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Discussion of:

Chari-Kehoe-McGrattan:

Are Structural VARs Useful Guides for Developing Business Cycle Theories?

by Larry Christiano

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Chari-Kehoe-McGrattan:

Are Structural VARs Useful Guides for Developing Business Cycle Theories?

- Jordi Gali Estimated the Dynamic Effects of Technology Shocks By Exploiting Three (Identification) Assumptions:
  a. Tech Shocks Are a Linear Combination of a Finite Number of Lags of Past Data.
  b. Tech Shocks Are Orthogonal to Other Structural Shocks.
  c. Tech Shocks are the **Only** Shocks that Have Long Run Effects on Labor Productivity.

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  – They Conjecture that their Critique Applies to VAR Methods More Generally.
- So, the Answer to the Question in the title of the Paper is **NO!**

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- CKM Conclusion: Identified VARs Are of No Use As A Guide for Developing Business Cycle Theories.
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- A Third Example:
  - Numerical Example In Which Gali's Assumptions Are True, and Estimation Is Nevertheless Distorted.
  - This Example Potentially Interesting, Is it a Problem in Practice?
  - Distortions Not Present in a Recent VAR Analysis.

Outline

- Overview (done!)
- Long Run Identification
- Equilibrium Model Used in Examples.
- The Three Examples
- Conclusion

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Long-Run Identification

- Data:

$$\text{DSVAR: } Y_t = \begin{bmatrix} \Delta \log\left(\frac{y_t}{l_t}\right) \\ \Delta l_t \end{bmatrix},\ \text{LSVAR: } Y_t = \begin{bmatrix} \Delta \log\left(\frac{y_t}{l_t}\right) \\ l_t \end{bmatrix}$$

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- Assumption about Fundamental Economic Shocks, ε_t :

$$u_t = C\varepsilon_t,\ CC' = V,$$

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{\text{technology},t} \\ \varepsilon_{\text{other},t} \end{pmatrix}$$

- In General:

$$\lim_{j\to\infty} E_t \log\left(\frac{y_{t+j}}{l_{t+j}}\right) = a \times \varepsilon_{\text{technology},t} + b \times \varepsilon_{\text{other},t}.$$

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- Long Run Identification Assumption:

$$b = 0.$$

Examples Constructed Using Variants of Following Model

- Resource Constraint:

$$c_t + G_t + k_{t+1} = k_t^{\alpha} \left(Z_t l_t\right)^{1-\alpha} + (1-\delta)k_t$$

- Intratemporal Euler equation:

$$\frac{U_{leisure,t}}{U_{c,t}} = (1-\tau_{lt})F_{l,t}$$

- Intertemporal Euler equation:

$$U_{c,t}(1+\tau_{xt}) = \beta E_t U_{c,t+1}\left[F_{k,t+1} + (1-\delta)\left(1+\tau_{x,t+1}\right)\right]$$

- Exogenous Processes:

$$Z_t,\ \tau_{lt},\ \tau_{xt},\ G_t$$

- Three Examples: Alternative Specifications of Exogenous Processes.

Examples

- Example #1: DSVAR Analysis Distorted by ‘Invertibility Problems’
- Example #2: An RBC Model Fit by Maximum Likelihood Methods to US Data Implies Identification Based on Long-Run Restrictions Severely Distorted.
- Example #3: Even when Identifying Restrictions Correct, Estimates of Impulse Response Functions Hopelessly Imprecise.

Example #1 Invertibility

- Exogenous Shocks:

$$\begin{pmatrix} \Delta \log Z_t \\ \tau_{lt} \end{pmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0.938 \end{bmatrix} \begin{pmatrix} \Delta \log Z_{t-1} \\ \tau_{lt-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{\text{technology},t} \\ \varepsilon_{\text{other},t} \end{pmatrix}$$

- Model Prediction: DSVAR Analysis Finds Hours Fall After Positive Shock To Technology, Even Though In Data Generating Mechanism Hours Rises.

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- (Partial) Explanation:
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  - Example: Suppose hours stationary in levels -
$$l_t = \rho l_{t-1} + \varepsilon_t, \ \ -1 < \rho < 1$$
so,
$$\Delta l_t = \rho \Delta l_{t-1} + \varepsilon_t - \varepsilon_{t-1}.$$

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Try and 'invert' this, i.e., express ε_t as function of current and past Δl_t's:
$$\Delta l_t = (\rho - 1)\left[\Delta l_{t-1} + \Delta l_{t-2} + \Delta l_{t-3} + ...\right] + \varepsilon_t$$
Can't do it...Not Invertible.

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  - Findings of Example #1 Closely Related to Similar Findings in Altig, Christiano, Eichenbaum and Linde (2002), Christiano, Eichenbaum and Vigfusson (2004a,2004b).

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Example #1 Invertibility, cont'd

- Source of Non-Invertibility Explored Here: Data Overdifferencing

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- Other Sources of Non-Invertibility
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  $$\Delta \log(Z_t) = \varepsilon_{\text{technology},t} + 2 \times \varepsilon_{\text{technology},t-1}.$$
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- These Sources of Non-Invertibility Deserve More Attention, But CKM are Silent About Them.

Example #2: A Model Estimated By Maximum Likelihood Implies Gali-Style VAR Identification Misleading

- Exogenous Shocks:

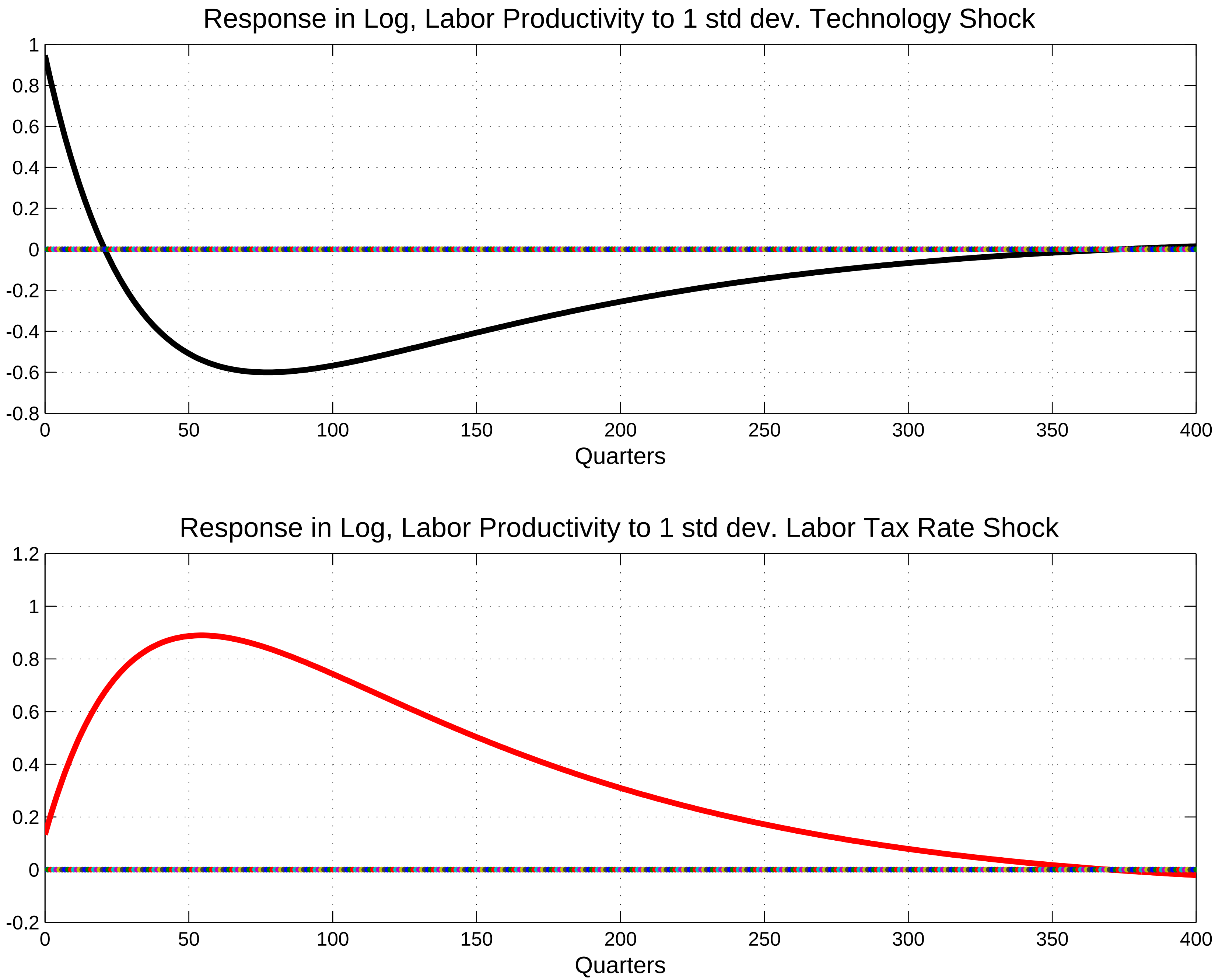
$$\begin{aligned}\log Z_t &= \alpha t + \log z_t, \\ \log G_t &= \beta t + \log g_t\end{aligned}$$

