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Assessing Structural VAR's

by

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Overview

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  - How Does the Economy Respond to Particular Economic Shocks?

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- To be useful in practice, SVARs must have good sampling properties.

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  - Investigate the Sampling Properties of SVARs, When
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    - Tiny Standard Errors: Pay Attention!

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    - Underlying DSGE Model Strongly Rejected by Data

Outline of Talk

- Analyze Performance of SVARs Identified with Long Run Restrictions

- Analyze Performance of SVARs Identified with Short Run Restrictions

- We Focus on the Question:

  – How do hours worked respond to a technology shock?

A Conventional RBC Model

- Preferences:

$$E_0 \sum_{t=0}^{\infty} (\beta (1+\gamma))^t [\log c_t + \psi \log (1-l_t)] .$$

- Constraints:

$$c_t + (1+\tau_x) [(1+\gamma) k_{t+1} - (1-\delta) k_t] \le (1-\tau_{lt}) w_t l_t + r_t k_t + T_t.$$

$$c_t + (1+\gamma) k_{t+1} - (1-\delta) k_t \le k_t^{\theta} (z_t l_t)^{1-\theta} .$$

- Shocks:

$$\begin{aligned} \Delta \log z_t &= \mu_Z + \sigma_z \varepsilon_t^z \\ \tau_{lt+1} &= (1-\rho_l) \bar{\tau}_l + \rho_l \tau_{lt} + \sigma_l \varepsilon_{t+1}^l \end{aligned}$$

- Information: Time t Decisions Made After Realization of All Time t Shocks

Parameterizing the Model

- Parameters:
  - Exogenous Shock Processes: We Estimate These
  - Other Parameters: Same as CKM

β	θ	δ	ψ	γ	$\bar{\tau}_x$	$\bar{\tau}_l$	μ_z
$0.98^{1/4}$	$\frac{1}{3}$	$1-(1-.06)^{1/4}$	2.5	$1.01^{1/4}-1$	0.3	0.243	$1.02^{1/4}-1$

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- Baseline Specifications of Exogenous Shocks Processes:
  - Our Baseline Specification
  - Chari-Kehoe-McGrattan (July, 2005) Baseline Specification
  - Both Parameterizations Based on Maximum Likelihood

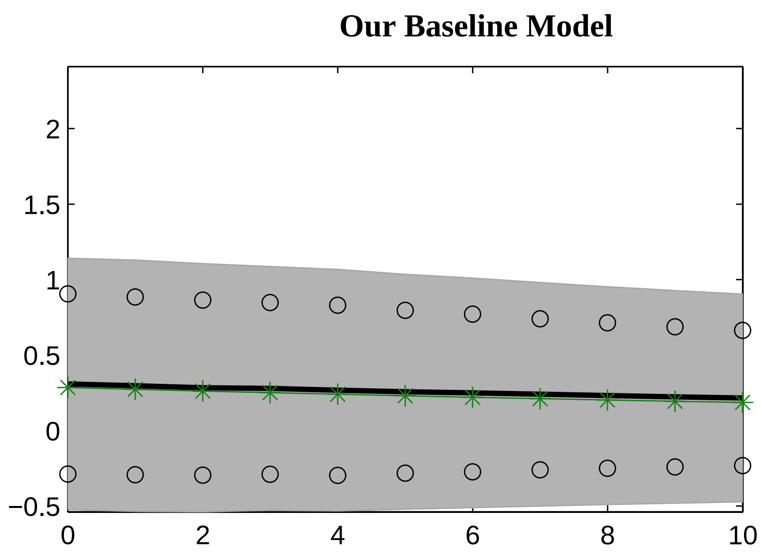
Experiments with Estimated Models

- Simulate 1000 data sets, each of length 180 observations, using DSGE model as Data Generating Mechanism.

- On Each Data Set: Estimate a four lag VAR.

