Adaptive Learning and Monetary Policy

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Introduction

– Macroeconomic models are usually based on **optimizing** agents in dynamic, stochastic setting and can be summarized by a **dynamic system,** e.g.

$$
\begin{aligned}
y_t &= Q(y_t^e, w_t) \text{ or} \\
y_t &= Q(y_{t-1}, y_{t+1}^e, w_t) \text{ or} \\
y_t &= Q\left(y_{t-1}, \left\{y_{t+1}^e\right\}_{j=0}^{\infty}, w_t\right)
\end{aligned}
$$

$y_t =$ vector of economic variables at time t (unemployment, inflation, investment, etc.), $y_{t+1}^e =$ expectations of these variables, $w_t =$ exogenous random factors at t. Nonstochastic models also of interest.

– The presence of **expectations** y_t^e or y_{t+1}^e, and the assumption that agents can solve dynamic programing problems, makes macroeconomics inherently different from natural science.

– The standard assumption of **rational expectations** (RE) assumes too much **knowledge** & **coordination** for economic agents. We need a **realistic** model of **rationality**. What form should this take?

– My general answer is given by the **Cognitive Consistency Principle** (CCP): economic agents should be about as smart as (good) economists, e.g.

—— model agents like **economic theorists – the eductive** approach, or

—— model them as **econometricians** – the **adaptive** approach.

– We also need to reflect on the optimization assumption. In dynamic stochastic settings the CCP and introspection suggest relaxing this assumption.

– Agents may fall short of the CCP standard but CCP is a good benchmark.

– In **this talk** I follow the **adaptive** approach. Agent/econometricians must select models, estimate parameters and update their models over time.

A Muth/Lucas-type Model

Consider a simple univariate reduced form:

$$p_t = \mu + \alpha E^*_{t-1} p_t + \delta' w_{t-1} + \eta_t, \text{ with } \alpha \neq 1. \tag{RF}$$

$E^*_{t-1} p_t$ denotes expectations of p_t formed at $t-1$, w_{t-1} is a vector of exogenous observables and η_t is an unobserved iid shock.

Muth cobweb example. Demand and supply equations:

$$\begin{aligned} d_t &= m_I - m_p p_t + v_{1t} \\ s_t &= r_I + r_p E^*_{t-1} p_t + r'_w w_{t-1} + v_{2t}, \end{aligned}$$

$s_t = d_t$, yields (RF) where $\alpha = -r_p/m_p < 0$ if $r_p, m_p > 0$.

Lucas-type monetary model. AS + AD + monetary feedback:

$$\begin{aligned} q_t &= \bar{q} + \lambda(p_t - E^*_{t-1} p_t) + \zeta_t, \\ m_t + v_t &= p_t + q_t \text{ and } m_t = \bar{m} + u_t + \rho' w_{t-1} \end{aligned}$$

leads to yields (RF) with $0 < \alpha = \lambda/(1+\lambda) < 1$.

Adaptive, Least-Squares Learning

The model $p_t = \mu + \alpha E_{t-1} p_t + \delta' w_{t-1} + \eta_t$ has the **unique REE**

$$\begin{aligned} p_t &= \bar{a} + \bar{b}' w_{t-1} + \eta_t, \text{ where} \\ \bar{a} &= (1-\alpha)^{-1}\mu \text{ and } \bar{b} = (1-\alpha)^{-1}\delta. \end{aligned}$$

Special case: If only white noise shocks or the model is nonstochastic then $\delta = 0$. In this case $\bar{b} = 0$ and the REE is $p_t = \bar{a} + \eta_t$, with $E_{t-1} p_t = \bar{a}$.

Under **LS learning**, agents have the beliefs or perceived law of motion (PLM)

$$p_t = a + b w_{t-1} + \eta_t,$$

but a, b are unknown. At the end of time $t-1$ they estimate a, b by LS (Least Squares) using data through $t-1$. Then they use the estimated coefficients to make forecasts $E^*_{t-1} p_t$.

– End of $t-1$: w_{t-1} and p_{t-1} observed. Agents **update estimates** of a, b to a_{t-1}, b_{t-1} and make forecasts

$$E^*_{t-1} p_t = a_{t-1} + b'_{t-1} w_{t-1}.$$

– **Temporary equilibrium at t:** (i) p_t is determined as

$$p_t = \mu + \alpha E^*_{t-1} p_t + \delta' w_{t-1} + \eta_t$$

and w_t is realized. (ii) agents update estimates to a_t, b_t and forecast

$$E^*_t p_{t+1} = a_t + b'_t w_t.$$

The dynamic system under LS learning is written recursively (RLS) as

$$\begin{aligned}
E^*_{t-1} p_t &= \phi'_{t-1} z_{t-1} \text{ where } \phi'_{t-1} = (a_{t-1}, b'_{t-1}) \text{ and } z'_{t-1} = (1, w_{t-1}) \\
p_t &= \mu + \alpha E^*_{t-1} p_t + \delta' w_{t-1} + \eta_t, \\
\phi_t &= \phi_{t-1} + t^{-1} R_t^{-1} z_{t-1} (p_t - \phi'_{t-1} z_{t-1}) \\
R_t &= R_{t-1} + t^{-1} (z_{t-1} z'_{t-1} - R_{t-1}).
\end{aligned}$$

Question: Will $(a_t, b_t) \rightarrow (\bar{a}, \bar{b})$ as $t \rightarrow \infty$?

