Testing Models of Low-Frequency Variability

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Motivation

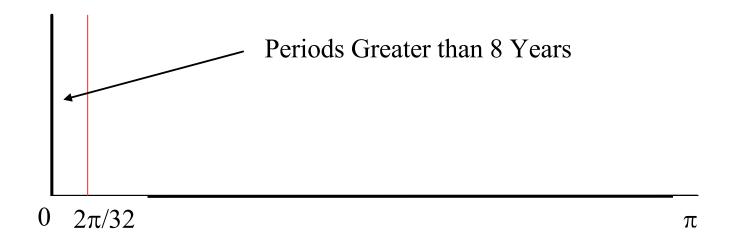
- Pronounced interest in understanding low frequency behavior of economic time series
- Typical questions about low-frequency behavior
 - 1. Is there a unit root?
 - 2. What is the size of the largest AR root?
 - 3. What is the value of d in a fractional model?
 - 4. Is there cointegration, i.e. is $x_t y_t$ an I(0) series?

What is 'Low Frequency'?

- ullet Consider I(0) model for a macroeconomic aggregate
 - ⇒ roughly stationary, no strong persistence
- Expect lots of particular dynamics at business cycle frequencies (and higher)
- Plausible definition of I(0) model for macro data: no additional fancy dynamics below business cycle frequencies (spectrum approximately flat below business cycle frequency)
- Focus on below business cycle frequencies = period greater than 8 years
- Similar arguments for other models

How Much Information about Low Frequencies?

Spectrum of quarterly data



- 50 years of data: about 7 periodogram ordinates
- ullet Asymptotic approximations with $\# \text{ordinates} { o} { o} { o}$ potentially misleading

Our Approach

- 1. Extract low-frequency information by computing q weighted averages of time series data, where weights are low frequency trigonometric series
- 2. Asymptotic analysis of properties of finite number of weighted averages in common models
- 3. Measure fit of model by comparing transformed data from (1) with implication of (2)

 \Rightarrow related literature: Bierens (1997), Phillips (1998), Müller (2004), Phillips (2006)

Plan of Talk

- 1. Introduction
- 2. Methodology
 - (a) Common time series models
 - (b) Asymptotic properties of weighted averages
 - (c) Choice of weights
 - (d) Tests
- 3. Empirical Results
- 4. Conclusion

Common Time Series Models

Data Generating Process for observed data $\{y_t\}_{t=1}^T$

$$y_t = d_t + u_t$$

where $d_t = \mu$ or $d_t = \mu + \beta t$.

1. Local-to-Unity AR model with parameter c (OU):

$$u_t=(1-c/T)u_{t-1}+\eta_t$$
 such that $T^{-1/2}u_{[\cdot T]}\Rightarrow \omega J_c(\cdot)$, where $dJ_c(s)=-cJ_c(s)ds+dW(s)$

2. Local-Level Model with parameter $g \ge 0$ (LLM):

$$u_t = w_t + \frac{g}{T} \sum_{s=1}^t \eta_s$$

such that $T^{-1/2} \sum_{t=1}^{[\cdot T]} u_t \Rightarrow \omega W_1(\cdot) + \omega g \int_0^{\cdot} W_2(t) dt$

Common Time Series Models

3. Stationary Fractional Model with parameter -1/2 < d < 1/2:

$$(1-L)^d u_t = \eta_t$$

such that $T^{-1/2-d}\sum_{t=1}^{[\cdot T]}u_t \Rightarrow \omega W^d(\cdot)$, where W^d is a 'type I' fractional Wiener process

+ Integrated version of these models, so that $u_t - u_{t-1}$ is modelled as above

Asymptotic Properties of Weighted Averages

All models satisfy

$$T^{-\alpha} \sum_{t=1}^{[\cdot T]} u_t \Rightarrow \omega G(\cdot) \tag{1}$$

for some α and ω , where G is a mean-zero Gaussian process with a covariance kernel k(r,s)=E[G(r)G(s)] that depends on the model and its parameter.

• Deal with deterministic component d_t by basing analysis on OLS residuals $\{u_t^i\}$ of a regression of $\{y_t\}$ on $\{1\}$ $(i=\mu)$ and $\{1,t\}$ $(i=\tau)$, respectively. By standard OLS algebra and (1)

$$T^{-\alpha} \sum_{t=1}^{[\cdot T]} u_t^i \Rightarrow \omega G^i(\cdot)$$

where the covariance kernel of G^i can be computed from k(r,s).