Response of Hours to A Technology Shock

Long−Run Identification Assumption



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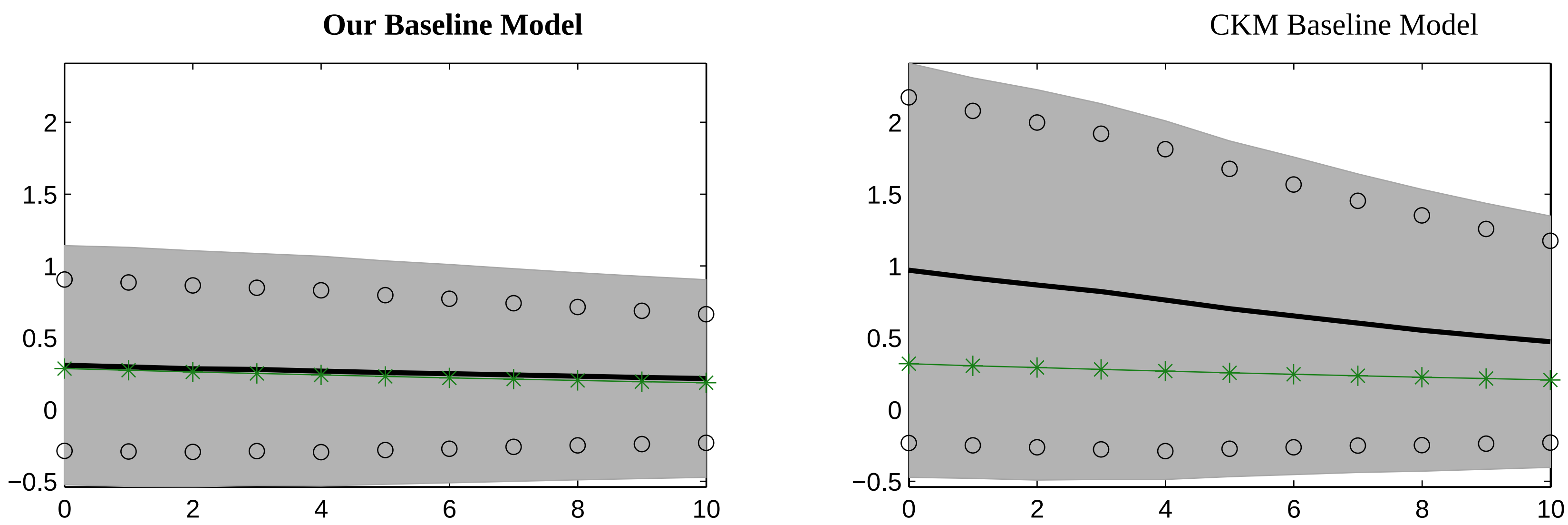

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- This Assumption Drives Baseline Results and is Overwhelmingly Rejected by the Data

CKM Baseline Model Assumption is Rejected

- CKM estimate their Baseline Model using MLE with Measurement Error.
  - Observed Data

$$Y_t \;=\; \left(\Delta \log y_t,\;\; \log l_t,\; \Delta \log i_t,\; \Delta \log G_t\right)',$$

  - Observer Equation:

$$Y_t \;=\; X_t + u_t,\; E u_t u_t' = R,$$

R is a diagonal matrix,

$$u_t \;:\; 4 \times 1 \text{ vector of iid measurement error,}$$

$$X_t \;:\; \text{model implications for } Y_t$$

CKM Baseline Model Embeds a *Remarkable* Assumption ...

- CKM Allow for Four Shocks

$$(\tau_{l,t}, z_t, \tau_{xt}, g_t)$$

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$$G_t \;=\; g_t z_t$$

- CKM fix the elements on the diagonal of R to equal $1/100 \times Var(Y_t)$

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- For Purposes of Estimating the Baseline Model, Assume:

$$g_t \; = \; \bar{g}, \; \tau_{xt} = \tau_x.$$

- So, CKM Baseline Model Assumption:

$$\Delta \log G_t \; = \; \Delta \log z_t + \text{small measurement error}_t \; .$$

CKM Baseline Model Embeds a *Remarkable* Assumption ...

