicate downward, the yellow bars indicate upward de-anchoring. The model does not account for neither for the effective lower bound nor for non-standard measures.
Latest observations: 2023Q4.

$$
\begin{aligned}
\widehat{w}_t \;=\;& \frac{\beta}{1+\beta}\,\mathrm{E}_t\left[\widehat{w}_{t+1}\right] + \frac{1}{1+\beta}\,\widehat{w}_{t-1} + \frac{\beta}{1+\beta}\,\mathrm{E}_t\left[\widehat{\pi}_{C,t+1}\right] \qquad \text{(A.} \\
& - \frac{1+\beta\chi_W}{1+\beta}\,\widehat{\pi}_{C,t} + \frac{\chi_W}{1+\beta}\,\widehat{\pi}_{C,t-1} - \frac{\beta(1-\chi_W)}{1+\beta}\,\mathrm{E}_t\left[\widehat{\bar{\pi}}_{C,t+1}\right] \\
& + \frac{1-\chi_W}{1+\beta}\,\widehat{\bar{\pi}}_{C,t} - \frac{\left(1-\beta\xi_W\right)\left(1-\xi_W\right)}{\left(1+\beta\right)\xi_W\,\Psi(\varphi^W,\zeta)}\left(\widehat{w}_t^{\tau} - \widehat{mrs}_t - \widehat{\varphi}_t^{W}\right),
\end{aligned}
$$

with

$$
\widehat{\bar{\pi}}_t = \widehat{\pi_t^*}
$$

Regime-Switching Kálmán Filter Learning Technical Details - Notation

Object of interest: The filtered regime probability in period t

- State space representation of regime i:

$$x_t^i = \mathbf{A^i} x_{t-1}^i + \mathbf{R^i} \varepsilon_t,$$
$$y_t = p_t^i \mathbf{H^i} x_t^i$$
$$\varepsilon_t \sim \mathcal{N}(0, I)$$

- Regime probabilities: p_t^i
- Regime transition matrix:

$$Z = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \end{bmatrix}$$

- Equivalently:

$$y_t \sim \sum_i p_t^i \cdot \mathcal{N}(\mu_t^i, \Sigma_t^i)$$

, where $\mu_t^i = \mathbf{H^i} \mathbf{A^i} x_{t-1}^i; \Sigma_t^i = (\mathbf{R^i})^T \mathbf{R^i}$.

- Regime probabilities: p_t^i
- Regime transition matrix:

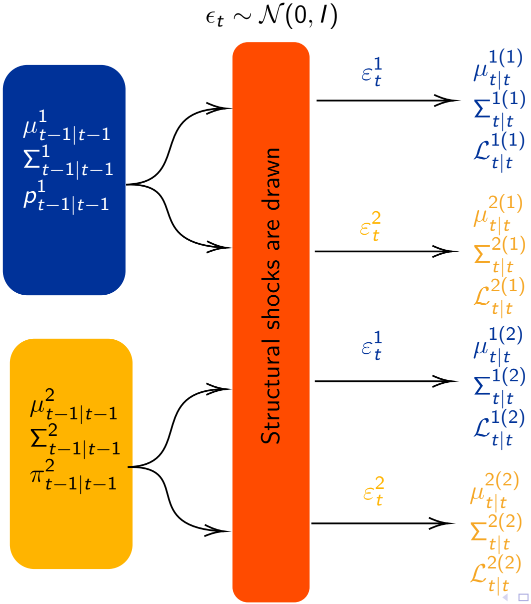
$$Z = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \end{bmatrix}$$

Stochastic Simulation with RSKF Learning - I. Initial Conditions

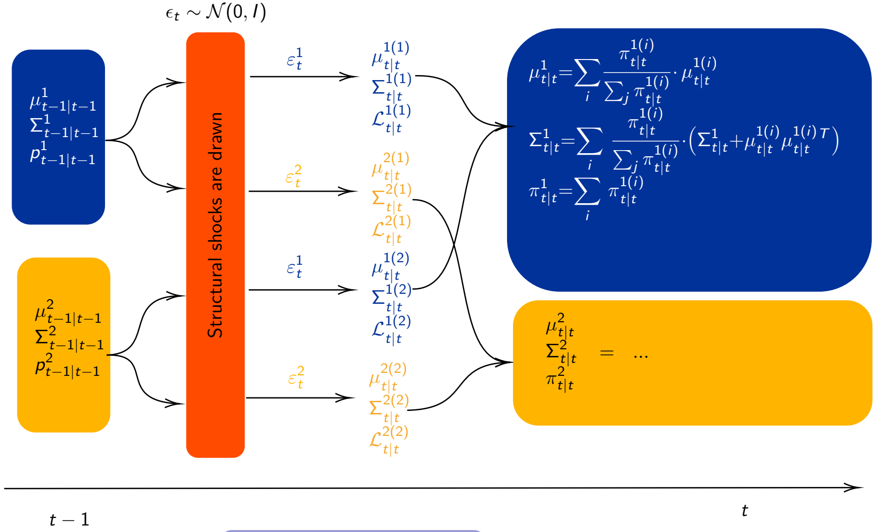
$\mu^1_{t-1|t-1}$
$\Sigma^1_{t-1|t-1}$
$p^1_{t-1|t-1}$

