The Effects of Professional Forecast Dissemination on Macroeconomic Volatility

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Introduction

- There has been evidence from past DSGE estimations that the introduction of learning and the relaxation of rational expectations can have a significant impact on parameter estimates and overall fit of the model compared to the data
- Milani (2005, 2007) shows that when rational expectations are exchanged for learning in a New-Keynesian model, the estimated parameters of indexation and other nominal frictions are close to zero. Suggesting that expectation formation modeling has significant effects in such models.
- Similar conclusions are found by Slobodyan and Wouters (2012a) who find that learning can fit business cycle fluctuations better when compared to rational expectations in more stylized DSGE models.

Motivation

- Caroll (2003) found that households update their inflation expectations based on a linear combination between their previous inflation expectations and the expectations of "professional" economic forecasters that are reported to the public at-large.

- I proceeded to take Caroll's findings on expectation formation and imbed them into a stylized New Keynesian DSGE Model.

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- What role, if any, do professional forecasts play in the expectation formation process of modeled economic agents?
  - **Significant, especially during business cycle turning points**
- Does the introduction of professional forecasts generated by a high dimensional data vector have an impact on macroeconomic volatility?
  - **Yes, can lower macroeconomic volatility by 25% for key macroeconomic variables**
- Do noisy or manipulated forecast dissemination have an impact on macroeconomic volatility?
  - **Yes and no**

Introducing Adaptive Learning

- I Introduce learning into the SWFF DSGE Model. I assume that agents do not have perfect knowledge of the reduced form parameters, exogenous processes or steady state values of the model when forming expectations about the future
- Agents must form expectations about the path of 5 forward variables
  - Inflation
  - Consumption
  - Wages
  - Investment
  - Relative Price of Capital (Q)

Linear DSGE Model Set Up

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$$A\left[\hat{Y}_t\right] = B\left[\hat{Y}_{t-1}\right] + CE_t^*\left[\hat{Y}_{t+1}\right] + Dv_t$$

Introducing Adaptive Learning

- Agents believe the economy follows one of the following laws of motion (PLMs):

$$y_t^f = a_{1,t} + b_{1,t} y_{t-1}^f + e_{1,t}$$
$$y_t^f = a_{2,t} + c_{2,t} Y_{t|t-1}^* + e_{2,t}$$
$$y_t^f = a_{3,t} + b_{3,t} y_{t-1}^f + c_{3,t} Y_{t|t-1}^* + e_{3,t}$$

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- PLMs 2 and 3 is where I introduce professional forecasts of future variables into the DSGE model with the inclusion of Y^*.

- All non-zero coefficients in the 3 equations are calculated using constant gain learning and ROLS.

Introducing Adaptive Learning

- Agents are uncertain about weather or not to use the professional forecast announcement.
- Thus agents use Bayesian weights to calculate the aggregate PLM. These Bayesian weights are derived by previous realizations of each models residuals.

$$B_{i,t} = t \cdot ln\ det \left(\frac{1}{t} \sum_{\tau=1}^{t} E_{i,\tau} E'_{i,\tau} \right) + \kappa_i \cdot ln(t)$$

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- If a model has produced large residuals over the recent past observations it will receive a lesser weight used in averaging across all PLMs.
  - I use a rolling window of residuals of 12 quarters

Introducing Adaptive Learning

- The inclusion of Bayesian weighting allows agents to choose between and weigh private signals derived from AR(1) processes (1), completely using the professional forecast (2) and using both the professional forecast and the private signal (3) when selecting their aggregate PLM.

- Aggregate PLM

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$$E_t^* Y_{t+1} = E_t^* y_{t+1}^f = a_{agg,t} + a_{agg,t} b_{agg,t} + b_{agg,t}^2 \Phi Y_{t-1} + b_{agg,t} c_{agg,t} Y_{t|t-1}^* + c_{agg,t} Y_{t+1|t-1}^*$$

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$$\left[Y_t\right] = \mu_t + G_t\left[Y_{t-1}\right] + H\left[v_t\right]$$

- G_t is a time dependent transition matrix that is a function of A, B, C and b_{agg}.
- The coefficient vector of μ_t is a time dependent function of A, a_{agg}, b_{agg}, c_{agg} and Y^*.
- The matrix H is not time dependent as agents are unaware of any properties of the exogenous processes

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1. Agents observe $t-1$ values of all endogenous values.
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3. Agents use all $t-1$ information and the professional forecasts previously announced to update the coefficients on each of their PLMs using constant gain ROLS.