- Overwhelming Evidence Against CKM Baseline Model Assumption

		Likelihood Ratio Statistic
	Likelihood Value	(degrees of freedom)
Estimated model	-328	
Freeing Measurement Error on $g = z$	2159	4974 (1)
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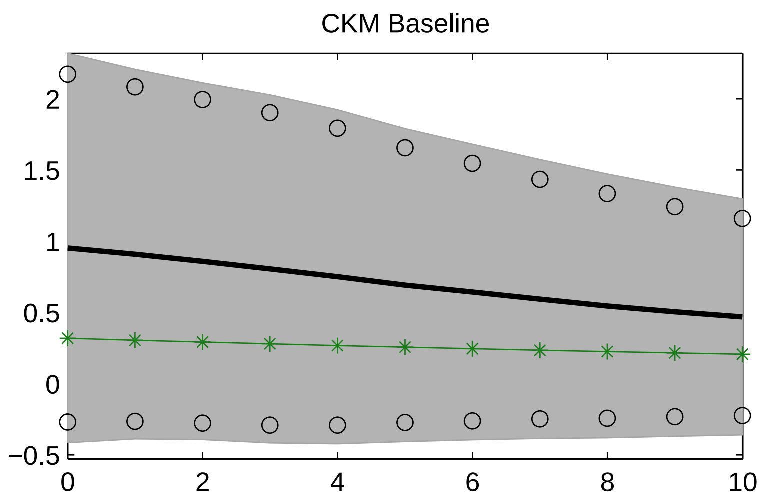
- Evidence of Bias in Estimated CKM Model Reflects CKM Baseline Model Assumption
  - Free Up Measurement error on $g = z$
    - Produces Model With Good Bias Properties: Similar to KP Benchmark Model

The Role of Δg



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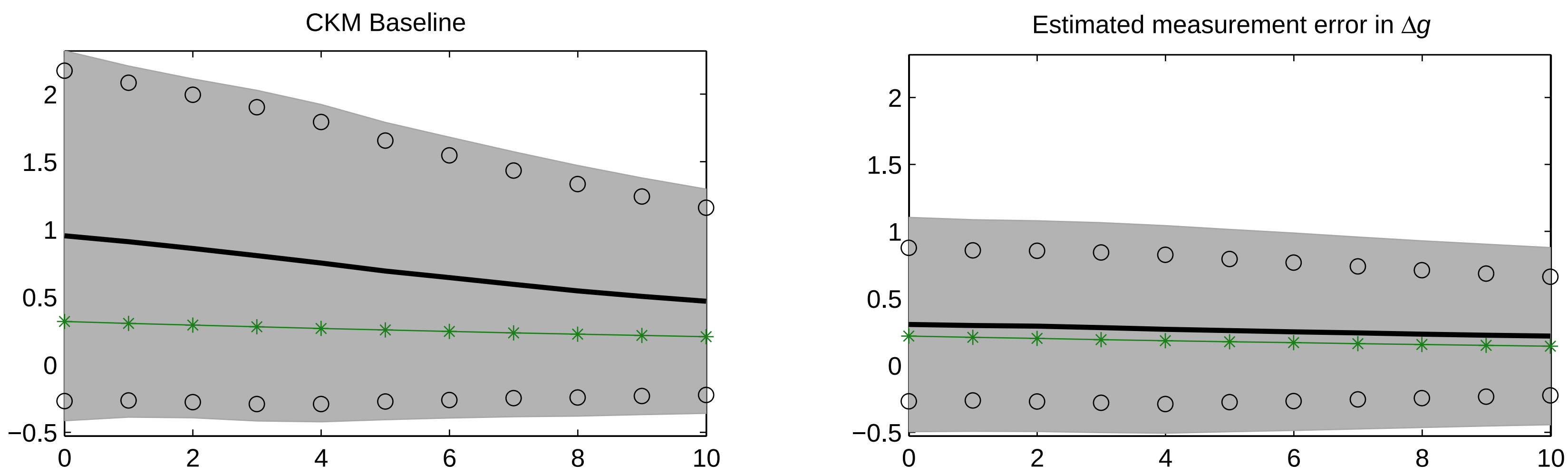

