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Endogenous Regime Switching Near the Zero Lower Bound¹

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¹Any opinions expressed here do not necessarily reflect the views of the Federal Reserve Bank of San Francisco or the Board of Governors of the Federal Reserve System.









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- Taylor rule + Fisher Eqn. + ZLB ⇒ Two steady states. (Benhabib, Schmitt-Grohé & Uribe AER, JET 2001a,b).
 - (1) Targeted: $i = r^* + \pi^* > 0$.
 - (2) <u>Deflation</u>: i = 0 and $\pi = -r^*$.

 r* = "natural rate of interest." <u>Evidence</u>: r* shifts over time and can drop below zero (Laubach & Williams 2016, Eggertsson, Mehrotra & Robbins 2017).









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- NK model with two local equilibria. Agent employs weighted-average of the two sets of local linear forecast rules. Weight optimized to minimize *RMSFE* over past T_w quarters.
- Unlike Arouba et al. (2018), regime switching here is endogenous.
- <u>Results</u>: Adverse shock ⇒ more weight on deflation forecast rules ⇒ deflation can become self-fulfilling. Episode accompanied by severe recession (highly negative output gap) with nominal rate at ZLB. Similar to 2007-09 Great Recession.
- But even in normal times, agent may place nontrivial weight on deflation forecast rules, causing central bank to consistently undershoot π^* (like now: $\pi_t^{U.S.} < 0.02$ since mid-2012).

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 Related literature (partial list)

- Transition between regimes driven by exogenous sunpots Aruoba, Cuba-Borda, & Schorfheide (2018, *REStud forthcoming*) Aruoba & Schorfheide (2016, *FRBKC Jackson Hole Symposium*
- Infrequent but long-lived ZLB episodes in global data Dordal-i-Carreras, Coibion, Gorodnichenko & Wieland (2016))
- Adaptive learning to select among multiple equilibria Evans & Honkapohja (2005, *RED*), Eusepi (2007, *JME*) Benhabib, Evans & Honkapohja (2014, *JEDC*) Arifovic, Schmitt-Grohé & Uribe (2018, *JEDC*)
- Optimal monetary policy with shifting natural rate Eggertsson and Woodford (2003, *BPEA*) Evans, Fisher, Gourio & Krane (2015, *BPEA*) Hamilton, Harris, Hatzius, & West (2016. *IMF Econ. Rev.*) Gust, Johannsen, López-Salido (2017, *IMF Econ. Rev.*) Basu & Bundick (2015, NBER WP 21838)

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Fisher relationship

$$y_t = E_t y_{t+1} - \alpha \left[\overline{i_t - E_t \pi_{t+1} - r_t} \right] + v_t, \qquad v_t = \rho_v v_{t-1} + \epsilon_{v,t}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa y_t + u_t, \qquad u_t = \rho_u u_{t-1} + \epsilon_{u,t}$$

$$i_{t}^{*} = \rho i_{t-1}^{*} + (1-\rho) \left[\frac{E_{t}r_{t}^{*}}{t} + \pi^{*} + g_{\pi} \left(\overline{\pi}_{t} - \pi^{*} \right) + g_{y} \left(y_{t} - y^{*} \right) \right]$$

$$\begin{array}{lll} \overline{\pi}_t &=& \omega \, \pi_t + (1 - \omega) \, \overline{\pi}_{t-1}, & \overline{\pi}_t \simeq \pi_{4,\,t} \equiv \, \text{4-qtr. inflation rate.} \\ i_t &=& \max \left\{ 0, \, \, i_t^* \right\}. \end{array}$$

$$\begin{array}{rcl} r_t & \equiv & -\log \underbrace{\left[\beta \exp\left(\zeta_t\right)\right]}_{\text{Discount factor}} & + & (1/\alpha) & \underbrace{E_t \Delta \bar{y}_{t+1}}_{\text{Expected potential output growth}} \\ r_t & = & \rho_r \, r_{t-1} + (1-\rho_r) \, r_t^* + \varepsilon_t, & \varepsilon_t \sim N\left(0, \, \sigma_{\varepsilon}^2\right) \\ r_t^* & = & r_{t-1}^* + \eta_t, & \eta_t \sim N\left(0, \, \sigma_{\eta}^2\right) \\ r_t^* & \equiv & \text{Natural rate of interest (long-run endpoint of } r_t) \end{array}$$

