Monetary Policy, Imperfect Information, and the Zero Lower Bound

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Motivation

- Communication about future path of FFR was important aspect of Fed policy during financial crisis/ELB epsiode.
- Effectiveness of FG depends on how it was interpreted by the public. Open to alternative interpretations:
  - Provided info about FOMC's forecasts.
  - Or, consistent with perception of a new, more accommodative reaction function.
- It's hard to distinguish between alternatives.
  - FOMC's reaction function is not observed.
  - Despite this, macro models typically assume agents observe it.
- Main Idea: Study FG in estimated model in which agents face uncertainty about CB's reaction function.

Key Questions

1. Was there a regime change in the reaction function when the FOMC was providing FG?
2. If so, did the public perceive a change in the reaction function and how quickly did they learn it?
3. How costly was any lack of credibility in terms of output and inflation outcomes?

What We Do

- Estimate a NK model with:
  - (Markov) regime changes in interest-rate rules.
    - imperfect committtment to a given rule/regime.
    - FG regime keeps desired interest rate lower for longer than other regimes.
  - Private agents uncertain about current policy regime.
    - Do not observe the policy regime but must infer it.
    - Update their beliefs using observed data and Bayes rule.
  - ZLB constraint.
    - Affects economic outcomes and how agents learn.
    - At ZLB, agents no longer observe changes in policy rate, making inferences about policy regime more difficult.

Very Tentative Findings

1. There is evidence of switch to FG regime beginning in 2010 or so that lasts through 2015.
   - Requires the hindsight of having all the data through 2016 to identify the FG regime that early.
2. In real time, difficult to identify the switch to the FG regime.
   - Agents only begin to believe in new FG regime in 2013 or 2014.
   - ZLB constraint confounds agents' ability to learn about the FG regime.
3. Imperfect credibility of FG regime costly:
   - Output gap about substantially lower, on average, during the ZLB period.

Related Literature

- Papers on FG:
  - Engen, Laubach, and Reifschneider (2015) provide evidence that FOMC's perceived reaction function changed over 2008-2015.
  - Campbell et al. (2017) evaluate effectiveness of FOMC FG using estimated DSGE model.
  - Also, Del Negro et al. (2015), De Graeve et al. (2014), Cole (2015).
- Papers with Bayesian learning in estimated DSGE models: Schorfheide (2005), Matthes (2015), Bianchi and Melosi (2017).

Imperfect Information about Monetary Policy

- Policy rate, R_t, satisfies ZLB constraint:

$$R_t = \max\left[0, f_R(X_t, j_t) + e_{Rt}\right].$$

- Interest-Rate reaction function depends on:
  - Observed data: R_t and $X_t = (R_{t-1}, \pi_t, \hat{y}_t)'$.
  - Unobserved regime: $j_t \in \{1, 2, 3\}$ follows a Markov process.
  - Unobserved innovation: $e_{Rt} \sim N(0, \sigma_R)$.

- For today:

$$f_R(X_t, j_t) = \rho_R R_{t-1} + (1 - \rho_R)\left[\bar{r} + \bar{\pi} + \gamma_\pi\left(\pi_t - \bar{\pi}\right) + \gamma_y \hat{y}_t\right] + \gamma_0(j_t).$$

Properties of Policy Regimes

- Time-varying, unobserved intercept:

$$\gamma_0(j_t) = \begin{cases} 0 & j_t = 1 \\ -\bar{\gamma}_0 & j_t = 2 \\ -2\bar{\gamma}_0 & j_t = 3, \quad \bar{\gamma}_0 > 0 \end{cases}$$

- $j_t \in \{1, 2, 3\}$ follows a Markov process with transition matrix, P:

$$P_{ij} = Prob(j_t = j | j_{t-1} = i).$$

- Description of Regimes:
  - $j_t = 1$: "Normal" Regime. Prior for P is such that it is persistent and occurs frequently.
  - $j_t = 2$: Easing Regime. Allows for easing cycles with sharp cuts in FFR. Prior implies transitory and infrequent.
  - $j_t = 3$: FG Regime. Allows FFR to be lower for longer than other regimes. Prior implies persistent and very infrequent.

Bayesian Learning

- Regimes are imperfectly credible as agents' beliefs can differ from truth.

- Agents enter period t with prior beliefs about regime j:

$$p_{j,t|t-1} = \text{Prob}(j_t = j|\Omega_{t-1})$$

  where Ω_{t-1}includes all variables at date $t-1$ and earlier except j_t and e_{Rt} and their lags.

- Beliefs are updated using observed data and Bayes rule:

$$p_{j,t|t} \propto \mathcal{L}(R_t, X_t|j_t = j)p_{j,t|t-1}$$

- Likelihood function, $\mathcal{L}(R_t, X_t|j_t = j)$, highlights novel and key feature of analysis — the interaction of the ZLB with BL.