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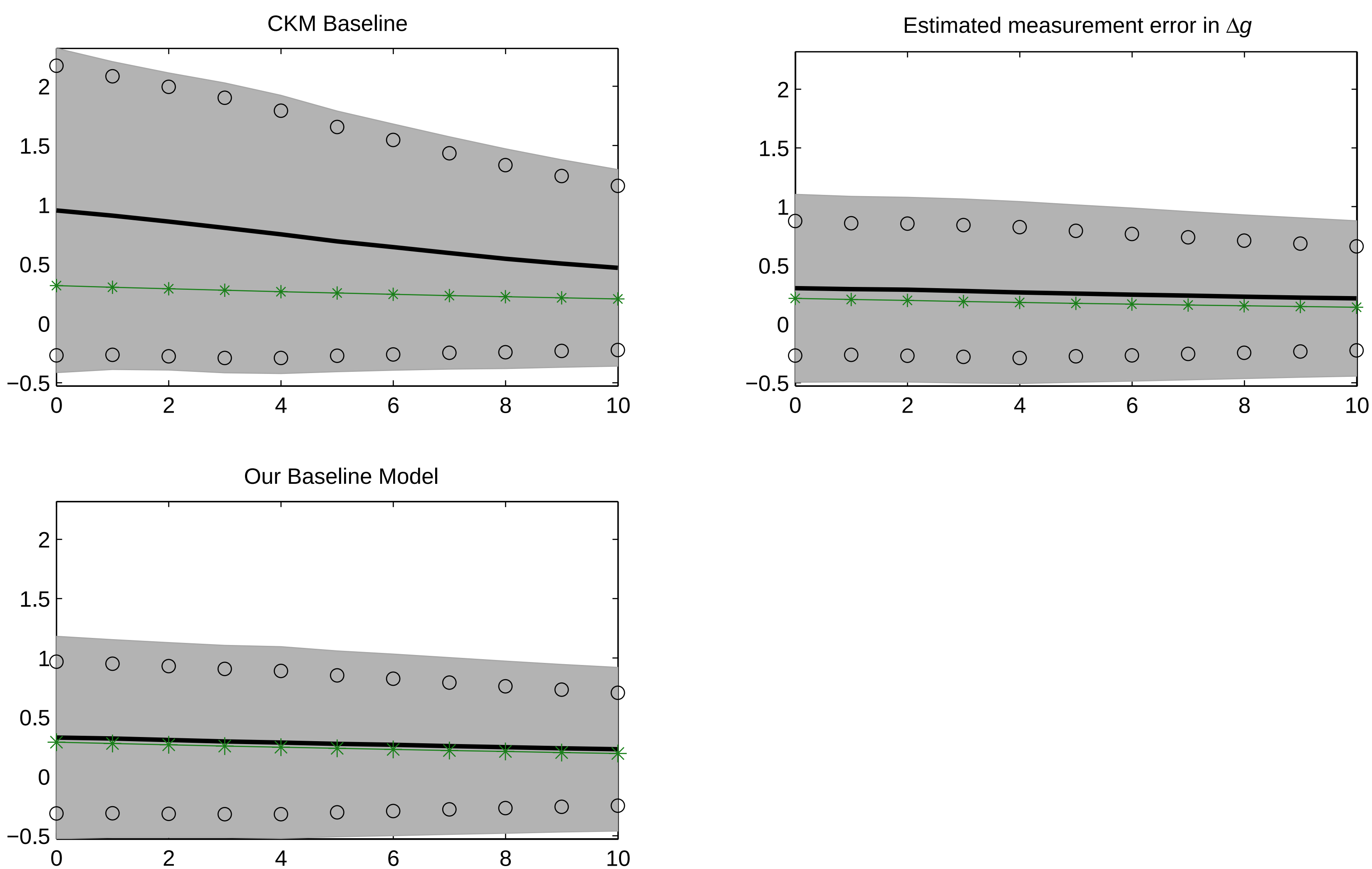


