

Bayesian Methods for DSGE models
Lecture 5
News, Noise and Structural Economic Models

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News and Noise

The Plan:

- ▶ News, Noise and Business Cycles
 - ▶ A theoretical framework
 - ▶ Empirical challenges
 - ▶ Quantifying the effects of noise shocks
 - ▶ Using survey data in state space models
- ▶ Concluding remarks for the course

Thanks for the filter and RIP



RENOWNED HUNGARIAN SCIENTIST, INVENTOR OF THE "KÁLMÁN FILTER"
RUDOLF KÁLMÁN DIES AGED 86

Sentiments, Animal Spirits and Undue Optimism/Pessimism

Shocks in macro economics models

"We have not found large, identifiable, exogenous shocks to account for the bulk of of output fluctuations...

...It would be nice to point to recognizable events, of the type that is reported by newspapers, as the source of economic fluctuations, rather than to residuals from some equations."

John Cochrane, 1995

Shocks in macro models

Measuring sources of exogenous variation in macro economic variables

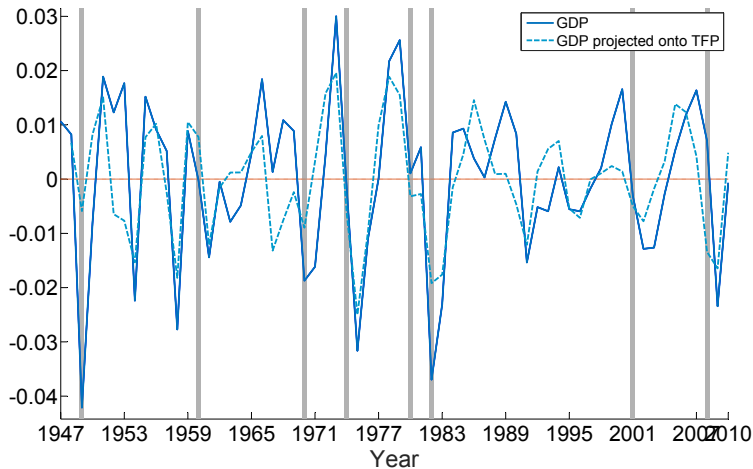
- ▶ Impulse vs propagation: If exogenous shocks are unobserved, assumptions about propagation determines impulses

Productivity can be measured more or less directly

- ▶ E.g. Fernald (2012), Jorgenson, Ho and Samuels (2013)

But productivity changes cannot explain all fluctuations

GDP projected onto TFP



What drives aggregate fluctuations?

"Business cycles are all alike", e.g. Blanchard (1993), Hall (1993), Cochrane (1995), Rebelo (2004)

- ▶ Investment and durables fall by more than GDP, non-durable consumption by less
- ▶ Consumption, investment and hours worked are strongly pro-cyclical

Some candidates

- ▶ Credit, oil price, monetary and fiscal policy shocks are either too small or imply counterfactual correlations

In Hall's and Cochrane's terminology, "consumption shocks" appear to be needed

Optimism, pessimism and aggregate fluctuations

Fluctuations in output due to exogenous variation in expectations is an old idea:

- ▶ Pigou cycles (Pigou 1932), animal spirits (Keynes 1936), sunspots (Cass and Shell 1983), news about future productivity (Beaudry and Portier 2004, 2006, 2007, Jaimovich and Rebelo 2009), noisy public signals about common productivity (Lorenzoni 2009), shocks to "sentiments" (Angeletos and La'o 2013)

To different degrees, these theories can match the co-movement of consumption, hours worked, investment etc

An Old Idea I

“The varying expectations of business men ... and nothing else, constitute the immediate cause and direct causes or antecedents of industrial fluctuations.”

A.C. Pigou

An Old Idea II

“Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of animal spirits, a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.”

J.M. Keynes

Optimism, pessimism and aggregate fluctuations

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Question: Can we quantify the importance of undue optimism empirically?

Some theory

A Theory of Demand Shocks, Lorenzoni (AER 2009)

Well known paper by former UPF student.

Basic set up

- ▶ Standard New-Keynesian model with sticky prices and monopolistic competition
- ▶ Aggregate productivity follows a random walk
- ▶ Optimal consumption determined by permanent income hypothesis

Introducing imperfect information

Two parts:

1. Representative agent and transitory productivity shocks
2. Dispersed information

Dispersed information

Islands are subject to idiosyncratic productivity shocks

Total island productivity is equal to aggregate + idiosyncratic productivity

Three tricks to prevent full revelation of aggregate state:

- ▶ Island inhabitants do not observe the components of productivity directly
- ▶ When shopping, inhabitants of an island do not travel to all other islands in the economy
- ▶ When selling goods, an island is not visited by inhabitants from all other islands

Neat, and more easily interpretable than pure noise

Production on island j

Firm i on island j produce good i, j using the technology

$$Y_{i,j,t} = \exp(a_{j,t}) N_{i,j,t}$$

(The log of) productivity $a_{j,t}$ is the sum of a common component x_t and the island specific component $\eta_{j,t}$

$$a_{j,t} = x_t + \eta_{j,t} : \eta_{j,t} \sim N(0, \sigma_\eta^2) \quad \forall \quad j, t.$$

The common productivity component x_t follows a random walk

$$x_t = x_{t-1} + \varepsilon_t$$

Dispersed information

Total island productivity is equal to aggregate + idiosyncratic productivity

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Neat, and and more easily interpretable than pure noise

A public signal

In addition to the island specific source of information, all islands also observe a public signal about aggregate productivity

$$s_t = x_t + e_t$$

Whatever interpretation we give to the public signal, that it does not perfectly reveal the state of the economy seems plausible

- ▶ MSNBC, CNN, Wall St Journal etc
- ▶ Revisions to statistical estimates etc
- ▶ Debate on Solow residual

Public signals improve average estimates, but at times must induce agents to respond to "false alarms" (i.e. \Rightarrow "demand shocks")

Solving the model

Lucas (1973) assumed that aggregate state observed between periods

- ▶ Makes dynamics due to information short lived

In Lorenzoni, the state is never perfectly revealed

- ▶ Solving model is harder as one need to worry about the “infinite regress of expectations” as in Townsend (1983) and the associated infinite dimensional state
- ▶ Lorenzoni takes similar approach to Townsend and assumes that variables lagged more than 50 periods are uninformative