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 Two long-run endpoints (steady states)

 $\begin{array}{l} \frac{\text{Targeted Endpoint}}{\pi_t = \pi^*} \\ y_t = y^* \equiv \pi^* \left(1 - \beta\right) / \kappa \\ i_t^* = r_t^* + \pi^* \\ i_t = i_t^* \end{array}$

 $\frac{\text{Deflation Endpoint}}{\pi_t = -r_t^*}$ $y_t = -r_t^* (1 - \beta) / \kappa$ $i_t^* = (r_t^* + \pi^*) \left[1 - g_\pi - \frac{g_y(1 - \beta)}{\kappa} \right]$ $i_t = 0$

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 Two long-run endpoints (steady states)



Shifting Endpoint Time Series Model (Kozicki-Tinsley, JMCB 2012)

$$E_t r_t^* = \lambda \left[\frac{r_t - \rho_r r_{t-1}}{1 - \rho_r} \right] + (1 - \lambda) E_{t-1} r_{t-1}^*$$

$$\begin{array}{ll} & \text{Kalman} \\ \text{gain} \end{array} \qquad \lambda \ = \ \frac{-(1-\rho_r)^2 \, \phi + (1-\rho_r) \sqrt{(1-\rho_r)^2 \phi^2 + 4\phi}}{2}, \qquad \phi \equiv \frac{\sigma_\eta^2}{\sigma_\varepsilon^2} \end{array}$$

 $E_t (r_{t+h} - r_{t+h}^*) = (\rho_r)^h (r_t - E_t r_t^*), \quad \rho_r = 0.86$

Two local rational expectations equilibria

Calibration

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Targeted (Unique). Forecast rules assume $i_t^* = i_t > 0$ for all t

$$\begin{bmatrix} y_t - \pi^* (1 - \beta) / \kappa \\ \pi_t - \pi^* \\ i_t^* - (E_t r_t^* + \pi^*) \end{bmatrix} = \mathbf{A} \times \begin{bmatrix} r_t - E_t r_t^* \\ \overline{\pi}_{t-1} - \pi^* \\ i_{t-1}^* - (E_t r_t^* + \pi^*) \\ v_t \\ u_t \end{bmatrix}$$

Deflation (MSV). Forecast rules assume $i_t^* \leq 0$, $i_t = 0$ for all t

$$\begin{bmatrix} y_{t} - (-E_{t} r_{t}^{*}) (1-\beta) / \kappa \\ \pi_{t} - (-E_{t} r_{t}^{*}) \\ i_{t}^{*} - (E_{t} r_{t}^{*} + \pi^{*}) [1 - g_{\pi} - g_{y} (1-\beta) / \kappa] \end{bmatrix} = \\ \mathbf{B} \times \begin{bmatrix} r_{t} - E_{t} r_{t}^{*} \\ \overline{\pi}_{t-1} - (-E_{t} r_{t}^{*}) \\ i_{t-1}^{*} - (E_{t} r_{t}^{*} + \pi^{*}) [1 - g_{\pi} - g_{y} (1-\beta) / \kappa] \\ v_{t} \\ u_{t} \end{bmatrix}$$

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Targeted (Unique). Forecasts assume $i_t^* = i_t > 0$ for all t

	0.594	-0.153	-0.386	3.221	-0.174
A =	0.069	-0.017	-0.033	0.275	1.396
	0.128	0.129	0.718	0.682	0.158

Deflation (MSV). Forecasts assume $i_t^* \leq 0$, $i_t = 0$ for all t

	1.247	0	0	5.397	0.092
B =	0.213	0	0	0.661	1.429
	0.279	0.162	0.8	1.171	0.215

Local solution coefficients for state variable $r_t - E_t r_t^*$:

$$\frac{\mathbf{B}_{11}}{\mathbf{A}_{11}} = 2.1 \qquad \frac{\mathbf{B}_{21}}{\mathbf{A}_{21}} = 3.1 \qquad \frac{\mathbf{B}_{31}}{\mathbf{A}_{31}} = 2.2$$

 \Rightarrow Deflation equilibrium exhibits much more volatility.

