

Re-estimating Potential GDP: New Evidence on Output Hysteresis

Diego Anzoategui Min Kim

Rutgers

MMF Annual Conference

September 2021

Motivation

- Potential GDP: key concept for policy decisions and forecasting
- Level of output absent price/wage rigidities (flexible-price output)
 - A counter-factual that requires estimation
- There is no consensus on the best method
- Coibion, Gorodnichenko and Ulate (2018):
 - Critical analysis of estimates from CBO, Fed, IMF, OECD
 - Their conclusion: estimates behave like HP trends
 - Need improvements in this area !
- A rough division of methods: DSGE-based vs non-DSGE-based

Motivation

- Methods that do not rely on structural models are generally simpler but have two main problems
 1. They depart from relevant theory \rightarrow estimates \neq flex-price output
 - Univariate Methods, methods using Blanchard and Quah (1989)
 2. Subject to the Lucas Critique
 - Production function approach (CBO's method)
- Current DSGE-based methods do not suffer from previous problems but,
 1. Estimates are model-specific
 2. Need to estimate model parameters \rightarrow identification issues

This Paper

- **First contribution:** new method getting strengths from both approaches
 1. DSGE-based
 2. As simple as any VAR-based method
 3. Does not require prior knowledge of all parameters
 4. Consistent with a set of DSGE models with different preferences/technologies/shocks
- **Second Contribution:** apply the method to the US
 - Contributes to the debate on whether potential GDP is affected by demand shocks

This Paper: Empirical Results

- New potential GDP series that
 1. It is highly correlated with CBO's estimates
 2. But large differences during and after the GR
 3. Result seems robust to different samples, methods, shock identification strategies
- Provide evidence supporting hysteresis hypothesis
 - Demand shocks seem to affect potential GDP

Related Literature

- **Limitations of methods.** Coibion, Gorodnichenko and Ulate (2018)
- **DSGE-based Potential Output Estimation.** Justiniano and Primiceri (2008), Basu and Fernald (2009), Gali, Smets and Wouters (2012) and many more..
- **Simple Methods to Estimate Counterfactuals.** Beraja (2019)
- **Hysteresis hypothesis.** Cerra and Saxena (2008), Blanchard et al. (2015), and Jordà et al. (2020)

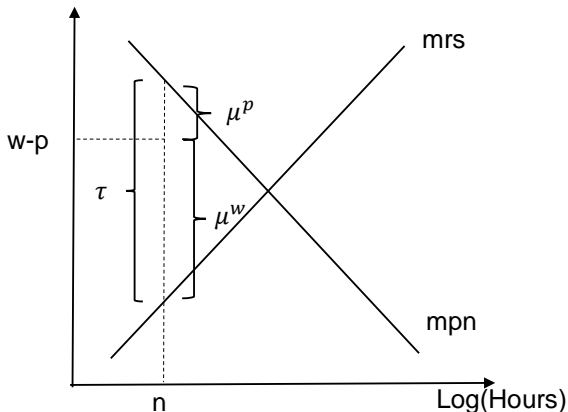
Plan

1. A general picture of the method
2. Baseline method: Derivation and application to US data
3. Robustness and Extensions
4. Analysis: is potential output affected by demand shocks ?

A General Picture

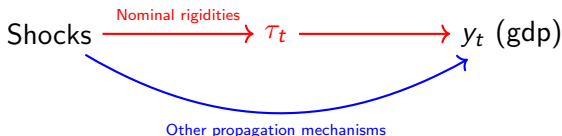
A General Picture

- NK DSGE models are RBC models with an endogenous labor wedge
 $\tau_t = mpn_t - mrs_t$
- Remember, $\tau_t = (mpn_t - w_t + p_t) + (w_t - p_t - mrs_t) = \mu_t^p + \mu_t^w$
 - μ_t^p : price markup, μ_t^w : wage markup



A General Picture

- τ_t changes over time due to wage or price rigidities
- Summarizes the propagation mechanism related to nominal rigidities



- Potential GDP: output only affected through **blue channel**
- Method kills the **red arrows** with the help of a structural model

Baseline Method

Method

- Underlying model: textbook NK model

1. Nominal wage rigidities (no price rigidities) $\rightarrow \tau_t = \mu_t^w$

2. No capital: $Y_t = A_t N_t^{1-\alpha}$, Y_t : output, N_t : Hours

3. TFP shocks: $\log A_t = g + \log A_{t-1} + \sigma_a \varepsilon_{at}$

4. Preferences consistent with BGP:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t Z_t \left[\log (C_t - h \bar{C}_{t-1}) - \chi \frac{N_t^{1+\varphi}}{1+\varphi} \right]$$

External habits, Z_t : preference shock

5. Taylor Rule: $R_t = R_{ss} \Pi_t^{\phi_\pi} \exp(\sigma_i \nu_t)$

Method

- What is potential output growth Δy_t^p in the model ?
- After some algebra ..

$$\Delta y_t^p = \theta_1 \Delta y_{t-1}^p + \theta_0 \varepsilon_{at}$$

where,

$$\theta_0 \equiv \frac{\frac{1+\varphi}{1-\alpha} \sigma_a}{\frac{1+g}{1+g-h} + \frac{\alpha+\varphi}{1-\alpha}} \quad \theta_1 \equiv \frac{\frac{h}{1+g-h}}{\frac{1+g}{1+g-h} + \frac{\alpha+\varphi}{1-\alpha}}$$

- Simple way of recovering θ_0 , θ_1 and ε_{at} !