Asymptotic Properties of Weighted Averages

- Let $\Psi(\cdot) = (\Psi_1(\cdot), \cdots, \Psi_q(\cdot))'$, where $\Psi_l : [0,1] \mapsto \mathbb{R}$, $l = 1, \cdots, q$, are functions with continuous derivative ψ_l .
- Let $S_t^i = \sum_{s=1}^t u_s^i$ (so that $S_T^i = 0$). If $T^{-\alpha}S_{[\cdot T]}^i \Rightarrow \omega G^i(\cdot)$ then

$$X_{T} \equiv T^{-\alpha} \sum_{t=1}^{T} \Psi(t/T) u_{t}^{i}$$

$$= T^{-\alpha} S_{T}^{i} \Psi(1) - T^{-\alpha} \sum_{t=1}^{T} S_{t-1}^{i} (\Psi(t/T) - \Psi((t-1)/T))$$

$$\Rightarrow -\omega \int_{0}^{1} G^{i}(\lambda) \psi(\lambda) d\lambda \sim \mathcal{N}(0, \omega^{2} \Sigma)$$

where the $q \times q$ matrix Σ depends on Ψ , k(r,s) and $i = \mu, \tau$.

Self-Normalized Weighted Averages

We found

$$X_T \equiv T^{-\alpha} \sum_{t=1}^T \Psi(t/T) u_t^i \Rightarrow \mathcal{N}(0, \omega^2 \Sigma) \equiv X$$

with Σ known for a given model and parameter. But what about ω (and α)?

ullet Restrict attention to scale invariant inference based on X_T . Maximal invariant is given by

$$v_T = \frac{X_T}{\sqrt{X_T'X_T}} \Rightarrow \frac{X}{\sqrt{X'X}} = v$$

and the density of v only depends on Σ (in fact, only on $\Sigma(d)/\operatorname{tr}\Sigma(d)$)

$$f_v(\mathbf{\Sigma}) \propto |\mathbf{\Sigma}|^{-1/2} (v'\mathbf{\Sigma}^{-1}v)^{-q/2}$$

Note on Continuity for Fractional Model

• Definition of stationary fractional model for -1/2 < d < 1/2:

$$T^{-1/2-d} \sum_{t=1}^{[\cdot T]} u_t \Rightarrow \omega W^d(\cdot)$$

For 1/2 < d < 3/2: $u_t - u_{t-1}$ is stationary fractional model with parameter d-1 (as in Velaso (1999)), so that

$$T^{-1/2-d} \sum_{t=1}^{[\cdot T]} u_t \Rightarrow \omega \int_0^{\cdot} W^{d-1}(l) dl$$

ullet Consider $oldsymbol{\Sigma} = oldsymbol{\Sigma}(d)$ in fractional model. It turns out that

$$\frac{\mathbf{\Sigma}(d)}{\mathsf{tr}\,\mathbf{\Sigma}(d)}$$

can be continuously extended at d=1/2 for $i=\mu,\tau,$ so that likelihood of v becomes continuous function of -1/2 < d < 3/2.

Choice of Weights

- Want to extract low-frequency information only.
- Consider \mathbb{R}^2 from regression of generic periodic series

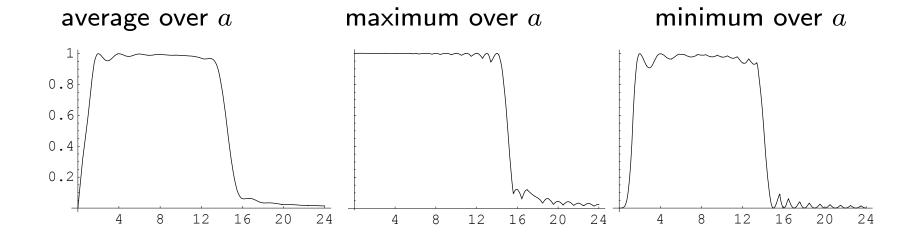
$$\sin(\pi rs + a)$$

on candidate $\Psi(\cdot) = (\Psi_1(\cdot), \cdots, \Psi_q(\cdot))'$.

- Ideally, $R^2=1$ for $r\leq r_0$ and $R^2=0$ for $r>r_0$ for all a, where r_0 is the business-cycle cut-off frequency.
- Choice of $\Psi_l(s) = \sqrt{2}\cos(\pi l s)$, $l=1,\cdots,q$, comes reasonably close to this ideal with $r_0=q$.