Alternate CKM Model With Government Spending Also Rejected

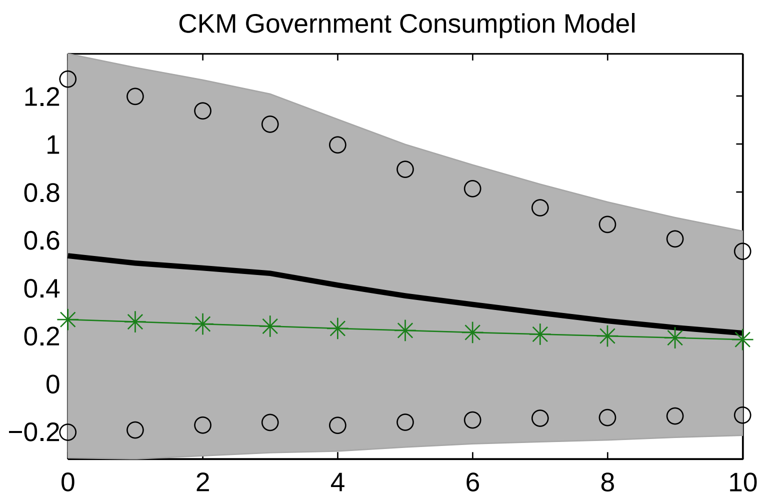
- CKM Model With G_t:

$$G_t = g_t z_t$$

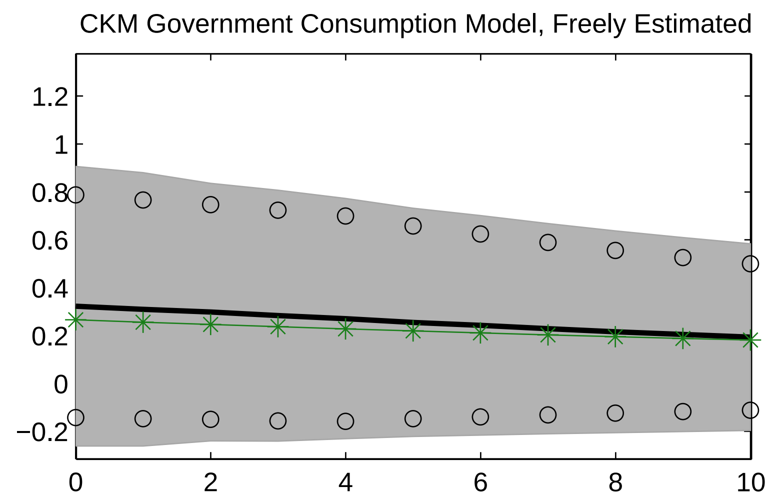
g_t First Order Autoregression

- Model Estimated Holding Measurement Error Fixed As Before.
  - Resulting Model Implies Noticeable Bias in SVARs
  - But, Sampling Uncertainty is Big and Econometrician Would Know it
  - When Restriction on Measurement Error is Dropped Resulting Model Implies Bias in SVARs Small

The Role of Government Spending



LLF = 2695.46



LLF = 2842.96

Likelihood Ratio Statistic: 295 with 4 degrees of freedom

CKM Assert that SVARs Perform Poorly for 'Large' Range of Parameter Values

- Problem With CKM Assertion
  - Allegation Applies only to Parameter Values that are Extremely Unlikely
  - Even in the Extremely Unlikely Region,
    - Econometrician Who Looks at Standard Errors is Innoculated from Error

