Identification at the Zero Lower Bound

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Motivation

- The ZLB is a challenge for conduct and analysis of macroeconomic policy:
 - Liquidity trap
 - Solving models more complicated
 - Econometric issues due to censoring
- So, ZLB generally viewed as a nuisance/problem
- I propose to view this as an opportunity to learn about the causal effects of policy!

Main insight

- When policy hits bound, agents' decision rules (may) change
- This change generates additional variation that can be used to identify causal effect of policy
- Intuition: behavior of economy across ZLB and non-ZLB regimes differs only due to impact of policy
 - If policy shuts down at ZLB (no unconventional policy), we identify the impact of (conventional) policy
 - If unconv pol is partially effective, we partially identify causal effects of policy and relative efficacy of conv v unconv policy
 - If unconv pol is fully effective (ZLB irrelevance), we get no identification

What the paper does

- Shows that occasionally binding constraints identify causal effects
 - If constraint fully (partially) binding, we get point (set) identification
 - Similar to identification via heteroskedasticity (Rigobon, 2003) or via structural change (Magnusson and Mavroeidis, 2014)
 - But change is endogenous so different methods needed
- ② Develops methodology for identification and estimation of SVARs with occasionally binding constraint
 - Method provides formal tests of "empirical (ir)relevance of the ZLB" (Debortoli et al 2019)
 - If empirical irrelevance is assumed, method can estimate SVARs with conventional identification schemes

Related literature

Long literature... Most closely related papers:

- Macro: Wu and Xia (2016), Hayashi and Koeda (2019), Wu and Zhang (2019), Aruoba et al (2020)
- Micro: Amemiya (1974), Nelson and Olson (1978), Gourieroux Laffont and Monfort (1980), Blundell and Smith (1994)
- None of the above points out implications for identification

Outline

Identification

Estimation

Application



Simultaneous equations model

Toy monetary policy model

$$\pi_t = c + \beta (r_t - r^n) + \varepsilon_{1t}$$

$$r_t^* = r^n + \gamma \pi_t + \varepsilon_{2t}$$

$$r_t = \max(r_t^*, 0)$$

- π : inflation, r: policy rate, ε_1 inflation shock, ε_2 policy shock
- Without ZLB constraint $(r_t = r_t^*)$, model is under-identified
- 'Shadow rate' r_t^* represents desired policy stance



Add unconventional policy channel

Model of bond mkt segmentation (Chen et al 2012, Ikeda et al 2020)

$$\pi_t = c + \beta \left(r_t - r^n + \varphi b_{L,t} \right) + \varepsilon_{1t}$$

- QE reduces $b_{l,t}$, amount of long-term bonds held by private sector
- φ depends on fraction of restricted households and elasticity of term premium wrt long-term bond holdings
- If $b_{l,t} = \min(\alpha r_t^*, 0)$, $\alpha \geq 0$, $r_t^* = r^n + \gamma \pi_t$ (Taylor rule), then

$$\pi_{t} = c + \beta (r_{t} - r^{n}) + \underbrace{\beta^{*}}_{\lambda \beta} \min (r_{t}^{*}, 0) + \varepsilon_{1t}$$



Solution of the model/decision rules

• If $(1 - \gamma \beta) / (1 - \lambda \gamma \beta) > 0$ (coherency), the solution for π_t is

$$\pi_t = \left\{ \begin{array}{ll} \frac{c}{1 - \gamma \beta} + \frac{\epsilon_{1t} + \beta \epsilon_{2t}}{1 - \gamma \beta}, & \text{if } r_t > 0 \\ \frac{c - r^n \beta (1 - \lambda)}{1 - \lambda \gamma \beta} + \frac{\epsilon_t + \lambda \beta \epsilon_{2t}}{1 - \lambda \gamma \beta} & \text{if } r_t = 0 \end{array} \right.$$

- This is piecewise linear and continuous at the kink
- Behaviour changes across regimes if $\lambda \neq 1$



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Reduced form

• The reduced-form can be written as

$$\pi_t = \mu_1 + u_{1t} - \tilde{\beta} D_t (\mu_2 + u_{2t}), D_t := 1_{\{r_t = 0\}}$$
 (1)
 $r_t = \max(\mu_2 + u_{2t}, 0), \text{ where}$

$$\widetilde{\beta} = \frac{(1-\lambda)\beta}{1-\lambda\beta\gamma}, \quad u_{1t} = \frac{\varepsilon_{1t}+\beta\varepsilon_{2t}}{1-\gamma\beta}, \quad u_{2t} = \frac{\gamma\varepsilon_{1t}+\varepsilon_{2t}}{1-\gamma\beta}$$

- Reduced form parameter $\widetilde{\beta}$ is identified
 - (1) is 'incidentally kinked' regression, estimable by variant of Heckit
- This gives extra bit of information about structural parameters



