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Designing Monetary Policies: Methods and Applications

Plenary Lecture

by

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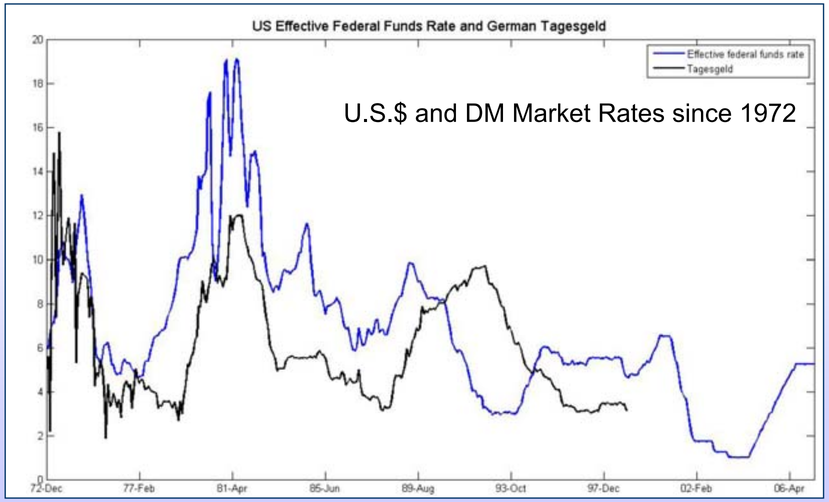
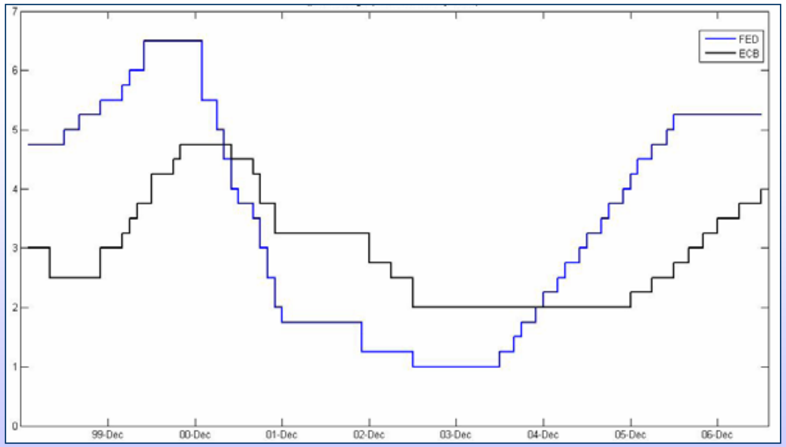
What Monetary Policies?

- ***Science of central banking*** for monetary authorities that have been put in charge of stabilizing prices (and economic activity).
  - ➔ After Bretton-Woods collapse in 1971: U.S., Canada, Japan, Germany, U.K.;
  - ➔ and other smaller industrial economies with floating exchange rates;
  - ➔ more recently the € area;
  - ➔ and emerging market economies that shy away from fixing exchange rates.

It's (Almost) All About Interest Rates!

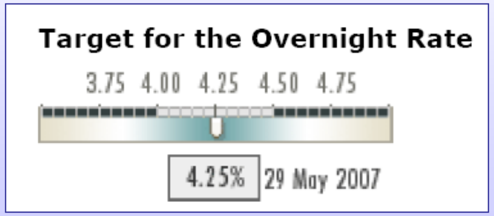


U.S. and € Area Policy Rates Since 1999



Eye on Canada Moment

- The Bank carries out monetary policy by influencing short-term interest rates. It does this by raising and lowering the **target for the overnight rate**.



Focus on Key Challenge: Decision-Making under Uncertainty!

Alan Greenspan

- Uncertainty is not just an important feature of the monetary policy landscape; it is the defining characteristic of that landscape.

Focus on Key Challenge: Decision-Making under Uncertainty!

- What are the basic sorts of uncertainty faced by central banks?

  In informal terms, we are uncertain about where the economy has been,

  where it is now, and

  where it is going.

Donald Kohn

Focus on Key Challenge: Decision-Making under Uncertainty!

- Dealing with uncertainty is the ***daily bread*** of central bankers and has been a central theme for the ECB since its inception.

  Central banks like other economic operators are continuously confronted with ***conflicting data*** as well as ***competing and evolving interpretations of the working of the economy***.

Otmar Issing

Focus on Key Challenge: Decision-Making under Uncertainty!

David Longworth

- If we could be certain that we had the **true model of the world** economy, complete with the right parameters and measurements, then being a macroeconomist would be extremely dull indeed.

  But it is **impossible to have such a model**, and that makes the work of macroeconomists—and central bank policy-makers—a lot more interesting.

.... so far the introduction.

- Now review some methods for designing interest rate policies using macroeconomic models ..
- ... then illustrate some challenges due to uncertainty;
- ... and proceed to focus on two aspects of decision-making under uncertainty: Learning and robustness.
- ..., in doing so highlight the practical usefulness of modern computational tools and conclude with a specific research proposal.

Outline

1. Two simple models for macroeconomists
2. Optimal policy design (for nonlinear-(nonquadratic specifications)
3. Some challenging uncertainties!
4. Key policy responses: Learning and robustness
5. Robustness and learning with models used in central banking
6. In conclusion: NO GUT but a work proposal

1. Two Simple Models for Macroeconomists

TK Model: A traditional Keynesian, dynamic, economy-wide macroeconomic model of output, inflation and interest rates.