Mode	el paramete	er val	ues				
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α	0.15	Interest rate coefficient in Euler equation.
β	0.995	Discount factor in Phillips curve.
κ	0.025	Output gap coefficient in Phillips curve.
σ_{v}	0.010	Std. dev. of demand shock.
σ_u	0.005	Std. dev. of cost push shock.
ρ_v	0.8	Persistence of demand shock.
ρ_u	0.3	Persistence of cost push shock.
π^*	0.02	Central bank inflation target.
ω	0.459	$\overline{\pi}_t \simeq$ 4-quarter inflation rate.
g_{π}	1.5	Policy rule response to inflation.
g _y	1.0	Policy rule response to output gap.
ρ	0.80	Interest rate smoothing parameter.
ρ_r	0.858	Persistence parameter for r_t .
σ_{ε}	0.010	Std. dev. temporary shock to r_t .
σ_{η}	0.002	Std. dev. permanent shock to r t.
$\lambda^{'}$	0.025	Optimal Kalman gain for $E_t r_t^*$.

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Bounds for simulations: $-0.004 \le r_t^* \le 0.037$



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Efficient real rate: Cúrdia, Ferrero, Ng & Tambalotti (JME, 2015)



Variables that the agent must forecast: y_{t+1} and π_{t+1}

$$\begin{aligned} \widehat{E}_t \, y_{t+1} \; &= \; \mu_t E_t^{\text{targ}} \, y_{t+1} \; + \; (1 - \mu_t) \, E_t^{\text{defl}} \, y_{t+1} \\ \widehat{E}_t \, \pi_{t+1} \; &= \; \mu_t E_t^{\text{targ}} \, \pi_{t+1} \; + \; (1 - \mu_t) \, E_t^{\text{defl}} \, \pi_{t+1} \end{aligned}$$

Choose μ_t to minimize $RMSFE_{t-1}$ for moving window of recent data

$$\begin{split} \min_{\mu_{t}} \frac{1}{T_{w}} \sum_{j=1}^{T_{w}} \left\{ \left[y_{t-j} - \mu_{t} E_{t-j-1}^{\text{targ}} y_{t-j} - (1-\mu_{t}) E_{t-j-1}^{\text{defl}} y_{t-j} \right]^{2} \\ + \left[\pi_{t-j} - \mu_{t} E_{t-j-1}^{\text{targ}} \pi_{t-j} - (1-\mu_{t}) E_{t-j-1}^{\text{defl}} \pi_{t-j} \right]^{2} \right\}^{0.5} \end{split}$$

For simulations, impose $0 \le \mu_t \le 1$, with $T_w = 8$ qtrs.

Variables that the agent must forecast: y_{t+1} and π_{t+1}

$$\begin{aligned} \widehat{E}_t \, y_{t+1} \; &= \; \mu_t E_t^{\text{targ}} \, y_{t+1} \; + \; (1 - \mu_t) \, E_t^{\text{defl}} \, y_{t+1} \\ \widehat{E}_t \, \pi_{t+1} \; &= \; \mu_t E_t^{\text{targ}} \, \pi_{t+1} \; + \; (1 - \mu_t) \, E_t^{\text{defl}} \, \pi_{t+1} \end{aligned}$$

Choose μ_t to minimize $RMSFE_{t-1}$ for moving window of recent data

$$\begin{split} \min_{\mu_{t}} \frac{1}{T_{w}} \sum_{j=1}^{T_{w}} \left\{ \left[y_{t-j} - \mu_{t} E_{t-j-1}^{\mathrm{targ}} y_{t-j} - (1-\mu_{t}) E_{t-j-1}^{\mathrm{defl}} y_{t-j} \right]^{2} \\ + \left[\pi_{t-j} - \mu_{t} E_{t-j-1}^{\mathrm{targ}} \pi_{t-j} - (1-\mu_{t}) E_{t-j-1}^{\mathrm{defl}} \pi_{t-j} \right]^{2} \right\}^{0.5} \end{split}$$

For simulations, impose $0 \le \mu_t \le 1$, with $T_w = 8$ qtrs.

Alternative (Binning and Maih 2017):

 $\mu_t = \exp{(\psi i_{t-1}^*)} / [1 + \exp{(\psi i_{t-1}^*)}]$, $\psi = 2000$.