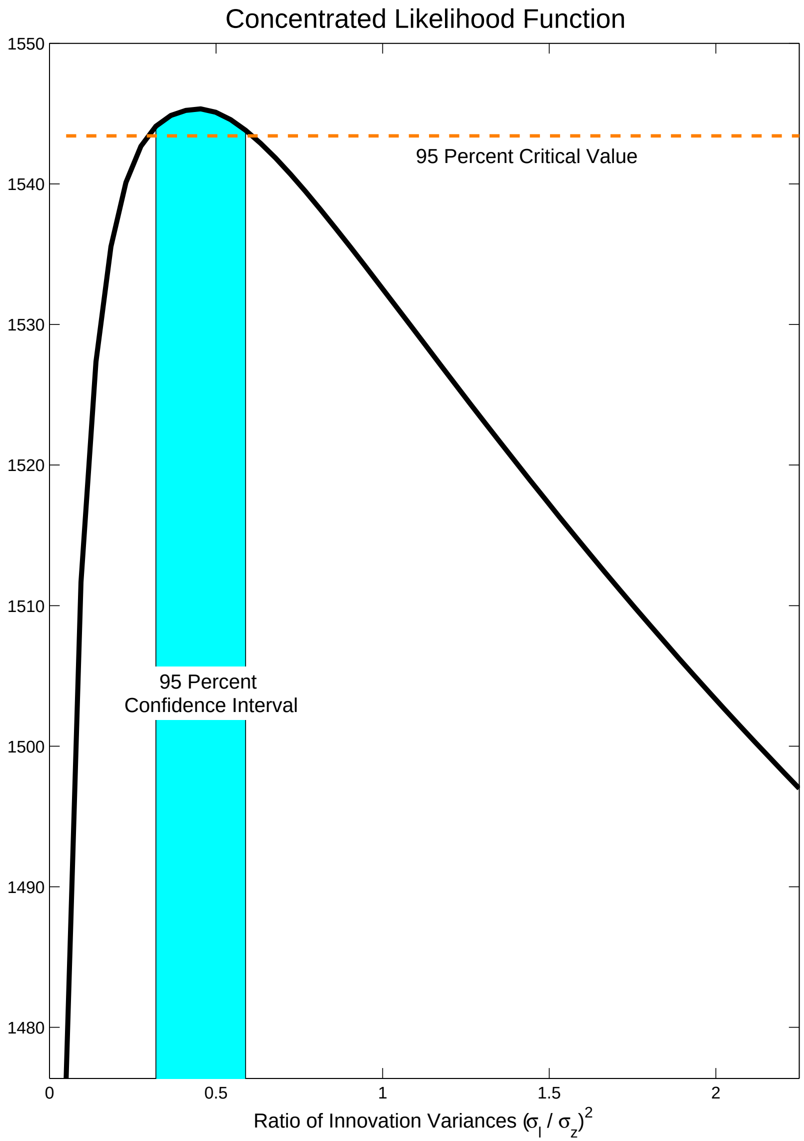
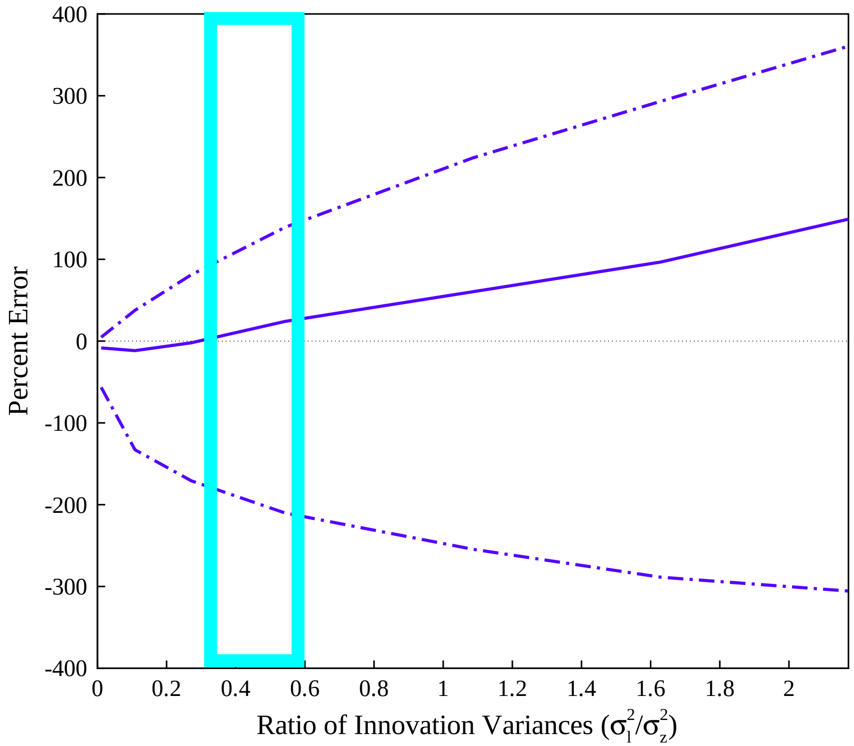


FIGURE A6

Combined Error in the Mean Impact Coefficient (solid line) and the Mean of 95% Bootstrapped Confidence Bands (dashed lines) Averaged Across 1,000 Applications of the Four-Lag LSVAR Procedure with $\rho = .99$ to Model Simulations of Length 180, Varying the Ratio of Innovation Variances



NOTE: The combined error is defined to be the percent error in the small sample SVAR response of hours to technology on impact relative to the model's theoretical response. This error combines the specification error and the small sample bias.