$$\begin{pmatrix}\log z_t \\ \tau_{lt} \\ \tau_{xt} \\ \log g_t\end{pmatrix} = P \begin{pmatrix}\log z_{t-1} \\ \tau_{lt-1} \\ \tau_{xt-1} \\ \log g_{t-1}\end{pmatrix} + Q \begin{pmatrix}\eta_{z,t} \\ \eta_{\tau_l,t} \\ \eta_{x,t} \\ \eta_{g,t}\end{pmatrix}.$$

- The matrix, Q Lower Triangular, $QQ' = V$.
- Enormous Persistence. Eigenvalues of P:

$$0.9952 \pm 0.0019i,\ 0.9927,\ 0.9598$$

Response to Shocks in CKM's Preferred Model



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- Gali's Long Run Identification Assumptions Wrong in This Example
  - No Shock Has A Truly Permanent Effect
  - Two Shocks Do Have Highly Persistent Effects On Labor Productivity
  - No Surprise that Gali's Identification Assumptions Could Produce Highly Distorted Results In this Case.

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    - Positive Innovation to Labor Tax $\Rightarrow$ Labor Productivity Up Persistently.
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    - Possibility: There Could Be Just One Shock That Has A Permanent (or, Highly Persistent) Effect on Labor Productivity, Which Drives Both $\log Z$ and τ_{lt}.

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- Without Further Analysis, Not Clear What this Example Implies For Gali, or VAR Methods Generally.

Example #3: Impulse Response Functions Hard To Pin Down Even If Identification Assumptions Are Correct

- Exogenous Shocks:

$$\begin{pmatrix} \Delta \log Z_t \\ \tau_{lt} \end{pmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0.938 \end{bmatrix} \begin{pmatrix} \Delta \log Z_{t-1} \\ \tau_{lt-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{\text{technology},t} \\ \varepsilon_{\text{other},t} \end{pmatrix}$$

- Do LSVAR Analysis, with

$$Y_t = \begin{bmatrix} \Delta \log \left(\frac{y_t}{l_t} \right) \\ l_t \end{bmatrix}.$$

- No Over Differencing!
- Seems As Though There Should Be No Problem.

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- Findings:
  a. In Small Samples, Estimated Impulse Responses Have Very Large Sampling Variance

     Analysis in Erceg, Guerrieri and Gust (2004) Suggests this May Be Because of High Persistence of τ_{lt}

  b. Bias in Large Samples. Goes Away With Longer Lags in VAR.
- Would the Analyst Using Standard Diagnostic Tests for Lag Lengths Discover that Lag Lengths Need to Be Very Long?
  – If ‘Yes’ then the Example is Perhaps Less Worrisome.
- Do the Problems Go Away With More Data? Here is an Example Which Suggests that Maybe The Answer is ‘yes’.

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Example #3, Cont'd

- Model Laboratory: Altig-Christiano-Eichenbaum-Linde Model, to be Presented and Defended Tomorrow by Marty.
- Model Parts:
  - Consumption, Investment, Employment, Transactions Motive for Holding Money Balances.
  - Investment Adjustment Costs, Wage Setting Frictions, Variable Capital Utilization.
  - Monetary Policy Shock, Neutral Shock to Technology (i.e., Z_t), Investment Specific Shock to Technology.

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- Basic Business Cycle Properties of the Model:

Comparison of Model and Data: Kydland-Prescott Statistics				
	(Rel.) Std. Dev.		Corr. w/Y	
Variable	Model	US Data	Model	US Data
Output	1.3	1.6	1	1
Hours	0.8	1.1	1.0	0.9
Productivity	0.3	0.5	0.8	0.07
Wage	0.2	0.5	0.4	0.1
Consumption	0.5	0.5	0.8	0.7
Investment	2.7	3.9	1.0	0.9