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$$y_t = \widehat{E}_t y_{t+1} - \alpha \left[i_t - \widehat{E}_t \pi_{t+1} - r_t \right] + v_t$$

$$\pi_t = \beta \widehat{E}_t \pi_{t+1} + \kappa y_t + u_t$$

$$i_{t}^{*} = \rho i_{t-1}^{*} + (1-\rho) \left[E_{t} r_{t}^{*} + \pi^{*} + g_{\pi} \left(\overline{\pi}_{t} - \pi^{*} \right) + g_{y} \left(y_{t} - y^{*} \right) \right]$$

$$i_t = 0.5 i_t^* + 0.5 \sqrt{(i_t^*)^2}$$

$$\overline{\pi}_t = \omega \pi_t + (1-\omega) \overline{\pi}_{t-1}$$

Given forecasts $\hat{E}_t y_{t+1}$, $\hat{E}_t \pi_{t+1}$, and $E_t r_t^*$, solve nonlinear system each period for y_t , π_t , and i_t^* .















Measures of expected inflation declined after 2008.Q4



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Given r_t , $E_t r_t^*$, i_t , i_t^* , y_t , π_t in U.S. data, solve for v_t , u_t , and μ_t .





"With the exception of 2011:Q4, when the probability of the deflation regime increased to about 70%, the U.S. has been in the targeted inflation regime."

U.S.

Figure 5: Filtered Probability of Targeted-Inflation Regime

Japan





Weight on targeted forecast rules can decline rapidly











Duration of ZLB Episode (Quarters)

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	U.S. Data Model Simul			ations		
Statistic	1988.Q1-2017.Q2	Targeted	Deflation	Switching		
% periods $i_t = 0$	24.6%	2.52%	80.2%	19.6%		
Mean ZLB duration	29 qtrs.	5.3 qtrs.	34.7 qtrs.	12.5 qtrs.		
Max. ZLB duration	29 qtrs.	37 qtrs.	346 qtrs.	133 qtrs.		
Mean <u>y_t</u>	-1.44%	0.40%	-0.38%	0.42%		
Std. Dev.	1.75%	1.65%	3.21%	2.19%		
Mean $\pi_{4,t}$	2.16%	1.99%	-1.70%	0.93%		
Std. Dev.	1.09%	0.85%	1.58%	1.46%		

Model results computed from 300,000 period simulation.

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Properties of representative agent's forecast errors

Statistic	Targeted	Deflation	Switching
$Corr(err_{t+1}^y, err_t^y)$	0.002	-0.007	0.019
$Corr(err_{t+1}^{\pi}, err_t^{\pi})$	0.003	0.002	0.074
$E\left(err_{t+1}^{y}\right)$	-0.001%	-0.045%	0.008%
$E\left(err_{t+1}^{\pi}\right)$	-0.003%	-0.004%	0.003%
$\sqrt{E[(err_{t+1}^y)^2]}$	1.11%	1.87%	1.35%
$\sqrt{{\it E}[\left({\it err}_{t+1}^{\pi} ight)^2]}$	1.31%	1.35%	1.34%

Model results computed from 300,000 period simulation.

•
$$err_{t+1}^x = x_{t+1} - F_t x_{t+1}$$
 for $x_{t+1} \in \{y_{t+1}, \pi_{t+1}\}$.

- Agent employs linear forecast rules in a nonlinear environment with an occasionally binding ZLB.
- Nevertheless, agent's forecast errors in all three model versions are close to white noise.

Effect	of natura	l rate	range	in switching	model		
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Statistic	$-0.004 \le r_t^* \le 0.037$	$-0.015 \le r_t^* \le 0.037$
% periods $i_t = 0$	19.6%	23.2%
Mean ZLB duration	12.5 qtrs.	12.4 qtrs.
Mean <mark>y</mark> t	0.42%	0.38%
Std. Dev.	2.19%	2.23%
Mean $\pi_{4,t}$	0.93%	1.08%
Std. Dev.	1.46%	1.40%

Model results computed from 300,000 period simulation.