Method

Proposition 1: θ_0 and θ_1 can be estimated from the SVAR

$$\begin{bmatrix} \Delta y_t \\ \mu_t^w \end{bmatrix} = \mathbf{B} \begin{bmatrix} \Delta y_{t-1} \\ \mu_{t-1}^w \end{bmatrix} + \mathbf{C} \begin{bmatrix} \varepsilon_{at} \\ \xi_t \end{bmatrix}$$

where ξ_t is a weighted average of demand shocks. In particular,

$$\theta_0 = c_{11} - \frac{c_{21}c_{12}}{c_{22}} \quad \theta_1 = b_{11} - \frac{b_{21}c_{12}}{c_{22}}$$

And ε_{at} can be calculated using forecast errors and \mathbf{C} Derivation

Method

- Method does not change with the following modifications to the model:
 1. Other preferences
 2. Other production functions in labor
 3. Adding wage markup shocks
 4. Other monetary rules: interest rate, money growth, etc
 5. Adding capital utilization (with capital stock in fixed supply)
$$Y_t = A_t(U_t \bar{K})^\alpha N_t^{1-\alpha}$$
 6. Other expectation formation assumptions
- Tested method with Monte Carlo simulations and it works for small samples [More](#)

Method: Estimation Details

$$\begin{bmatrix} \Delta y_t \\ \mu_t^w \end{bmatrix} = \mathbf{B} \begin{bmatrix} \Delta y_{t-1} \\ \mu_{t-1}^w \end{bmatrix} + \mathbf{C} \begin{bmatrix} \varepsilon_{at} \\ \xi_t \end{bmatrix}$$

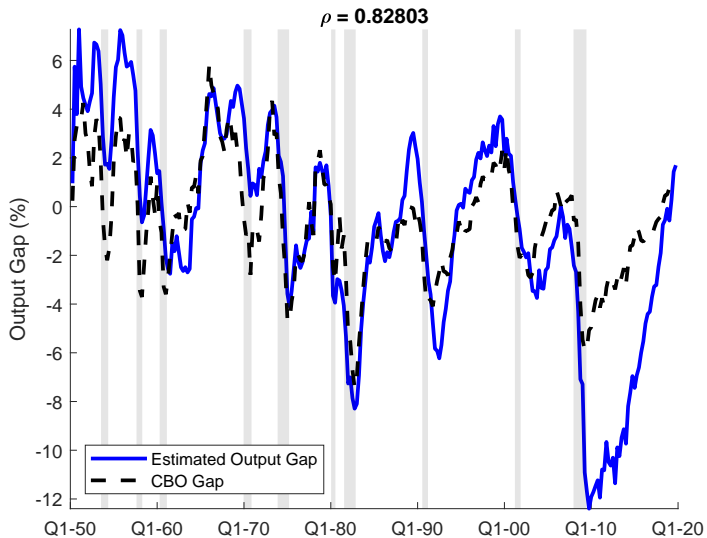
1. Estimation of \mathbf{C}

- SVAR-IV as in Stock and Watson (2008) - Baseline IV: Fernald's TFP
- Why not LR restrictions? A: not so robust to changes in samples or detrending - Fernald (2007)

2. How to get a series for μ_t^w ?

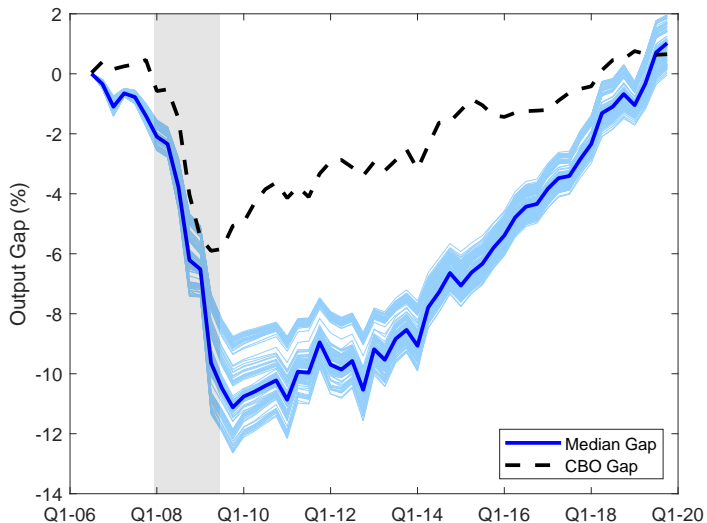
- Follow Gali et al. (2007) and labor wedge lit: assume log utility and Frisch Elast = 1
- Highly correlated with other measures of business cycle like unemployment [More](#)

Baseline Method: Gap (1950q1-2019q4)



Series of output and markups detrended using a 3rd order polynomial before VAR estimation.