The ZLB and the Likelihood Function

- Like a Tobit model, the likelihood function is a mixture of two distributions:

$$\begin{aligned}\mathcal{L}(R_t, X_t | j_t = j) &= \underbrace{\left[\frac{1}{\sigma_R}\phi\left(\frac{R_t - f_R(X_t, j)}{\sigma_R}\right)\right]^{\mathbb{I}_t}}_{\text{Away From ZLB}} \\ &\times \underbrace{\left[1 - \Phi\left(\frac{f_R(X_t, j)}{\sigma_R}\right)\right]^{1-\mathbb{I}_t}}_{\text{At ZLB}}\end{aligned}$$

- If $R_t > 0$, $\mathbb{I}_t = 1$: Compute the location of $\hat{e}_{Rt}(j) = R_t - f_R(X_t, j)$ on normal pdf to determine likelihood of regime j.

- If $R_t = 0$, $\mathbb{I}_t = 0$: No longer observe notional rate. Determine likelihood by a regime's probability to induce negative notional rate.

- Prior work on Bayesian learning has focused on $\mathbb{I}_t = 1 \ \forall t$.

Evolution of Beliefs

- Bayes rule describes updating $p_{j,t|t-1}$ to $p_{j,t|t}$.
- Update current beliefs to next period's using transition matrix, P:

$$p_{j,t+1|t} = P' p_{j,t|t}$$

- P distinguishes easing and FG regimes as $\gamma_0(j_t) \in \{0, \bar{\gamma_0}, 2\bar{\gamma_0}\}$.
- Regime 1=Normal, Regime 2=Easing, Regime 3=FG with

$$P = \begin{pmatrix} P_{11} & 1 - P_{11} & 0 \\ P_{21} & P_{22} & 1 - P_{21} - P_{22} \\ \frac{1-P_{33}}{2} & \frac{1-P_{33}}{2} & P_{33} \end{pmatrix}$$

- Priors imply $P_{22} << P_{33}$.
- Different restrictions lead to somewhat different results.

Rest of the Model

- We use 3-equation New Keynesian model with:
  - Price rigidities with lagged inflation indexation and markup shocks.
  - Habits in consumption.
  - Household preferences for risk-free bonds as in Fisher (2015) to allow for risk premium shocks.
- Learning influences the model's dynamics through its effect on expectations.
  - Expectations of all future variables involves weighting by $p_{j,t|t}$.
  - Through expectations, these beliefs (and their evolution) matter for current outcomes.
  - Learning about regimes harder at ZLB since do not observe notional rate.

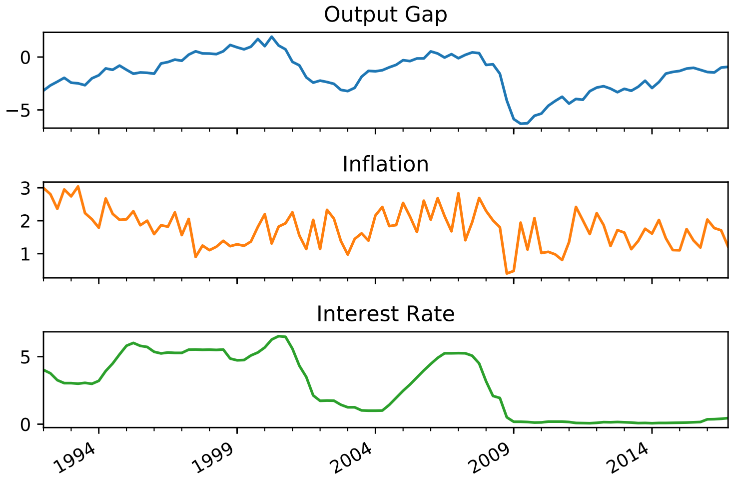
Solution and Estimation

- We need to estimate the model's parameters as well as filtered and smoothed model objects.
- To do so, we follow an approach similar to Gust et. al. (2017):
  - Because of nonlinearities (ZLB and learning), we use a projection method to solve the model.
  - We estimate it using Bayesian methods (similar to our agents).
- Econometrician and agents' filtering problem for the rule similar.
  - They use same data (nominal rate, output gap, and inflation) to make inferences about regimes and policy innovation.
  - Unlike agents, econometrician uses particle filter (PF) to compute likelihood.
- Depart from Gust et. al. (2017) by using tempered PF.
  - Tempered PF of Herbst and Schorfheide (2017) keeps measurement error very small relative to standard implementation.