The effects of noise shocks

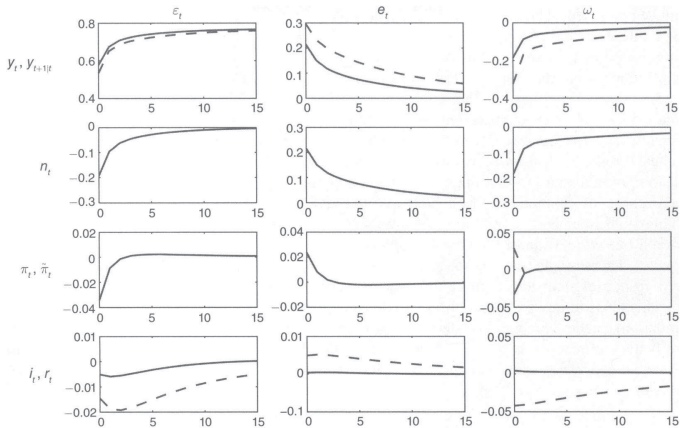


FIGURE 1. IMPULSE RESPONSES OF OUTPUT, EMPLOYMENT, INFLATION, AND THE INTEREST RATE

The effects of noise shocks

Noise shocks thus look like demand shocks (hence the title)

A better “theory” than shocks to preferences (which we would like to think are pretty stable)

Lorenzoni reports that

- ▶ “Noise” shocks can explain a substantial fraction of output volatility

But:

- ▶ What happens when $\sigma_e^2 \rightarrow 0$?
- ▶ What happens when $\sigma_e^2 \rightarrow \infty$?

The non-monotonic effect on dynamics of variances

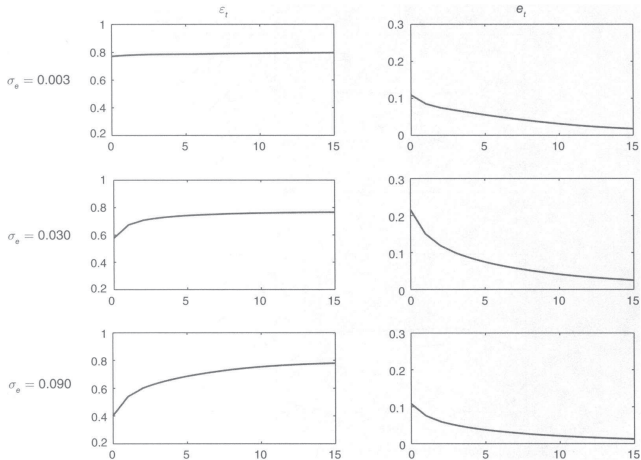


FIGURE 4. OUTPUT RESPONSES FOR DIFFERENT VALUES OF σ_e

Summing up *A Theory of Demand Shocks*

Noisy public information can explain what looks like demand shocks in the data

- ▶ Agents become unduly optimistic after a positive noise shock and unduly pessimistic after a negative noise shock
- ▶ There is an upper bound on how much aggregate volatility that can be explained by noise shocks

But how can we empirically quantify the importance of undue optimism/ pessimism?

Quantifying the importance of optimism shocks empirically

Quantifying the importance of optimism shocks empirically

How can we quantify the role of optimism shocks empirically?

Questions:

- ▶ Do we have direct empirical measures of sentiments or undue optimism/pessimism?
- ▶ What type of identification strategies can be used to quantify the effect of noise shocks?

Potential strategies:

- ▶ Long-run restrictions a la Blanchard and Quah (1989)
- ▶ Using structural models, e.g. Barsky and Sims, AER 2012 and Blanchard, L'Huillier and Lorenzoni, AER 2014.

Empirical measures of sentiments, animal spirits and/or undue optimism/pessimism

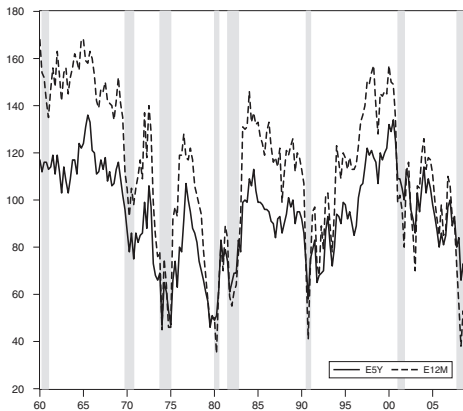
Barksy and Sims (2014) argue that survey data on *Consumer Confidence* may be helpful.

Main Survey Question:

Turning to economic conditions in the country as a whole, do you expect that over the next five years we will have mostly good times, or periods of widespread unemployment and depression, or what?

Other questions ask about personal economic conditions.

Consumer Confidence and Recessions



Direction of causation

Clearly, the confidence index dips during recessions.

But:

- ▶ Is confidence low because of the recessions?
- ▶ Is there a recessions because confidence is low?

There are some interesting challenges involved in identifying the direction of causality that are particular to confidence shocks.

Identifying the Effect of Noise Shocks using SVARs

SVARs will generally not work:

- ▶ If there is a response to a pure noise shock, then this is a “mistake” from the perspective of the agents
- ▶ We cannot identify a mistake made by rational agents from variables that the agents also can observe

Identifying the Effect of Noise Shocks using SVARs

From the projection theorem we know that if $E[X | \Omega] = \beta Y$ then

$$E[(X - \beta Y)\omega'] = 0$$

for any $\omega, Y \in \Omega$.