All Statistics Computed on Logged, HP-filtered Data

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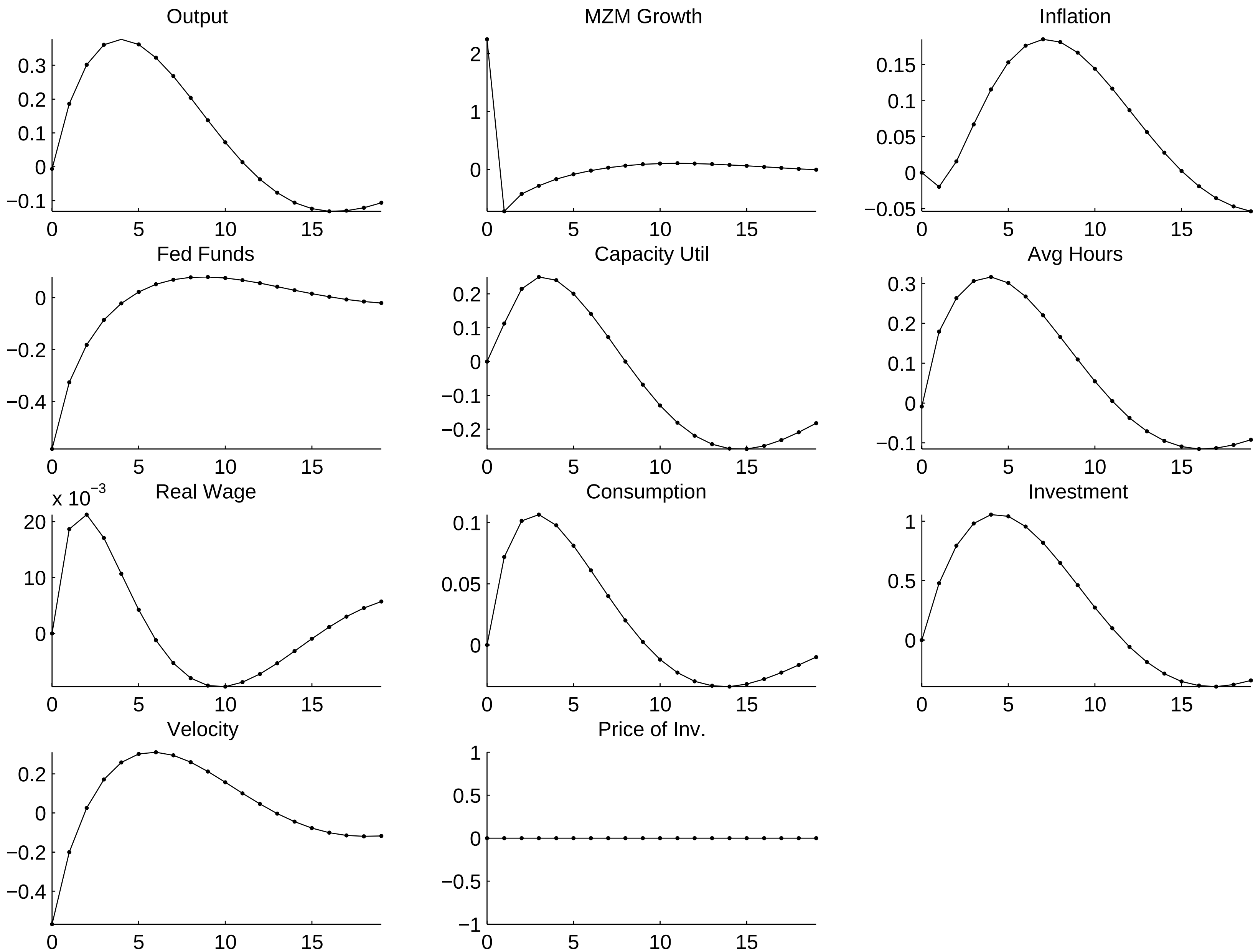
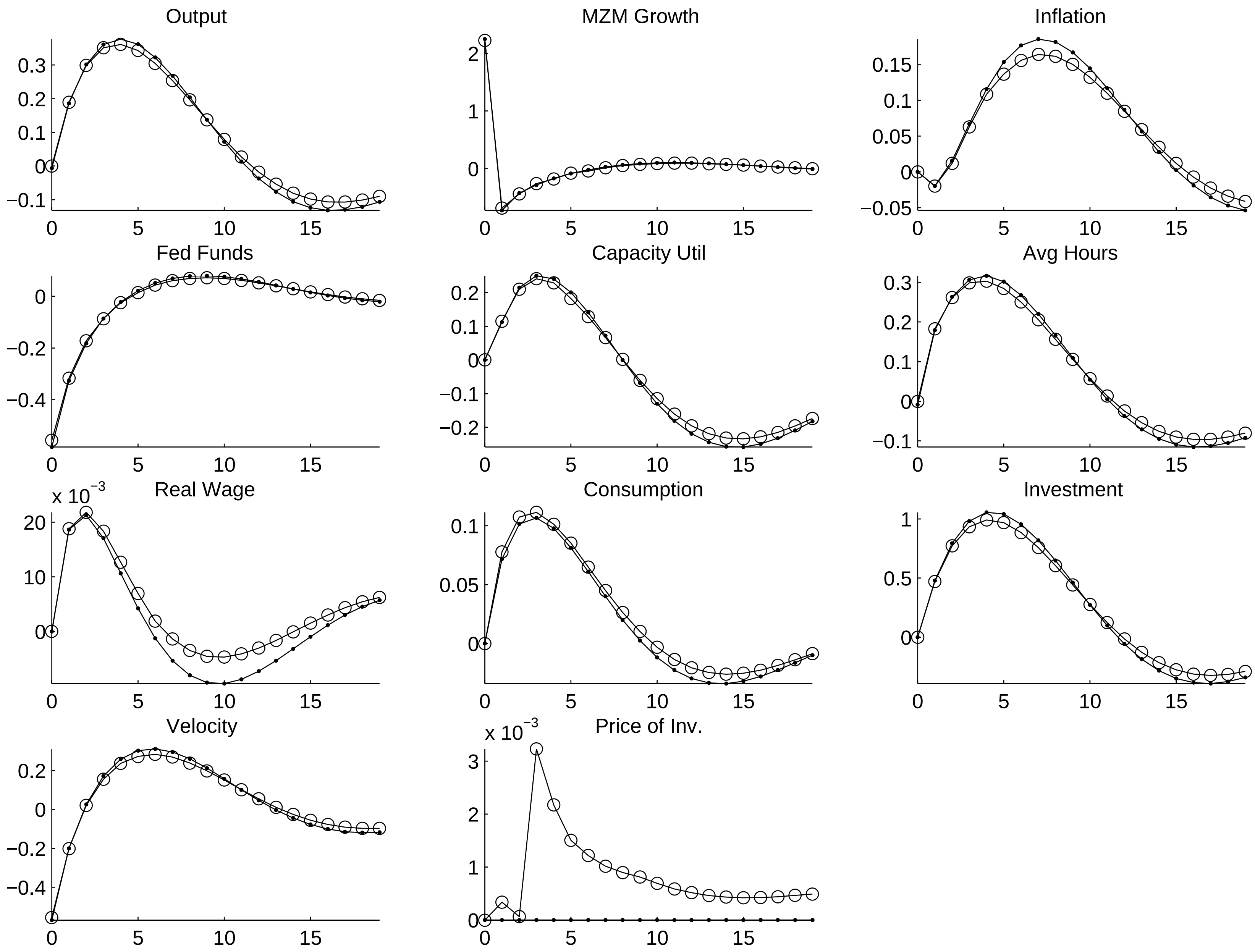
- Experiment:
  - Report Impulse Responses of 10 Model Variables to Three Shocks (This is 'Truth', for Purposes of Experiment)
  - Simulate Artificial Data From Model
  - Estimate a 10-Variable, 4-Lag VAR (with a little measurement error, for non-singularity) in Artificial Data.
  - Use Long-Run Identifying Restrictions and Monetary Policy Shock Identification to Estimate Impulse Response Functions
    - Large Sample
    - Small Sample

Dynamic responses to a monetary policy shock: true model



Dynamic responses to a monetary policy shock: true model (.) vs. VAR on simulated data (o)