NK Model: A New-Keynesian, dynamic, economy-wide macroeconomic model of output, inflation and interest rates.

Don‘t get me wrong ...

- These models can be extremely useful.
- They can be fitted to the data.
- They serve as laboratories for exploring the basic implications of alternative novel policy proposals.
- But when moving to policy practice, models will be needed that offer richer settings linking a variety of key macroeconomic variables. (Will come back to that later).

1.1. A Simple Traditional Keynesian Model

- Svensson (1997), Ball (1999), Orphanides and Wieland (2000)
- The variables: inflation (*π*), output gap *(y)*, nominal interest rate *(i)*
- The model equations:
  - (1) Phillips curve
  - (2) Aggregate demand (IS) curve
  - (3) central bank objective function determines setting of policy instrument *(i)*.

Simple Traditional Keynesian Model

(1) $$\pi_{t+1} = \pi_t + \lambda y_{t+1} + u_{t+1}$$

(2) $$y_{t+1} = \rho y_t - \varphi(i_t - \pi_t) + g_{t+1}$$

(3) $$L_t = L(\pi_t - \pi^*, y_t)$$

TK Model

- Advantages:
  - ➔Endogenous dynamics match empirically observed inflation and output persistence.
  - ➔Straightforward to apply (non)linear-(non)quadratic dynamic programming tools to design policies.
- Drawbacks:
  - ➔No role for forward-looking behavior.
  - ➔Not derived from optimizing behavior of fully rational, forward-looking, market participants.

1.2. A Simple New-Keynesian Model

- Clarida, Gali, Gertler (1999), Rotemberg and Woodford (1999). (here follow CGG).
- Variables: inflation, output and interest rates.
- Equations:
  - (4) Forward-looking Phillips curve
  - (5) Forward-looking IS curve
  - (6) Policymakers‘ objective

Simple New-Keynesian Model

(4) $$\pi_t = \beta E_t \pi_{t+1} + \lambda y_t + u_t$$

(5) $$y_t = E_t y_{t+1} - \varphi(i_t - E_t \pi_{t+1}) + g_t$$

(6) $$L_t = L(\pi_t - \pi^*, y_t)$$

NK Model

- Advantages:
  - ➔Consistent with optimizing behavior of representative, rational market participants (linear approximations of nonlinear first-order-conditions of households and firms under imperfect competition and Calvo contracts).
  - ➔Allows study of the role of expectations (credibility, communication,...) .
  - ➔ Loss function may be related to welfare (for example quadratic approximation of household utility).

NK Model

- Drawbacks:
  - ➔To match empirical inflation and output persistence one needs to introduce exogenous persistence via shocks.
  - ➔Model is not recursive and standard dynamic programming tools do not apply.
- Buts:
  - ➔ Possible extensions allow for endogenous persistence (indexation, adaptive learning).
  - ➔ Transformation to achieve recursiveness.

Outline

2. Optimal Policy Design

- Monetary policy transmission:

$$i \rightarrow \text{real interest rate} \longrightarrow y \longrightarrow \pi$$

2.1. Optimal Policy Design in TK Model

- Choose interest rates to minimize expected discounted losses

$$\min_{\{i_\tau\}} E_t \sum_{t=0}^{\infty} \beta^t L(\pi_t, y_t)$$

$$s.t. \quad \pi_{t+1} = \pi_t + \lambda y_{t+1} + u_{t+1} \qquad (1)$$

$$y_{t+1} = \rho y_t - \varphi(i_t - \pi_t) + g_{t+1} \qquad (2)$$

Optimal Policy in TK Model

- Standard linear, **recursive** framework.
- If the loss function (3) is quadratic then it is a standard stochastic optimal linear regulator problem, which generalizes easily to much larger models.
- If the loss function (3) is non-quadratic and/or any of the transition equations (1) and (2) are nonlinear, we can still use numerical dynamic programming methods.

Bellman Equation

$$V(\pi_t, y_t) = \min_{i_t}\{L(\pi_t - \pi^*, y_t) + E_t V(\pi_{t+1}, y_{t+1})\}$$

(7)

$s.t.$ equations (1) and (2).

Dynamic Programming and Policy

- Iteration over Bellman equation converges to the true value function. Can be implemented numerically.
- Obtain optimal policy function:

$$i_t = H(\pi_{t-1}, y_{t-1}) \qquad (8)$$

2.2. Optimal Policy in NK Model

$$\min_{\{i_\tau\}} E_t \sum_{t=0}^{\infty} \beta^t L(\pi_t, y_t)$$

$$s.t. \quad \pi_t = \beta E_t \pi_{t+1} + \lambda y_t + u_t \qquad (4)$$

$$y_t = E_t y_{t+1} - \varphi(i_t - E_t \pi_{t+1}) + g_t \qquad (5)$$

- Difficulty: the optimization problem as stated is not **recursive, expected future output and inflation show up on the right-hand side.**
- Commitment versus discretion!