Theorem (Bray & Savin (1986), Marcet & Sargent (1989)). Convergence to RE, i.e. $(a_t, b_t') \rightarrow (\bar{a}, \bar{b}')$ a.s. if $\alpha < 1$. If $\alpha > 1$ convergence with prob. 0.

Thus the REE is stable under LS learning both for Muth model ($\alpha < 0$) and Lucas model ($0 < \alpha < 1$), but is not stable if $\alpha > 1$.

In general models, stochastic approximation theorems are used to prove convergence results. However the **expectational stability** (E-stability) principle, below, gives the stability condition.

Special case: If $\delta = 0$ and agents have the PLM $p_t = a + \eta_t$, then they only regress on an intercept, i.e. $\phi_t = a_t$. The system then is

$$
\begin{aligned}
p_t &= \mu + \alpha E_{t-1}^* p_t + \eta_t \\
E_{t-1}^* p_t &= a_{t-1} \\
a_t &= a_{t-1} + t^{-1}(p_t - a_{t-1})
\end{aligned}
$$

and $a_t \rightarrow \bar{a}$ a.s. if $\alpha < 1$ (a_t does not converge if $\alpha > 1$).

E-Stability

There is a simple way to obtain the stability condition. Start with PLM

$$p_t = a + b' w_{t-1} + \eta_t,$$

and suppose (a, b) were fixed at some (possibly non-REE) value. Then

$$E^*_{t-1} p_t = a + b' w_{t-1},$$

which would lead to the Actual Law of Motion (ALM)

$$p_t = \mu + \alpha(a + b' w_{t-1}) + \delta' w_{t-1} + \eta_t.$$

The implied ALM gives the mapping T: PLM $\longrightarrow$ ALM:

$$T(a, b) = (\mu + \alpha a, \delta + \alpha b).$$

The REE $\bar{a}, \bar{b}$ is a fixed point of T.

Expectational-stability ("E-stability) is defined by the ODE

$$\frac{d}{d\tau}(a, b) = T(a, b) - (a, b),$$

where τ is notional time. $\bar{a}, \bar{b}$ is **E-stable** if it is stable under this ODE. Here T is linear and the REE is E-stable when $\alpha < 1$.

Intuition: under LS learning the parameters a_t, b_t are slowly adjusted, on average, in the direction of the corresponding ALM parameter.

This technique can be used in multivariate linear models, nonlinear models, and if there are multiple equilibria.

For a wide range of models **E-stability** governs stability under LS learning, see Evans & Honkapohja (2001). This is the **E-stability principle**.

In **NK models** some interest rate rules fail to deliver stability under learning.

E-Stability in Multivariate Linear Models.

Often macro models can be set up in a standard form

$$y_t = ME_t^* y_{t+1} + Ny_{t-1} + Pv_t.$$

The usual RE solution takes the form $y_t = \bar{a} + \bar{b}y_{t-1} + \bar{c}v_t$, with here $\bar{a} = 0$.

Under LS learning agents use a PLM to make forecasts:

$$\begin{aligned} y_t &= a + by_{t-1} + cv_t \\ E_t^* y_{t+1} &= (I+b)a + b^2 y_{t-1} + (bc + cF)v_t, \end{aligned}$$

based on estimates (a_t, b_t, c_t) which they update using LS.

Inserting the forecasts into the model yields the ALM

$$y_t = M(I+b)a + (Mb^2 + N)y_{t-1} + (Mbc + NcF + P)v_t$$

This gives a **mapping from PLM to ALM:**

$$T(a,b,c) = (M(I+b)a, Mb^2 + N, Mbc + NcF + P).$$

The REE $(\bar{a}, \bar{b}, \bar{c})$ is a fixed point of $T(a,b,c)$. If

$$d/d\tau(a,b,c) = T(a,b,c) - (a,b,c)$$

is locally asymptotically stable at the REE it is said to be **E-stable**. See EH, Chapter 10, for details. The **E-stability conditions** can be stated in terms of the derivative matrices

$$\begin{aligned} DT_a &= M(I+\bar{b}) \\ DT_b &= \bar{b}' \otimes M + I \otimes M\bar{b} \\ DT_c &= F' \otimes M + I \otimes M\bar{b}, \end{aligned}$$

where $\otimes$ denotes the Kronecker product and $\bar{b}$ denotes the REE value of b.

E-stability governs stability under LS learning. **This issue is distinct from the "determinacy" question.**

Variation 1: constant-gain learning dynamics

– For **discounted LS** the "gain" t^{-1} is replaced by a constant $0 < \gamma < 1$, e.g. $\gamma = 0.04$. Often called "constant gain" (or "perpetual") learning.

– Especially plausible if agents are worried about structural change.

– With (small) constant gain in the **Muth/Lucas** and $\alpha < 1$ convergence of (a_t, b_t) is to a stochastic process around $(\bar{a}, \bar{b})$.

– In the **Cagan/asset-pricing** model

$$\begin{aligned} p_t &= \mu + \alpha E_t^* p_{t+1} + \delta w_t \\ w_t &= \rho w_{t-1} + \varepsilon_t \end{aligned}$$

constant gain learning leads to excess volatility, correlated excess return, etc.

– **Escape dynamics** can also arise (Cho, Williams and Sargent (2002)).

