Local Projections vs. VARs for Structural Parameter Estimation

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20th Annual Dynare Conference

June 2nd, 2026

Motivation

- Starting with Jordà (2005), **local projections** (LP) have become a common tool to understanding the dynamic effects of economic shocks
  * An alternative to vector autorregresions (VARs) when estimating impulse responses
- Other studies analyze the performance of these two models when estimating IRFs
  * VARs and LPs estimate the same impulse responses in population (Plagborg-Møller and Wolf, 2020)
  * However, there is a *bias-variance trade off* in finite samples (Li et al., 2024)
- My focus is instead on the **structural parameters** of any DSGE model
  * Follow Smith (1993) in estimating structural parameters through an indirect inference exercise in which the auxiliary model is a macro-econometric model
- *How should we **choose between VARs and LPs** when estimating – via **minimum distance** – the structural parameters of our DSGE model?*

Monte-Carlo Experiments

The DGP & the hyper-parameters

- The **log-linearized version of the Smets and Wouters (2007)** model is used to generate **S repeated samples** of macroeconomic aggregates
- The model is simulated each time at the estimated values from their paper using a sample of **T observations**
  * $T = 300$ used as baseline
  * $T = 100$ to address the issue of small sample bias of LPs (Herbst & Johannsen, 2023)
- We concentrate in **8 structural parameters** of the model:
  * σ_c : intertemporal elasticity of substitution
  * h : habit parameter
  * σ_l : elasticity of labor supply
  * φ : investment adjustment cost parameter
  * ξ_w, ξ_p : Calvo adjustment probabilities
  * ι_w, ι_p : Degree of indexation to past inflation
- **Simulated series are 10 times larger** than the sample size during the optimization stage
- The importance of the coefficients used to summarize the data is **weighted** by a squared matrix **W**
  * Identity matrix: I_m
  * Inverse of the VCM of the moments: Ω^{-1}
  * Diagonal matrix with $1/h$ elements: I_d

▷ Smets & Wouters (2007)

Targeted Responses

- We focus on the ***estimated* impulse responses of four variables**: *output*, *consumption*, *investment and hours worked* to one of **three main aggregate shocks**: *monetary policy, fiscal policy and technology*

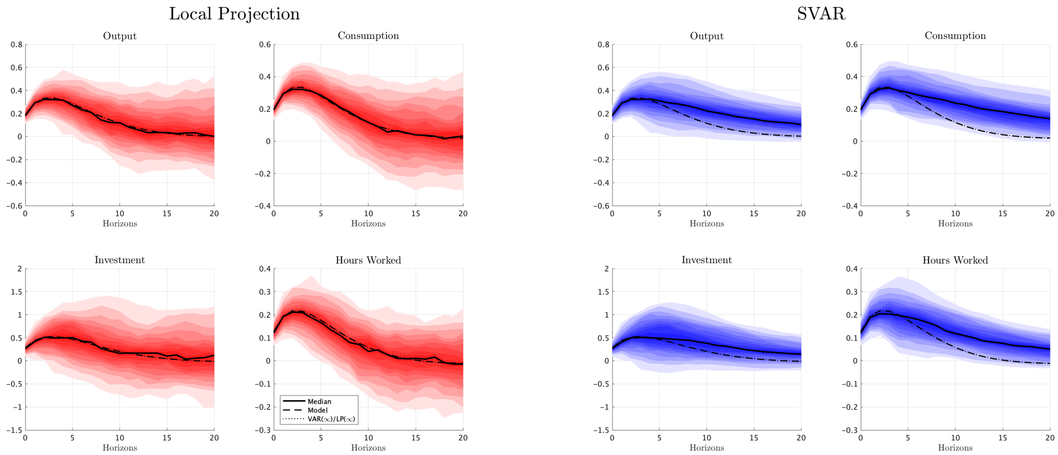
- Shocks are treated by the econometrician as
    * *observed*, i.e. $\tilde{x}_t = \eta_t^i$
    * *inferred via recursive ordering*
    * *observed with error*, i.e. $\tilde{x}_t = \eta_t^i + \sigma_\nu \nu_t$

- The IRFs are estimated using a ***VAR*** or a ***Local Projections***.
    * If the sample size is small ($T = 100$), we also consider the bias-corrected LP (Herbst & Johannsen, 2023) or the procedure by Killian (1998) for the SVAR

- In either case, the econometrician still needs to decide on at least two more things:
    * The impulse response horizon, H. We set $H = 20$.
    * The number of lags, p. We experiment with various p's, i.e. $p \in \{2, 4, 8, 12\}$.