- ▶ If we run a VAR in variables that are publicly available, then if we can back out the shocks, so can the agents
- ▶ If agents form expectations rationally, VAR shocks must be orthogonal to expectational errors

Identifying Noise and News Shocks using DSGEs

DSGEs could potentially work:

- ▶ Use ML to estimate deep parameters and quantify the contribution to overall variance made by noise shocks
- ▶ Kalman smoother can be used to back out time series of noise shocks

This strategy is pursued by Blanchard, L'Hullier and Lorenzoni (AER 2013)

News, Noise and Fluctuations: An empirical Investigation (BLL 2013)

Sets up a simplified representative agent version of the model
Lorenzoni (AER 2009)

- ▶ Standard New-Keynesian model with sticky prices and monopolistic competition
- ▶ Permanent and transitory productivity shocks
- ▶ Optimal consumption determined by permanent income hypothesis
- ▶ Estimate model using standard macro time series

A public noisy signal will introduce undue optimism and pessimism

A public signal

The representative household observes a noisy signal about permanent productivity x_t

$$s_t = x_t + e_t$$

Observing the signal improves productivity estimates on average, but at times induce agents to respond to "false alarms" (i.e. \Rightarrow "demand shocks")

Prior and posterior estimates

TABLE 5—FULL DSGE: ESTIMATED PARAMETERS

	Parameter	Prior	Posterior	Conf. bands		Distribution	Prior SD
h	Habit	0.5	0.5262	0.4894	0.5787	Beta	0.1
α	Production function	0.3	0.1859	0.1748	0.1933	Normal	0.05
ζ	Inv. Frisch elasticity	2	2.0871	1.0571	3.3012	Gamma	0.75
ξ	Capacity cost	5	3.4919	2.8912	4.3021	Normal	1
χ	Adjustment cost	4	4.3311	3.6751	5.5079	Gamma	1
θ	Calvo prices	0.66	0.8770	0.8545	0.8998	Beta	0.1
θ_w	Calvo wages	0.66	0.8690	0.8227	0.9183	Beta	0.1
γ_π	Taylor rule inflation	1.5	1.0137	1.0102	1.0568	Normal	0.3
γ_y	Taylor rule output	0.005	0.0050	0.0037	0.0061	Normal	0.05
<i>Shock processes</i>							
Neutral technology and noise							
ρ		0.6	0.9426	0.9230	0.9618	Beta	0.2
σ_u		0.5	1.1977	1.0960	1.2975	Inv. Gamma	1
σ_v		1	1.4738	0.7908	2.3176	Inv. Gamma	1
Investment-specific							
ρ_d		0.6	0.4641	0.3263	0.5743	Beta	0.2
σ_d		0.15	11.098	8.4323	14.910	Inv. Gamma	1.5
Markups							
ρ_p		0.6	0.7722	0.6991	0.8461	Beta	0.2
ϕ_p		0.5	0.4953	0.3749	0.6557	Beta	0.2
σ_p		0.15	0.1778	0.1508	0.2027	Inv. Gamma	1
ρ_w		0.6	0.9530	0.9534	0.9650	Beta	0.2
ϕ_w		0.5	0.9683	0.9700	0.9739	Beta	0.2
σ_w		0.15	0.3057	0.2847	0.3264	Inv. Gamma	1
Policy							
ρ_r		0.5	0.5583	0.5125	0.6224	Beta	0.2
ρ_q		0.4	0.0413	0.0024	0.0807	Beta	0.2
σ_q		0.15	0.3500	0.3148	0.3782	Inv. Gamma	1
ρ_g		0.6	0.9972	0.9938	0.9998	Beta	0.2
σ_g		0.5	0.2877	0.2680	0.3078	Inv. Gamma	1

Impulse Response Functions (Quantities)

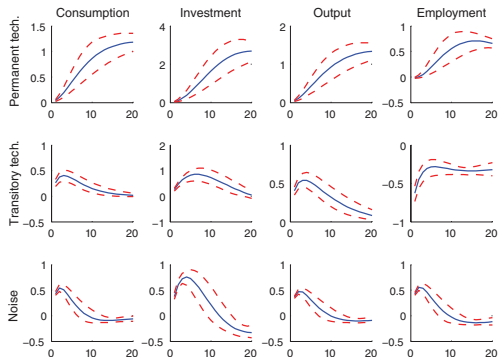


FIGURE 5. IMPULSE RESPONSES, BAYESIAN DSGE, QUANTITIES

Impulse Response Functions (Prices)

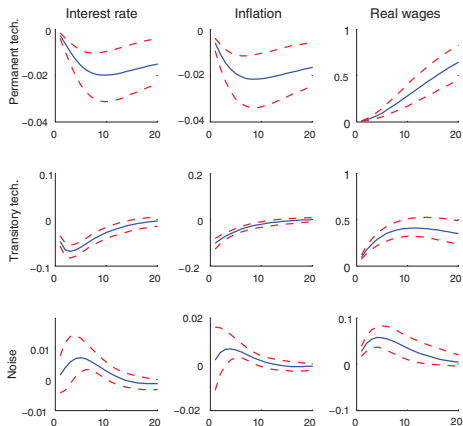


FIGURE 6. IMPULSE RESPONSES, BAYESIAN DSGE, PRICES

Variance decompositions

TABLE 6—VARIANCE DECOMPOSITION

Quarter	Perm. tech.	Trans. tech.	Noise	Inv. specific	Price markup	Wage markup	Monetary	Fiscal
<i>Consumption</i>								
1	0.004	0.186	0.512	0.001	0.205	0.037	0.001	0.055
4	0.064	0.246	0.430	0.002	0.117	0.039	0.006	0.095
8	0.331	0.198	0.245	0.003	0.063	0.024	0.015	0.121
12	0.577	0.117	0.134	0.003	0.034	0.013	0.017	0.106
<i>Investment</i>								
1	0.000	0.005	0.011	0.971	0.006	0.006	0.000	0.000
4	0.003	0.017	0.021	0.936	0.008	0.016	0.000	0.000
8	0.031	0.036	0.027	0.869	0.009	0.027	0.000	0.001
12	0.120	0.046	0.025	0.769	0.009	0.029	0.000	0.003
<i>Output</i>								
1	0.003	0.249	0.200	0.372	0.083	0.026	0.001	0.066
4	0.040	0.272	0.198	0.363	0.057	0.039	0.003	0.028
8	0.228	0.270	0.134	0.267	0.036	0.035	0.006	0.024
12	0.477	0.200	0.083	0.167	0.023	0.023	0.008	0.020

Variance decompositions

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Estimating the agents' mistakes using the Kalman Smoother