- Wide uncertainty bands around empirical estimates of r_t^*
- Eggertsson, Mehrotra, & Robbins (2017): Steady state r* in a life cycle model calibrated to U.S. data in 2015 is -1.5%.
- Endpoint of π_t in deflation equilibrium is $-r_t^*$. So negative r_t^* \Rightarrow positive inflation in the "deflation" equilibrium.

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Effect Yellen, 6	t of higher 5-14-2017: "This	inflat	of the mos	g <mark>et ir</mark> t import	n switch	ing mo	del nonetary	policy."
	Statistic		$\pi^*=0$	0.02	$\pi^{*} = 0.03$	$\pi^*=0$	0.04	
	% periods i_t	= 0	19.6	5%	14.2%	9.5	%	
	Mean ZLB dı	iration	12.5 c	qtrs.	12.4 qtrs.	11.7 c	ltrs.	
	Std. Dev. yt		2.19	%	2.12%	2.04	.%	

1.46% 1.56%

1.61% 2.75% 2.04%

Loss value, $ heta=1$	2.84%	2.66%	2
Loss value, $ heta=$ 0.25	2.12%	1.91%	2

Model results computed from 300,000 period simulation.

Std. Dev. π_{4t}

- Higher π^{*} can reduce switching to volatile deflation equilibrium where recessions are more severe.
- Similar to Kiley and Roberts (BPEA, 2017):

Loss =
$$E\left\{\left[\pi_{4,t} - 0.02\right]^2 + \theta \left[y_t - 0.02 \left(1 - \beta\right) / \kappa\right]^2\right\}$$
.

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Statistic	$\pi^* = 0.02$	$\pi^*=$ 0.03	$\pi^*=$ 0.04
ho = 0.8			
% periods $i_t = 0$	19.6%	14.2%	9.5%
Mean ZLB duration	12.5 qtrs.	12.4 qtrs.	11.7 qtrs.
ho=0			
% periods $i_t = 0$	30.0%	24.4%	19.6%
Mean ZLB duration	4.9 qtrs.	5.0 qtrs.	5.0 qtrs.

Model results computed from 300,000 period simulation..

- No smoothing ($\rho = 0$) implies higher frequency of hitting ZLB, but episodes are shorter on average.
- From ZLB perspective, no clear advantage from reducing the degree of interest rate smoothing in the policy rule.

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- Impose $\rho = \rho_v = \rho_u = 0$ (no persistence), $\omega = 1$ (policy targets quarterly inflation), and $\sigma_\eta = 0$ (r^* is constant).
- <u>Version 1</u>: Agent estimates correctly-specified decision rules:

$$y_t = c_{0,t} + c_{1,t} (r_t - r^*) + c_{2,t} v_t + c_{3,t} u_t$$

$$\pi_t = d_{0,t} + d_{1,t} (r_t - r^*) + d_{2,t} v_t + d_{3,t} u_t$$

• <u>Version 2</u>: Agent estimates misspecified decision rules:

$$y_t = c_{0,t} + c_{1,t} (r_t - r^*)$$

$$\pi_t = d_{0,t} + d_{1,t} (r_t - r^*)$$

Subjective forecasts:

$$\widehat{E}_t y_{t+1} = c_{0,t-1} + c_{1,t-1} \rho_r (r_t - r^*) \widehat{E}_t \pi_{t+1} = d_{0,t-1} + d_{1,t-1} \rho_r (r_t - r^*)$$

 c_{i,t} and d_{i,t} estimated each period using OLS for a rolling window of 16 quarters (4 years) of model-generated data.



Learning with correctly specified decision rules





Learning with misspecified decision rules



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Conclusion								

- Most NK studies ignore the deflation equilibrium. But no clear reason why this equilibrium should be ruled out.
- Switching model can produce Great Recessions when $r_t E_t r_t^*$ is persistently negative, causing agent to place large weight on deflation forecast rules. Escape from ZLB occurs endogenously when $r_t E_t r_t^*$ eventually starts rising.
- In normal times, non-trivial weight on deflation forecast rules may cause central bank to undershoot π^{*} (like today?).
- Model (with shocks) can replicate U.S. data since 1988.
- A simple loss function approach favors a modest increase in π^* to around 3%. But even with $\pi^* = 4\%$, the ZLB binding frequency is 9.5% and the average duration of a ZLB episode is 11.7 quarters.