▷ LP - IRFs ▷ SVAR - IRFs

Targeted Impulse Responses (S=100, T=300, p=4)



Impulse Response Matching vs. Indirect Inference

- When estimating a subset of the structural parameters Θ of any DSGE model by matching impulse responses, there are two approaches:
  * **Target empirical** responses but **match with model** impulse responses

$$J^{irf} = \min_{\Theta} \left(\beta - \text{IRF}(\Theta)\right)' W \left(\beta - \text{IRF}(\Theta)\right) \tag{1}$$

    - It doesn't require a simulated dataset, only structural IRFs
  * **Target and match with** empirical responses

$$J^{smm} = \min_{\Theta} \left(\beta - \beta(\Theta)\right)' W \left(\beta - \beta(\Theta)\right) \tag{2}$$

    - It uses the same econometric approach in the real and simulated data

- How does the **choice of the econometric model** affects parameter estimates?
  * J^{irf} speaks about potential misspecification of the model economy
  * J^{smm} relates to misspecification of both the model and the binding function

How to asses the performance of the estimation?

- **Overall performance**

$$J^* = \left(\text{IRF}(\Theta^*) - \text{IRF}(\hat{\Theta})\right)' \left(\text{IRF}(\Theta^*) - \text{IRF}(\hat{\Theta})\right) \tag{3}$$

$$J^{smm} = \left(\beta(\Theta^*) - \beta(\hat{\Theta})\right)' \left(\beta(\Theta^*) - \beta(\hat{\Theta})\right) \tag{4}$$

$$J^{irf} = \left(\beta(\Theta^*) - \text{IRF}(\hat{\Theta})\right)' \left(\beta(\Theta^*) - \text{IRF}(\hat{\Theta})\right) \tag{5}$$

- **Parameter-by-parameter performance**

$$\mathcal{L}_\omega(\hat{\Theta}_i, \Theta_i^*) = \omega \times \underbrace{\left(\mathbb{E}\left[\hat{\Theta}_i\right] - \Theta_i^*\right)^2}_{\text{bias}} + (1-\omega) \times \underbrace{\text{Var}(\hat{\Theta}_i)}_{\text{variance}} \tag{6}$$

- **Model fit**
  * Similar to (3), compute the unweighted distance between the structural IRFs but to other non-targeted shocks in the economy
  * For example, if targeting monetary policy shocks, look at fiscal and technology

5 Main Lessons

1. *IRF matching is more* ***sensitive to bias*** *in targeted responses and hence using LP-IRFs is preferable, while Ind. Inf. is* ***robust to misspecification*** *and hence benefits from the lower variance of VAR-IRFs.*

2. *When the* ***lag length*** p ***is large****, then IRFs and estimated parameters are* ***similar*** *independently of the econometric model. On the other hand, when* p ***is small****,* ***LP-IRFs*** *are less biased and hence better for IRF matching, while* ***SVAR-IRFs*** *have a larger bias but lower variance and hence better for Ind. Inf.*

3. ***Small sample bias*** *worsens the performance of the estimation specially for IRF matching when bias correction partly offsets the problem.*

4. ***Incorrect recursive identifications*** *are not an issue for parameter estimation when employing Ind. Inf.. Not true for IRF matching.*

5. ***Measurement error*** *worsens the structural estimation outcome and unit normalization only ameliorates the problem.*

Lessons 1, 2 & 3:
Observed shock assumption

IRF matching vs. Indirect Inference

- Simplifying assumptions for comparison:
  * Observed shock assumption
  * Target IRFs estimated with a LP or SVAR model and $T = 300$ observations
  * Weight all responses equally during the estimation stage, i.e. $W = I$
- **Overall performance measures** are averaged across estimations using different lag lengths ($p \in \{2, 4, 8, 12\}$) and shocks (TFP, fiscal, monetary)

	IRF matching				**Indirect Inference**			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
Local Projection	35.10	0.27	3.49 min	18.70	32.54	0.39	42.88 min	17.91
Structural VAR	35.23	0.41	3.93 min	17.93	33.87	0.33	14.47 min	18.39

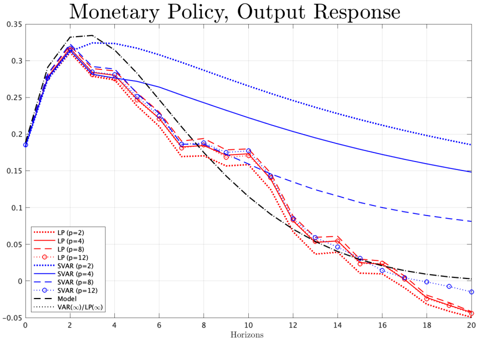
▷ Parameter-by-Parameter ▷ Weighting Matrix

Lag length and IRF matching

- In the *IRF matching* estimator we are minimizing a distance that can be decomposed as:

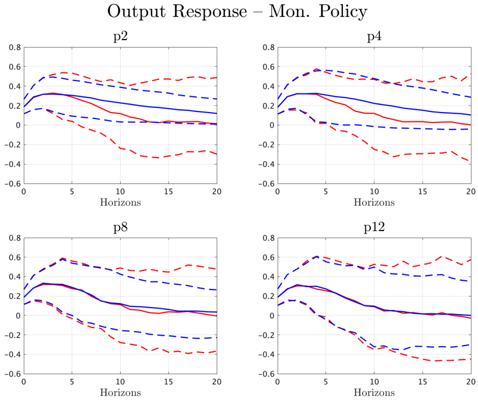
$$\underbrace{[\beta(p, T|\Theta) - \beta(p, T = \infty|\Theta)]}_{\text{small sample bias}} + \underbrace{[\beta(p, T = \infty|\Theta) - IRF(\Theta)]}_{\text{lag truncation bias}} \qquad (7)$$

- *Small sample bias* is common to both Local Projections and VARs
- *Lag truncation bias* only matter for VARs!
    * Local Projection IRFs are independent of the lag length when the shock is observed
    * VAR IRFs are heavily biased at short lag lengths and this truncation bias shrinks as we increase p



Lag Length and Indirect Inference

- **Point estimates**
  * Local Projection IRFs are independent of the lag length when the shock is observed
  * SVAR IRFs approximately agree with LP IRFs up to horizon *p*, then extrapolates using the first *p* sample autocovariances
- **Confidence Intervals**
  * Local Projection IRFs have a much wider bands, specially at long horizons
  * SVAR IRFs converge towards the sample uncertainty of LPs as p gets large

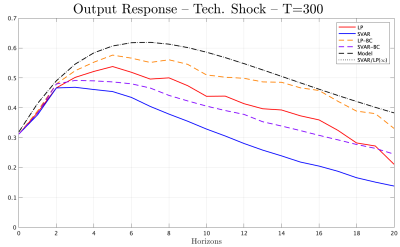


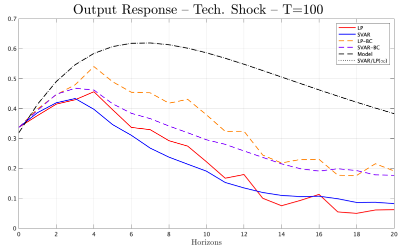
Decomposition by lag length

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
				p=2				
Local Projection	35.75	0.24	3.30 min	18.97	25.47	0.34	18.93 min	18.02
Structural VAR	34.61	0.61	4.32 min	17.00	26.25	0.16	11.88 min	19.32
				p=4				
Local Projection	35.68	0.25	3.40 min	18.74	30.26	0.37	28.99 min	17.95
Structural VAR	36.01	0.39	3.89 min	17.75	31.49	0.26	15.35 min	18.26
				p=8				
Local Projection	34.69	0.28	3.83 min	18.47	35.91	0.44	45.06 min	17.69
Structural VAR	34.92	0.34	3.85 min	18.36	37.26	0.49	13.35 min	18.01
				p=12				
Local Projection	34.27	0.29	3.44 min	18.63	38.52	0.41	78.53 min	17.98
Structural VAR	35.39	0.30	3.67 min	18.61	40.47	0.41	17.29 min	17.98

Small sample bias & bias correction

- P-M & W (2023) show that $LP(p)$ exactly agree with true responses and that $SVAR(p)$ agrees up to lag p
- However, **sample uncertainty** matters!
  * In finite samples, e.g. $T = 300$, *both* LP and SVAR are biased after horizon p, with SVARs having a more severe bias as long as the response is persistent
  * The sample size typically found in empirical applications is even shorter and around T=100 (H&J, 2023), which makes these biases worse.
- **Bias correction** partially offsets the small sample bias, but two questions arise in our context
  * Q1: Does Indirect Inference improves upon IRF matching when this bias is severe?
  * Q2: Does targeting bias corrected responses improve the model estimation?





IRF matching vs. Indirect Inference in small samples

- Higher sample uncertainty associated with fewer observations ($T = 100$) leads to a **worse fit** of the model **for both estimation strategies**
- IRF matching suffers more its consequences as **Ind. Inf. is robust to misspecification** of the binding function
- For the same reason, applying **bias correction** to the targeted IRFs is more useful for IRF matching