Obtain Recursive Dual Saddlepoint Problem

- Following Marcet & Marimon (1998) (Svensson & Williams (2007)) we obtain a recursive problem for deriving the **optimal policy under commitment.**
- Setting up the Lagrangian we have:

$$\tilde{L} \equiv E_0 \sum_{t=0}^{\infty} \beta^t [L(\pi_t, y_t) + \gamma_{1t}(\pi_t - \lambda y_t - u_t - \beta E_t \pi_{t+1}) + \gamma_{2t}(y_t + \varphi i_t - g_t - E_t y_{t+1} - \varphi E_t \pi_{t+1})]. \qquad (9)$$

Step 1

- Using the law of iterated expectations:

$$\tilde{L} = E_0 \sum_{t=0}^{\infty} \beta^t [L(\pi_t, y_t) + \gamma_{1t}(\pi_t - \lambda y_t - u_t) - \gamma_{1t}\beta\pi_{t+1} + \gamma_{2t}(y_t + \varphi i_t - g_t) - \gamma_{2t}(y_{t+1} + \varphi\pi_{t+1})]$$

Step 2

- Expanding the terms dated t+1:

$$\begin{aligned} \tilde{L} = {} & E_0 \sum_{t=0}^{\infty} \beta^t [L(\pi_t, y_t) + \gamma_{1t}(\pi_t - \lambda y_t - u_t) + \gamma_{2t}(y_t + \varphi i_t - g_t)] \\ & - \beta E_0(\gamma_{1,0}\pi_1 + \beta\gamma_{1,1}\pi_2 + \dots) - E_0(\gamma_{2,0}y_1 + \beta\gamma_{2,1}y_2 + \dots) \\ & - E_0 \frac{1}{\sigma}(\gamma_{2,0}\pi_1 + \beta\gamma_{2,1}\pi_2 + \dots) \end{aligned}$$

Step 3

- Re-arranging:

$$\tilde{H} \equiv E_0 \sum_{t=0}^{\infty} \beta^t [L(\pi_t, y_t) + \gamma_{1t}(\pi_t - \lambda y_t - u_t) + \gamma_{2t}(y_t + \varphi i_t - g_t) - \mu_{1t}\pi_t - \frac{\mu_{2t}}{\beta}(y_t + \varphi\pi_t)],$$

where $\mu_{1t+1} = \gamma_{1t}, \quad \mu_{2t+1} = \gamma_{2t}$

and $\mu_{1,0} = 0, \quad \mu_{2,0} = 0$

Recursive Dual Saddle Point Problem

- Marcet and Marimon (1998) show that the preceding program of the form (9) subject to (4) and (5) can be stated as a recursive dual saddle point problem:

$$\max_{\{\gamma_{1t}, \gamma_{2t}\}} \min_{\{i_t\}} E_0 \sum_{t=0}^{\infty} \beta^t [L(\pi_t, y_t) + \gamma_{1t}(\pi_t - \lambda y_t - u_t) + \gamma_{2t}(y_t + \varphi i_t - g_t) - \mu_{1t}\pi_t - \frac{\mu_{2t}}{\beta}(y_t + \varphi\pi_t)] \quad (10)$$

Bellman Equation

- The value function associated with the SPP satisfies a Bellman equation:

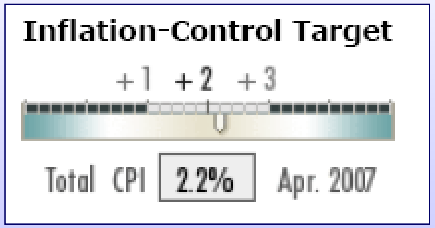
$$
\begin{aligned}
V(\mu_1,\mu_2) \quad &= \quad \max_{\gamma_1,\gamma_2}\min_{i}\left\{h(\mu_1,\mu_2,\gamma_1,\gamma_2,\pi,y,i,u,g)+\beta \mathrm{E}\left[V(\mu_1',\mu_2')\right]\right\} \qquad (11)\\
\text{s.t.} \quad & \mu_1'=\gamma_1, \quad \mu_2'=\gamma_2,\\
\text{and} \quad & h(\mu_1,\mu_2,\gamma_1,\gamma_2,\pi,y,i,u,g)\equiv L(\pi_t,y_t)+\gamma_1(\pi-\lambda y-u)\\
& +\gamma_2(y+\varphi i-g)-\mu_1\pi-\frac{\mu_2}{\beta}(y+\varphi\pi)
\end{aligned}
$$

Implementation

- Now we can apply the same optimal control techniques as for the TK Model.
- If loss function is quadratic (see also Svensson, Svensson and Williams (2007), this is again a stochastic OLRP and generalizes easily to larger linear models.
- If problem is nonlinear-nonquadratic then we can again implement numerical techniques and iterate over Bellman equation.