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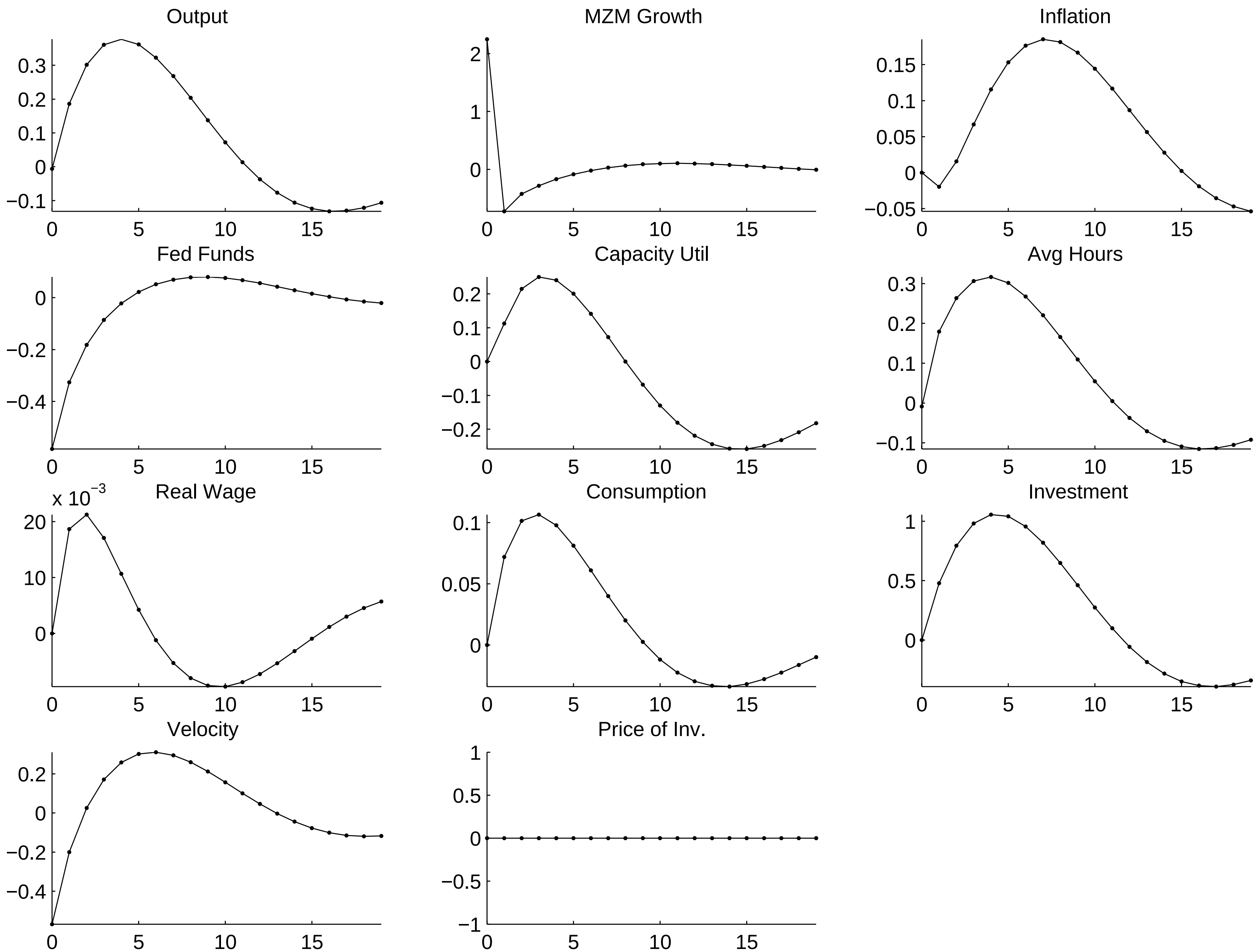

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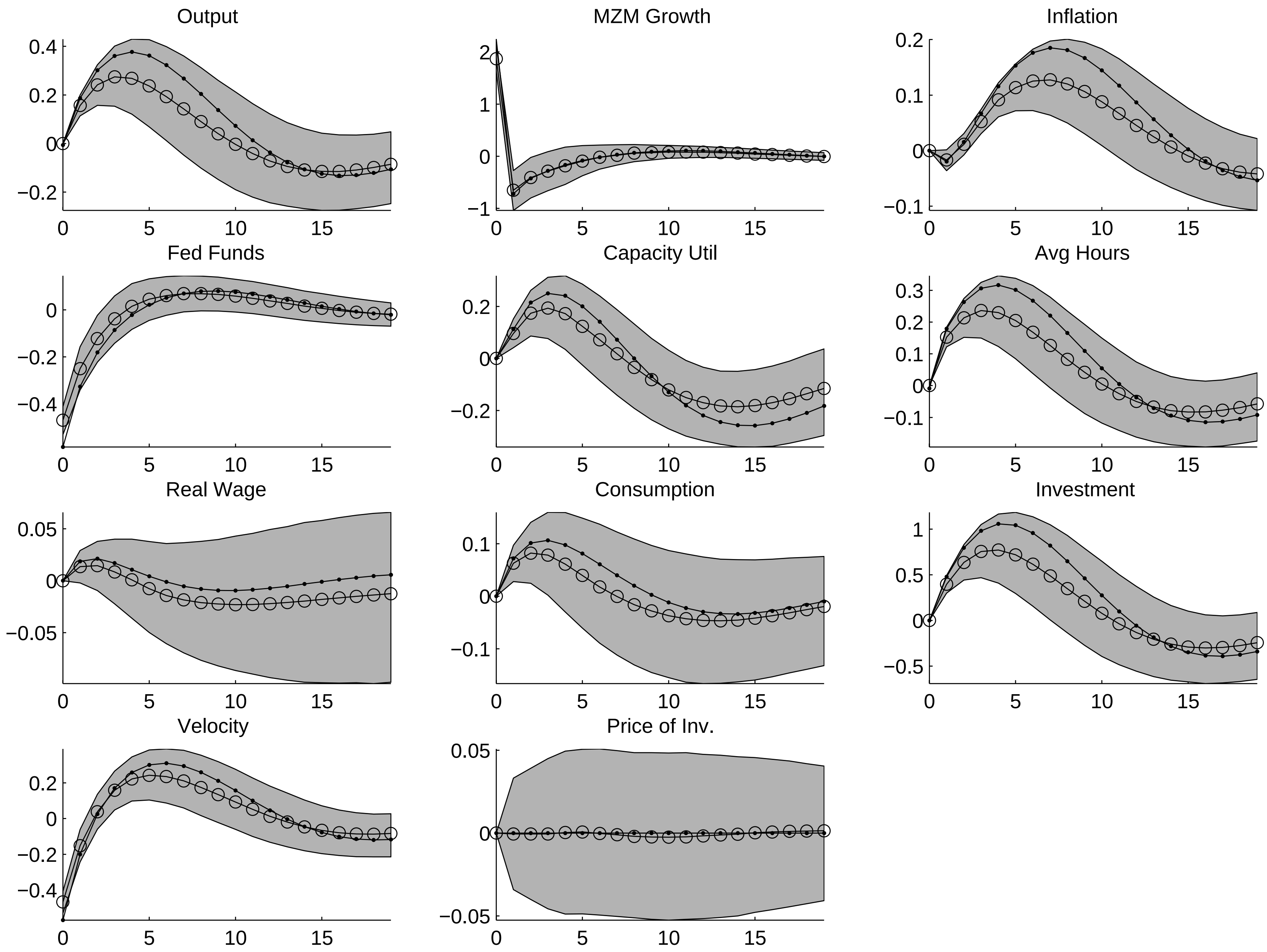
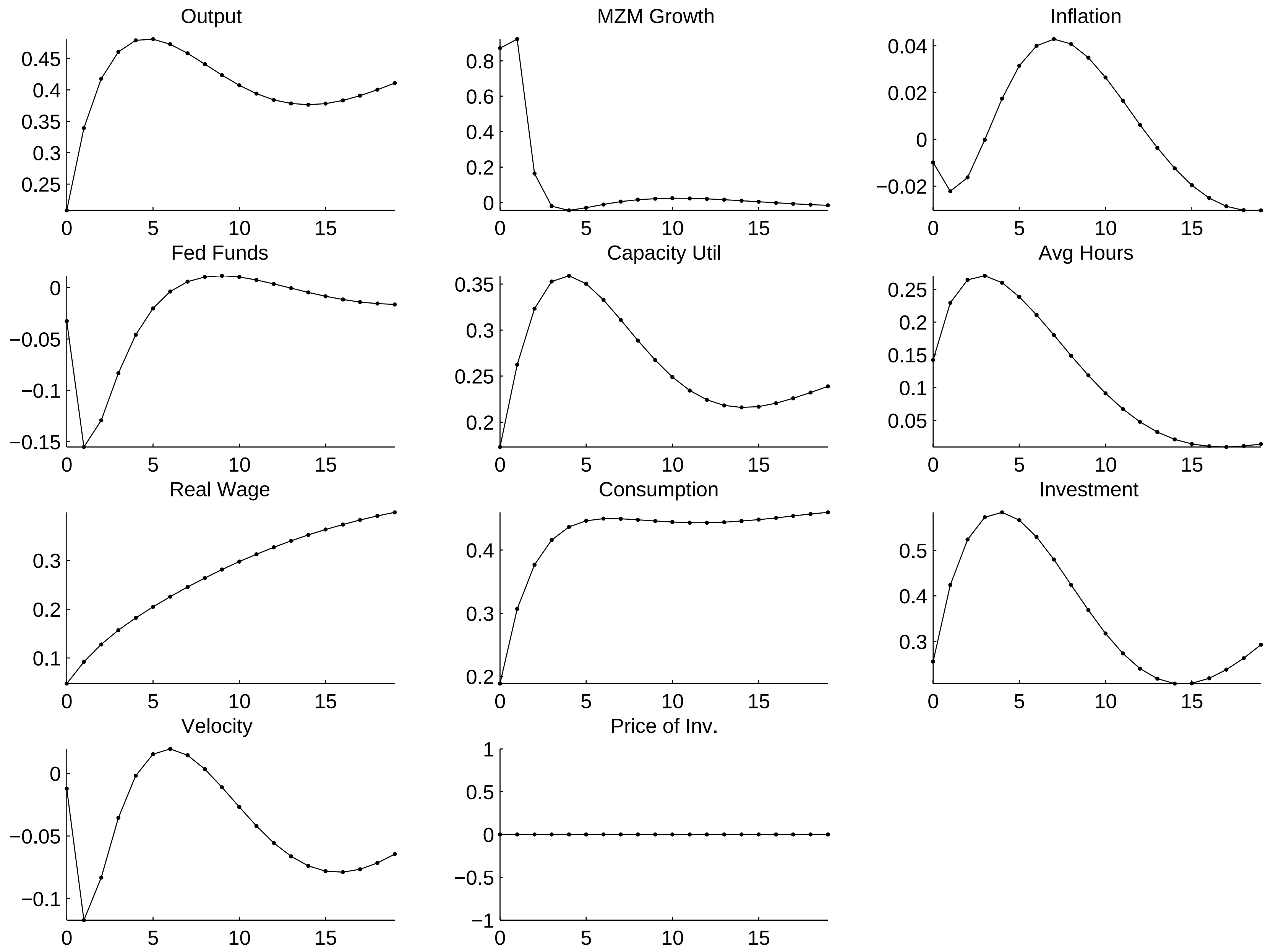