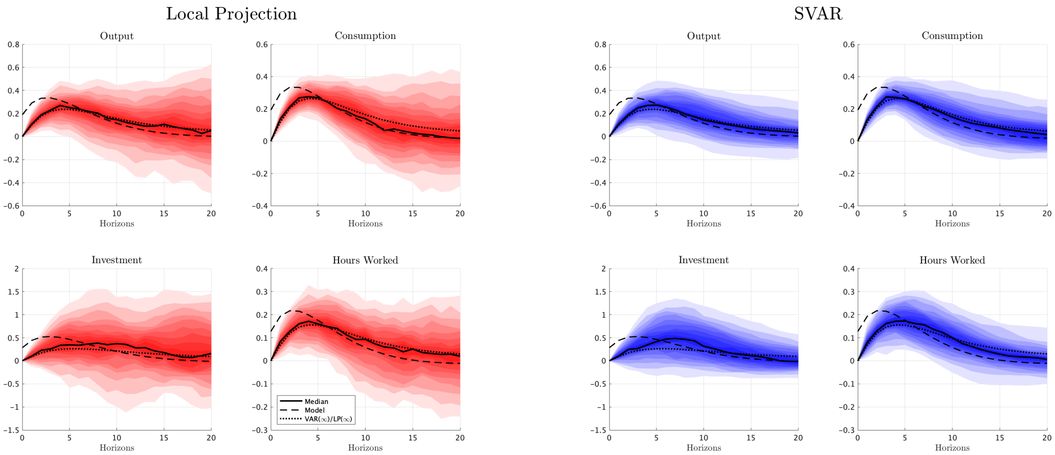
	IRF matching				**Indirect Inference**			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
				T=300				
Local Projection	35.10	0.27	3.49 min	18.70	32.54	0.39	42.88 min	17.91
Structural VAR	35.23	0.41	3.93 min	17.93	33.87	0.33	14.47 min	18.39
				T=100				
Local Projection	29.71	0.53	3.56 min	18.13	22.00	0.46	18.46 min	19.03
Structural VAR	31.62	0.47	3.33 min	17.98	25.16	0.36	9.78 min	19.50
Bias Corrected LP	31.55	0.32	3.26 min	19.18	23.29	0.35	20.48 min	19.50
Bias Corrected SVAR	33.48	0.32	3.42 min	18.65	26.06	0.33	11.02 min	20.11

Lesson 4:
Recursive Identification

Cholesky Orthogonalized Shocks

- Shocks are not observable in applied work. Thus, there is a need for **identification**
- The most commonly used identification method in macroeconomics imposes **recursive zero restrictions on contemporaneous coefficients**
- As shown by Ramey (2016), there are two widely used alternatives:
  * *Policy variable does not respond within the period to the other endogenous variable*
    - We use this assumption to identify **technology shocks** and **government spending shocks** within the Smets and Wouters model
    - TFP and government spending are the policy variables, ordered first. Output, consumption, investment and hours worked are included in the VAR or as lagged controls in the LP
  * *Other endogenous variables do not respond to the policy shock within the period*
    - We use this assumption to identify **monetary policy shocks** within the Smets and Wouters model
    - We order the policy rate last in a VAR that also includes output, consumption, investment, hours worked, wages, and inflation. Similarly, these variables are added as contemporaneous controls in the LP

Mon. policy: real variables respond at $t = 0$ in the Sm & Wo model



▷ Technology Shocks

Monetary policy: overall performance

- Main results still hold when targeting IRFs to monetary policy shock and it is a **better idea** in the Smets-Wouters world: lower J^*_{unt}
- When *identification assumption are* *incorrect*, then **Ind. Inf. is robust to such misspecification**
  * Targeting consistently wrong responses helps with parameter identification as long as they have low variance

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
	Observed Shock							
Local Projection	50.65	0.07	3.46 min	9.36	48.46	0.31	41.39 min	9.40
Structural VAR	54.07	0.11	4.38 min	9.26	53.60	0.30	14.65 min	9.44
	Recursive Shock							
Local Projection	48.11	0.29	3.34 min	9.60	56.91	0.18	78.57 min	9.34
Structural VAR	47.09	0.34	3.78 min	9.31	58.70	0.12	11.44 min	9.34