Point identification when constraint is fully binding

• With Gaussian errors, β estimable via control function approach

$$\begin{split} E\left(\pi_{t}|r_{t}\right) &= c + \beta\left(r_{t} - r^{n}\right) + \rho h_{t}\left(\mu_{2}, \omega_{22}\right), \\ h_{t}\left(\mu_{2}, \omega_{22}\right) &= \left(1 - D_{t}\right)\left(r_{t} - \mu_{2}\right) - D_{t}\frac{\sqrt{\omega_{22}}\phi\left(a\right)}{\Phi\left(a\right)}, \quad a = -\frac{\mu_{2}}{\sqrt{\omega_{22}}} \end{split}$$

 $m{\circ}$ γ can then be obtained from orthogonality of errors $m{\it{E}}\left(\epsilon_{1t}\epsilon_{2t}
ight)=0$

$$\gamma = rac{\omega_{12} - \omega_{22}eta}{\omega_{11} - \omega_{12}eta}, \quad egin{pmatrix} \omega_{11} & \omega_{12} \ \omega_{12} & \omega_{22} \end{pmatrix} = \mathit{var}\left(\mathit{u}_t
ight)$$



Partial identification when constraint is partially binding

- We've established that $\widetilde{\beta} = \frac{(1-\lambda)\beta}{1-\lambda\beta\gamma}$ is identified
- Without further restrictions, β is not point-identified
- BUT we get bounds on β (and λ) by solving

$$\widetilde{eta} = rac{\left(1-\lambda
ight)eta}{1-\lambdaetarac{\omega_{12}-\omega_{22}eta}{\omega_{11}-\omega_{12}eta}}$$



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SVAR with occasionally binding constraint

- $Y_t = (Y'_{1t}, Y_{2t})'$ vector of $k = k_1 + k_2$ endogenous variables
- Y_{1t} are k_1 unconstrained variables (e.g., inflation, unemployment)
- Y_{2t} are k_2 variables subject to occ bin constraint (e.g., policy rate)
- Censored and Kinked SVAR (CKSVAR): includes contemporaneous and lagged values of both observed Y_{2t} and latent (shadow rate) Y_{2t}^*
 - Important to capture forward-guidance, e.g., a la Reifschneider & Williams (2000) or Debortoli et al (2019)
- Special cases:
 - Kinked SVAR (KSVAR): no lags of latent variable Y_{2t}^*
 - ② Censored SVAR (CSVAR): linear SVAR in (Y_{1t}, Y_{2t}^*)



CKSVAR(p)

Ignoring deterministic terms and external variables:

$$A_{11}Y_{1t} + A_{12}Y_{2t} + A_{12}^*Y_{2t}^* = B_{11}X_{1t} + \sum_{j=1}^{p} B_{12,j}Y_{2,t-j} + \sum_{j=1}^{p} B_{1,j}^*Y_{2,t-j}^* + \varepsilon_{1t},$$

$$A_{22}^*Y_{2t}^* + A_{22}Y_{2t} + A_{21}Y_{1t} = B_{21}X_{1t} + \sum_{j=1}^{p} B_{22,j}Y_{2,t-j} + \sum_{j=1}^{p} B_{2,j}^*Y_{2,t-j}^* + \varepsilon_{2t},$$

$$Y_{2t} = \max(Y_{2t}^*, b_t),$$

 X_{1t} includes lags of Y_{1t} , and the lower bound b_t is observed



Reparametrization

$$Y_{1t} = \overbrace{-A_{11}^{-1}\left(A_{12} + A_{12}^*\right)}^{\beta} Y_{2t} + \overbrace{\left(-A_{11}^{-1}A_{12}^*\right)}^{\beta^* = \lambda\beta} D_t Y_{2t}^* + \overbrace{A_{11}^{-1}\epsilon_{1t}}^{\overline{\epsilon}_{1t}} + lags,$$

$$Y_{2t}^* = \begin{cases} \underbrace{-\left(A_{22}^* + A_{22}\right)^{-1}A_{21}}^{\gamma} Y_{1t} + \underbrace{\left(A_{22}^* + A_{22}\right)^{-1}\varepsilon_{2t}}^{\bar{\varepsilon}_{2t}} + \textit{lags}, & \text{if } D_t = 0 \\ -\left(A_{22}^*\right)^{-1}A_{21} Y_{1t} + \underbrace{\left(A_{22}^*\right)^{-1}\varepsilon_{2t}}_{\zeta\bar{\varepsilon}_{2t}} + \textit{lags}, & \text{if } D_t = 1 \end{cases}$$

- $\zeta = (A_{22}^* + A_{22}) / A_{22}^*$ allows policy response to vary across regimes
- Coherency condition: $\zeta(1-\gamma\beta)(1-\gamma^*\beta^*)>0$

