Common Factors, Trends, and Cycles in Large Datasets

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10^{th} ECB Workshop on Forecasting Techniques:
Economic Forecasting with Large Datasets
June 18-19, 2018

Disclaimer: the views expressed in this paper are those of the authors and do not necessarily reflect those of the Board of Governors or the Federal Reserve System.

Measuring US Aggregate Output and Output Gap using Large Datasets

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This paper: what it is about

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- **Non-parametric Trend-Cycle decomposition**

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   - Since 2015 growth was on average 0.4 p.p. higher than BEA's estimate
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2. **Output gap**
   - Growth before the GFC was heavily boosted by temporary factors
   - Growth after the financial crisis is due primarily to permanent factors
   - Our estimate indicates that as of 2017:Q4 there is still slack

Outline

- **The non-stationary Dynamic Factor Model**

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- $\mathbf{f}_t \sim I(1)$ and $\xi_{it} \sim I(1)$ for some i
- $q - d$ "permanent shocks" and d "transitory shocks"
- $q - d$ common trends drive the dynamics of $\boldsymbol{f}_t$
- $\boldsymbol{f}_t$ has cointegration rank d

Estimation: the "static" representation

Standard practice: estimate different representation

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  Stock & Watson, 2005; Bai & Ng, 2007; Forni, Giannone, Lippi & Reichlin, 2009; BLL, 2016b.

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Same constraints on the co-movement of the data

Estimation: quasi maximum likelihood

- ML estimation via EM algorithm with Kalman smoother.
  Doz, Giannone & Reichlin, 2011, 2012.
- Initialization: BLL, 2016b & Koopman, 1997

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2. The **non-stationary ξ_{it} are additional states**:

$$\xi_{it} = \rho_i \xi_{it-1} + e_{it}, \quad e_{it} \sim \mathcal{N}(0, \sigma_i^2),\ \rho_i = \begin{cases} 1 & \text{if} \quad \xi_{it} \sim I(1), \\ 0 & \text{if} \quad \xi_{it} \sim I(0). \end{cases}$$

Outline

- **Model Set-up**

Model set-up

- $n = 103$ US macroeconomic time series;
- quarterly from 1960:Q1 to 2017:Q4, sample size $T = 232$

- log of all variables in levels which are not p.p.
- variables that are $I(1)$ are not transformed,
- variables that are $I(2)$ are differenced once
- inflation rates, unemployment rate, interest rates are in levels;
- $\mathbf{x}_t$ are de-trended data—when necessary

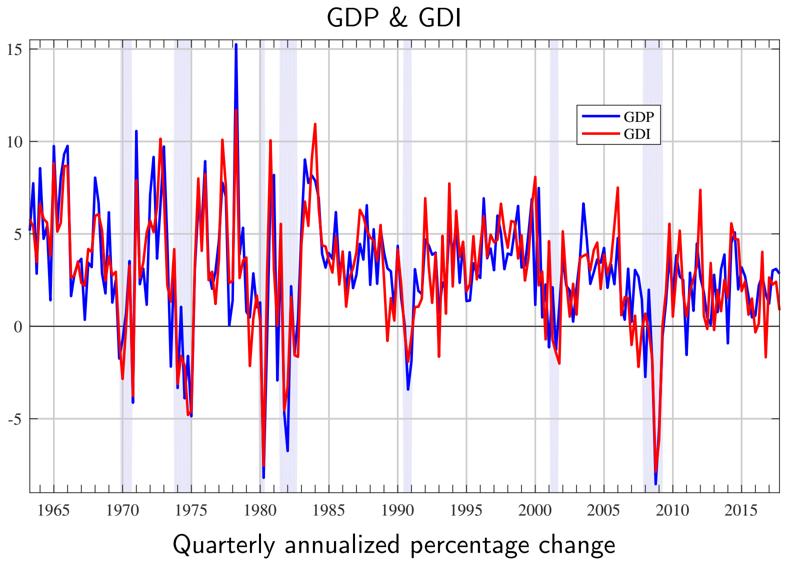
- $q = 3$;
- $q - d = 1$;
- $r = 6$.

- unit-root test on estimated idiosyncratic components;
- idiosyncratic of most aggregated variables are assumed $I(0)$
  GDP, GDI, UR, FFR, CPI inflation, PCE inflation.