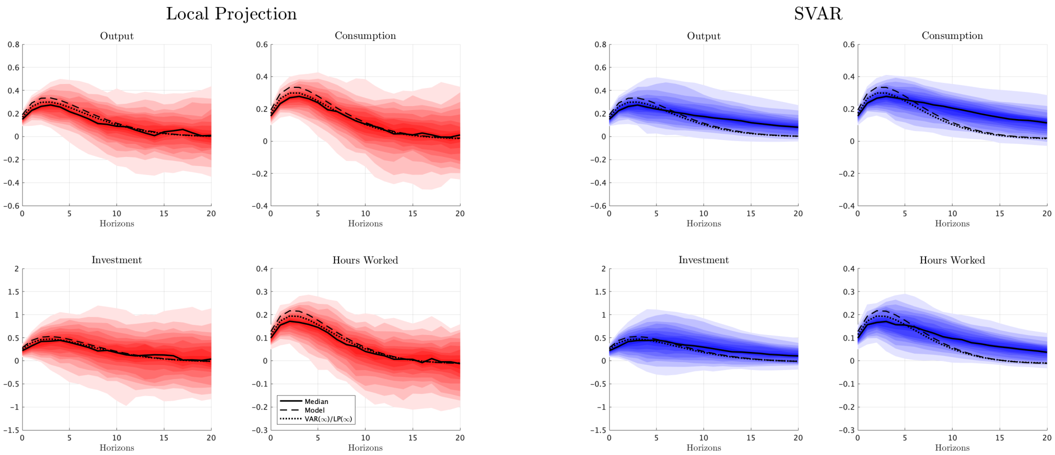
▷ Parameter-by-Parameter

Lesson 5: Measurement Error

Direct measures of the shock of interest

- A popular identification approach consist of constructing a series from historical documents to identify policy shocks, e.g.
  * Romer and Romer (2004) monetary shock series based on FOCM meetings
  * Ramey (2011) defense news series based on *Business Week* articles
- These series are used in dynamic single equation regressions or embedded in a Choleski decomposition, as we have done for the observed shock scheme
- In practice, there are good reasons to expect that these shocks suffer from **measurement error** or capture only part of the shock. Hence, I distinguish 3 cases:
  1. Study classical measurement error case, $\eta_t^{obs} = \eta_t + \sigma_\nu \nu_t$
  2. Proxy is correlated with other shocks, e.g. government spending with technology shock
  3. Unit normalization (Stock & Watson, 2018)

Attenuation bias in IRFs



▷ Technology Shocks ▷ Fiscal Policy

Stock & Watson unit normalization

- Unit normalization corrects the bias in estimated responses through rescaling.
- Great fix for the structural estimation as well, specially for *IRF matching*.

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
	True Monetary policy shock (η_t^m)							
Local Projection	50.65	0.07	3.46 min	9.36	48.46	0.31	41.39 min	9.40
Structural VAR	54.07	0.11	4.38 min	9.26	53.60	0.30	14.65 min	9.44
	Proxied monetary policy shock ($\eta_t^{a,obs} = \eta_t^a + \sigma_\nu \nu_t$)							
Local Projection	1.79	1.25	3.05 min	34.30	1.35	1.40	40.23 min	33.31
Structural VAR	3.41	1.70	2.80 min	33.47	1.70	1.18	13.74 min	34.39
	A 1% increase in r_0 (Stock and Watson (2018) normalization)							
Local Projection	50.77	0.08	3.83 min	19.34	49.49	0.52	49.84 min	17.85
Structural VAR	53.41	0.32	4.04 min	18.86	51.23	0.42	12.49 min	17.93

Key Message

*(Indirect Inference > IRF Matching)**

** LPs + IRF Matching can still be the most accurate option conditional on correct identification and a sufficiently long sample*

Appendix

Data Generating Process

The Model Economy

- The discussion about which binding function to use, VAR or LP, is best made in the context of a specific model, but **which model to use?**
- **Many applications** that estimate their economies by matching impulse responses **concern linearized models**, e.g. Rotemberg and Woodford (1998), Christiano et al. (2005), Iaccoviello (2005), etc.
  * Indirect inference was initially proposed as a method to estimate non-linear models
  * Nonetheless we still need to understand how to choose the binding function in this simpler set up
- The responses to monetary, fiscal and technology shocks are the most widely studied in empirical applications (Ramey, 2016). Hence, we want a model that is able to speak about the responses to these aggregate shocks
- Given the relevance in the academic literature and in policy circles, the **Smets and Wouters (2007) model** seems a sensible choice

▷ Back

Smets and Wotuers Model – Main Ingredients I

- Representative household with **habit formation** and preference for **leisure**

$$c_t = c_1 c_{t-1} + (1 - c_1)\mathbb{E}_t[c_{t+1}] + c_2 (l_t - \mathbb{E}_t[l_{t+1}]) - c_3 \left(r_t - \mathbb{E}_t[\pi_{t+1}] - \varepsilon_t^b\right)$$

- Households **invest in capital** given the **capital adjustment cost** they face

$$i_t = i_1 i_{t-1} + (1 - i_1)\mathbb{E}[i_{t+1}] + i_2 q_t + \varepsilon_t^i$$

where

$$q_t = q_1 \mathbb{E}[q_{t+1}] + (1 - q_1)\mathbb{E} r_{t+1}^k - \left(r_t - \mathbb{E}_t[\pi_{t+1}] - \varepsilon_t^b\right) \quad : \text{ value of capital}$$

$$k_t = k_1 k_{t-1} + (1 - k_1) i_t + k_2 \varepsilon_t^i \quad : \text{ installed capital LoM}$$

- **Aggregate production** uses installed capital ($k_t^s = k_{t-1} + z_t$) and labor services

$$y_t = \phi_p \left(\alpha k_t^s + (1 - \alpha) l_t + \varepsilon_t^a\right)$$

▷ Back

Smets and Wotuers Model – Main Ingredients II

- **Price stickiness** as in Calvo (1983) and **partial indexation** to lagged inflation gives rise to New-Keynesian Phillips curve

$$\pi_t = \pi_1 \pi_{t-1} + \pi_2 \mathbb{E}[\pi_{t+1}] - \pi_3 \mu_t^p + \varepsilon_t^p$$