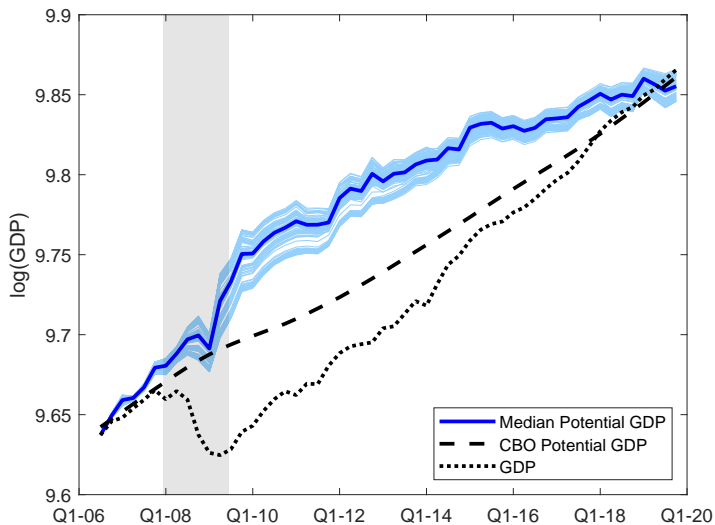
Baseline Method: Gap



Light blue lines represent different starting quarters in the sample: from 1950q1 to 1990q1. Last quarter in every sample is 2019q4. Series of output and markups detrended using a 3rd order polynomial before VAR estimation.

Baseline US Potential GDP Estimates, IV: TFP

LR



Light blue lines represent different starting quarters in the sample: from 1950q1 to 1990q1. Last quarter in every sample is 2019q4. Series of output and markups detrended using a 3rd order polynomial before VAR estimation.

Baseline US Potential GDP Estimates

- Estimated series highly correlated with CBO's
- But with a stark difference during and after the GR
- It points to an increase in Y^P during the crisis, but poor potential growth afterwards
- Related to Fernald's TFP evolution during and after the crisis

Identification

Real-time

More

Extensions and Robustness

Extensions and Robustness

1. Baseline Method with other IVs [More](#)
2. Adding price rigidities [More](#)
3. Adding government spending [More](#)
4. The issue of endogenous capital [More](#)

Analysis: Is Y^P affected by demand shocks ?

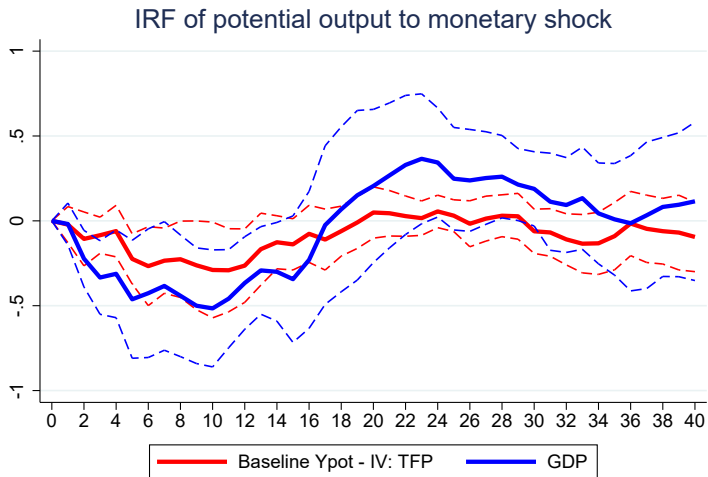
Y^P response to Demand Shocks

- Current debate on whether hysteresis is quantitatively relevant
- Hysteresis hypothesis claims that demand shocks can have long lasting impacts on GDP
- In other words, TFP and potential GDP can react to demand shocks
- We provide new evidence supporting this view
 - Estimate IRFs of Y^P to demand shocks
 - Use local projection methods as in Jordà (2005):

$$\log \left(Y_{t+j}^P \right) = \beta_0 + \beta_j \epsilon_t + \text{Controls} + u_t \quad j \geq 0$$