Special case: If $\delta = 0$, agents have the PLM $p_t = a + \eta_t$, and they use constant-gain learning with gain $0 < \gamma \leq 1$, then (in e.g. the cobweb model)

$$E_{t-1}^* p_t = a_{t-1} \text{ and } a_t = a_{t-1} + \gamma(p_t - a_{t-1}),$$

which is equivalent to

$$E_t^* p_{t+1} = E_{t-1}^* p_t + \gamma \left(p_t - E_{t-1}^* p_t \right).$$

This, of course, is simply "**adaptive expectations**" with AE parameter γ. Thus AE is a special case of LS learning with constant gain in which the only regressor is an intercept.

Variation 2: misspecified models

- Actual econometricians make specification errors. What happens if our agents make such errors, e.g. underparameterization of the list of regressors or underparameterization of dynamics?

- LS learning still converges if a modified E-stability condition is met, but convergence is to a **Restricted Perceptions Equilibrium** (RPE).

- In an RPE agents are using the best (minimum MSE) econometric model within the class they consider.

Variation 3: heterogeneous expectations

In practice, there is **heterogeneity** of expectations across agents.

– This arises, at least in transitional learning dynamics, if different agents have **different** initial expectations (**priors**), different (possibly random) **gains**, and/or **asynchronous updating** of estimates.

– Heterogeneity also arises from **dynamic predictor selection** (Brock & Hommes): alternative heuristic forecasting models with discrete choice ('behavioral rationality,' Hommes)

– Dynamic predictor selection **can also be combined with LS learning** of parameters of alternative forecasting models, including misspecified models. (Branch and Evans (2006), 'misspecification equilibria').

General Implications of Adaptive Learning (AL)

- Can assess **plausibility** of RE based on stability under LS learning

- Use local stability under learning as a **selection criterion** in models with **Multiple Equilibria**
  - Multiple steady states in nonlinear models
  - Cycles and sunspot equilibria (SSEs) in nonlinear models
  - Sunspot equilibria in linear models with indeterminate steady states

- **Persistent learning dynamics** arise with modified adaptive learning rules

- **Policy implications**: Policy should facilitate learning by private agents of the targeted REE.

Methodological issue: Short-horizon vs. Long-horizon Decision-making

- Most macromodels, including RBC and NK (DSGE) models, assume **infinitely-lived** (or long-lived) **agents** who solve dynamic optimization problems. Under bounded rationality there are two main approaches.

- **Short-horizon decision-making.** Based on 1-step ahead forecasts agents make decisions that satisfy a necessary condition for optimal decisions.
  – **Shadow-Price Learning** is developed in Evans and McGough (2018). In LQ models SP-learning converges to fully optimal decisions.
  – **Euler-equation Learning** (e.g. Evans and Honkapohja (2006)) can be viewed as a special case of SP-learning.

- **SP-learning** and **EE-learning** are boundedly optimal as well as boundedly rational in forecasts. These approaches are generally easy to apply.

- **Infinite-horizon decision-making.** Agents solve their dynamic decision problems each period, given their forecasts over the infinite horizon of variables that are exogenous to their decisions.
  – Agents are fully optimizing given their forecasts but use adaptive learning to update their boundedly rational forecast rules.
  – See Preston (2005, 2006) and numerous papers by Eusepi and Preston.

- **IH-learning** is particularly useful if agents foresee a future change in policy.

- **Finite-horizon decision-making** is also possible. See Branch, Evans and McGough (2013).

The New Keynesian Model and Monetary Policy

- Log-linearized New Keynesian model (CGG 1999, Woodford 2003 etc.).

  1. "IS" equation (IS curve)

  $$x_t = -\varphi(i_t - E_t^* \pi_{t+1}) + E_t^* x_{t+1} + g_t$$

  2. the "New Phillips" equation (PC curve)

  $$\pi_t = \lambda x_t + \beta E_t^* \pi_{t+1} + u_t,$$

where x_t =output gap, π_t =inflation, i_t = nominal interest rate. $E_t^* x_{t+1}$, $E_t^* \pi_{t+1}$ are expectations. Parameters $\varphi, \lambda > 0$ and $0 < \beta < 1$.

- Observable shocks follow independent stationary AR(1) processes.

- Under Euler-equation learning these are behavioral equations. Preston and Eusepi-Preston have closely related results for IH-learning.

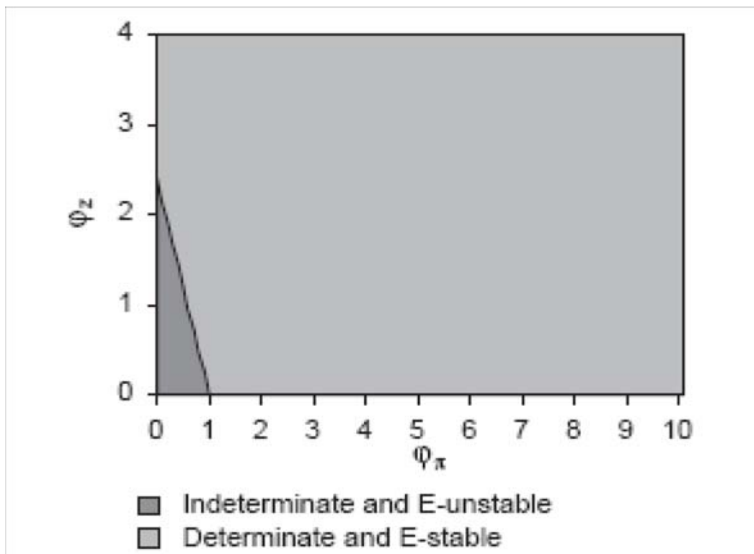
- Interest rate setting by a standard **Taylor rule,** e.g.