Dynamic responses to a neutral technology shock: true model



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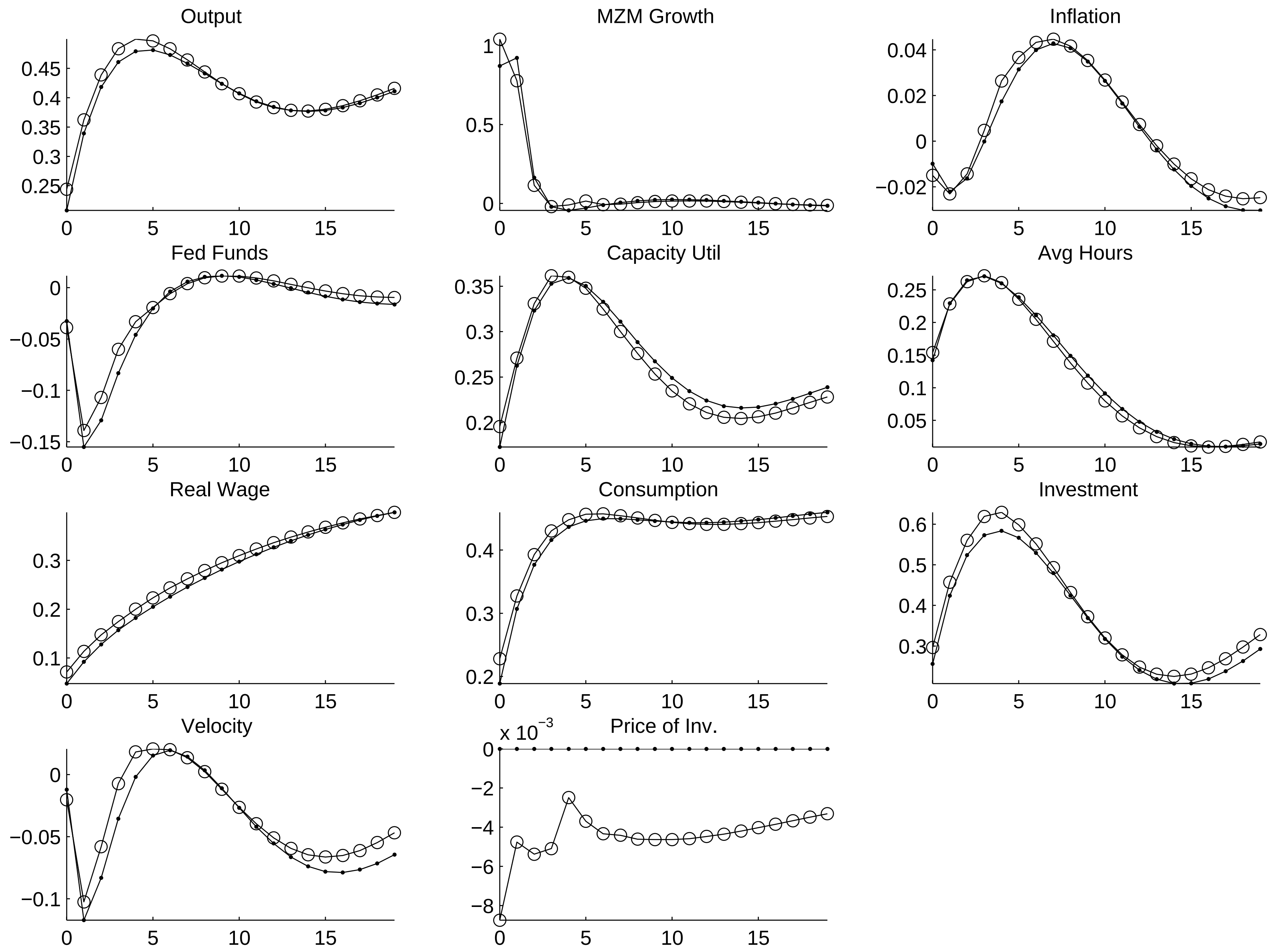