Application: Inflation-Range Targeting

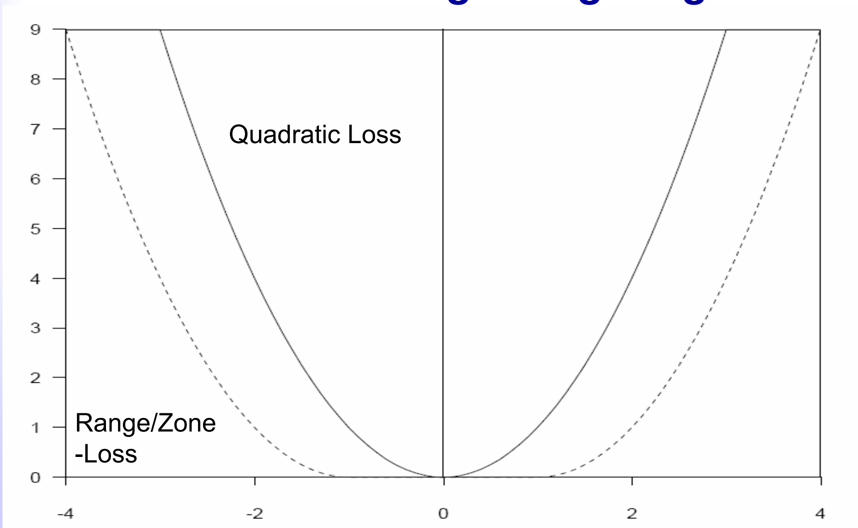
- The BoC aims to keep the growth rate of total CPI within an inflation-control range of 1 to 3 percent, with a midpoint of 2 percent.



Inflation-Range Targeting

- **Intuition:** with such a range in place, marginal loss due to small variations of inflation within the range won‘t be proportional to small variations of inflation outside the range.
- Thus, non-quadratic loss function.

Inflation-Range Targeting



Inflation Range Targeting

- Choose y to minimize

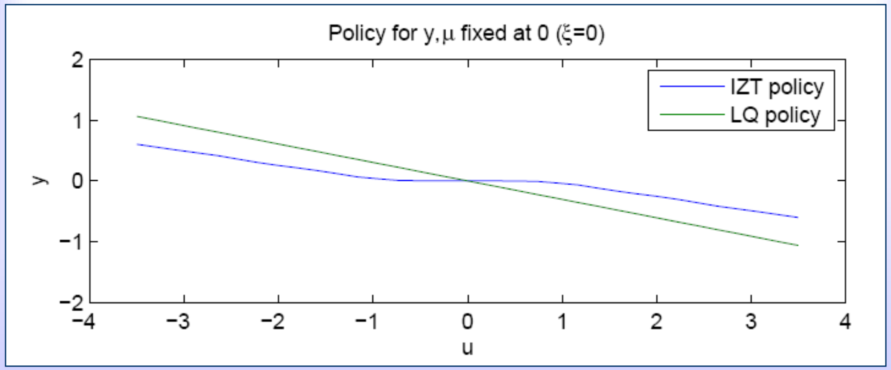
$$E_0 \sum_{t=0}^{\infty} \beta^t \{ Z(\pi_t)^2 + \alpha y_t^2 \},$$

$$Z(x) \equiv x - \frac{1}{2}\sqrt{c + \left(x + \frac{\xi}{2}\right)^2} + \frac{1}{2}\sqrt{c + \left(-x + \frac{\xi}{2}\right)^2}.$$

s.t.

$$\pi_t = \beta E_t \pi_{t+1} + \lambda y_t + u_t, \qquad (12)$$

Result: Stabilize Output Gap more Effectively within the Inflation Range



Joint research project with Joachim Goeschel (Ph.D. Candidate, Boston College).

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3. Some Challenging Uncertainties!

- So far we have considered uncertainty due to additive economic shocks (u,e) only.
- Note in NK they were assumed observed, but it is straightforward to add unobserved additive noise to these shocks.
- Linear-quadratic versions exhibit certainty-equivalence but not non-quadratic-nonlinear versions.

➔ Further challenges?

Conflicting data!

3.1. Data Uncertainty

- **Example 1:** Euro area GDP revisions 1999-2001

Quarter after initial publication	1	2	3	4	5
Real GDP[a]					
Largest upward revision	1.49	1.21	1.14	0.20	0.19
Largest downward revision	−0.91	−0.95	0	−0.02	−0.08
Mean absolute revision	0.80	0.69	0.47	0.11	0.14

Source: Coenen, Levin, Wieland (EER 2005).

Data Revisions

- Can easily include additive measurement error and Kalman filtering in linear quadratic models; certainty-equivalence of optimal policy applies. (Svensson& Woodford 03/04, CLW 05...)
- Nethertheless, real-time data leads to unreliability of output gap estimates and inflation forecasts (van Norden&Orphanides, Cayen&van Norden).
- At conference: Chen & Zadrozny on estimating final GDP numbers for US in real time.

3.2. Parameter and Model Uncertainty

Competing and evolving interpretations of the working of the economy!

- Estimated parameters (TK,NK).
- Key unobservable variables such as potential output, equilibrium interest rate, natural unemployment rate.
- Competing models: linear versus nonlinear, backward-versus forward-looking.

➔Let's look at some examples.

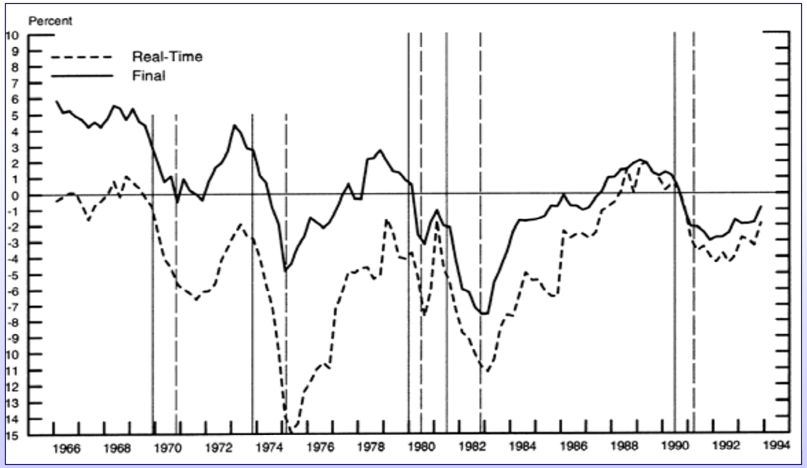
Example 2: Multiplicative Parameter Uncertainty