The standard Kalman filter gives an optimal *real time* estimate of the latent state

- Sometimes we are interested in the best estimate given the complete sample, i.e. $X_{t|T}$

$$X_{t|T} = E \left[X_t \mid Z^T, X_{0|0} \right]$$

The *Kalman smoother* can be used to find $X_{t|T}$

Because we use more information than what is available to agents in *real time* we can quantify their mistakes

Estimated true and expected productivity

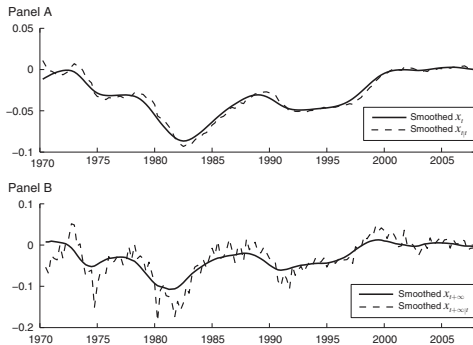


FIGURE 3. SMOOTHED ESTIMATES OF THE PERMANENT COMPONENT OF PRODUCTIVITY, OF LONG-RUN PRODUCTIVITY, AND OF CONSUMERS' REAL TIME EXPECTATIONS

Estimated history of exogenous shocks

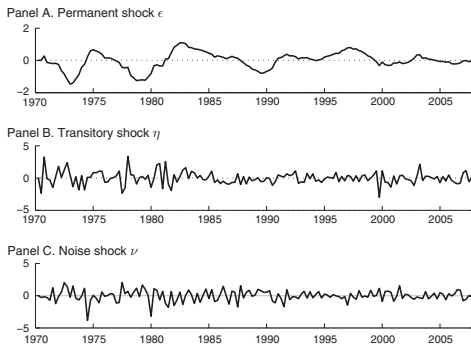


FIGURE 4. SMOOTHED ESTIMATES OF THE SHOCKS

Using survey data in estimation

Using survey data when estimating DSGE models

Blanchard et al use only macro economic time series to estimate their model

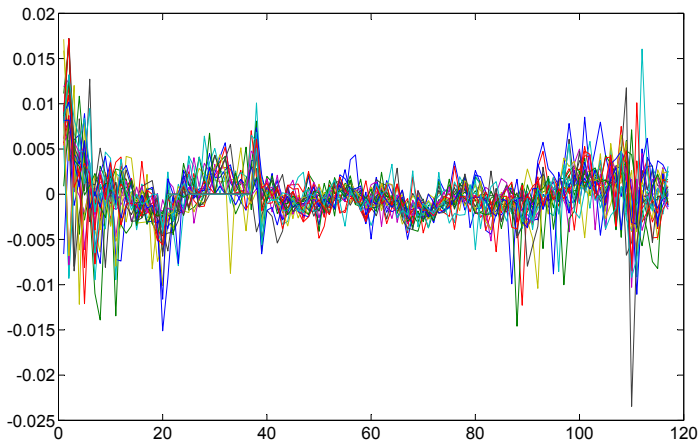
- ▶ Given the importance of expectations for the theory, is there any data that directly measures expectations?

One option is to use survey data such as the *Survey of Professional Forecasters*. We have two choices:

1. Use mean or median forecast as a measure of the representative agent's expectations
2. Use individual forecasts as being representative of the forecasts of agents with heterogeneous expectations

We will pursue the second approach.

Individual SPF inflation forecasts



Using individual survey responses

If we have a model where agents disagree about future variables, each survey response can be treated as an independent draw from the model implied cross-sectional distribution of expectations

$$f_{t,\pi} \sim N \left(\int E[\pi_{t+1} \mid \Omega_{j,t}] dj, \sigma_{f\pi}^2 \right)$$

If we observe 25 forecasts, we will have 25 lines corresponding to each forecast in the measurement equation.

- ▶ The "measurement error" variance depends on deep parameters.

Using individual survey responses

The equilibrium law of motion of X_t is a vector autoregression of the form

$$X_t = MX_{t-1} + N\mathbf{u}_t : \mathbf{u}_t \sim N(0, I) \quad (1)$$

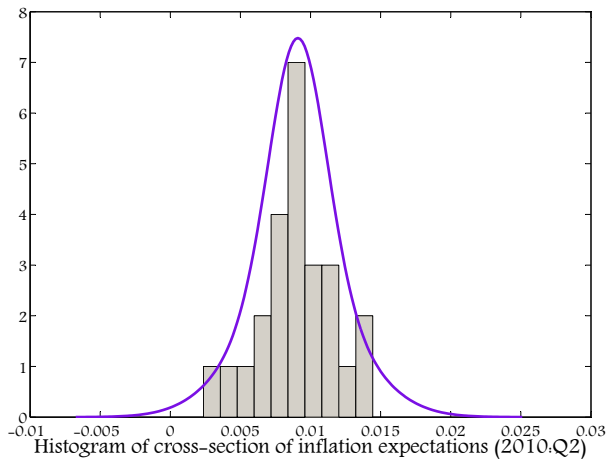
The observed vector

$$Z_t = [a_t \quad \pi_t \quad y_t \quad r_t \quad \mathbf{f}'_t] \quad (2)$$

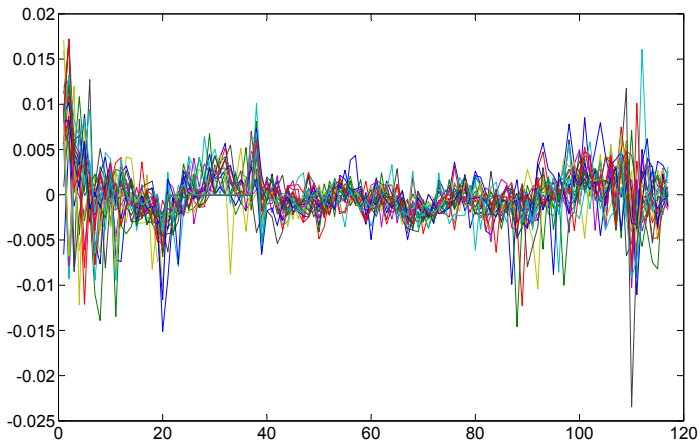
and linked to the state of the model by the measurement equation

$$Z_t = \overline{D}_t X_t + D_r r_{t-1} + \overline{R} \mathbf{u}_t \quad (3)$$

Using individual survey responses



Individual SPF inflation forecasts: Time-varying dispersion



The Role of News Media in the Business Cycle

Man-bites-dog business cycles, Nimark (AER 2014)