Outline

- **Gross domestic output**

Measures of aggregate output



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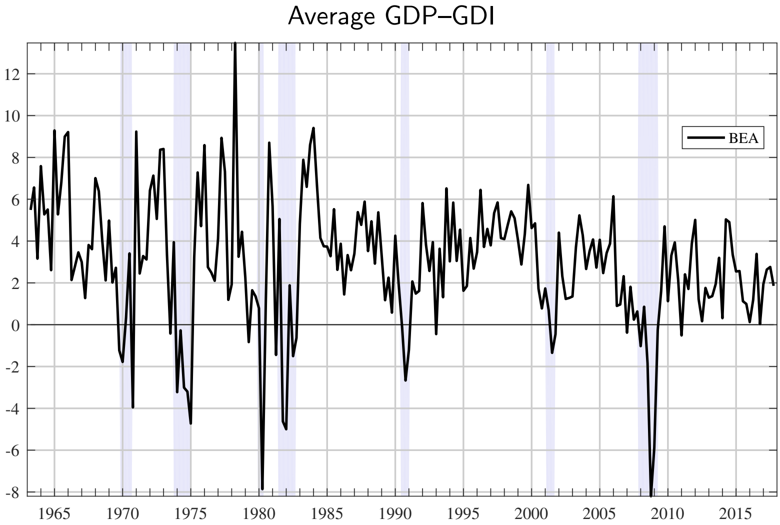
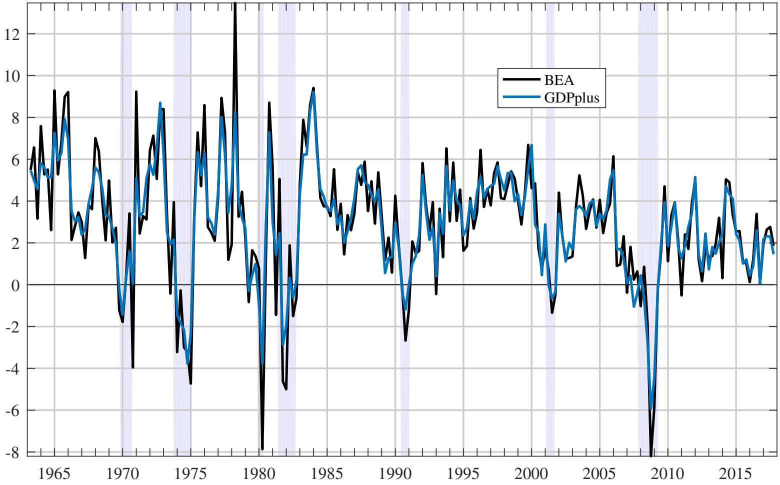


Quarterly annualized percentage change

Measures of aggregate output

Average GDP–GDI & Philly FED DFM of GDP–GDI



Quarterly annualized percentage change

Our measure of GDO

- GDO = part of GDP and GDI driven by $\mathbf{u}_t$

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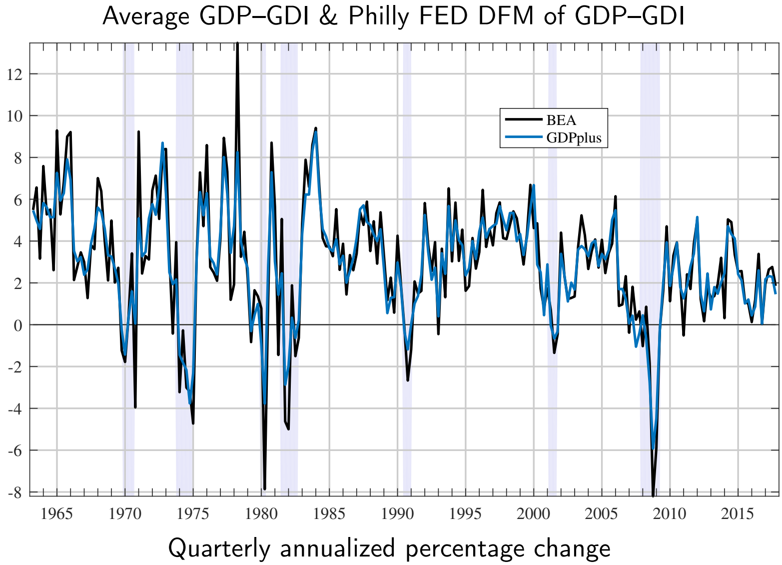
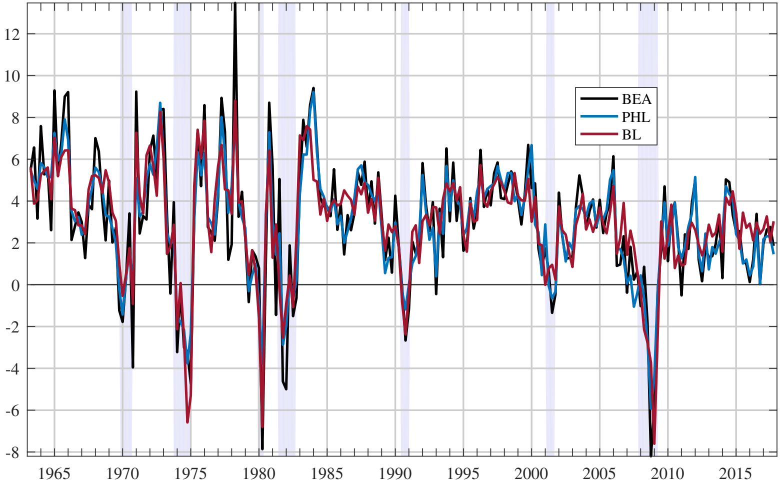
- Estimation base on two assumptions:
  1. GDP and GDI respond to $\mathbf{u}_t$ in the same way
     $\Longrightarrow \chi_t^{GDP} = \chi_t^{GDI}$
  2. the long run dynamics of GDP and GDI are entirely driven by $\mathbf{u}_t$
     $\Longrightarrow \xi_t^{GDP}, \xi_t^{GDI} \sim I(0)$