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- Golden Rule: Pay Attention to Standard Errors!

SVARS with Short Run Identifying Restrictions

- Adapt our Conventional RBC Model, to Study VARs Identified with Short-run Restrictions

  – Results Based on Short-run Restrictions Allow Us to Diagnose Results Based on Long-run Restrictions

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- *Recursive version of the RBC Model*
  - First, τ_{lt} is observed
  - Second, labor decision is made.
  - Third, other shocks are realized.
  - Then, everything else happens.

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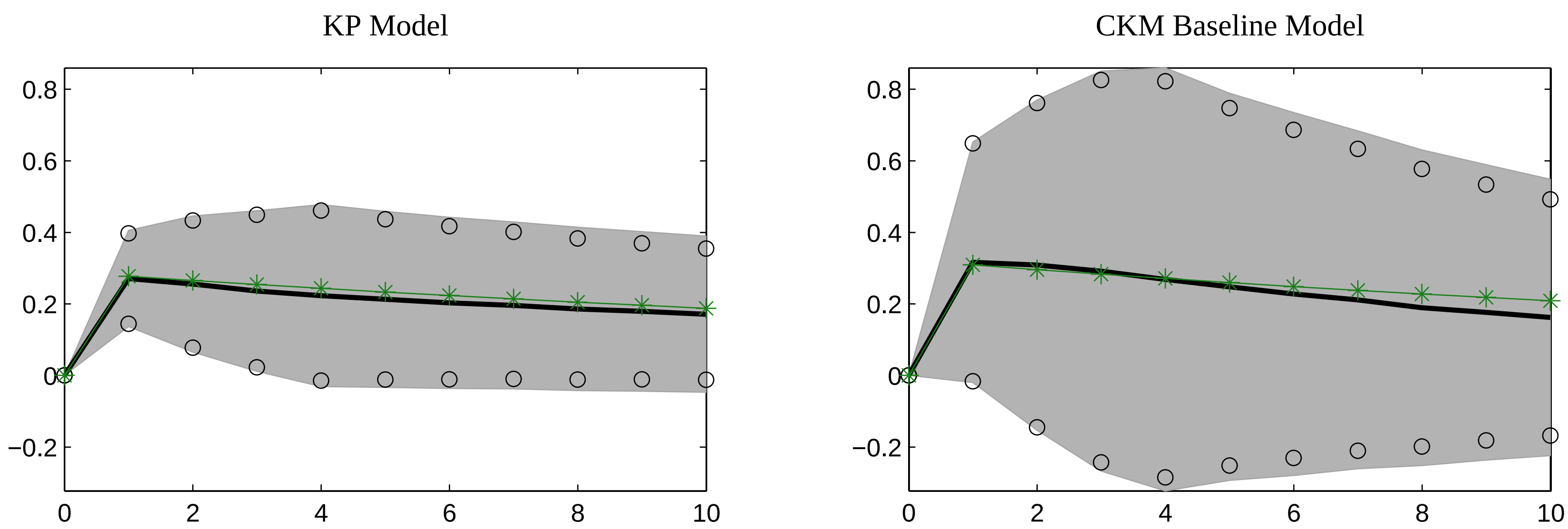