$$
\begin{aligned}
i_t &= \chi_\pi \pi_t + \chi_x x_t \text{ where } \chi_\pi, \chi_x > 0 \text{ or} \\
i_t &= \chi_\pi \pi_{t-1} + \chi_x x_{t-1} \text{ or} \\
i_t &= \chi_\pi E_t^* \pi_{t+1} + \chi_x E_t^* x_{t+1}
\end{aligned}
$$

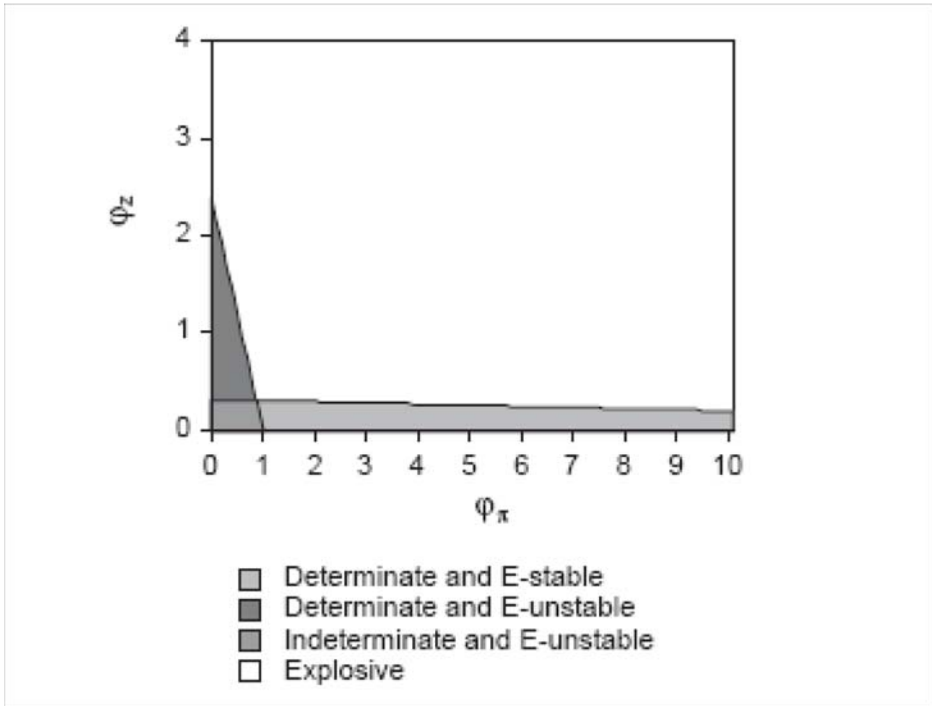
- Bullard and Mitra (JME, 2002) studied determinacy and E-stability for each rule.

Results for Taylor-rules in NK model (Bullard & Mitra, JME 2002)

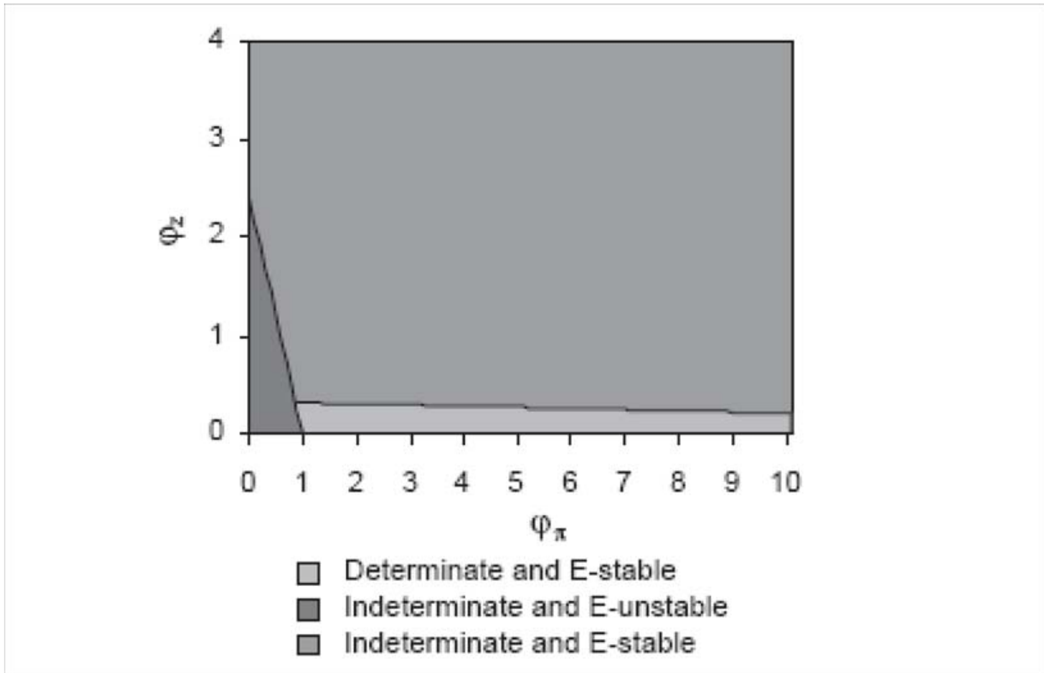
$i_t = \chi_\pi \pi_t + \chi_x x_t$ yields **determinacy and stability** under LS learning **if** $\lambda(\chi_\pi - 1) + (1-\beta)\chi_x > 0$. Note that $\chi_\pi > 1$ is sufficient.