$\mu^2_{t-1|t-1}$
$\Sigma^2_{t-1|t-1}$
$\pi^2_{t-1|t-1}$

Stochastic Simulation with RSKF Learning - II. Shocks, Prediction, Update



$$Z = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \end{bmatrix} \qquad \pi^{j(i)}_{t|t} = \frac{\mathcal{L}^{j(i)}_{t|t} \cdot z_{ij} \cdot \pi^{i}_{t-1|t-1}}{\sum_j \sum_i \mathcal{L}^{j(i)}_{t|t} \cdot z_{ij} \cdot \pi^{i}_{t-1|t-1}}$$



Source: Authors' illustration. Jump back to Regime-Switching Kálmán Filter overview.

Adam, K. and M. Woodford (2012). Robustly optimal monetary policy in a microfounded new keynesian model. *Journal of Monetary Economics 59*(5), 468–487.

Bahaj, S., R. Czech, S. Ding, and R. Reis (2023). The market for inflation risk.

Bianchi, F. (2012). Regime switches, agents' beliefs, and post-world war ii us macroeconomic dynamics. *Review of Economic studies 80*(2), 463–490.

Bianchi, F. and C. Ilut (2017, October). Monetary Fiscal Policy Mix and Agent's Beliefs. *Review of Economic Dynamics 26*, 113–139.

Carvalho, C., S. Eusepi, E. Moench, and B. Preston (2023). Anchored inflation expectations. *American Economic Journal: Macroeconomics 15*(1), 1–47.

Choi, J. and A. Foerster (2021). Optimal monetary policy regime switches. *Review of Economic Dynamics 42*, 333–346.

Christiano, L., M. S. Eichenbaum, and B. K. Johannsen (2024). Slow learning. Technical report, National Bureau of Economic Research.

Clarida, R., J. Gali, and M. Gertler (1999, December). The science of monetary policy: A new keynesian perspective. *Journal of Economic Literature 37*(4), 1661–1707.

Cogley, T. and A. M. Sbordone (2008). Trend inflation, indexation, and inflation persistence in the new keynesian phillips curve. *American Economic Review 98*(5), 2101–2126.

Corsello, F., S. Neri, and A. Tagliabracci (2021). Anchored or de-anchored? that is the question. *European Journal of Political Economy 69*, 102031.

Davig, T. and E. M. Leeper (2007, June). Generalizing the taylor principle. *American Economic Review 97*(3), 607–635.

Dovern, J., G. Kenny, et al. (2020). Anchoring inflation expectations in unconventional times: Micro evidence for the euro area. *International Journal of Central Banking 16*(5), 309–347.

Erceg, C. J. and A. T. Levin (2003). Imperfect credibility and inflation persistence. *Journal of monetary economics 50*(4), 915–944.

Farmer, R. E., D. F. Waggoner, and T. Zha (2009). Understanding markov-switching rational expectations models. *Journal of Economic theory 144*(5), 1849–1867.

Foerster, A., J. F. Rubio-Ramírez, D. F. Waggoner, and T. Zha (2016). Perturbation methods for markov-switching dynamic stochastic general equilibrium models. *Quantitative Economics 7*(2), 637–669.

Gasteiger, E. (2021). Optimal constrained interest-rate rules under heterogeneous expectations. *Journal of Economic Behavior & Organization 190*, 287–325.

Gáti, L. (2023). Monetary policy & anchored expectations—an endogenous gain learning model. *Journal of Monetary Economics 140*, S37–S47.

Gobbi, L., R. Mazzocchi, and R. Tamborini (2019). Monetary policy, de-anchoring of inflation expectations, and the "new normal". *Journal of Macroeconomics 61*, 103070.

Hamilton, J. D. (1990). Analysis of time series subject to changes in regime. *Journal of econometrics 45*(1-2), 39–70.

Maih, J. (2015). Efficient perturbation methods for solving regime-switching dsge models. *Norges Bank Working Paper 1— 2015*.

Marcet, A. and J. P. Nicolini (2003). Recurrent hyperinflations and learning. *American Economic Review 93*(5), 1476–1498.

Marcet, A. and T. J. Sargent (1989). Convergence of least squares learning mechanisms in self-referential linear stochastic models. *Journal of Economic theory 48*(2), 337–368.

Milani, F. (2007). Expectations, learning and macroeconomic persistence. *Journal of monetary Economics 54*(7), 2065–2082.

Milani, F. (2014). Learning and time-varying macroeconomic volatility. *Journal of Economic Dynamics and Control 47*, 94–114.

Nakata, T. and S. Schmidt (2022, October). Expectations-driven liquidity traps: Implications for monetary and fiscal policy. *American Economic Journal: Macroeconomics 14*(4), 68–103.

Slobodyan, S. and R. Wouters (2012). Learning in an estimated medium-scale dsge model. *Journal of Economic Dynamics and control 36*(1), 26–46.

Woodford, M. (2010). Robustly optimal monetary policy with near-rational expectations. *American Economic Review 100*(1), 274–303.