*"The phrase **man bites dog** describes a phenomenon in journalism in which an unusual, infrequent event is more likely to be reported as news than an ordinary, everyday occurrence (such as *Dog bites man*). The result is that rare events often appear in headlines while common events rarely do."*

from Wikipedia

This paper investigates the implications of this aspect of news reporting for the business cycle

Man-bites-dog business cycles

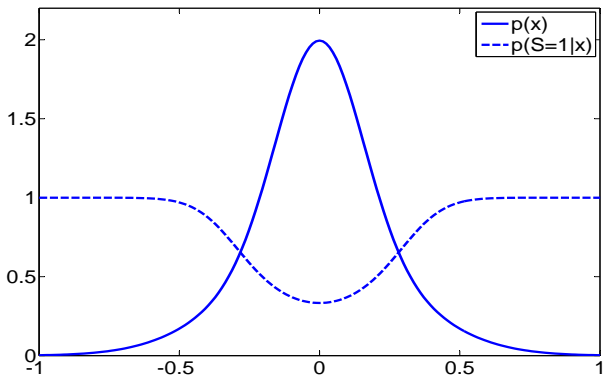
Three different sources of information:

- ▶ Economic interactions in markets
- ▶ Statistics: scheduled release dates, reported regardless of content
- ▶ News (or man-bites-dog signals): Signals that are more likely to be available about unusual events

That unusual events are more likely to be reported as news may suggest that we should be better informed about unusual events.

- ▶ But flip side of that argument is that conditional on that a signal is available, the likelihood of an unusual event has increased and uncertainty may then go up

Unusual events and the availability of signals



Unconditional distribution $p(x)$ of latent variable x and conditional probability of observing signal about x $p(S = 1|x)$

Man-bites-dog business cycles

Man-bites-dog signals can help us understand why we observe

- ▶ Large changes in macro aggregates without a correspondingly large change in fundamentals
- ▶ Persistent periods of high macro economic volatility
- ▶ A positive correlation between the volatility of macro aggregates and the cross-sectional dispersion of forecasts

Defining Man-bites-dog signals

Definition 1: The signal y is said to be a *man-bites-dog signal* if for any two realizations x' and x'' such that

$$p(x') < p(x'')$$

the inequality

$$p(S = 1 \mid x') > p(S = 1 \mid x'')$$

holds and where S is an indicator variable that takes the value 1 when the signal y is available.

The more unlikely realization x' is thus more likely to generate the signal y .

Conditional distributions implied by Bayes' Rule

Combining Bayes' rule

$$p(x | S = 1) p(S = 1) = p(S = 1 | x) p(x)$$

for x' and x'' gives

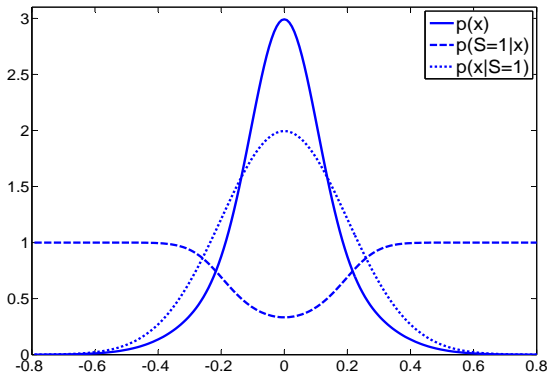
$$\frac{p(x' | S = 1)}{p(x'' | S = 1)} = \frac{p(S = 1 | x')}{p(S = 1 | x'')} \frac{p(x')}{p(x'')}$$

so that by Definition 1 we get

$$\frac{p(x' | S = 1)}{p(x'' | S = 1)} > \frac{p(x')}{p(x'')}$$

The more unusual realization x' is thus relatively more likely when the signal y is available.

Conditional probabilities implied by Bayes' Rule



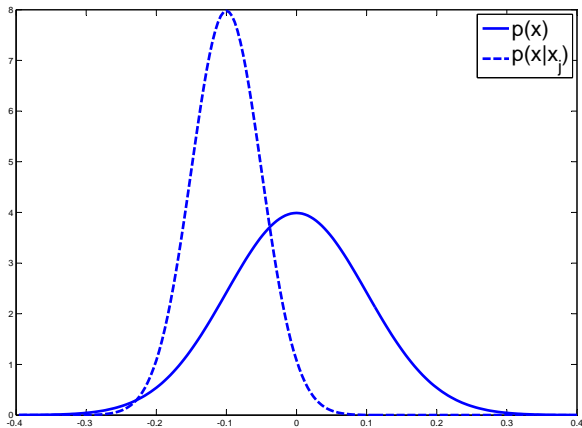
3 (theoretical) results

Proposition 2 Agents' posterior uncertainty about latent state x can be larger when the man-bites-dog signal y is observed

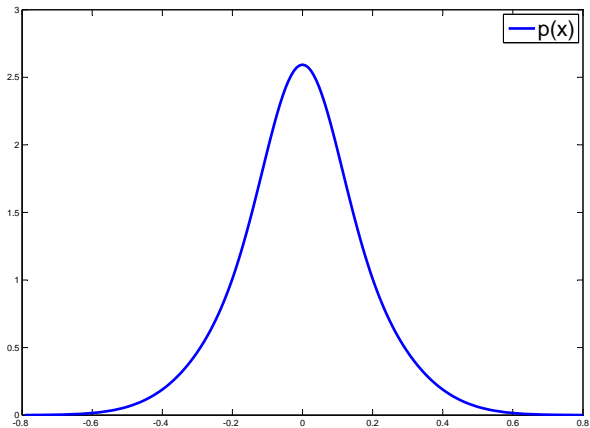
Corollary 1 The cross-sectional dispersion of expectations may increase when the public man-bites-dog signal y is observed

Proposition 5 Agents respond stronger to a change in fundamentals when a man-bites-dog signal is observed, compared to a standard signal of the same precision.