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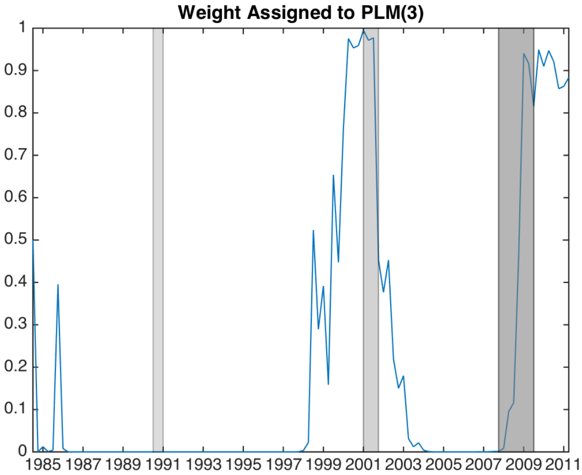
6. Time t exogenous shocks occur and all time t endogenous variables are then realized in the economy.

Bayesian Model Selection

	PLM(1)	PLM(2)	PLM(3)	BW	EW	REE
Marginal Likelihood	-781.268	-805.320	-799.832	-781.862	-780.252	-846.71
NW Standard Error	0.331	0.121	0.114	0.126	0.110	0.164
Model Probability	0.232	0.000	0.000	0.128	0.640	0.000

- Marginal likelihood calculated using the Modified Harmonic Mean estimator

Weight assigned to Professional Forecast PLMs



Simulation Procedures

- I start every simulation at 2012Q1 and simulate for 200 quarters into the future and use the posterior median estimates of the BW model for each parameter
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  - VAR
  - Dynamic Factor Model
  - Rational Expectations Forecast

SPF and VAR Forecast Correlation

	1 Quarter Ahead Forecast	2 Quarters Ahead Forecast
Inflation	0.93	0.92
Output Growth	0.68	0.67
Consumption Growth	0.44	0.43
Investment Growth	0.57	0.63
Unemployment Rate	0.87	0.90

Simulation Procedures

- Seven different expectation procedures are simulated
  - PLM(1)
  - PLM(3)
  - Bayesian Weights on each PLM
  - Bayesian Weights with a small/large noise shock around the professional forecast
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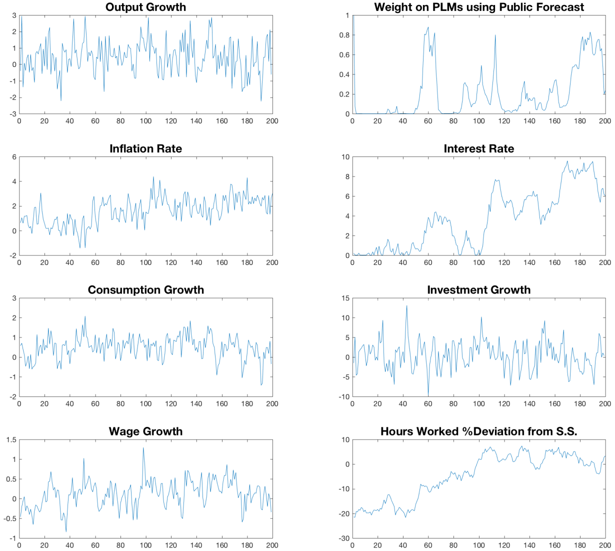
- $y_t^f = a_{3,t} + b_{3,t} y_{t-1}^f + c_{3,t}(Y^*_{t|t-1} + \eta_t^f) + e_{3,t}$

- where η_t^f is normally distributed with a mean of $\mu\, std(y^f)$ and variance of $\sigma std(y^f)$

Simulated Example



Simulation Results (Standard Deviations)

	PLM(1)	BW	PLM(3)	BW Low Noise	BW High Noise
Standard Deviations					
π	1.13	1.06	0.87	1.07	1.10
R	2.46	2.51	2.31	2.51	2.49
L	7.59	7.33	6.66	7.34	7.38
Y	5.86	5.60	5.05	5.62	5.67
C	5.47	5.16	4.06	5.18	5.24
I	24.56	23.10	21.82	23.15	23.64
W	2.86	2.71	2.24	2.72	2.85
S	3.81	3.66	3.39	3.68	3.87

Summary

- Further evidence that adaptive learning raises the marginal likelihood in empirically estimated DSGE models.
  - Changes in parameter estimates and nominal frictions
- Provides analytical estimates of the effects of professional forecasts on the volatility of Output, Inflation and other aggregate variables
  - The existence of accurate and well communicated professional forecasts can lower economic volatility by significant margins.
  - If the professional forecast is not communicated to the agents accurately macroeconomic volatility has the potential to increase with the existence of such professional forecasts.