Gross domestic output



Gross domestic output

Average GDP–GDI & Philly FED DFM of GDP–GDI & BL



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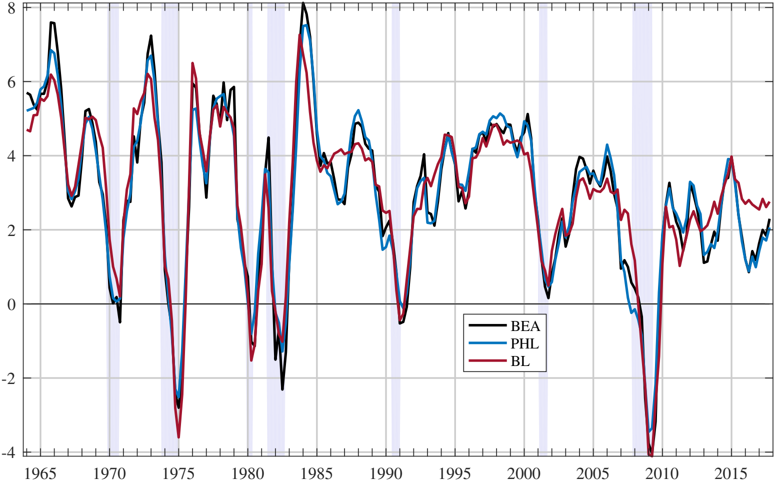
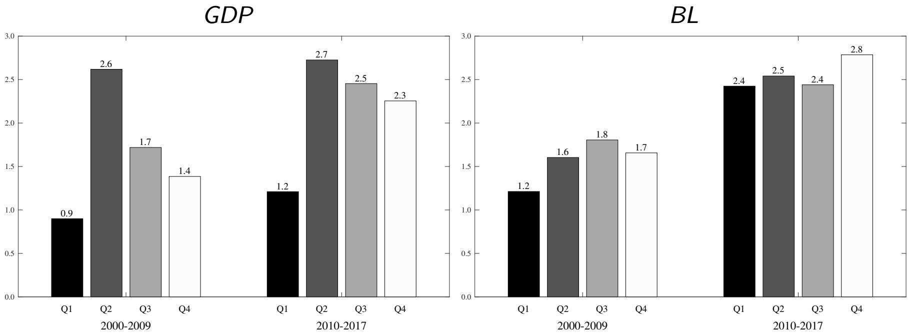