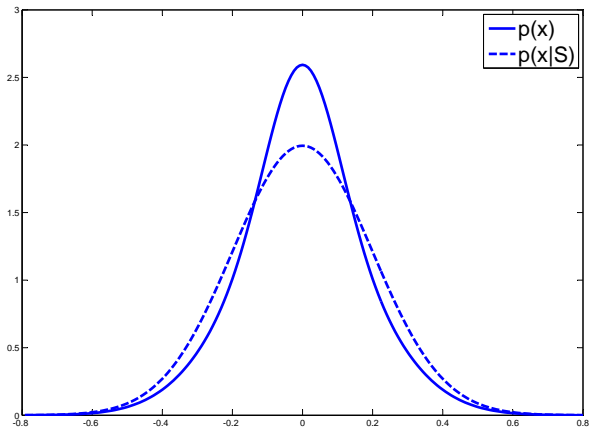
Bayesian updating to standard signals



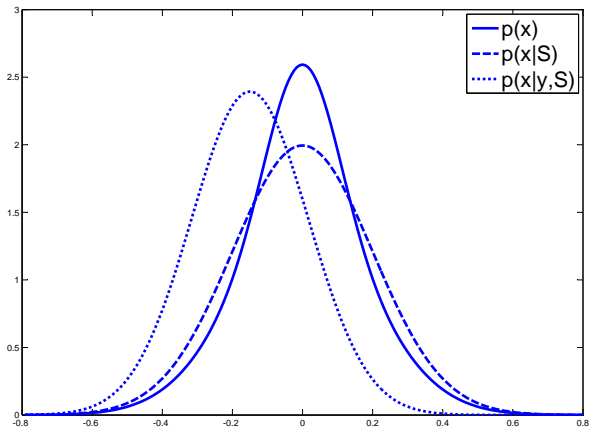
Unconditional prior distribution



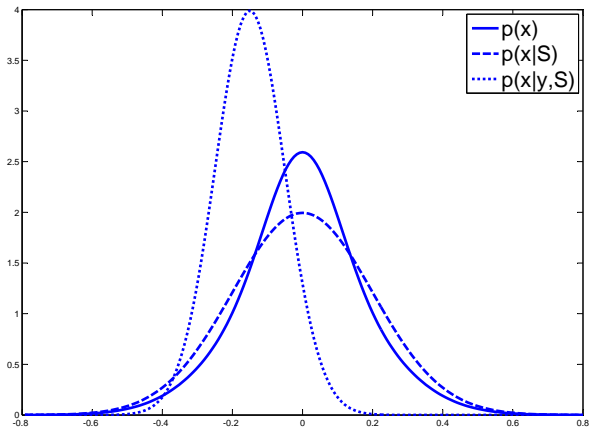
Prior and distribution conditional on $S=1$



Prior, distribution conditional on $S=1$ and
conditional on observing y



Prior, distribution conditional on $S=1$ and
conditional on observing y



A simple business cycle model

Follows closely Lorenzoni (2009) but with a man-bites-dog information structure

- ▶ Island economy with common and island specific productivity shocks
 - ▶ A large innovation to productivity is more likely to generate a public signal
- ▶ Each island consume only a subset of goods and sell their own good only to a subset of islands
 - ▶ Prevents local interactions from revealing aggregate state
- ▶ Strategic complementarities in consumption and prices
- ▶ Nominal interest rate follows a Taylor rule

What are the dynamic effects of man-bites-dog signals?

Production on island j

Firm i on island j produce good i, j using the technology

$$Y_{i,j,t} = \exp(a_{j,t}) N_{i,j,t}$$

(The log of) productivity $a_{j,t}$ is the sum of a common component a_t and the island specific component $\varepsilon_{j,t}$

$$a_{j,t} = a_t + \varepsilon_{j,t} : \varepsilon_{j,t} \sim N(0, \sigma_\varepsilon^2) \quad \forall j, t.$$

The common productivity component a_t follows an AR(1) process

$$a_t = \rho_a a_{t-1} + u_t^a$$

where the innovation u_t^a is distributed as a mixture normal

$$u_t^a \sim (1 - \omega) N(0, \sigma^2) + \omega N(0, \gamma \sigma^2).$$

A simple business cycle model

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- ▶ Each island consume only a subset of goods and sell their own good only to a subset of islands
 - ▶ Prevents local interactions from revealing aggregate state
- ▶ Strategic complementarities in consumption and prices
- ▶ Nominal interest rate follows a Taylor rule

What are the dynamic effects of man-bites-dog signals?

Time-varying information structure

Number of observables and conditional distribution of productivity depends on realization of s_t

- ▶ A public signal about productivity is available in period t when $s_t = 1$

In every period agents observe

- ▶ Local productivity, prices and demand
- ▶ The nominal interest rate

Dynamics in period t depend on history s^t

Endogenous time-varying dynamics

The agents solve a Kalman filtering problem

$$X_{t|t}(j) = [I - K(s^t)D(s^t)]\underbrace{X_{t|t-1}(j)}_{\text{prior}} + K(s^t)\underbrace{Z_t(j)}_{\text{signal}}$$

where the state X_t is a vector of higher order expectations of productivity and demand shocks.