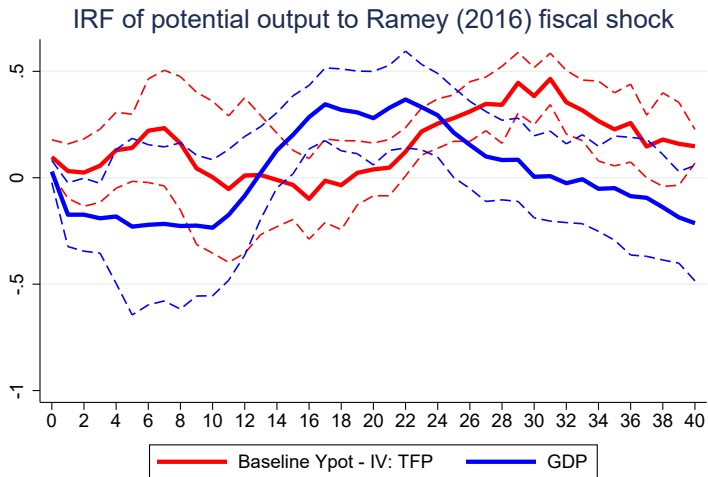
β_j : impact of shock after j quarters

Y^P response to Monetary Shocks

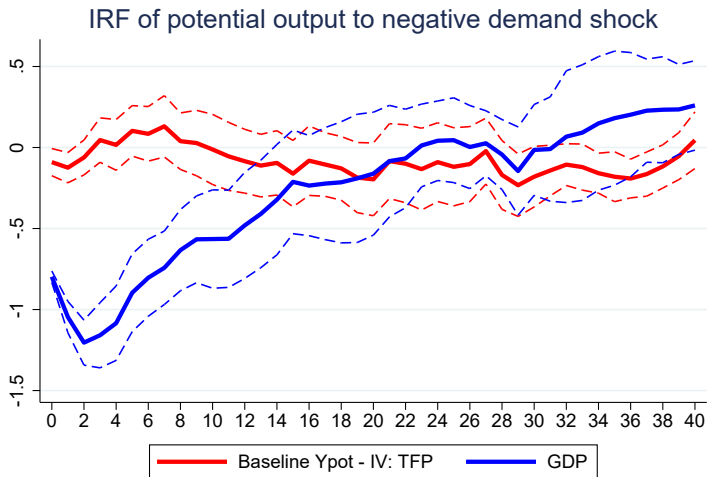


90% confidence bands. full sample(50Q2-08Q4).

Y^P response to Defense Spending Shocks



Y^P response to demand shock ξ_t



90% confidence bands. long sample(50Q2-19Q4).

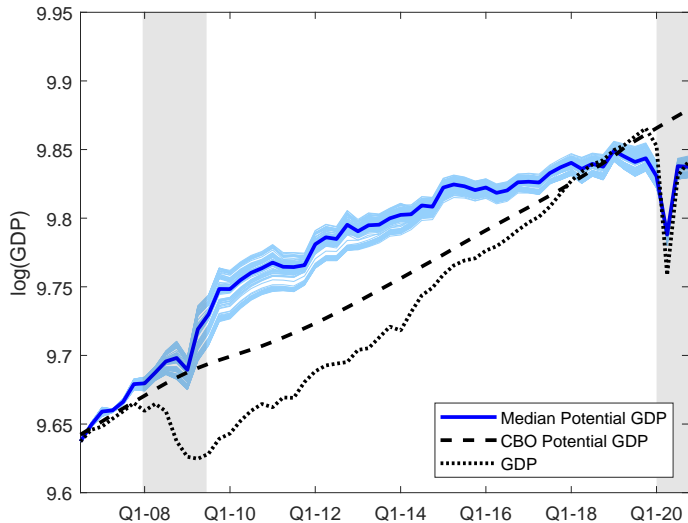
Y^P response to Demand Shocks

- Evidence indicating that demand shocks affect both Y and Y^P
- Similar results for other estimates of Y^P
- Y^P tends to be affected with a lag

Conclusion

- Simple method to compute potential GDP
- Method can be adapted to many more modifications in the underlying model
- Results:
 1. Estimated potential GDP series highly correlated with CBO's but important deviation during and after GR
 2. Evidence indicating that demand shocks affect potential GDP

COVID-19



Appendix

Endogenous Capital

- Method is based on a model without endogenous capital
- A more general model would assume $Y_t = A_t (U_t K_t)^\alpha N_t^{1-\alpha}$ where K_t is endogenously determined
- How costly is to assume capital is exogenously given ?
- We show that the cost is low ! Especially if short-run wealth effects are not important

Endogenous Capital

- Strategy:
 1. DGP: Two versions of Smets and Wouters (2007) - with and without short-run wealth effects
 2. Simulate model 10,000 times for 160 quarters
 3. Estimate potential output using our method and compare with model
- Results (median values):

	Model Δy_t^p	Estimated Δy_t^p
(A) Original SW Model		
Standard Deviation	0.751	0.788
Minimum	-2.029	-2.126
Maximum	2.033	2.127
Correlation with SW Δy_t^p		0.92
(B) SW without short-run wealth effects		
Standard Deviation	1.155	1.079
Minimum	-3.117	-2.920
Maximum	3.123	2.929
Correlation with SW Δy_t^p		0.99