Data and Estimation

- Estimate the model over 1992-2016 with 3 observables:
  - core PCE inflation, CBO output gap, and FFR.
- We estimate the learning and full information versions of the model with 3 regimes and 3 shocks:
  - Markup, risk-premium, and monetary.
- Plan to incorporate forward rates in model and re-estimate with 4 observables.
- We also compare DSGE estimates to nonlinear single-equation estimation.
  - Interest rate rule with regimes s.t. ZLB.

Data



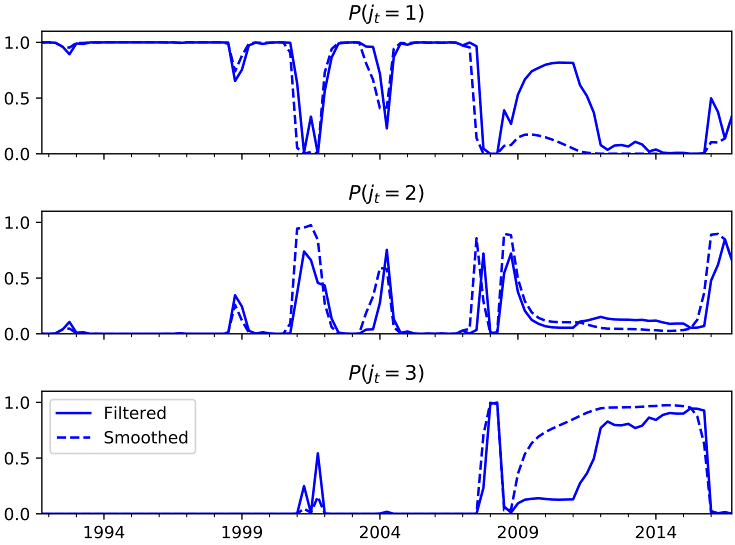
Output Gap
0
−5
Inflation
3
2
1
Interest Rate
5
0
1994
1999
2004
2009
2014

Posterior Distributions of Selected Parameters

	Full Information		Learning	
	Mean	[05,95]	Mean	[05,95]
ρ_r	0.82	[0.79, 0.84]	0.83	[0.80, 0.86]
γ_π	1.74	[1.49, 2.00]	1.78	[1.57, 2.08]
γ_x	0.37	[0.30, 0.43]	0.39	[0.28, 0.47]
$\bar{\gamma}_0$	0.09	[0.07, 0.12]	0.17	[0.16, 0.20]
P_{11}	0.96	[0.94, 0.98]	0.94	[0.93, 0.96]
P_{22}	0.46	[0.21, 0.63]	0.47	[0.23, 0.64]
P_{33}	0.92	[0.82, 0.98]	0.94	[0.91, 0.98]
P_{21}	0.34	[0.21, 0.40]	0.42	[0.23, 0.50]

- Intercept estimates $\bar{\gamma}_0$ much smaller under full information model.
- Rule estimates for DSGE model differ from single-equation (not shown): endogenous feedback important.

Estimated Regime Probabilities



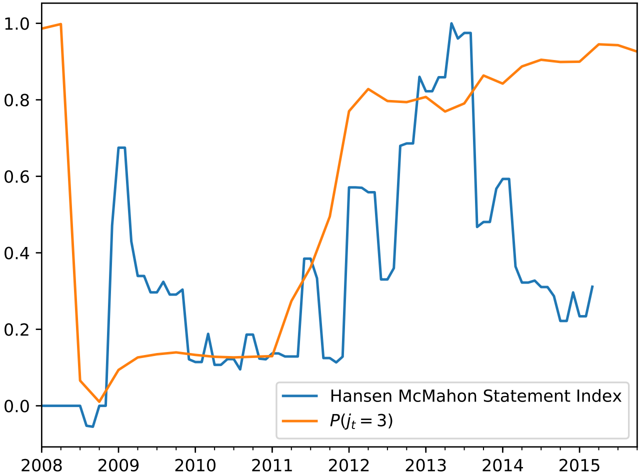
Evidence for Regime Switches

- How much should we take from previous figure?
- Marginal Data Density – measure of overall model fit:

No switching	-233.46
Regime Switching, Full Information	-228.33
Regime Swtiching, Learning	-225.22

- Moderate evidence in favor of 3 state model versus 1 state model.
- Improved fit concentrated during ZLB period.
- Not trivial to get a better fit: similar paper pre-ZLB, Schorfheide (2005), finds overwhelming evidence in favor FI model.