4-quarter percentage change

Our estimate does not show residual seasonality



Average quarterly annualized percentage change per quarter 2010–2016

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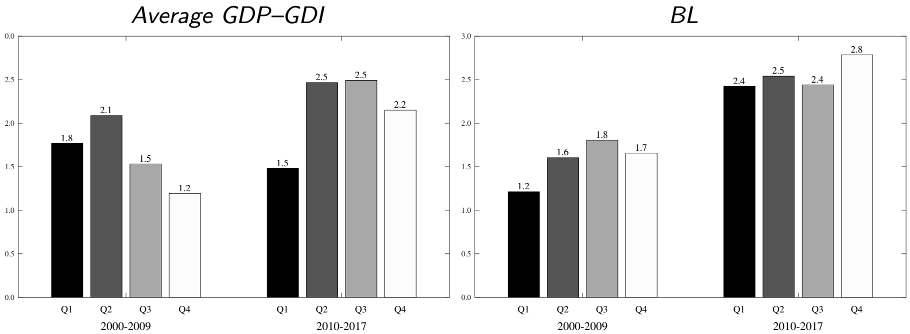

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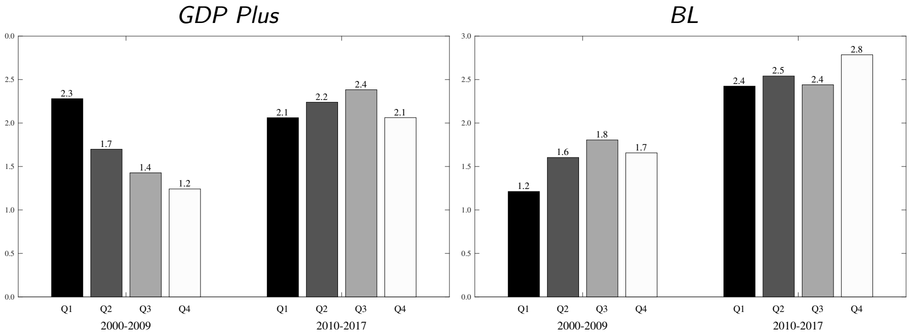
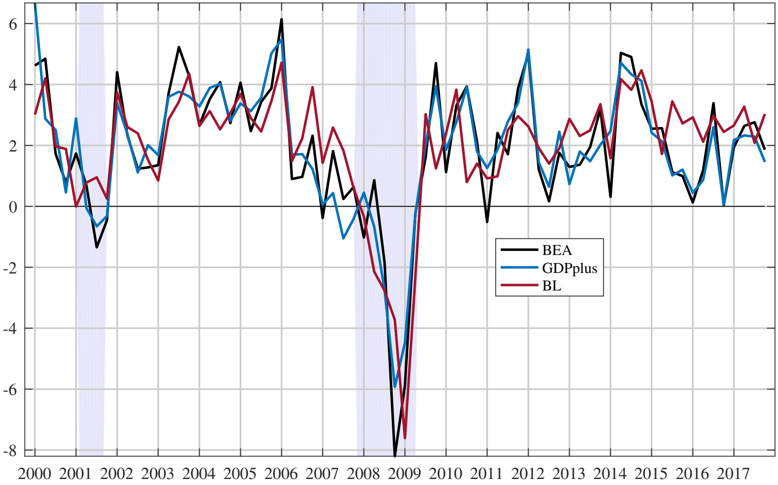


Average quarterly annualized percentage change per quarter 2010–2016

US economy grew faster than NA statistics

Average GDP–GDI & Philly FED DFM of GDP–GDI & BL



Quarterly annualized percentage change

Outline

- **Output gap**

Trend-Cycle decomposition common factors

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Since $\mathsf{F}_t = \mathsf{K}(\boldsymbol{f}'_t \cdots \boldsymbol{f}'_{t-s})'$, then:

- F_t has $(q - d)$ unit roots
- F_t is with a rank of cointegration c, $d \leq c \leq (r - q + d)$

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- $\boldsymbol{\Gamma}_t$ is stationary

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$$\widehat{\mathbf{T}}_t = \widehat{\boldsymbol{\Phi}}'\widehat{\mathbf{F}}_t$$

$$\widehat{\boldsymbol{\Gamma}}_t = \widehat{\boldsymbol{\Phi}}_{\perp}\widehat{\boldsymbol{\Phi}}_{\perp}'\widehat{\mathbf{F}}_t = \widehat{\boldsymbol{\Phi}}_{\perp}\widehat{\mathbf{G}}_t$$

$$\widehat{\chi}_{it} = \widehat{\boldsymbol{\lambda}}_i'\widehat{\boldsymbol{\Phi}}\widehat{\mathbf{T}}_t + \widehat{\boldsymbol{\lambda}}_i'\widehat{\boldsymbol{\Phi}}_{\perp}\widehat{\mathbf{G}}_t,$$