Extension: Government Spending

- We add a non-permanent shock that might affect potential GDP
- Why ?
 - Way to show that our method can estimate potential GDP series that are affected by non-permanent shocks
 - Big spending shocks in our sample: US wars
- Introduce fiscal authority that collects lump-sum taxes and follows rule:

$$g_t = \rho_g g_{t-1} + \rho_{gy} y_{t-1} + \sigma_g \varepsilon_{gt}$$

where g_t and y_t are gov't spending and GDP (in log-dev from SS)

- Rest of model is similar to Baseline

Extension: Government Spending

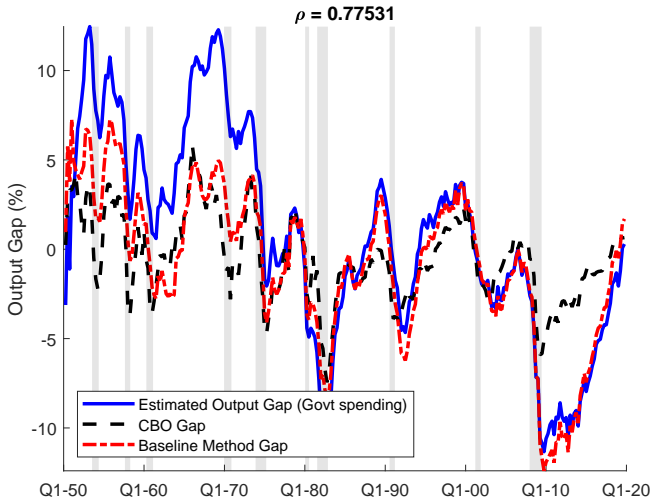
- In this new model potential GDP growth is given by

$$\Delta y_t^P = \theta_3^g \Delta g_{t-1}^P + \theta_2^g \sigma_g \Delta \varepsilon_{gt} + \theta_1^g \Delta y_{t-1}^P + \theta_0^g \varepsilon_{at}$$

- Now potential GDP is not only a function of TFP
- Government spending shocks can affect potential GDP through labor supply wealth effects
- Paper shows a straightforward way of estimating θ^g 's

Extension: Government Spending

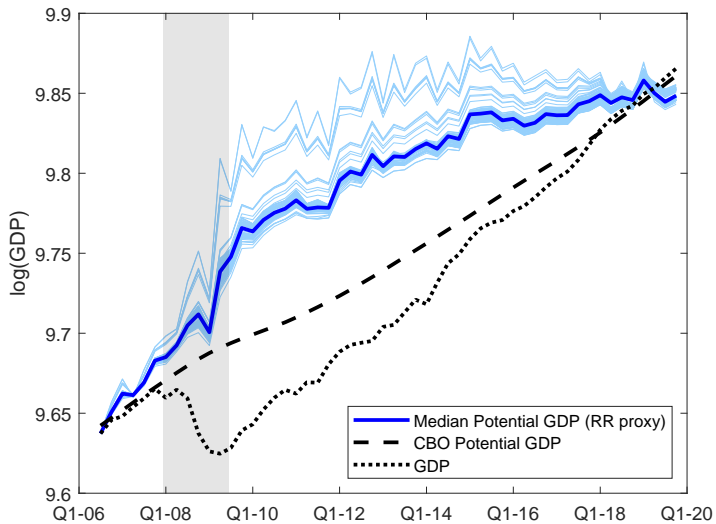
Figure: Including Government Spending: Output Gap



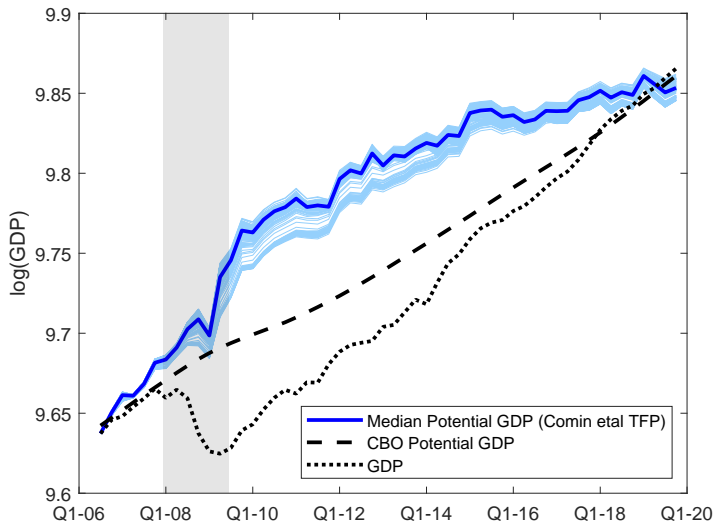
Robustness: other IVs

- We check our results using other IVs to estimate the SVAR
- We use:
 - Comin et al. (2020) TFP measure as an IV for ε_{at}
 - Romer and Romer (2004) monetary policy shocks as an IV for ξ_t
- Results are similar: predict an increase in potential GDP during the GR and a poor growth afterwards