- **Nominal wage stickiness** and partial indexation of wages to inflation

$$w_t = w_1 w_{t-1} + (1 - w_1)\mathbb{E}[w_{t+1} + \pi_{t+1}] - w_2 \pi_t + w_3 \pi_{t-1} - w_4 \mu_t^w + \varepsilon_t^w$$

- **Government spending** is exogenous and correlated with technology

$$\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga} \eta_t^a$$

- The central bank sets the short-term interest rate according to the **monetary policy rule**

$$r_t = \rho_r r_{t-1} + (1 - \rho_r) \left(r_\pi \pi_t + r_y \left(y_t - y_t^p \right) \right) + r_{\Delta y} \left[\left(y_t - y_t^p \right) - \left(y_{t-1} - y_{t-1}^p \right) \right] + \epsilon_t^r$$

▷ Back

Moment Generating Functions

Local Projections (LP - IRFs)

- Some notation:
  * Let $\tilde{y}_t \in \{y_t, c_t, i_t, hw_t\}$ denote one of response variables of interest.
  * Let $\tilde{x}_t \in \{\eta_t^a, \eta_t^g, \eta_t^m\}$ denote the innovation of one of the three aggregate shocks.
  * Define the vector of contemporaneous r_t and lagged controls $w_t = \{\tilde{x}_t, \tilde{y}_t\}$
- Then, consider for each horizon $h = 0, 1, 2, \ldots, H$ the *linear projections*:

$$\tilde{y}_{t+h} = \mu_h + \beta_h \tilde{x}_t + \gamma_h' r_t + \sum_{\ell=1}^{p} \delta_{h,\ell}' w_{t-\ell} + \xi_{h,t} \tag{8}$$

  where $\xi_{h,t}$ is the projection residual and $\mu_h, \beta_h, \gamma_h, \{\delta_{h,\ell}'\}_{\ell=1}^{p}$ are the projection coefficients.

- **Definition**. *The LP - IRFs of $\tilde{y}_t$ with respect to $\tilde{x}_t$ is given by $\{\beta_h\}_{h\geq 0}$ in the equation above.*

▷ Back

Structural Vector Autoregression (SVAR - IRFs)

- Consider the multivariate linear *VAR(p) projection*:

$$w_t = c + \sum_{\ell=1}^{p} A_\ell w_{t-\ell} + u_t \tag{9}$$

  where u_t is the projection residual and c, $\{A_\ell\}_{\ell=1}^{p}$ are the projection coefficients.

- Let $\Sigma_u \equiv \mathbb{E}\left[u_t u_t'\right]$ and define the *Cholesky decomposition* $\Sigma_u = BB'$ where B is lower triangular with positive diagonal entries.

- Consider the corresponding recursive *SVAR representation*:

$$A(L) w_t = c + B\eta \tag{10}$$

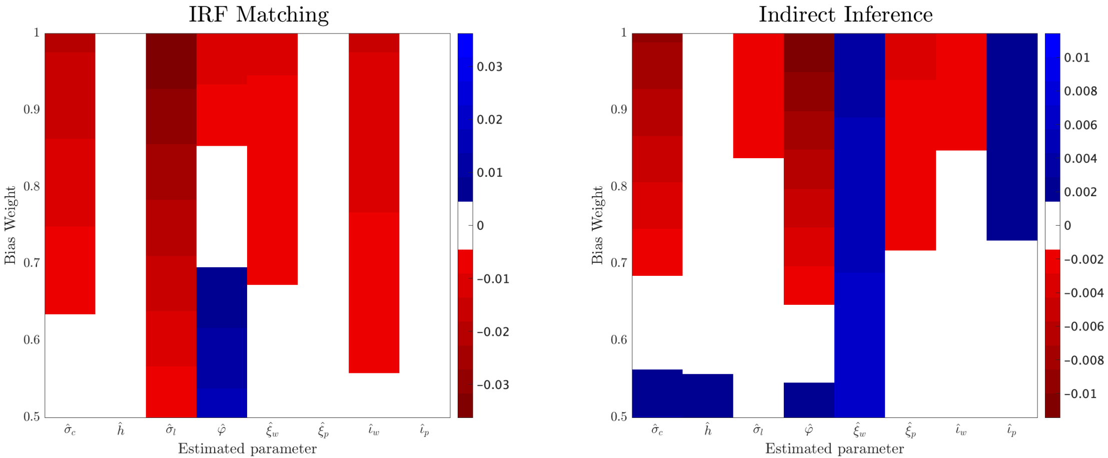
  where $A(L) = I - \sum_{\ell=1}^{p} A_\ell L^\ell$ and $\eta = B^{-1} u_t$. Define the lag polynomial $\sum_{\ell=0}^{p} C_\ell L^\ell = C(L) = A(L)^{-1}$.