- Estimates of TK Model in Orphanides and Wieland (EER, 2000):

Parameter	Estimate	Stand. dev.
Rho	0.77	(0.11)
Phi	0.40	(0.10)
Sigma_e	0.84	
Lambda	0.34	(0.13)
Sigma_u	0.96	

- **However, output gap treated as known!**

Example 3: Historical Output Gap Misses in the US



Orphanides, Journal of Monetary Economics, 2000.

Example: Historical Output Gap Misses in Germany

C. Gerberding et al. / North American Journal of Economics and Finance 16 (2005) 277–292

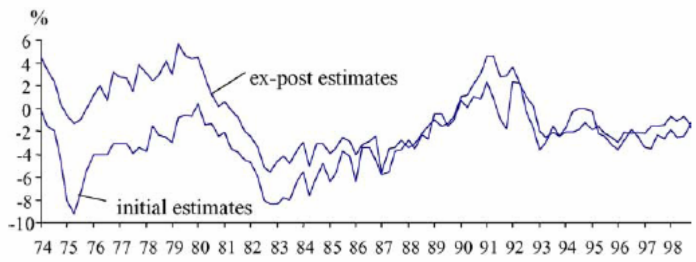


Fig. 1. Initial and ex-post estimates of the output gap.

Gerberding, Seitz, Worms, How the Bundesbank *really* conducted policy, North American Journal of Economics and Finance, 2005.

Example 4: Cayen&van Norden(05) on Canadian Output Gap

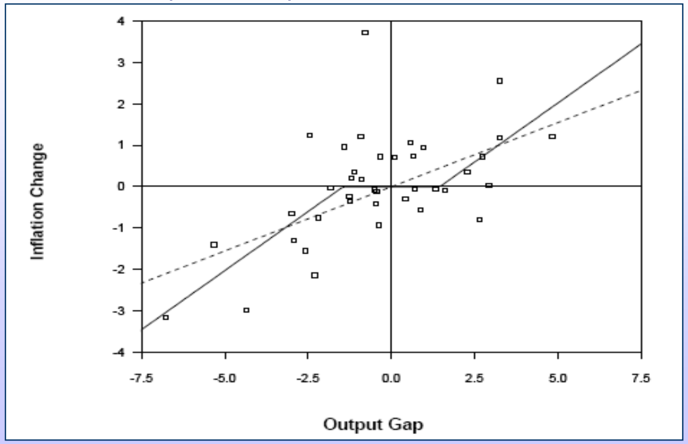
- Results from a variety of measures and a broad range of output gap estimates suggest that measurement error in the Canadian data may be more severe than previously thought.
- Relative to similar recent work for the U.S. (van Norden and Orphanides) we find revisions in Canadian output gaps are more important.

Example 5: Competing Models – Linear versus Nonlinear Tradeoffs

- Laxton, Rose and Tetlow, „Monetary Policy, Uncertainty and the Presumption of Linearity“, report to BoC, 1993.
- ... when a monetary authority cannot know the true structure of the economy it minimizes risks ... by assuming it faces the more difficult task of controlling inflation in a non-linear environment (convex trade-off).

Example: Competing Models – Linear versus Nonlinear Tradeoffs

- Zone-linear Phillips curve trade-offs U.S. 1966-98 (OW 00).



Example 6: Competing Models of Market Participants Expectations

- Completely backward-looking (TK) versus fully rational expectations (NK).
- But market participants may not fall in these extreme categories:
  - ➔ see growing literature on monetary policy with adaptive learning by market participants a la Evans &Honkapohja (Orphanides and Williams (at conf.), Milani, Gaspar, Smets and Vestin)
  - ➔Others at conference: Adam (limited processing power), Arifovic et al (social learning), Slobodyan&Wouters (in DSGE), Bullard, ...)

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4. Key Policy Responses: Learning and Robustness

- Central bank learning:
  - ➔ form estimates of unknowns and update them over time (Bayesian).
  - ➔ may involve optimal experimentation
- Preference for robustness:
  - ➔ unsure how to form probabilities.
  - ➔ Guard against worst-cases (Minimax).
  - ➔ Shocks, parameters, competing models.

4.1. Central Bank Learning

- So far the central bank designs optimal policy to minimize expected loss based on its beliefs regarding underlying probability distributions (***Bayesian approach***).
- Logical extension as new data becomes available is to update beliefs over time (***Bayesian learning***).
- Learning adds additional transition equations, which may be considered in optimization (***optimal experimentation***) or not (***passive learning***).

Application: Bayesian Learning about Phillips Curve

- Wieland 06: Central bank is learning about Phillips curve trade-off and natural unemployment rate.
  - ➔ Similar to TK model but allowing for partially forward-looking behavior.
  - ➔ Bayesian learning with normal beliefs.
  - ➔ Consider passive learning versus optimal experimentation.