Baseline Method: RR monetary shocks



Baseline Method: Comin et al. (2020) TFP



Extension: Price Rigidities

- Previous method assumes flexible prices
- At odds with micro evidence
 - Avg freq of price changes: 3 quarters- Nakamura and Steinsson (2008)
- However, μ_t^W strongly countercyclical and μ_t^P acyclical or mildly countercyclical in the data
 - μ_t^P plays a secondary role affecting the labor wedge τ_t
 - Main reason for not including price rigidities in baseline method

Extension: Price Rigidities

Proposition 2:

With a model with price rigidities, θ_0 and θ_1 can be estimated from the system

$$\begin{bmatrix} \Delta y_t \\ \tau_t \end{bmatrix} = \mathbf{B} \begin{bmatrix} \Delta y_{t-1} \\ \mu_{t-1}^w \\ \mu_{t-1}^p \end{bmatrix} + \mathbf{C} \begin{bmatrix} \varepsilon_{at} \\ \xi_t \end{bmatrix}$$

where ξ_t is a weighted average of demand shocks. In particular,

$$\theta_0 = c_{11} - \frac{c_{21}c_{12}}{c_{22}} \quad \theta_1 = b_{11} - \frac{b_{21}c_{12}}{c_{22}}$$

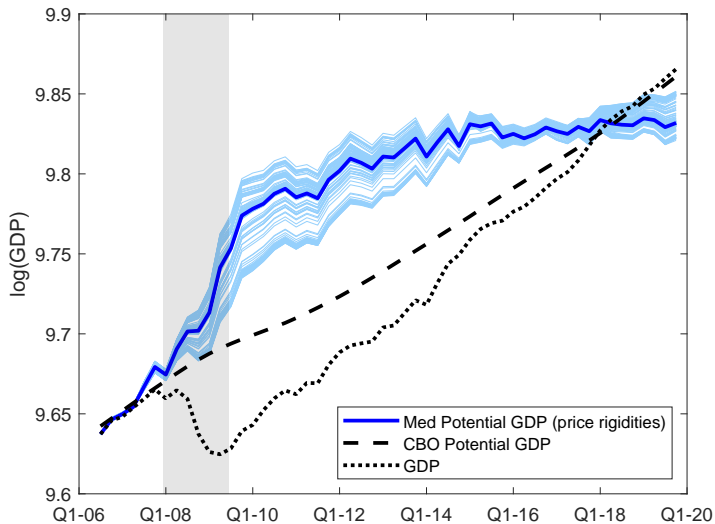
And ε_{at} can be calculated using forecast errors and **C** [Back](#)

Extension: Price Rigidities

- Method is very similar, but not a SVAR anymore
- Need series of price markups μ_t^P
- Calculated using $\mu_t^P = mpn_t - (w_t - p_t)$

[Back](#)

US Potential GDP Estimates (Price Rigidities)

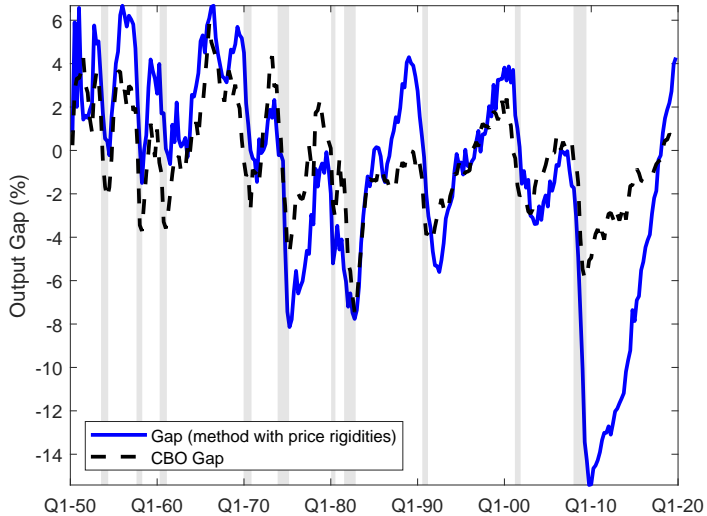


Light blue lines represent different starting quarters in the sample: from 1950q1 to 1990q1. Last quarter in every sample is

2019q4. Series detrended using a 3rd order polynomial.