- **Definition**. *The SVAR - IRFs of $\tilde{y}_t$ with respect to $\tilde{x}_t$ is given by $\{\theta_h\}_{h\geq 0}$ with $\theta_h \equiv C_{2,\bullet,h} B_{\bullet,1}$ where $\{C_\ell\}$ and B are defined above.*

▷ Back

Monte-Carlo Results (Observed Shock)

Parameter by parameter performance



$$z = \left(\mathcal{L}_\omega(\hat{\Theta}_i^{LP}, \Theta_i^*) - \mathcal{L}_\omega(\hat{\Theta}_i^{SVAR}, \Theta_i^*) \right) / \Theta_i^*$$

▷ Back

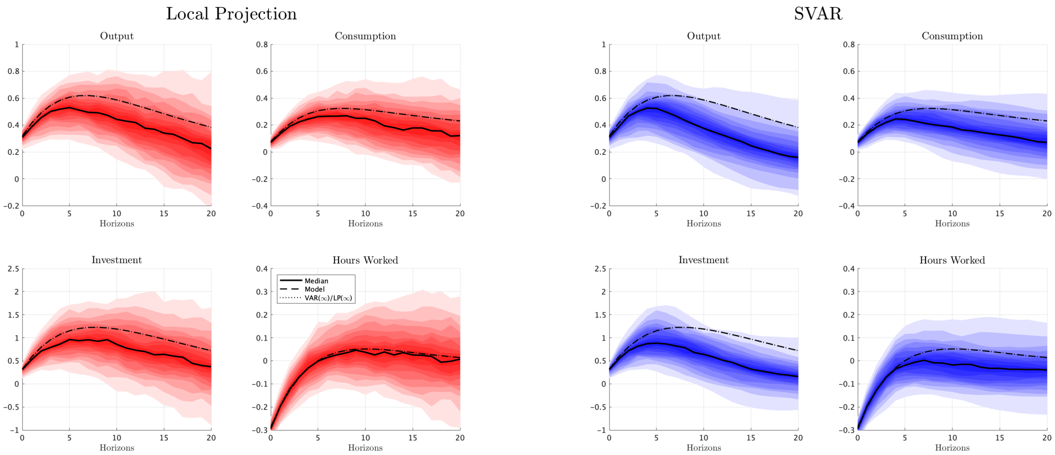
The role of the weighting matrix

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
	Identity Matrix							
Local Projection	35.10	0.27	3.49 min	18.70	32.54	0.39	42.88 min	17.91
Structural VAR	35.23	0.41	3.93 min	17.93	33.87	0.33	14.47 min	18.39
	Diagonal Matrix							
Local Projection	34.44	0.22	3.61 min	18.87	32.82	0.35	40.56 min	18.22
Structural VAR	34.87	0.27	3.85 min	18.20	34.17	0.31	11.55 min	18.62
	Optimal Weighting Matrix							
Local Projection	33.63	0.04	3.07 min	21.56	32.69	0.06	35.56 min	21.41
Structural VAR	34.17	0.05	3.20 min	20.80	34.26	0.08	10.69 min	20.90

▷ Back

Monte-Carlo Results (Recursive Identification)

TFP Shock: recursive assumption is correct in Sm & Wo (2007)



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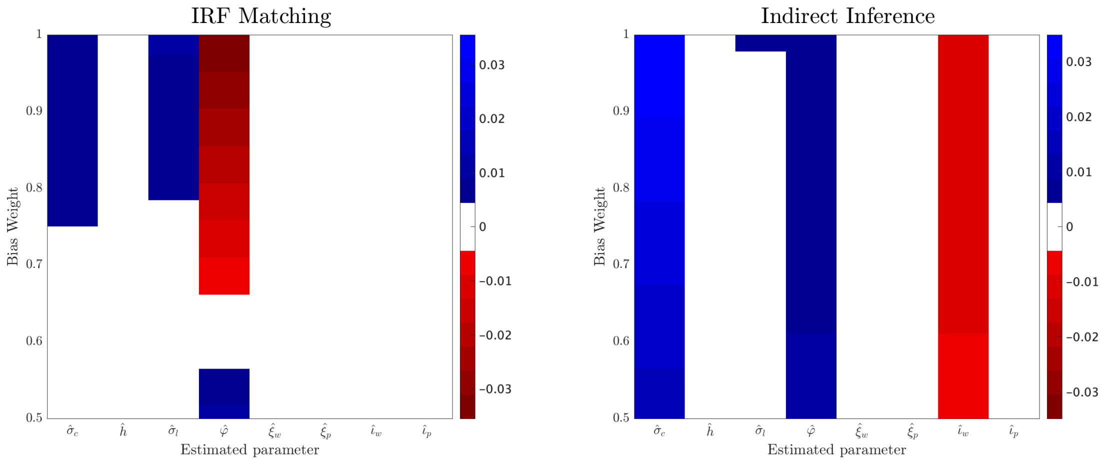
TFP Shock: if assumptions are right, identification does not matter