With $i_t = \chi_\pi \pi_{t-1} + \chi_x x_{t-1}$, **determinacy & E-stability** for $\chi_\pi > 1$ and $\chi_x > 0$ small. Also an **explosive region** ($\chi_\pi > 1$ and χ_x large) and a **determinate E-unstable** region ($\chi_\pi < 1$ and χ_x moderate).



For $i_t = \chi_\pi E_t^* \pi_{t+1} + \chi_x E_t^* x_{t+1}$, **determinacy & E-stability** for $\chi_\pi > 1$ and $\chi_x > 0$ small. **Indeterminate & E-stable** for $\chi_\pi > 1$ and χ_x large. Honkapohja and Mitra (JME, 2004) and Evans and McGough (JEDC, 2005) find **stable sunspot solutions** in that region.



Note: for $\chi_x = 0$ the Taylor principle $\chi_\pi > 1$ and χ_π not too large gives stability under AL for all versions.

Instability of an Interest Rate Peg

- An implication of the Bullard and Mitra (JME, 2002) results is that an **interest rate peg**, i.e. setting

$$i_t = \bar{\imath}$$

  is always unstable under learning.

- This specific point was made earlier by Howitt (JPE, 1992).

- Evans and Honkapohja (REStud, 2003) showed instability in the NK model for interest-rate rules that respond only to exogenous shocks, even for rules consistent with optimal discretionary policy under RE.

- For optimal policy with commitment Evans and Honkapohja (ScandJE, 2006) showed i_t rules responding just to exogenous and predetermined variables are unstable under learning.

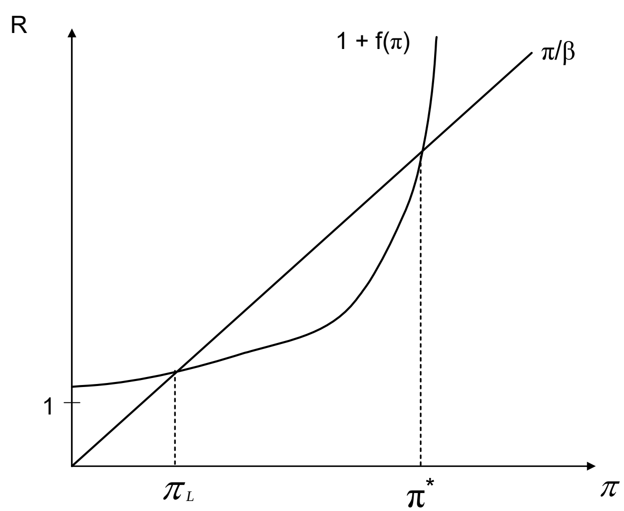
- **Stability under learning** of optimal policy **is obtained if** i_t also responds appropriately to private sector expectations.

- Eusepi and Preston have obtained analogous instability results for pegs under IH learning.

The zero lower bound (ZLB), stagnation and deflation

Evans, Guse, Honkapohja (EER, 2008), “Liquidity Traps, Learning and Stagnation” consider issues of liquidity traps and deflationary spirals under learning.

Possibility of a “liquidity trap” under a global Taylor rule subject to zero lower bound. Benhabib, Schmitt-Grohe and Uribe (2001, 2002) analyze this for RE.



Multiple steady states with global Taylor rule.

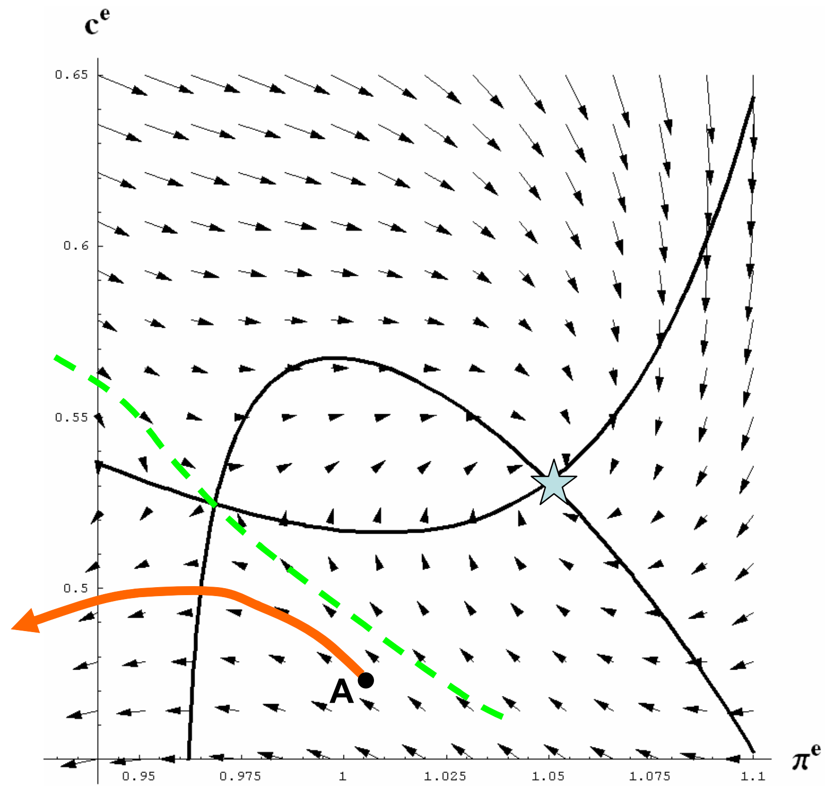
– What happens under learning? EGH2008 consider a standard NK model. Monetary policy follows a global Taylor-rule, which implies two steady states.