Bayesian Learning about Phillips Curve

- Estimation equation:

$$\pi_t = \pi_{t-1} + \lambda\, y_t + u_t \qquad (13)$$

$$\Rightarrow \Delta\pi_t = \lambda y_t + u_t$$

- Belief:

$$(\hat{\lambda}, \Sigma) \qquad (14)$$

Bayesian Learning

- Bayesian updating with normal beliefs:

$$\hat{\lambda}_t = \hat{\lambda}_{t-1} + \Sigma_{t-1} y_t F^{-1} \left(\Delta\pi_t - \hat{\lambda}_{t-1} y_t \right)$$

$$\Sigma_t = \Sigma_{t-1} - \Sigma_{t-1} y_t F^{-1} y_t \Sigma_{t-1} \qquad (15)$$

$$\text{where} \quad F = y_t \Sigma_{t-1} y_t + \sigma_u^2$$

Optimal Bayesian Learning

- Choose y to minimize

$$E_t \sum_{t=0}^{\infty} \beta^t L(\pi_t, y_t) \qquad (16)$$

$$s.t. \quad \pi_t = \pi_{t-1} + \lambda y_t + u_t$$

$$\hat{\lambda}_t = \hat{\lambda}_{t-1} + \Sigma_{t-1} y_t F^{-1} \left(\Delta\pi_t - \hat{\lambda}_{t-1} y_t \right)$$

$$\Sigma_t = \Sigma_{t-1} - \Sigma_{t-1} y_t F^{-1} y_t \Sigma_{t-1}$$

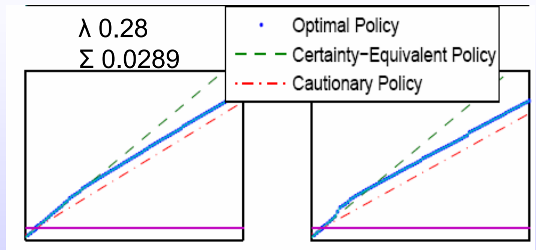
Optimal Bayesian Learning

- Learning introduces a nonlinearity.
- Nonlinear DP methods can be applied.
- If learning is not considered in optimization (passive learning) LQ methods work.
- Wieland (06) considers extensions that allow for learning about natural unemployment rate and weight on backward- vs forward-looking inflation expectations.

Result: Caution vs Activism

- Experimentation dominates near uninformative steady-state.

Unempl. gap
= - Outp. gap

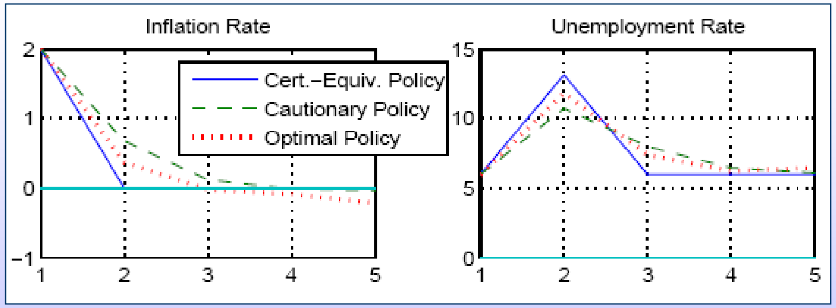


Inflation gap

Wieland (2006) with prior belief from Fuhrer (1995).

Result: Caution vs Activism

- A Disinflation with learning.



Wieland (2006) with prior belief from Fuhrer (1995).

Literature

- For NK Model using SPP see Svensson and Williams (2005, 2006), Ellison (2006).
  - ➔However, in examples learning is restricted to two modes: (p = probability that economy is in mode 1, (1-p) = prob. of mode 2)
- For methods that can be scaled to larger problems see papers by Amman&Kendrick (at conference) and Cosimano&Gapen.
- Also contributions by Schaling et al (at conf.) and Cogley, Sargent.

4.2. Robustness

- Scepticism regarding the beliefs in probability distributions needed to conduct Bayesian decision-making.
- Alternative: Policymaker focuses on analysis of worst-case scenarios. No need for forming expectations based on probability distributions.
- Robust control - MiniMax.

Worst-Case Analysis

- Drop expectations operator ➔ instead assume nature chooses scenarios to maximize loss while central bank chooses policy to minimize loss.

$$\min_{\{i_t\}} \max_{\{v_t\}} \sum_{t=0}^{\infty} \beta^t L(\pi_t, y_t) \qquad (17)$$

$$\text{where} \quad v_t \in \{\text{shocks,parameters,.}\}$$

Application: MiniMax in TK Model

- Parpas, Rustem, Wieland (06) minimax with box constraints:

$$\min_{\{\kappa_\pi,\kappa_y\}} \max_{\{v_t\}} \sum_{t=0}^{\infty} \beta^t L(\pi_t, y_t) \qquad (18)$$

$$\begin{aligned} s.t. \quad & \pi_{t+1} = \pi_t + \lambda y_{t+1} + u_{t+1} \\ & y_{t+1} = \rho y_t - \varphi(i_t - \pi_t) + g_{t+1} \\ & i_t = \pi_t + \kappa_\pi(\pi_t - \pi^*) + \kappa_y y_t \qquad (19) \\ and \quad & \underline{v} \le v_t \le \overline{v} \qquad (20) \\ where \quad & v_t \in \{e_t, u_\tau, \lambda, \rho, \varphi\} \end{aligned}$$