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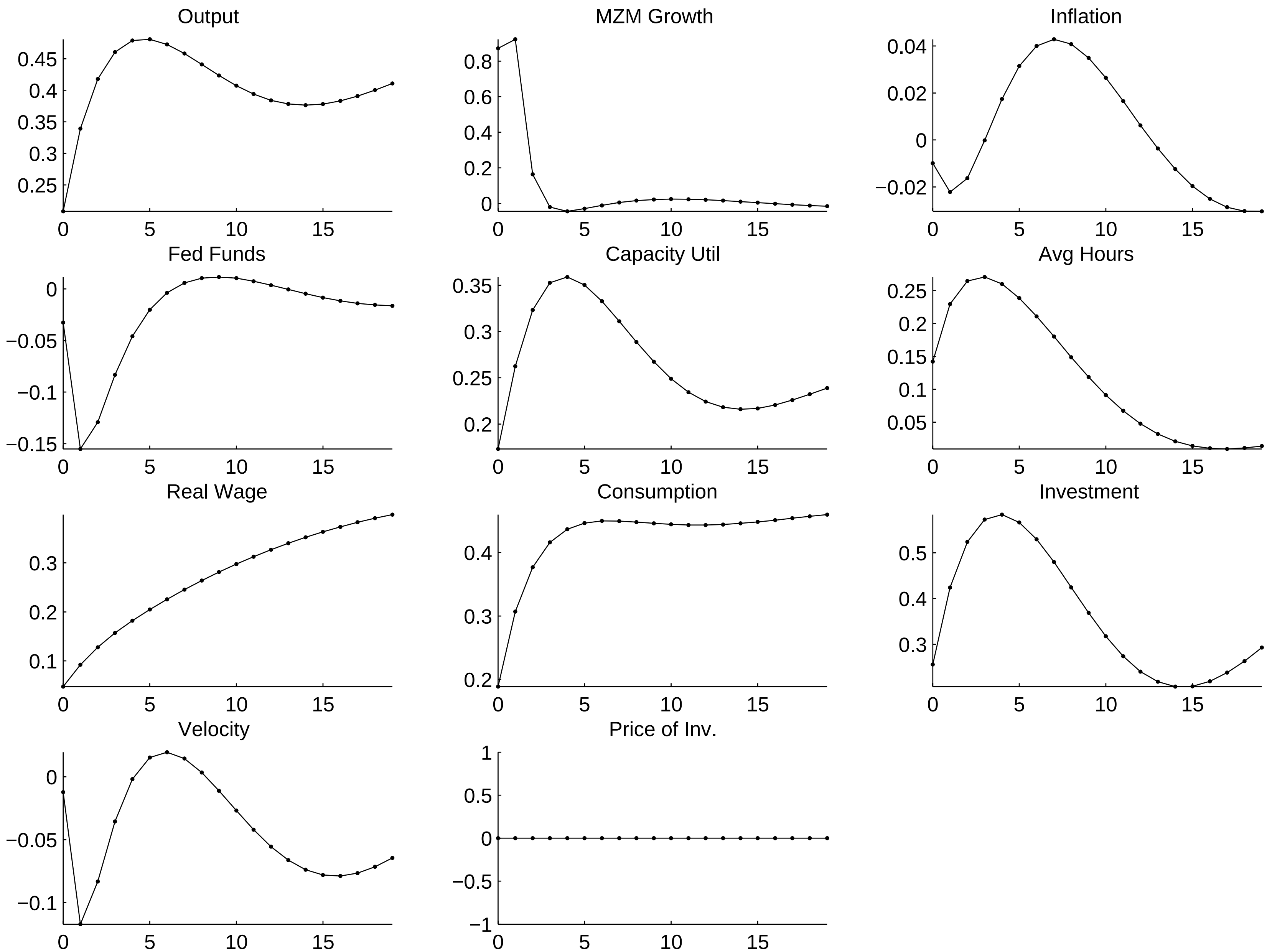