- ▶ Weight on signal vector, i.e. the Kalman gain, is inversely related to the precision of the prior
- ▶ Increased posterior uncertainty in period t translates into increased prior uncertainty in period $t + 1$
- ▶ A single man-bites-dog event can thus potentially increase the sensitivity to new information for several periods

Estimating the model

Model is conditionally linear and straightforward to estimate using likelihood based methods

- ▶ The data (1981:Q3 - 2010:Q3):
 - ▶ Fed funds rate, CPI inflation and detrended real GDP
 - ▶ Individual survey responses on one quarter ahead forecasts of CPI inflation and nominal GDP from Survey of Professional Forecasters
 - ▶ Quarterly time series of Total Factor Productivity constructed by Fernald (2010)
- ▶ Use Multiple-Block Metropolis Algorithm (Chib 2001) to construct posterior estimates of
 - ▶ Parameters of preferences and technology
 - ▶ Parameters governing the man-bites-dog information structure
 - ▶ The history of s_t

Using individual survey responses

Each survey response is treated as an independent draw from the model implied cross-sectional distribution of one quarter ahead inflation expectations

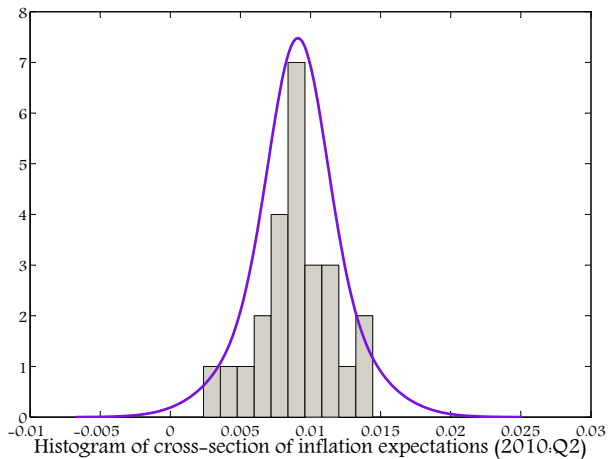
$$f_{t,\pi} \sim N \left(\int E[\pi_{t+1} | \Omega_{j,t}] dj, \sigma_{f\pi}^2(s^t) \right)$$

and nominal GDP growth expectations

$$f_{t,\pi+\Delta y} \sim N \left(\int E[\Delta y_{t+1} + \pi_{t+1} | \Omega_{j,t}] dj, \sigma_{f\pi+\Delta y}^2(s^t) \right)$$

- Note that cross-sectional dispersion depends on s^t

Using individual survey responses



Estimating the model

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 - ▶ Parameters of preferences and technology
 - ▶ Parameters governing the man-bites-dog information structure
 - ▶ The history of s_t
- ▶ Uniform truncated priors for all parameters

Multiple-Block Metropolis-Hastings algorithm

1. Specify initial values Θ_0 and s_0^T .

2. Repeat for $j = 1, 2, \dots, J$

2.1 Block 1: Draw Θ_j from $p(\Theta | s_{j-1}^T, Z^T)$

2.1.1 Generate the candidate parameter vector Θ^* from $q_{\Theta}(\Theta^* | \Theta_{j-1})$

2.1.2 Calculate

$$\alpha_j^{\Theta} = \min \left\{ \frac{L(Z^T | s_{j-1}^T, \Theta^*) p(s^T | \Theta^*) p(\Theta^*) q_{\Theta}(\Theta_{j-1} | \Theta^*)}{L(Z^T | s_{j-1}^T, \Theta_{j-1}) p(s^T | \Theta_{j-1}) p(\Theta_{j-1}) q_{\Theta}(\Theta^* | \Theta_{j-1})}, 1 \right\}$$

2.1.3 Set $\Theta_j = \Theta^*$ if $U(0, 1) \leq \alpha_j^{\Theta}$ and $\Theta_j = \Theta_{j-1}$ otherwise.

2.2 Block 2: Draw s_j^T from $p(s^T | \Theta_j, Z^T)$

2.2.1 Generate s^{*T} from the proposal density $q_S(s^{*T} | s_{j-1}^T)$

2.2.2 Calculate $\alpha_j^s = \min \left\{ \frac{L(Z^T | s^{*T}, \Theta_j) p(\Theta_j | s^{*T}) q_S(s_{j-1}^T | s^{*T})}{L(Z^T | s_{j-1}^T, \Theta_j) p(\Theta_j | s_{j-1}^T) q_S(s^{*T} | s_{j-1}^T)}, 1 \right\}$

2.2.3 Set $s_j^T = s^{*T}$ if $U(0, 1) \leq \alpha_j^s$ and $s_j^T = s_{j-1}^T$ otherwise.

3. Return values $\{\Theta_0, \Theta_1, \dots, \Theta_J\}$ and $\{s_0^T, s_1^T, \dots, s_J^T\}$

Empirical results

Posterior IRFs

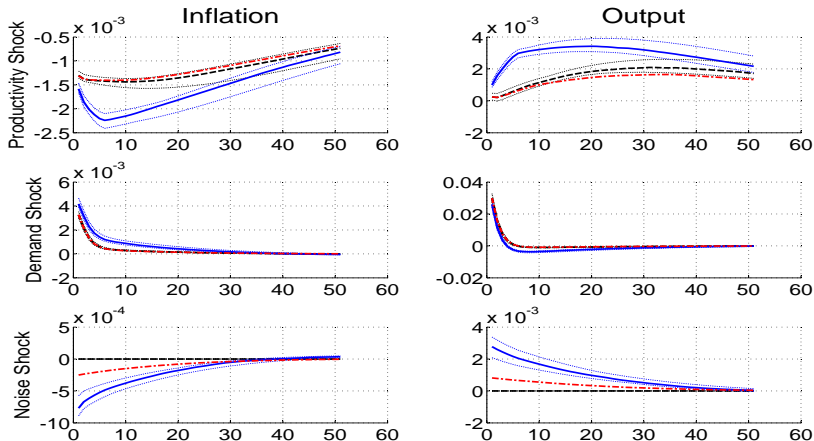
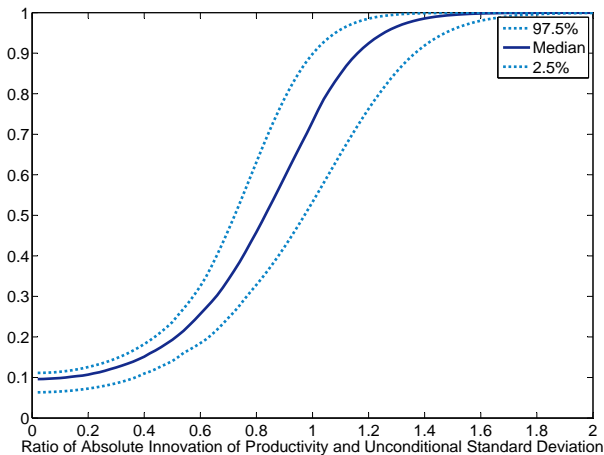
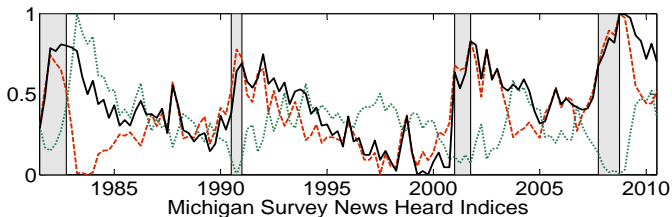
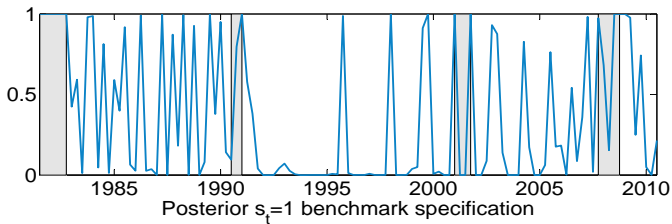