Result: Caution vs Activism

- Focus on response coefficients in policy rule:

$$i_t = \pi_t + \kappa_\pi(\pi_t - \pi^*) + \kappa_y y_t$$

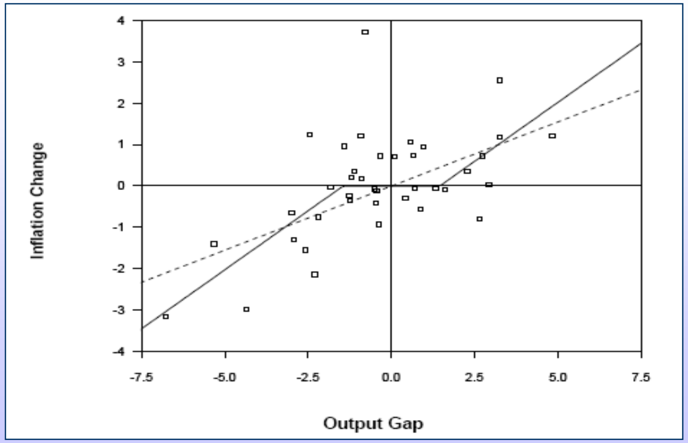
- As uncertainty bounds increase, response coefficients (κ_π, κ_y) decrease.
  - ➔Brainard-style caution.
- But, (κ_π, κ_y) under minimax remain greater than under Bayesian loss minimization.
  - ➔ More activism relative to Bayesian.

Literature

- Many contributions by Hansen and Sargent (robust control approach), also Onatski, Williams, Stock, ...
- NK model: Giannoni, Soderstrom, Söderlind (nice toolboxes).
- Rustem and various co-authors also offer nonlinear minimax. Application by Parpas, Rustem, Wieland to zone-linear Phillips curve tradeoff.

MiniMax on Linear versus Nonlinear Tradeoffs

- Phillips curve trade-offs U.S. 1966-98 (OW 00).



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5. Robustness and Learning in Models used in Central Banking

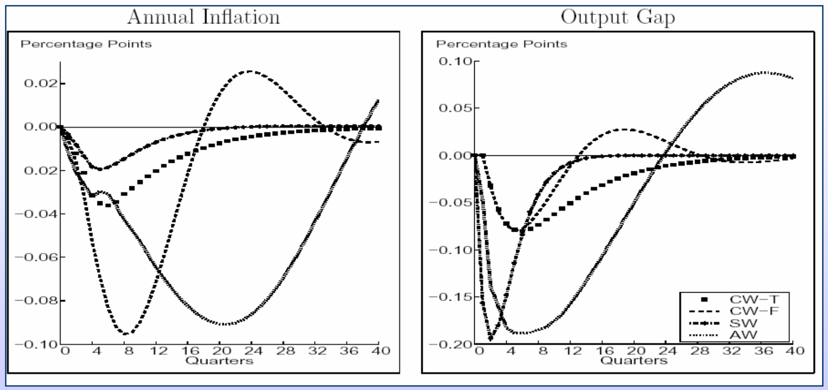
- Smaller models nevertheless may be useful benchmark.
- Models used in practice in central banking need richer specifications and bring in more variables of interest to policy makers.
- Next, some examples of how to use ideas on robustness and learning in the world of larger policy models.
  - ➔ Using results from Kuester and Wieland (2005) and subsequent research.

Some Models for the € Area

- AW: ECB's Area-Wide Model (ECB-WP)**
- SW: Smets and Wouter's Model, (JEEA 2003)
- CW-F: Coenen and Wieland's Model with Fuhrer-Moore Contracts (EER 2005)
- CW-T: Coenen-Wieland with Taylor Contracts.
  - ➔ At this conference: NAWM presented, several other new DSGE models.

Range of Uncertainty Implied by Models

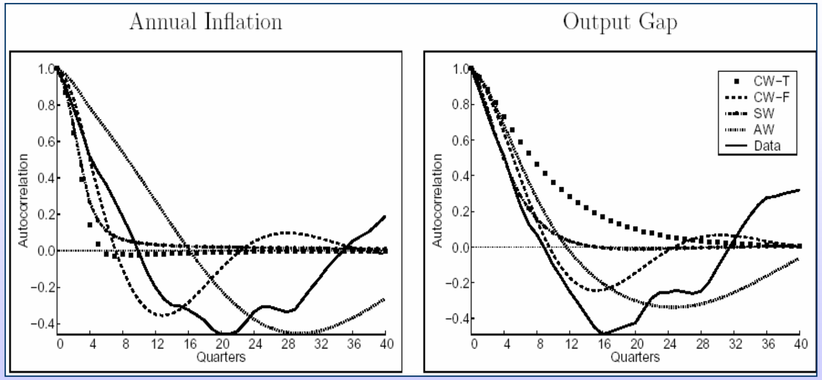
- Regarding policy transmission:



Use same interest rate rule in models, 100 basis point shock.

Uncertain Inflation & Output Persistence

- Serial correlations reflecting all shocks.