– The key equations are the (nonlinear) PC and IS curves

$$\begin{aligned}\frac{\alpha\gamma}{\nu}(\pi_t - 1)\pi_t &= \beta\frac{\alpha\gamma}{\nu}\left(\pi^e_{t+1} - 1\right)\pi^e_{t+1} \\ &\quad +(c_t + g_t)^{(1+\varepsilon)/\alpha} - \alpha\left(1 - \frac{1}{\nu}\right)(c_t + g_t)c_t^{-\sigma_1} \\ c_t &= c^e_{t+1}(\pi^e_{t+1}/\beta R_t)^{1/\sigma_1}.\end{aligned}$$

– Two stochastic steady states at π_L and π^*. Under "steady-state" learning, π^* is locally stable but π_L is not.

– Pessimistic expectations c^e, π^e can lead to deflation and falling output.



π^e and c^e dynamics under normal policy

- To avoid this we recommend **adding aggressive fiscal policies** at an **inflation threshold** $\tilde{\pi}$, where $\pi_L < \tilde{\pi} < \pi^*$.

- Benhabib, Evans and Honkapohja (JEDC, 2014) obtain similar qualitative results for an IH-learning specification and study policy in greater detail.

- Evans, Honkapohja and Mitra (2016) "Expectations, Stagnation and Fiscal Policy" further develop this model by adding **inflation and consumption lower bounds**. This generates an additional locally **stable stagnation steady state**.

Neo-Fisherian Monetary Policy

"Interest Rate Pegs in New Keynesian Models" (Evans and McGough, JMCB, 2018)

- Following the Financial Crisis of 2008-9, the US federal funds rate was essentially at the ZLB for the whole period 2009 – 2015.

- With the economic recovery the Fed has been discussing when to "normalize" interest rates.

- We interpret **normalization** as a return to Taylor rule. Much of the US policy debate during 2016 was on whether to **normalize then or to wait** until inflation expectations were closer to target and output growth was stronger.

- The **Neo-Fisherian view** (Cochrane, 2011, 2017 and Williamson, 2016) is that **normalization** should instead be **to a fixed interest rate peg** at the steady state level consistent with the 2% inflation target.

- Evans and McGough (JMCB, 2018 and JME, 2018) argued using AL that the neo-Fisherian view is misguided. We also interpret the recent US policy debate using our learning framework.

- Neo-Fisherianism starts from the Fisher equation

$$R = r\pi$$

  where R is the nominal interest rate factor, r is the real interest rate factor and π is the inflation factor. In steady state r is determined by β and the growth rate.

- The **neo-Fisherian argument** is: given r, if the inflation target is π^* then R should be set at $R^* \equiv r\pi^*$. In the basic NK model, and for simplicity ignoring exogenous shocks, the **steady state is an REE** and must satisfy $\pi^e = \pi = R^*/r = \pi^*$.

- The **neo-Fisherian policy conclusion**: if interest rates are low and if inflation and expected inflation are below target, then **announce a fixed interest rate peg** at the higher level $R^* = r\pi^*$. The Fisher equation ensures that π, π^e must increase in line R^*.

- This argument goes against conventional wisdom that low R increases π by increasing demand. EMcG (2018) argue the conventional view is right. Neo-Fisherian policies can lead to **instability and recession**.

- We use the **NK model with IH-learning** developed in Eusepi and Preston (AEJmacro, 2010) and extended in Evans, Honkapohja and Mitra (2016).

- Agents use linearized decision rules

$$
\begin{aligned}
\tilde{c}_t^i &= (1-\beta)\hat{E}_t \sum_{s\geq 0} \beta^s \tilde{y}_{t+s}^i - \frac{\beta^2 \bar{y}}{\pi^*} \hat{E}_t \sum_{s\geq 0} \beta^s \tilde{R}_{t+s} + \frac{\bar{y}}{\pi^*} \hat{E}_t \sum_{s\geq 1} \beta^s \tilde{\pi}_{t+s}, \\
\tilde{\pi}_t^j &= (1-\gamma_1)\hat{E}_t \sum_{s\geq 0} (\beta\gamma_1)^s \, \tilde{\pi}_{t+s} + \frac{a_2 \pi^*}{\bar{y}} \hat{E}_t \sum_{s\geq 0} (\beta\gamma_1)^s \, \tilde{y}_{t+s}, \\
\tilde{y}_t &= \tilde{c}_t = \tilde{c}_t^i \text{ and } \tilde{\pi}_t = \tilde{\pi}_t^j.
\end{aligned}
$$

- The first equation is a consumption function and the second comes from forward-looking price-setting. For simplicity $g = 0$. Tildes denote deviations from the targeted steady state.