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Reduced form

Proposition 2: If CC holds, the reduced-form of CKSVAR for $t \ge 1$ is

$$Y_{1t} = \overline{C}_1 X_t + \overline{C}_1^* \overline{X}_t^* + u_{1t} - \widetilde{\beta} D_t \left(\overline{C}_2 X_t + \overline{C}_2^* \overline{X}_t^* + u_{2t} - b_t \right)$$
 (1)

$$Y_{2t} = \max\left(\overline{Y}_{2t}^*, b_t
ight), \qquad D := 1_{\{Y_{2t} = b_t\}}$$

$$\overline{Y}_{2t}^* = \overline{C}_2 X_t + \overline{C}_2^* \overline{X}_t^* + u_{2t}$$
 (2)

$$Y_{2t}^{*} = (1 - D_{t}) \overline{Y}_{2t}^{*} + D_{t} \left(\kappa \overline{Y}_{2t}^{*} + (1 - \kappa) b_{t} \right)$$
(3)

where $u_t \sim N\left(0,\Omega\right)$, \overline{Y}_{2t}^* : reduced-form shadow rate, \overline{X}_t^* : lags of $D_t \overline{Y}_{2t}^*$, $\kappa = \zeta\left(1-\gamma\beta\right)/\left(1-\zeta\gamma\beta^*\right)$ (unidentified) and

$$\widetilde{\beta} = \left(A_{11} - A_{12}^* A_{22}^{*-1} A_{21}\right)^{-1} \left(A_{12}^* A_{22}^{*-1} A_{22} - A_{12}\right) \tag{4}$$

Identification of structural parameters

- Reduced-form parameters (including k_1 coefficients on kink $\widetilde{\beta}$) are identified iff $0 < \Pr(D_t = 1) < 1$
- If policy is completely ineffective at the ZLB, monetary policy shock
 ε_{2t} and its IRF are point-identified!
- Otherwise, we get bounds on β , γ and $\xi = \lambda \zeta$, by collecting all solutions to

$$egin{aligned} \widetilde{eta} &= \left(1 - \xi
ight) \left(\mathit{I} - \xi eta \gamma
ight)^{-1} eta, \ \mathsf{and} \ \gamma &= \left(\Omega_{12}' - \Omega_{22} eta'
ight) \left(\Omega_{11} - \Omega_{12} eta'
ight)^{-1} \end{aligned}$$

• Note that $\xi = \lambda \zeta$, so λ and ζ are not separately identified



Likelihood

- Gaussian likelihood computed by simulation (except for KSVAR) using two alternative algorithms developed in the paper:
 - SIS: Sequential Importance Sampling (Lee 1999)
 - FAPF: Fully Adapted Particle Filter (Pitt and Shephard 1999)
- Ox and Python code for frequentist estimation available from my website
- Bayesian implementation in follow-up paper



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Three-equation SVAR of Stock and Watson (2001)

- Intended purely as an empirical illustration of the method
- SVAR(4) in inflation (GDP deflator), unemployment rate and Federal funds rate
- Sample: 1960q1-2018q2,
- For a serious application, see Ikeda Li Mavroeidis and Zanetti (2020)
 "Testing the effectiveness of unconventional monetary policy in Japan and the USA"

Tests of efficacy of unconventional policy

Model	log lik		# of	LR	Asym.	Boot.
	(SIS)	(FAPF)	restr.	stat.	p-val.	p-val.
CKSVAR(4)	-81.64	-81.94				
KSVAR(4)	-97.05	-	12	30.82	0.002	0.011
CSVAR(4)	-94.86	-94.87	14	26.43	0.023	0.117

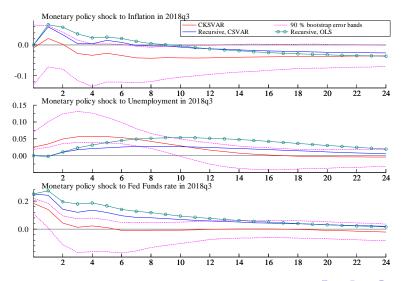
Sample: 1960q1-2018q2 (234 obs, 11% at ZLB)

Estimated using 1000 particles, 999 bootstrap replications

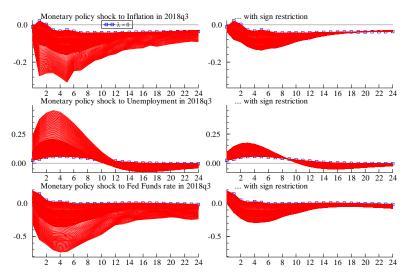
- Reject hypothesis that UMP is completely ineffective (KSVAR) more strongly than the (opposite) hypothesis that ZLB is empirically irrelevant (CSVAR)
- BUT: simulations show LR test of latter is less powerful



IRFs



Partially identified IRFs



Conclusions

- I developed a method for estimating SVARs with occasionally binding constraints
- This applies to models with a zero-lower bound constraint on policy rates
- I showed that the ZLB (partially) identifies the causal effects of policy
- The method can also be used to formally test whether ZLB is empirically irrelevant