Policy Design

- Focus on simple rules:

$$i_t = \kappa_i i_{t-1} + \kappa_\pi \pi_t + \kappa_y y_t \qquad (21)$$

- Loss function:

$$L = Var(\pi_t) + \alpha_y Var(y_t) + \alpha_i Var(\Delta i_t) \qquad (22)$$

Policy Design

- Imagine being at the start of monetary union with four models estimated from synthetic, historical data.
- You checked and found out that optimized policy rules from one model do not always perform well in all other three models (lack of robustness).

Bayesian versus Worst-Case Analysis

- **Bayesian:** Consider all four models equally likely (initial prior) and derive policy rule that minimizes expected loss across models:

$$L^B = \min_{(\kappa_i, \kappa_\pi, \kappa_y)} E_M \left[L_m \right] = \min_{(\kappa_i, \kappa_\pi, \kappa_y)} \sum_{m \in M} p_m L_m \qquad (23)$$

Bayesian versus Worst-Case Analysis

- **Worst-Case Analysis:** Minimize loss assuming nature will confront you with the worst-case scenario (meaning model)

$$L^B = \min_{(\kappa_i, \kappa_\pi, \kappa_y)} \max_{(m \in M)} L_m \qquad (24)$$

Result: Worst-Case Analysis Leans Towards One Model – Extremist / Activist

- MiMa rule (α_y=0.5) corresponds to a Bayesian rule when probabilities are as follows: $p_{CW\text{-}F}$ = 0.989, p_{AW} = 0.011, $p_{CW\text{-}W}$ = p_{SW} = 0.
- However, coefficients differ not that much (CW-F also weighs heavily in Bayesian):
  Bayesian: κ_i=0.7, κ_π =0.7, κ_y =0.8
  MiMa: κ_i=0.8, κ_π =0.7, κ_y =0.6

Learning with New Euro Area Data

- Increasing popularity of Bayesian estimation techniques (following Geweke 1999, Schorfheide 2000) in estimation of DSGE models.
- Several papers here at conference.
- Next, some results from current project Kuester and Wieland.

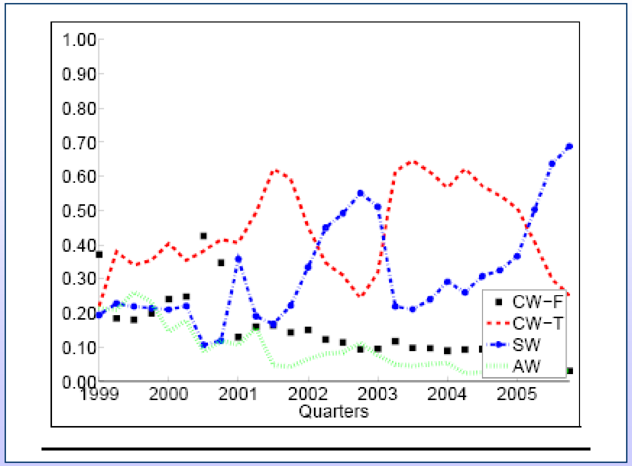
Learning with New Euro Area Data

- Compute posterior model probabilities of model *i* conditional on data up to *T*, $p(M_i|Y^T)$
- Let $p(M_i)$ be model priors and $p(Y^T|M_i)$ the likelihood of model i.
- Neglect parameter uncertainty, model is a set of structural equations + parameters, then by Bayes law:

$$p(M_i|Y^T) = \frac{p(Y^T|M_i) \cdot p(M_i)}{\sum_{j=1}^{M} p(Y^T|M_j) \cdot p(M_j)}$$

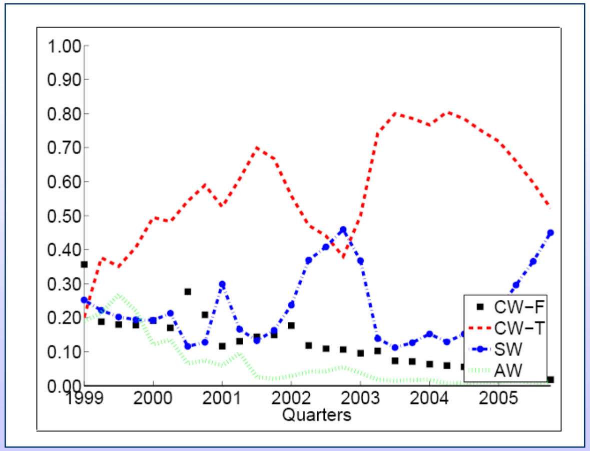
Posterior Model Probabilities

- Assuming same interest rate rule



Posterior Model Probabilities

- Estimating coefficients of interest rate rule



Outline

1. Two simple models for macroeconomists
2. Optimal policy design
3. Some challenging uncertainties!
4. Key policy responses: Learning and robustness
5. Robustness and learning with models used in central banking
6. **In conclusion: NO GUT but a work proposal**

6. No GUT but a Work Proposal

- Situation:
  - ➔There are many, many disparate, policy-relevant macro models!
  - ➔Most researchers just play with their own model.
- Proposal: BUILD A MODEL-BASE
  - ➔Bring models (+data used in estimation) together in place.
  - ➔Objective: Easy access for comparative studies – robustness, learning, etc. ..

Proposal

- Put models on common platform
  - ➔ Michel Juillard's DYNARE
  - ➔ Matlab compatible
  - ➔ Already offers many tools for linear and nonlinear RE models
  - ➔ Starting effort at Center for Financial Studies with basic set of models for the Euro area and the U.S.

THE END