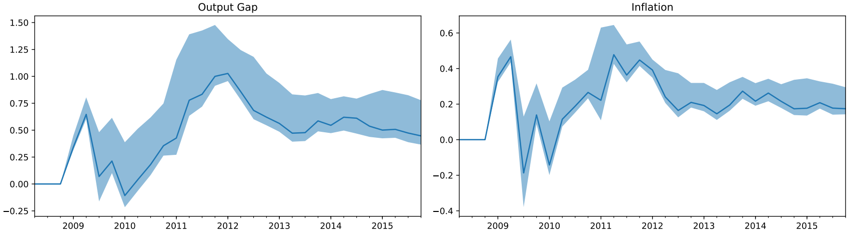
Comparison with Statement-Based FG Index



FG Experiment

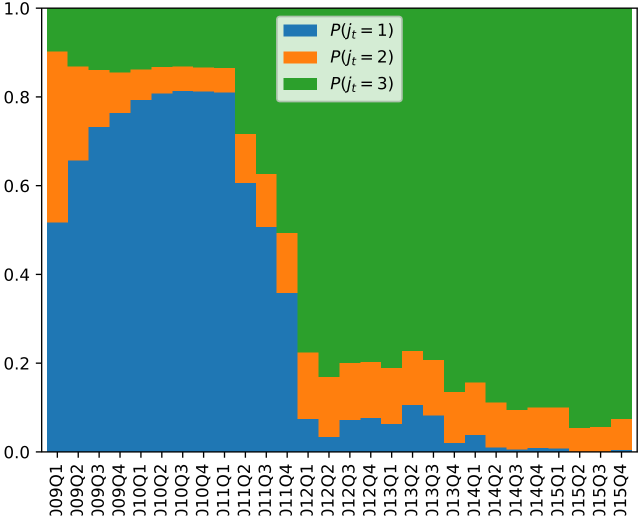
- Suppose FG regime is announced in 2009Q1 when hit ZLB.
- What are differences in outcomes under learning and full information?
- To address this question, we simulate the model forward through 2015Q4:
  - Use the filtered model states in 2008Q4.
  - Assume regime lasts until 2015Q4.
  - Compute the difference in output and inflation under full info and learning.

Outcome Differences in FG Experiment



- Large improvements in output and inflation.

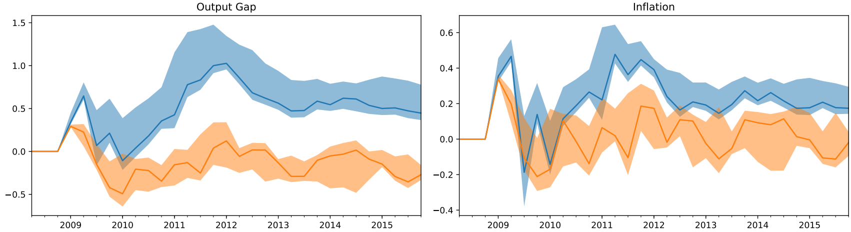
Evolution of Beliefs in FG Experiment



Role of ZLB

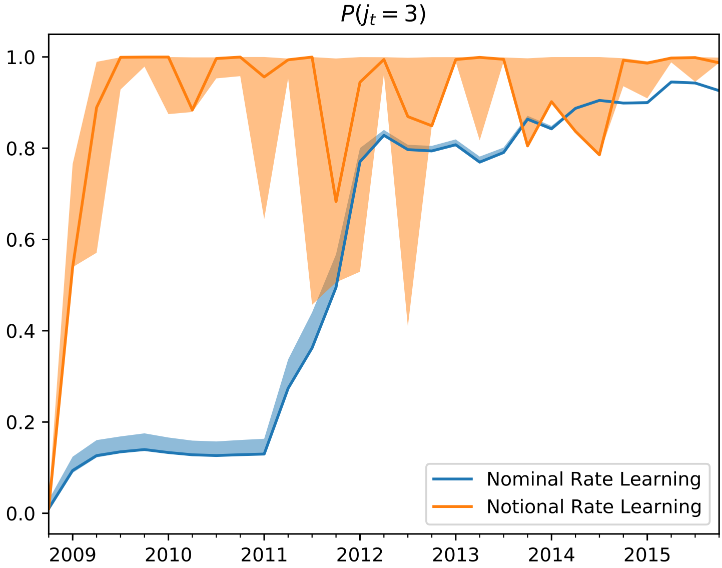
- What happens when we eliminate the ZLB's role in learning?
- Show the agents the notional rate, drop Tobit from the likelihood function?
- Agents learn extremely quickly, differences between learning and full information disappear.

FG Experiment: Role ZLB for learning



- Differences between learning and full information vanish!

Learning Rates – Role of ZLB



Conclusion

- Find evidence of regime switches in US Monetary Policy.
- Interaction of Learning and ZLB extremely important.
- Much more work to be done:
  - Matching expectations data.
  - Interaction of forward guidance with other unconventional policies.
- Thanks!