- If *recursive assumptions are correct*, the identification strategy does not play a role in the estimation
- **Main lesson still holds**: use LPs for *IRF matching* exercises and VARs for *Ind. Inf.*
- **Model fit:** J^*_{unt} is large $\implies$ not great idea to target just TFP shocks in the Smets-Wouters model

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
Local Projection	1.05	0.67	2.87 min	37.30	0.70	0.84	42.41 min	35.92
Structural VAR	2.53	1.07	3.11 min	35.74	0.97	0.66	14.34 min	37.31

▷ Back

TFP Shock: it is all about the investment adjustment cost $\hat{\varphi}$



$$z = \left(\mathcal{L}_\omega(\hat{\Theta}_i^{LP}, \Theta_i^*) - \mathcal{L}_\omega(\hat{\Theta}_i^{SVAR}, \Theta_i^*) \right) / \Theta_i^*$$

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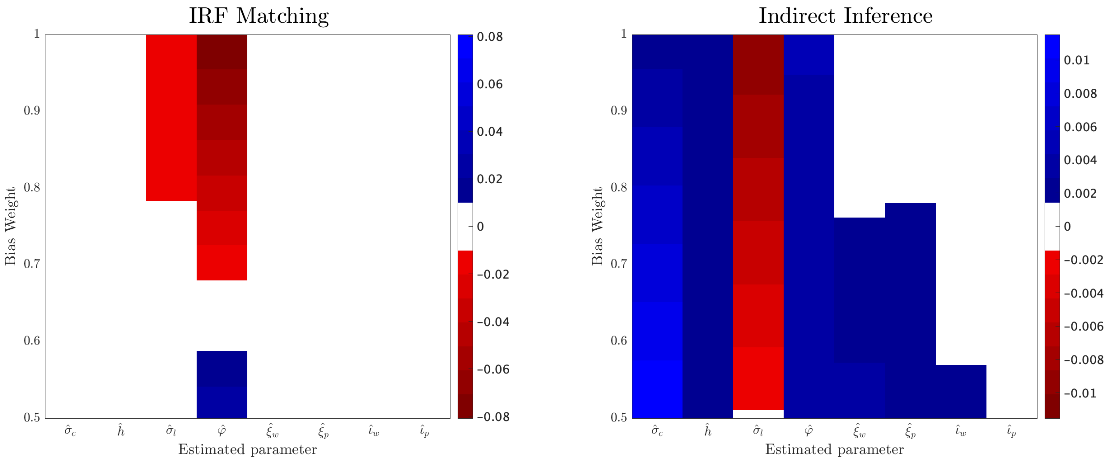
Monetary Policy: parameter by parameter performance



$$z = \left(\mathcal{L}_\omega(\hat{\Theta}_i^{LP}, \Theta_i^*) - \mathcal{L}_\omega(\hat{\Theta}_i^{SVAR}, \Theta_i^*) \right) / \Theta_i^*$$

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Monte-Carlo Results (Measurement Error)

Proxy shocks: bad news for the structural estimates

- The **estimation outcome is significantly worse** for both LPs and VARs as well as for the *IRF matching* and *Ind. Inf.* estimators relative to the observed shock case.
- These findings also apply to other sources of variation such as monetary or fiscal policy shocks.
- Does it get worse when the proxy is correlated with other shocks? Does unit normalization of the IRFs help in identifying responses?

	IRF matching				**Indirect Inference**			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
	True technology shock (η_t^a)							
Local Projection	1.05	0.67	2.87 min	37.30	0.70	0.84	42.41 min	35.92
Structural VAR	2.53	1.07	3.11 min	35.74	0.97	0.66	14.34 min	37.31
	Proxied technology shock ($\eta_t^{a,obs} = \eta_t^a + \sigma_\nu \nu_t$)							
Local Projection	1.79	1.25	3.05 min	34.30	1.35	1.40	40.23 min	33.31
Structural VAR	3.41	1.70	2.80 min	33.47	1.70	1.18	13.74 min	34.39

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Govn't spending and its correlation with technology

- The J^* is again much larger than in the observed shock case or in the proxy measure with classical measurement error, and for both estimation approaches.
  - *Ind. Inf.* is not robust to this type of misspecification, unlike for (misspecified) recursive shocks
- The model fit, J^*_{unt}, improves in the *IRF matching* because the IRF with the shock (not just the innovation) captures some information about technology shocks.

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J^*_{unt}	J_{smm}	J^*	Time	J^*_{unt}
	Government spending innovation (η^g_t)							
Local Projection	53.59	0.07	4.14 min	9.43	48.45	0.02	44.82 min	8.40
Structural VAR	49.09	0.05	4.32 min	8.79	47.03	0.03	14.42 min	8.42
	A correlated government spending proxy ($\varepsilon^{g,obs}_t$)							
Local Projection	30.82	0.34	4.09 min	7.80	39.05	0.35	46.13 min	10.15
Structural VAR	31.45	0.34	4.19 min	7.78	42.42	0.40	14.20 min	10.53

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