- The interest rate, as in EHM (2016), follows a Taylor rule subject to ZLB

$$\tilde{R}_t = \max\left\{\frac{\psi}{\beta}\hat{E}_t\tilde{\pi}_{t+1}, 1 + \varphi - R^*\right\}, \text{ where } \psi \equiv \chi_\pi$$

  Here $\varphi > 0$ is the wedge between the policy and market interest rates.

- EHM (2016) adds lower bounds, which can lead to an additional stagnation steady state, and looks at the role of fiscal policy.

- EMcG (2018) focuses on the instability of interest rate pegs and the policy normalization debate.

Instability of fixed interest rate peg

Suppose **initially in steady state** with π^* target 1% per year (1.0025 quarterly). At $t = 10$ the CB increases the target to 3%. The steady state interest rate increases from 2% to 4% (i.e. from $R^* = 1.005$ to $R^* = 1.01$ quarterly).

Neo-Fisherian policy implements this by announcing new π^* of 3% and increasing R^* to a fixed 4%. Suppose agents immediately adjust π^e from 1% to 2.8%, i.e. almost all the way to 3%. Thereafter π^e is revised in response to observed inflation using AL. Figure 2 of EMcG (2018) gives the result.

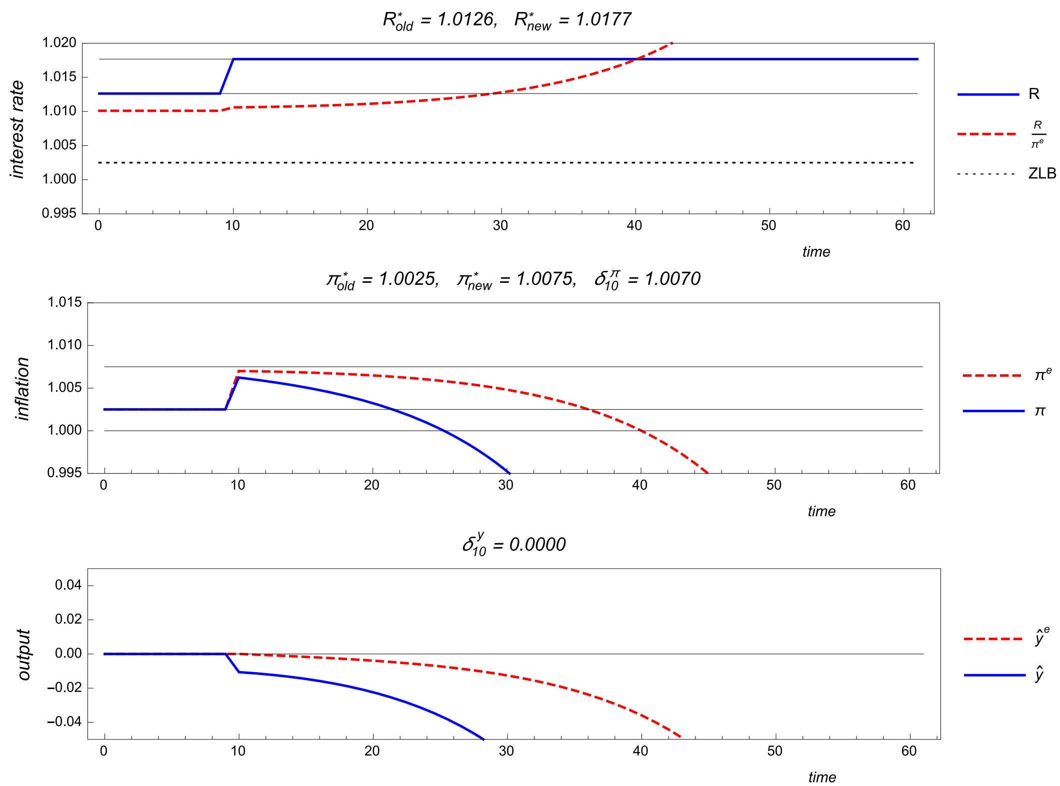


Figure 2: Increase in interest rate peg with almost full adjustment of inflation expectations.

The economy moves into recession, which becomes increasingly severe. π initially falls somewhat short of its target and this feeds back into π^e. This increases the real interest rate, which leads to contracting output. The result is a **cumulative self-fulfilling recession** with falling π, y:

$$\pi < \pi^e \longrightarrow \downarrow \pi^e \longrightarrow \uparrow R/\pi^e \longrightarrow \downarrow y \longrightarrow \downarrow \pi.$$

Because R is held at a **fixed peg** nothing impedes the recession.

Suppose, even more favorably to the neo-Fisherian hypothesis, π^e at $t = 10$ increases the *full way* to the target. Suppose at $t = 11$ there is small one-time negative shock to aggregate demand. This again sets off a cumulative process that leads to falling inflation and recession (Figure 3).