Price Rigidities: Gap

Back



Back

Extension: Price Rigidities

- Similar pattern as before: poor potential GDP growth after GR
- Jump in productivity during recession more important than baseline case
- Overall, again, a different picture from CBO's estimates

[Back](#)

Baseline Method: Monte Carlo Simulations

Back

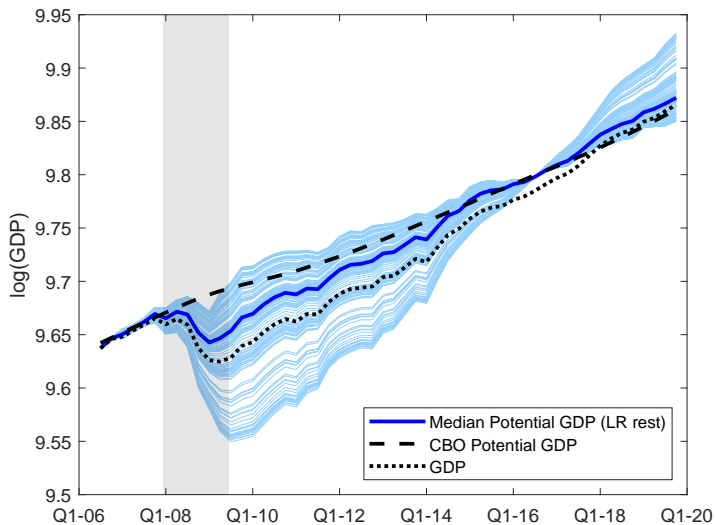
The table below reports median values of 10,000 simulations
(sample size: 70*4 quarters)

	Model Δy_t^P	Estimated Δy_t^P
Standard Deviation	0.578	0.575
Minimum	-1.620	-1.614
Maximum	1.622	1.614
Correlation with Model Δy_t^P		0.997

Model parameters set to standard values in literature. SD of shocks are set to match the following moments: (i) SD of Fernald's TFP, (ii) SD of wage markup, (iii) SD of Fed Funds rate and (iv) correlation of Fed Funds rate with GDP growth.

Baseline Method: LR restrictions

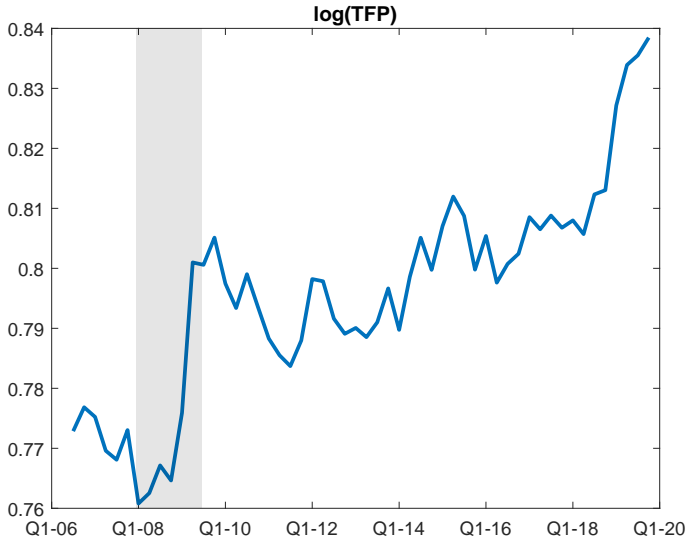
Back



Light blue lines represent different starting quarters in the sample: from 1950q1 to 1990q1. Last quarter in every sample is

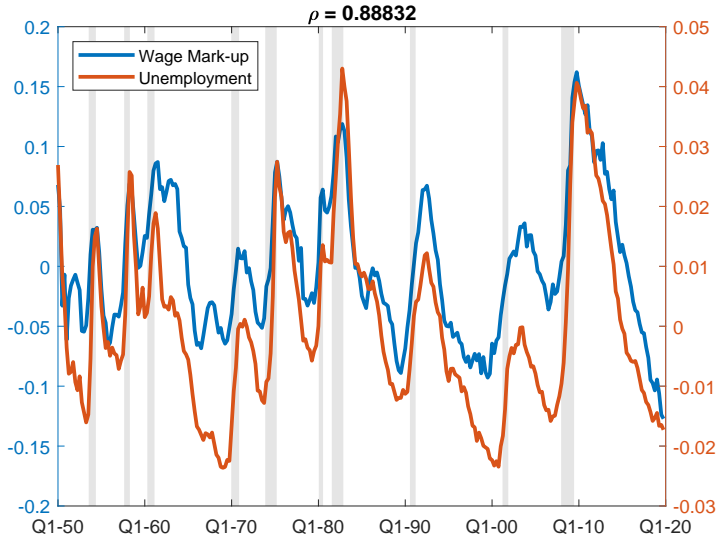
2019q4. Series detrended using a 3rd order polynomial.

TFP



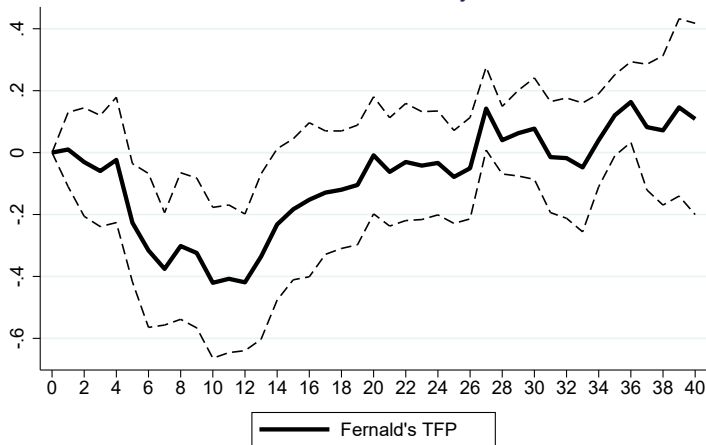
Back

Wage Markups vs Unemployment



TFP

IRF of TFP to monetary shock



90% confidence bands. full sample(50Q2-08Q4).