Figure: Blue line: $s^t = 1, 0, 0, \dots$ Black line: $s^t = 0, 0, 0, \dots$

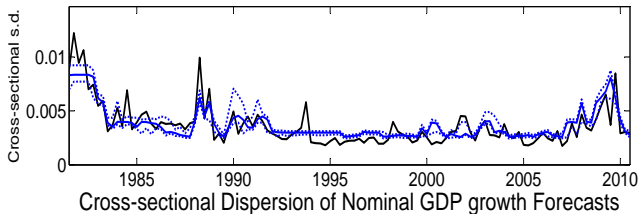
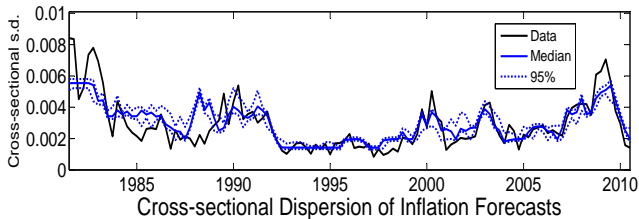
The conditional probability of observing a man-bites-dog signal



Historical probabilities of man-bites-dog episodes



Actual and model implied dispersion of expectations



Endogenous time varying dynamics

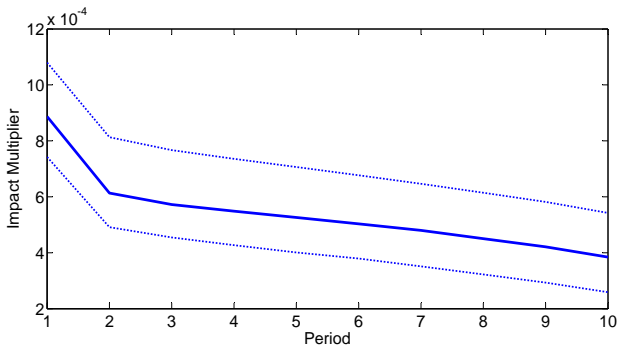
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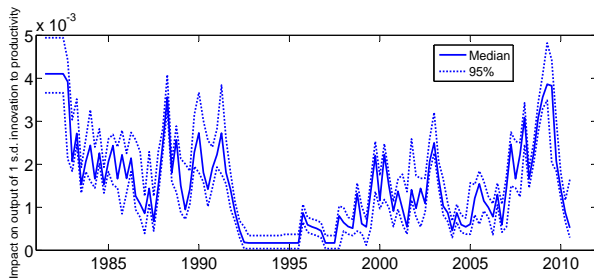
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Endogenous persistence in volatility



Posterior estimate of historical output multiplier



Conclusions

A tractable framework to model availability of information as correlated with tail events

- ▶ Uncertainty and cross-sectional dispersion may go up after public signal is observed

When embedded in a business cycle model, the mechanism can explain

- ▶ Large changes in macro aggregates but without a correspondingly large change in fundamentals
- ▶ Persistent periods of increased volatility of endogenous variables

Model can help us understand some aspects of a “crisis mentality” that were arguably present in the recent financial crisis

Final remarks

What have we learned?

- ▶ Solving a DSGE model
 - ▶ Mapping f from parameters θ to a state space system :
 $f(\theta) : \Theta \rightarrow A, C, D, \Sigma_v$
- ▶ The Kalman filter
 - ▶ Form recursive estimate of latent state
 - ▶ Evaluate the likelihood function
- ▶ M-H algorithm
 - ▶ Numerically approximate target distribution by MCMC methods
- ▶ Make probabilistic statement about functions of θ

Some caveats

1. The Lucas Critique and policy change
2. Representative agent and aggregation
3. Limitations of using historical data

The Lucas Critique, e.g. Lucas (1976)

Historical correlations are not a reliable guide for making predictions when policy changes

- ▶ Inflation-unemployment correlation in the data does not imply an exploitable trade off

The Lucas Critique has made many people sceptical of using SVAR and other more statistically oriented models in favour of micro founded models

Sims' (Chris, not Eric) Critique of the Lucas Critique

Sims (1998) argues that people often unthinkingly perform counterfactual experiments using micro founded model

- ▶ If we as researchers want to use a structural model to study the implications of a counterfactual policy change, does it make sense to think of the agents in the model as believing that the considered policy change is impossible?

Maybe not.

Who is the representative agent representing?

One advantage of DSGE models is that we can easily interpret many model parameters

Using priors on micro foundations when using aggregate models

- ▶ Naive use of priors based on studies of individual behaviour may be inappropriate if aggregation is not straightforward

Example: Aggregate elasticity of labour supply may be very different from the elasticity of an individual's labour supply

Can historical data help when something happens for the first time?

Uniformity of nature assumption

- ▶ The laws of the universe are the same everywhere and at all times

Economists using statistical models make a similar assumption

- ▶ The past can help predict the present/the future
- ▶ The behaviour of one group of people can help us predict the behavior of others

But what about when something happens for the first time?

- ▶ We need to ask ourselves if our models have measured something that can reasonable be thought of as being constant and still relevant

That's it for this week.

Thank you!