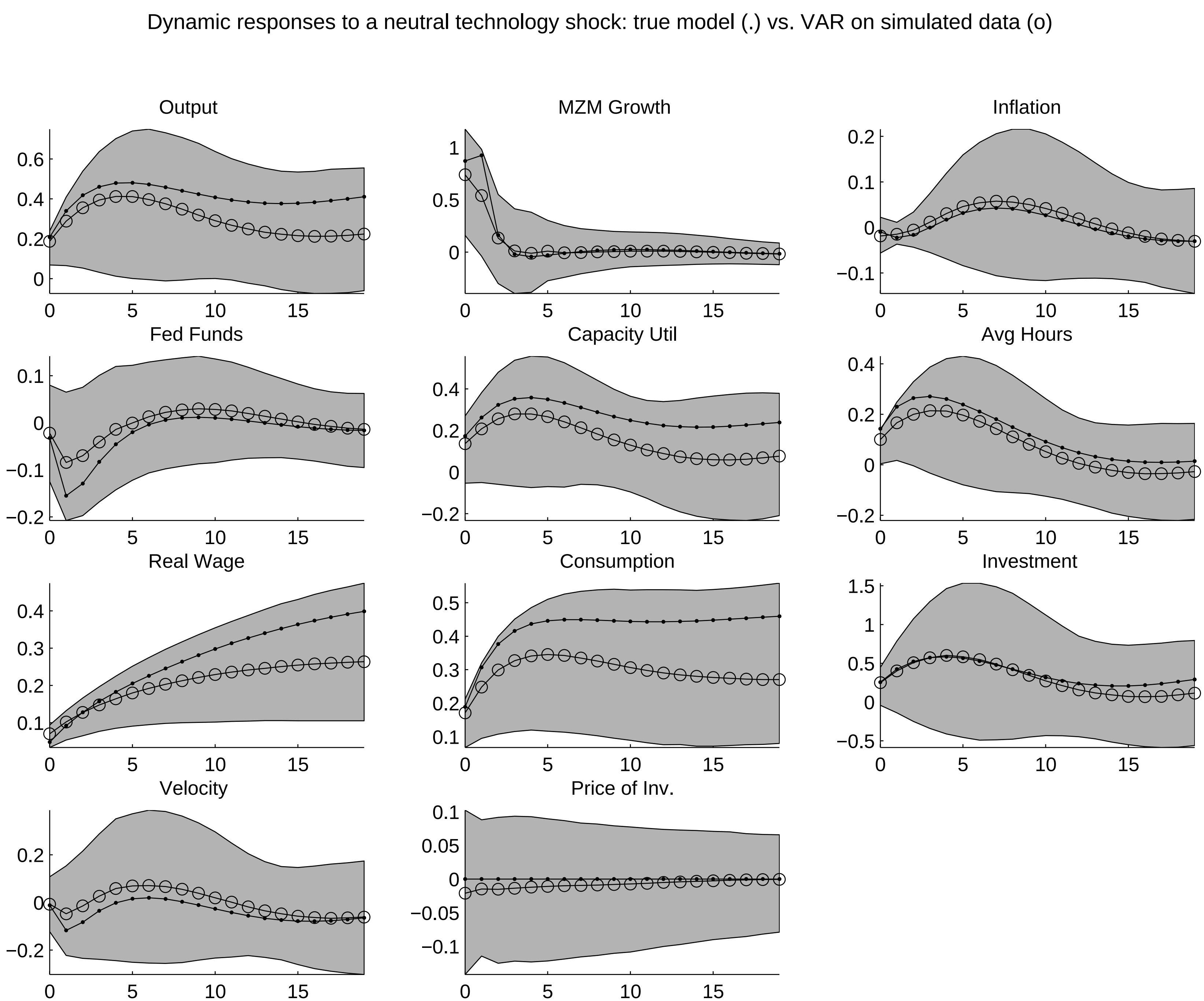
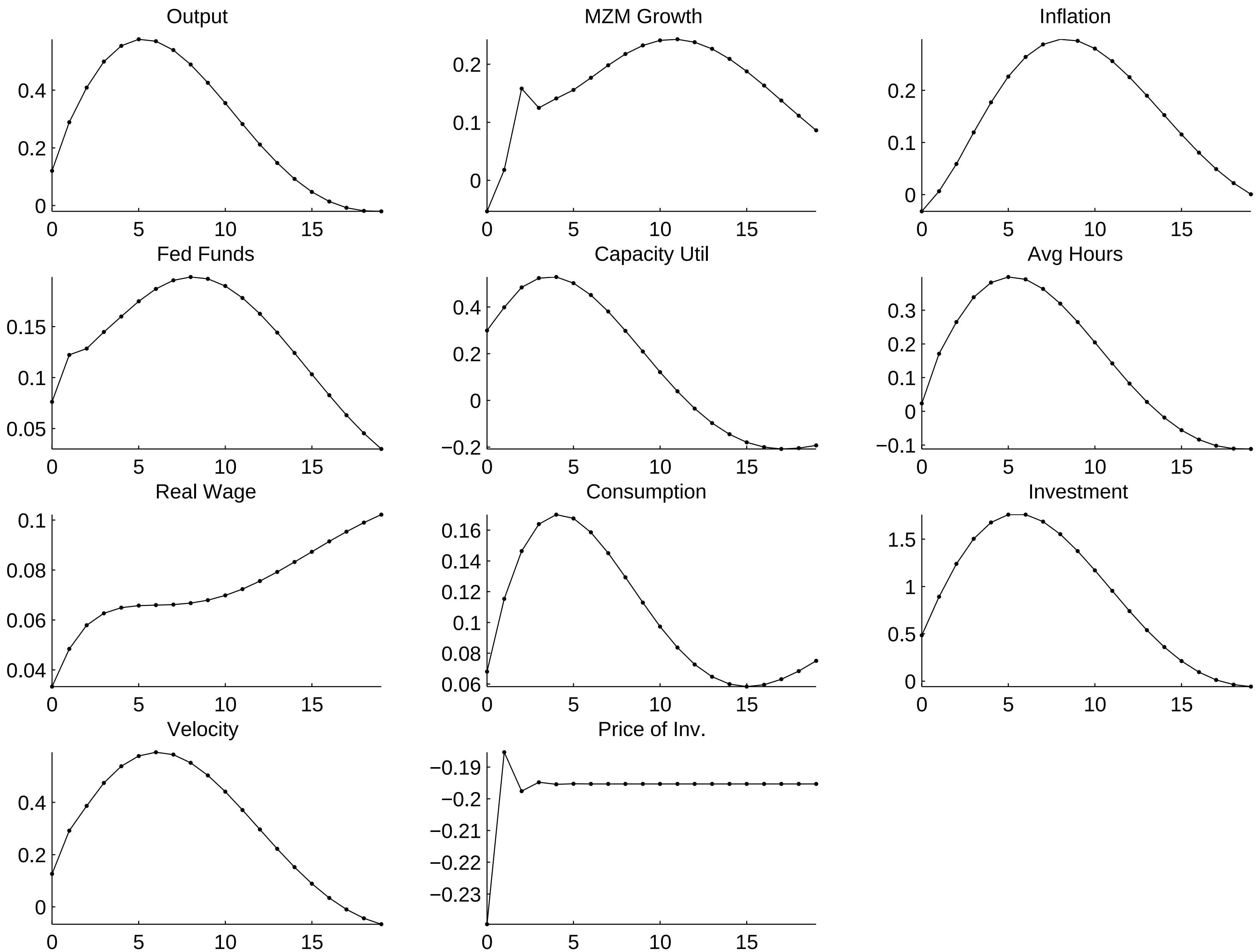
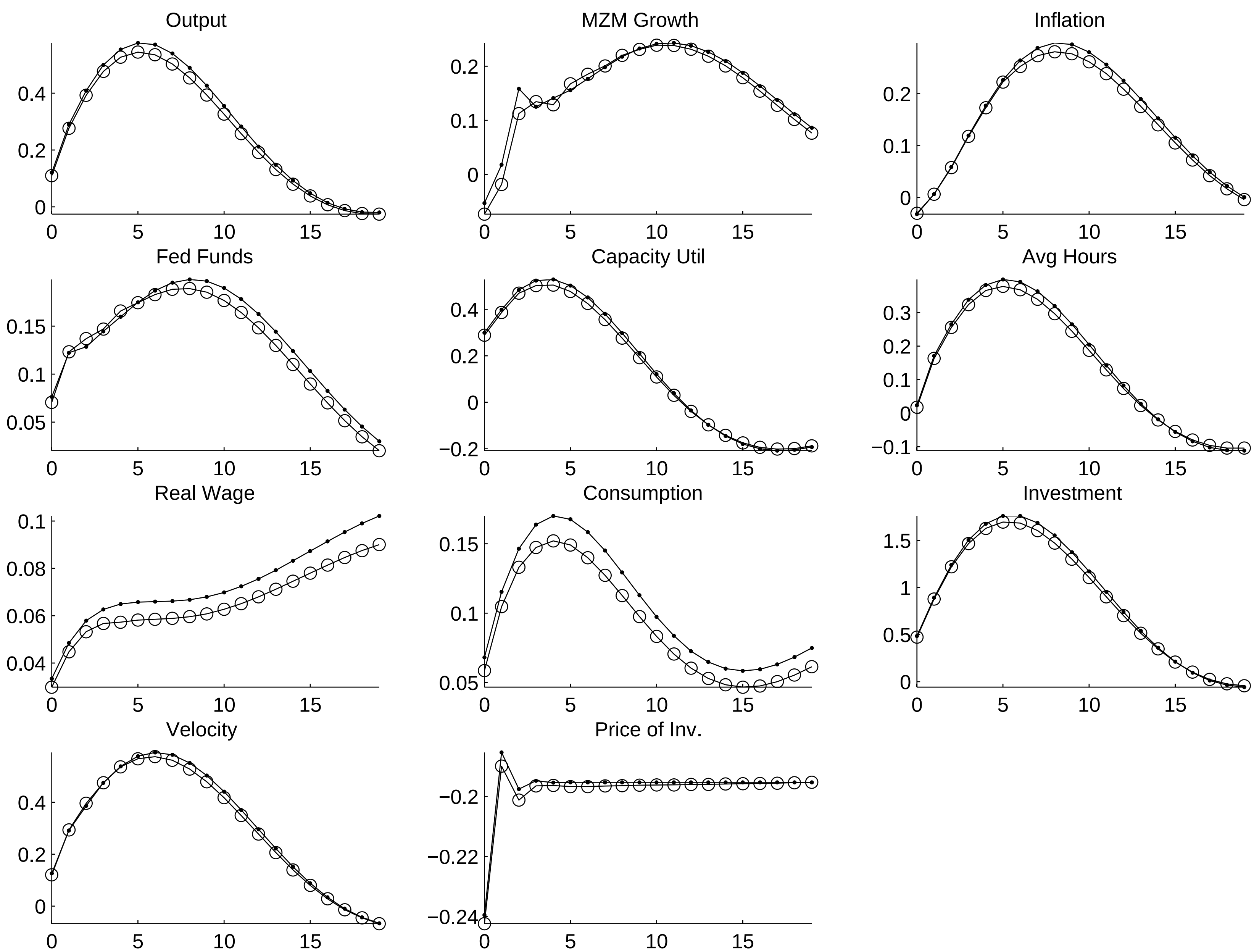