Back

Method: SVAR derivation

Back

- Start from the fact that μ_t^w is a function of the states and shocks

$$\mu_t^w = \gamma_a \varepsilon_{at} + \gamma_z z_t + \gamma_\nu \nu_t + \gamma_\mu \mu_{t-1}^w + \gamma_y \Delta y_{t-1}$$

where the γ 's are function of deep parameters of the model

- Define $\xi_t = \frac{\gamma_z}{\sqrt{\gamma_z^2 + \gamma_\nu^2}} z_t + \frac{\gamma_\nu}{\sqrt{\gamma_z^2 + \gamma_\nu^2}} \nu_t$ and $\gamma_\xi = \sqrt{\gamma_z^2 + \gamma_\nu^2}$, thus

$$\mu_t^w = \gamma_a \varepsilon_{at} + \gamma_\xi \xi_t + \gamma_\mu \mu_{t-1}^w + \gamma_y \Delta y_{t-1} \quad (1)$$

- Second, use the wage mark up equilibrium condition

$$\mu_t^w - \mu_{t-1}^w = \frac{1 + \varphi}{1 - \alpha} \sigma_a \varepsilon_{at} - \frac{\alpha + \varphi}{1 - \alpha} \Delta y_t + \Delta m u_t \quad (2)$$

- Equations (2) and (1) form the SVAR

Proxy SVAR

Back

- Forecast errors from estimating VAR satisfy

$$\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} = \mathbf{C} \begin{bmatrix} \varepsilon_{at} \\ \xi_t \end{bmatrix}$$

- Letting \mathbf{V} be the Var-Cov matrix of forecast errors, then $\mathbf{V} = \mathbf{C}\mathbf{C}'$
 - 4 parameters \rightarrow need 4 constraints
 - $\mathbf{V} = \mathbf{C}\mathbf{C}'$ provides only 3
- Proxy SVAR:
 - Assume we have a proxy for TFP shocks $\omega_t = \gamma\varepsilon_{at} + \epsilon_t$
 - ϵ_t measurement error, $\gamma \neq 0$
 - Then, $\frac{\mathbb{E}(u_{1t}\omega_t)}{\mathbb{E}(u_{2t}\omega_t)} = \frac{c_{11}}{c_{21}}$ provides an additional constraint

Identification

- Why TFP and potential GDP increase during the great recession?
- Need to clarify how our method identifies TFP shocks
- From SVAR, GDP growth and wage mark-up forecast errors ($u_t^{\Delta y}$, $u_t^{\mu^w}$) are linear combinations of structural shocks:

$$\begin{bmatrix} u_t^{\Delta y} \\ u_t^{\mu^w} \end{bmatrix} = \mathbf{C} \begin{bmatrix} \varepsilon_{at} \\ \zeta_t \end{bmatrix}$$

- After some algebra

$$u_t^{\Delta y} = \frac{c_{12}}{c_{22}} u_t^{\mu^w} + \theta_0 \varepsilon_{at}$$

Identification

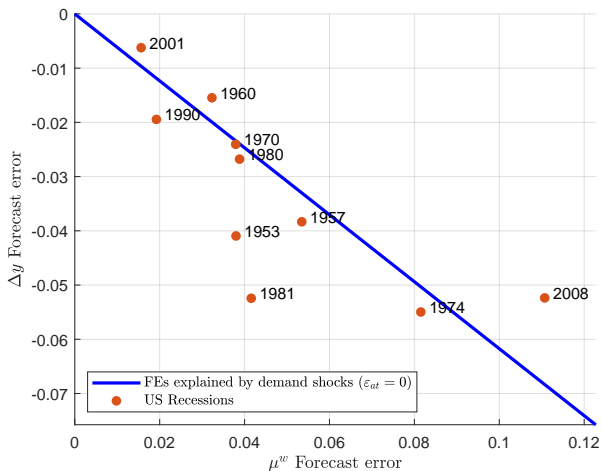
$$u_t^{\Delta y} = \frac{c_{12}}{c_{22}} u_t^{\mu^w} + \theta_0 \varepsilon_{at}$$

- $\frac{c_{12}}{c_{22}} < 0$: absent productivity shocks there should be a negative relationship between growth and wage mark-ups forecast errors
- Relationship reminiscent of Okun's Law
- In a “demand-driven” recession the economy should move along this downward sloping line
- Any deviation from this relationship is explained by productivity shocks

Identification

- Taking a look at the US recessions..

Figure: Identification of productivity shocks



Real-time estimation