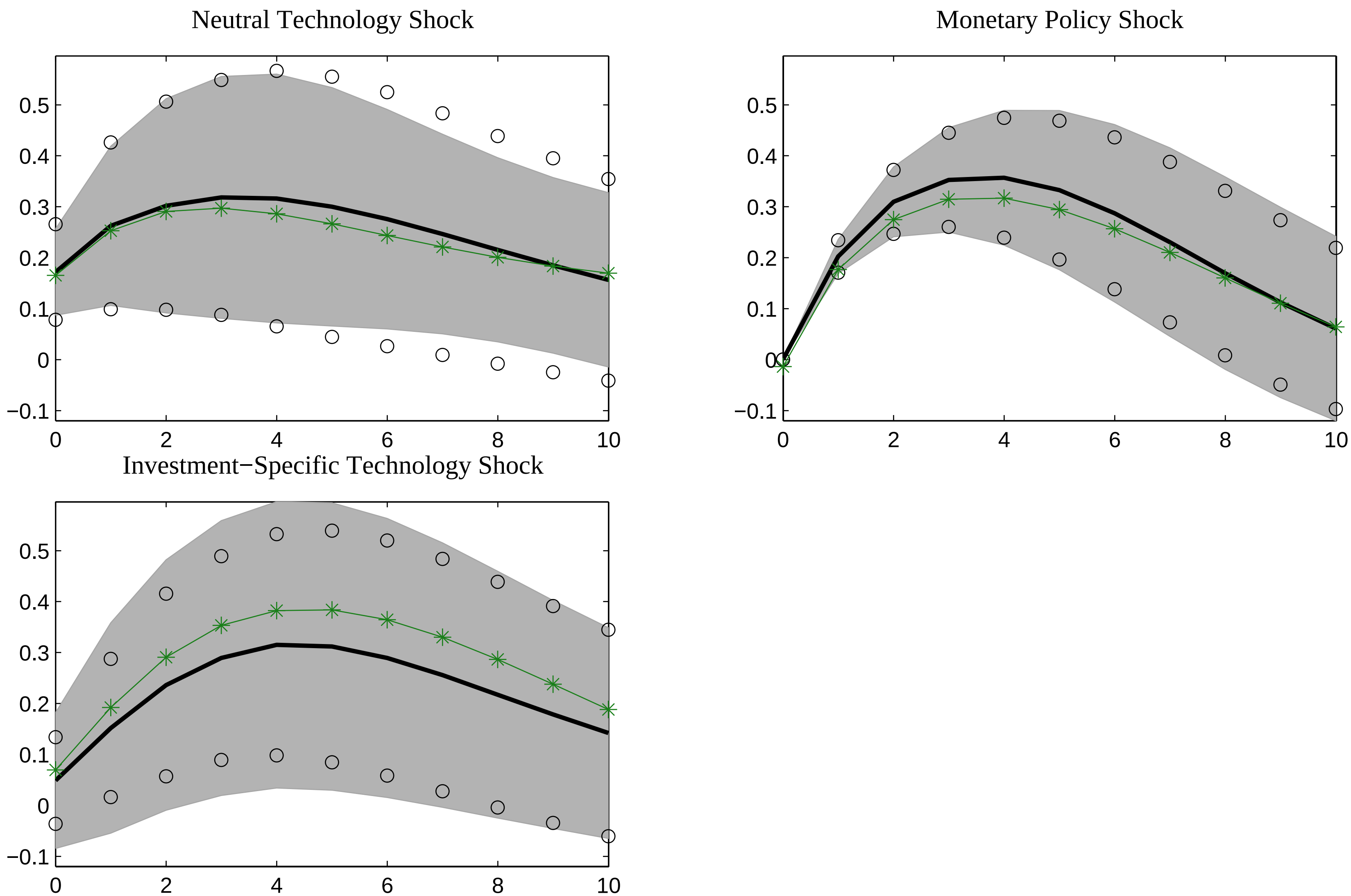
SVARs with Short Run Restrictions

- Perform remarkably well
  - Inference is Precise and Correct

VARs and Models with Nominal Frictions

- Data Generating Mechanism: an estimated DSGE model embodying nominal wage and price frictions as well as real and monetary shocks ACEL (2004)
- Three shocks
  - Neutral shock to technology,
  - Shock to capital-embodied technology
  - Shock to monetary policy.
- Each shock accounts for about 1/3 of cyclical output variance in the model

Analysis of VARS using the ACEL Model as DGP



Conclusion

- We studied the properties of SVARs.
  - With short run restrictions, SVARs perform remarkably well in All Examples Considered
  - With long run restrictions, Will Not Be Misled as Long as You:

$\boxed{\text{Pay Attention to Standard Errors!!}}$