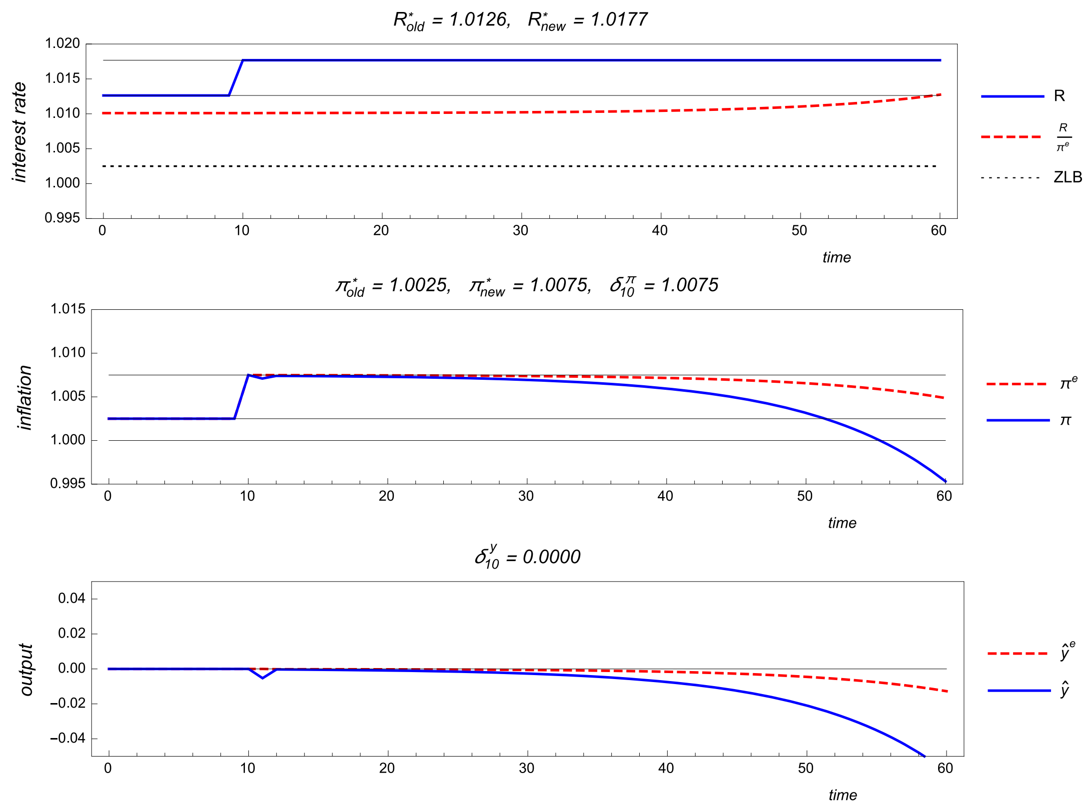


Figure 3: Increase in interest rate peg with full adjustment of inflation expectations.

- The neo-Fisherian policy necessarily generates instability if there is *any sensitivity whatsoever* of expectations to actual data.

- The central mechanism given here is essentially the same as in Howitt (1992), Bullard and Mitra (2002), Evans and Honkapohja (2003), Eusepi and Preston (2010), Benhabib, Evans and Honkapohja (2014) and Evans, Honkapohja and Mitra (2016).

- As in Bullard and Mitra (2002), the Taylor principle is key: to stabilize the economy the interest rate must be adjusted more than one-for-one in response to deviations of inflation or inflation expectations from target.

Pace of normalization of US monetary policy

- EMcG (2018) also looked at a **stylized policy situation** like the US in 2016, when output growth was low, inflation was still below target, and there was concern about possible adverse demand shocks.

- **Delaying normalization can avoid or mitigate a recession** that would arise under immediate normalization to a Taylor rule. The **asymmetry** when comparing bad shock/no shock cases favored delayed normalization.

- **Neo-Fisherian policy** of immediately increasing R to a fixed peg consistent with steady-state π^* of 2% of course delivers bad results.

Increase inflation target?

- As emphasized in EHM2016 (and earlier papers), due to the ZLB large negative demand shocks or expectation shocks can push the economy under AL into a destabilizing path leading to stagnation.

- There is an argument the likelihood of this can be reduced if steady state π^* is increased: this gives more room for reductions in R.

- While this is may be true, there is a caveat noted in Branch and Evans "Unstable Inflation Targets" (JMCB, 2017): the process of moving to a higher π^* can be destabilizing if not implemented with care.

- Suppose you are initially in a steady state and then increase the inflation target and the corresponding Taylor rule.

- If agents use an AR(1) PLM then it is possible the increase in π leads agents to believe in a random walk model, which makes the economy less stable and can lead to a large overshooting of the inflation target.

- To avoid this the CB could temporarily use a large Taylor coefficient χ_π.

Conclusions

- REE requires a story for how expectations are coordinated.

- Adaptive least-squares learning (AL) by agents is one natural way to implement CCP.

- The E-stability tools make assessment of local stability of an REE under adaptive learning straightforward.

- Additional dynamics arising from the learning transition, constant gain, misspecification and model selection can give interesting and plausible learning dynamics.

Implications of AL for monetary policy:

– For interest-rate rules the Taylor principle $\chi_\pi > 1$ is important for enhancing stability under AL.

– Fixed interest-rate pegs generate instability under AL.

– Monetary policy should respond to private sector expectations and/or current endogenous aggregates.

– The unintended low-inflation steady state created by the ZLB is not locally stable under AL. Large pessimistic expectations shocks can lead to large recessions, deflation and stagnation.

– In severe recessions monetary policy may needed to be supplemented by fiscal stimulus.

– The Neo-Fisherian policy of pegging the interest rate at a level consistent with the desired π^* leads to instability under AL.

– When π^e is persistently below target and R is at or near the ZLB, there is an argument for delayed normalization to a Taylor rule, especially if there are concerns about near-future adverse shocks.