Dynamic responses to a neutral technology shock: true model (.) vs. VAR on simulated data (o)
Output
MZM Growth
Inflation
Fed Funds
Capacity Util
Avg Hours
Real Wage
Consumption
Investment
Velocity
Price of Inv.

Dynamic responses to an embodied technology shock: true model



Dynamic responses to an embodied technology shock: true model (.) vs. VAR on simulated data (o)



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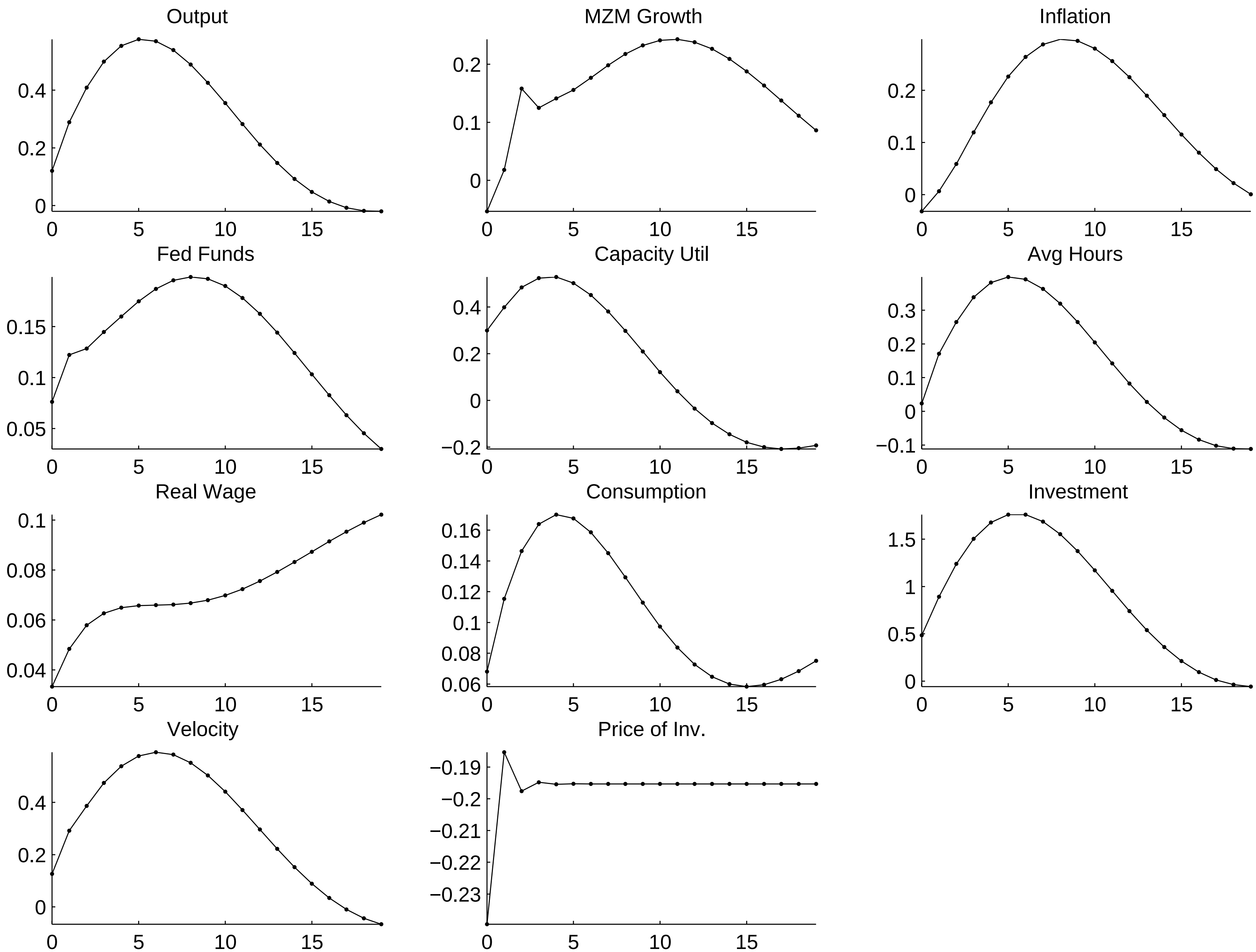

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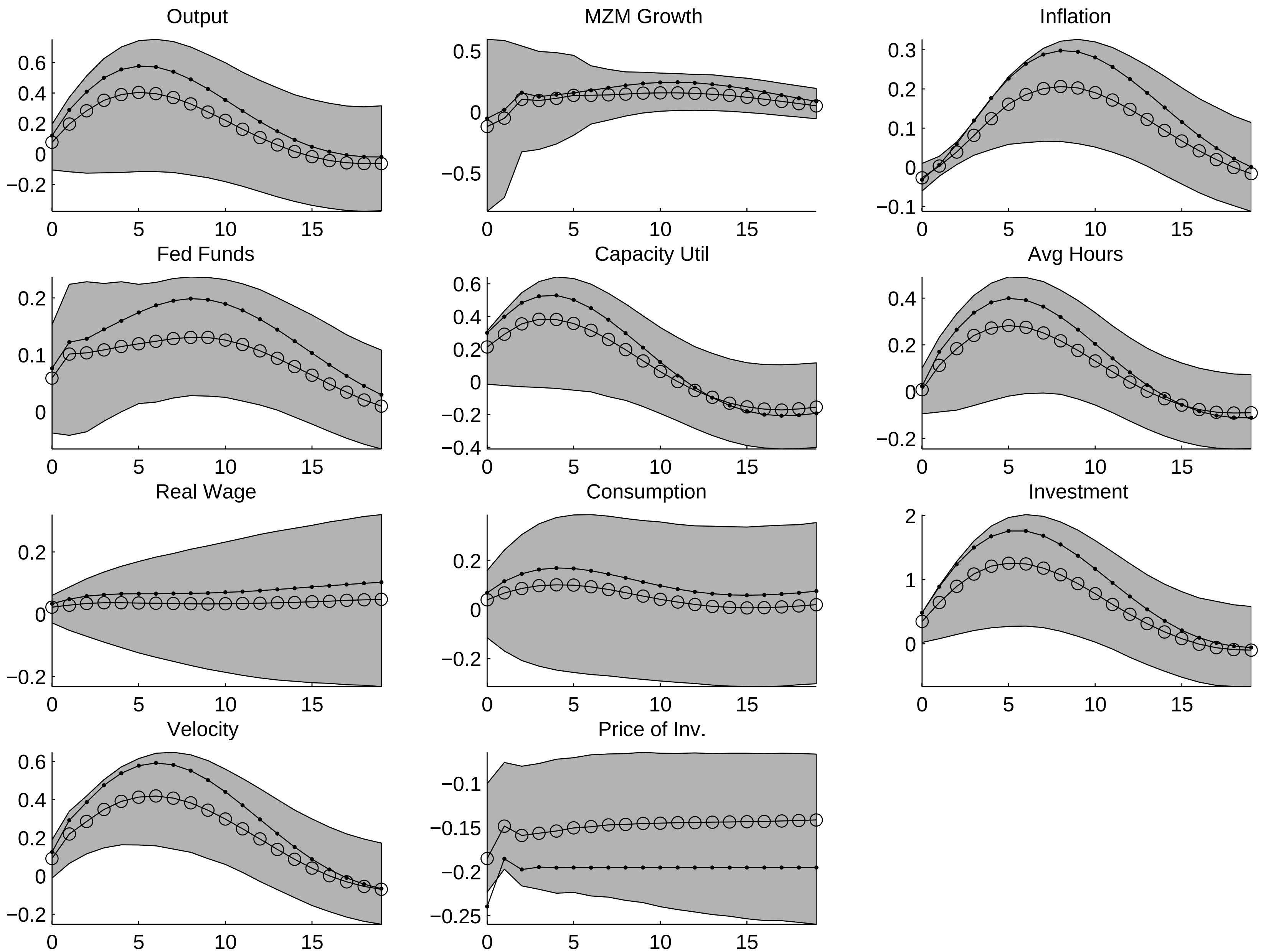

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- In the Example, Performance of VAR Seems Adequate:
  - Little Large or Small Sample Bias,
  - Sampling Variation, Though Large in Some Cases, Not Out of Line With Standard Estimates of Sampling Uncertainty.
- Perhaps Different Result From CKM Has to do With Presence of Many More Variables in VAR.

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Concluding Remarks

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  - In Practice, There are Things the Researchers Can Do To Guard Against Mistakes.
- One Example is Presented in Which Impulse Responses From VARs May be Distorted, Even Without Wrong Assumptions.
  - Not Clear that this Poses a Problem in Practice.
  - I Presented an Example Drawn from a Research Study in Which the Problem Is Not Present.

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  - Tomorrow, We Will Present a Paper Which May Convince You that Identified VARs are Useful For Constructing Dynamic Business Cycle Model.