Output gap: definition

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Our measure

- Output gap = cyclical component of GDO

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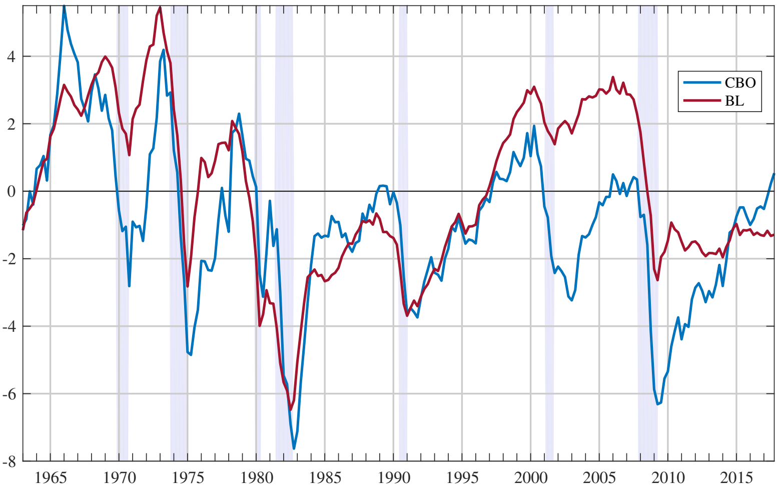
Congressional Budget Office

- Output fap = GDP - potential output
  - Solow growth model
  - Okun's law
  - NAIRU

Output gap


CBO
BL
4
2
0
-2
-4
-6
-8
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015

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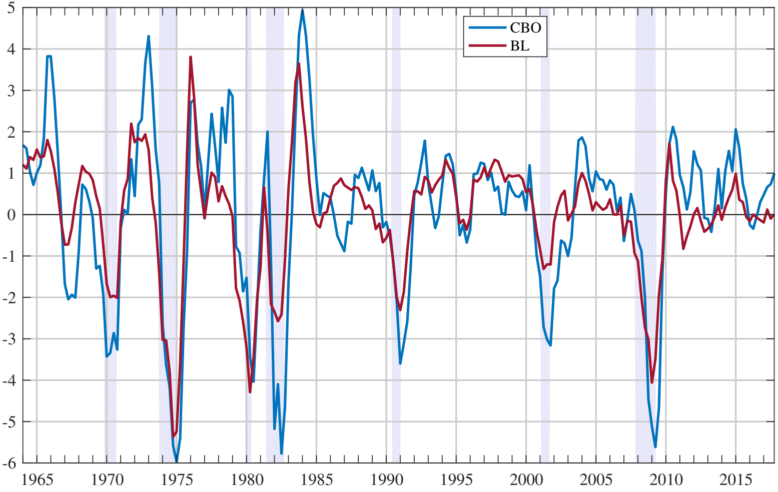

4-quarter percentage change

Growth before the GFC was not sustainable

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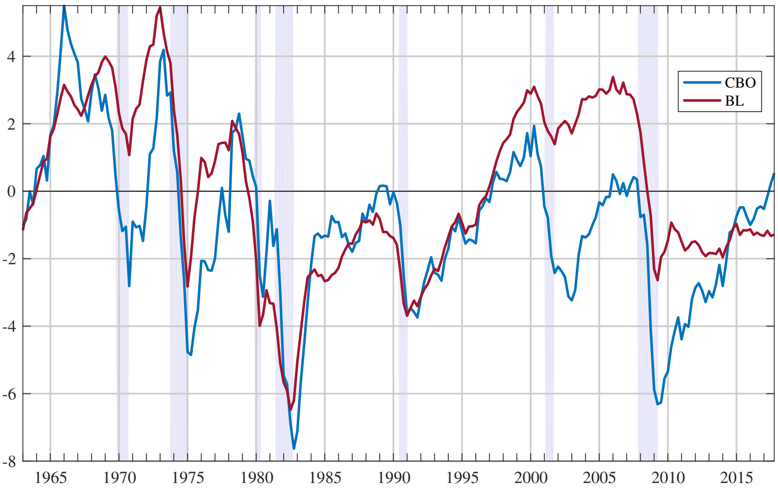

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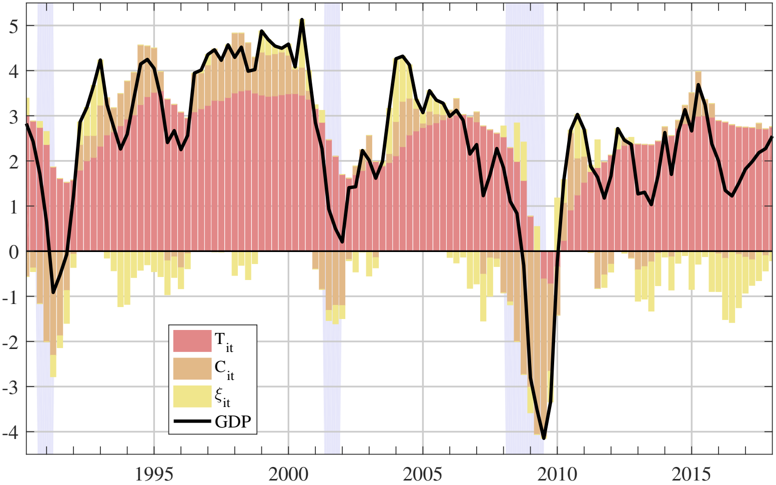

4-quarter percentage change

Labor market sends different signal

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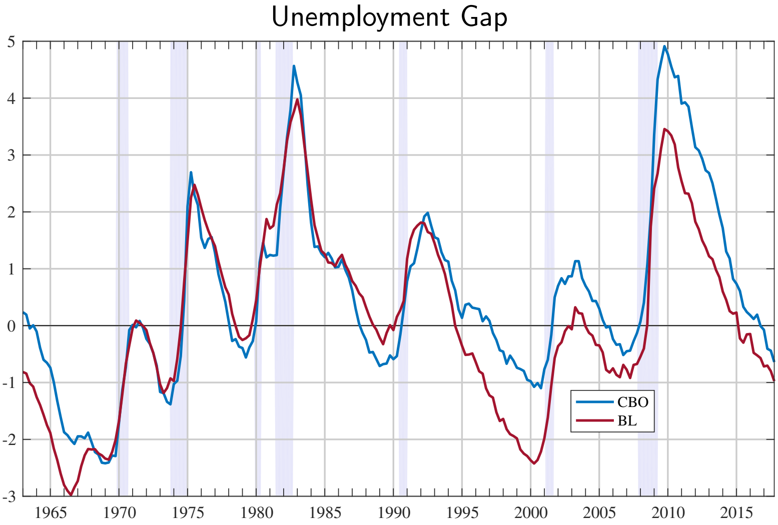
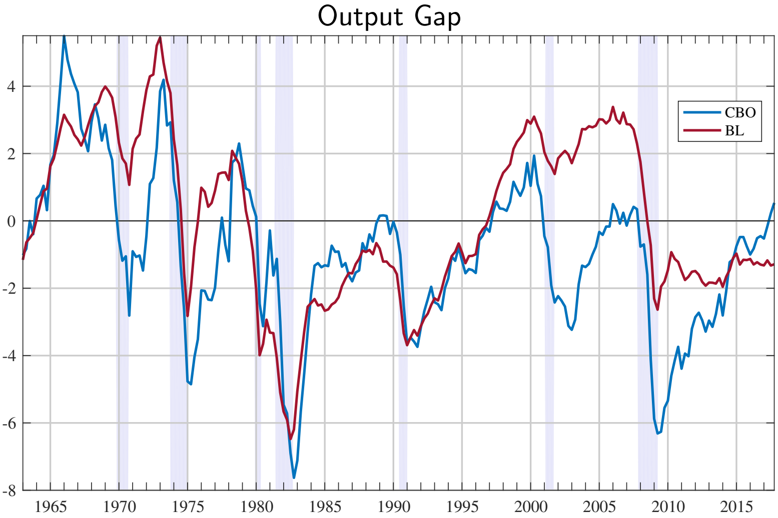


Labor market sends different signal



Outline

- **Summary and conclusions**

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Aggregate output

Output gap

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Aggregate output ⇒ Non-Stationary Dynamic Factor Model

Output gap ⇒ Non-parametric Trend-Cycle

Summary and conclusions

Aggregate output ⇒ Non-Stationary Dynamic Factor Model

- Since 2015 growth was on average 0.4 p.p. higher than GDP
- Higher growth has been concentrated in Q1
- GDP Q1 weakness due to mismeasurement rather than seasonality

Output gap ⇒ Non-parametric Trend-Cycle

- Growth before the GFC was heavily boosted by temporary factors
- Growth after the financial crisis is due primarily to permanent factors
- Our estimate indicates that as of 2017:Q4 there is still slack

Measuring US Aggregate Output and Output Gap using Large Datasets

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