${\cal R}^2$ as Function of r for q=14

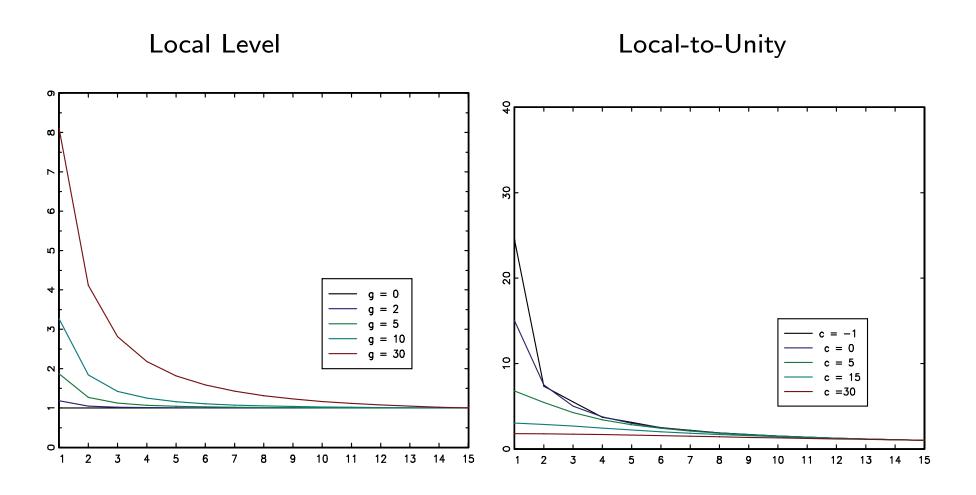
demeaned case $i = \mu$



Choice of Weights

- With $\Psi_l(s) = \sqrt{2}\cos(\pi l s)$, $\Sigma = I_q$ in I(0) model and exactly diagonal in unit root model.
- Obtain same result for detrended case $i = \tau$ by choosing Ψ_l as the eigenfunctions of the covariance kernel of detrended Wiener process.
- ullet This choices lead to Σ that are close to diagonal for all models and relevant parameter values (average absolute correlation with q=14 is <0.03 for all models)

Square Root of Diagonal Elements of Σ



Tests

• For each model and parameter value, $X_T \Rightarrow \mathcal{N}(0, \omega^2 \Sigma)$, which implies specific asymptotic distribution for

$$v_T = \frac{X_T}{\sqrt{X_T' X_T}}$$

that only depends on Σ .

ullet Observe v_T . Is it compatible with a specific model and parameter?

Test of Heteroskedasticity in X_T

• Let $X \sim \mathcal{N}(0, \Sigma)$ and $v = X/\sqrt{X'X}$. Consider test of

$$H_0: \Sigma = \Sigma_0$$
 against $H_1: \Sigma = \Lambda \Sigma_0 \Lambda$

where $\Lambda = \text{diag}(\exp(\delta_1), \cdots, \exp(\delta_q))$, and $\delta \sim \mathcal{N}(0, \gamma^2\Omega)$.

- \Rightarrow Tests the implication for the variance of X_T of the various models of persistence for u_t against a more flexible alternative
- We derive locally best test statistic (as $\gamma \to 0$) for $\delta = (\delta_1, \dots, \delta_q)'$ a demeaned random walk, denoted LBIM.

Test of Low-Frequency Heteroskedasticity in u_t

ullet Models imply time invariant long-run variance. For instance, I(0) model for u_t is defined as

$$T^{-1/2} \sum_{t=1}^{[\cdot T]} u_t \Rightarrow \omega \int_0^{\cdot} dW(l)$$
 (2)

• Alternative I(0) model with time varying long-run variance $h(\cdot)$:

$$T^{-1/2} \sum_{t=1}^{[\cdot T]} u_t \Rightarrow \int_0^{\cdot} h(l) dW(l)$$

Under this model, $X_T = T^{-1/2} \sum_{t=1}^T \Psi(t/T) u_t^i \Rightarrow \mathcal{N}(0, \Sigma(h))$ with Σ a function of h (and $h(\cdot) = \omega$ recovers (2))

Test of Low-Frequency Heteroskedasticity in u_t

- We consider weighted average power maximizing tests H, where the weight for alternative long-run variance paths $h(\cdot)$ is the distribution of $\exp[\kappa W^*(\cdot)]$
- For more general models than the I(0) model, the alternative model with low-frequency heteroskedasticity has time varying variances of the in-sample part of the "natural" MA representation of the asymptotic model
- Example: Stationary Ornstein-Uhlenbeck model

$$J_c(s) = \int_{-\infty}^{0} e^{-c(s-l)} dW(l) + \int_{0}^{s} e^{-c(s-l)} h(l) dW(l)$$

Likelihood Ratio Tests

• With $X \sim \mathcal{N}(0, \Sigma)$, best scale invariant test statistic to distinguish

$$H_0: \Sigma = \Sigma_0$$
 against $H_1: \Sigma = \Sigma_1$

is

$$LR = \frac{v' \Sigma_1^{-1} v}{v' \Sigma_0^{-1} v} = \frac{X' \Sigma_1^{-1} X}{X' \Sigma_0^{-1} X}$$

- Applications:
 - 1. Point-optimal test LFUR of unit root model against local-to-unity alternatives with c=7.5 in mean case and c=13.5 in trend case, analogous to Elliott, Rothenberg, Stock (1996)
 - 2. Point-optimal test LFST of I(0) model against Local Level Model with g=8 and g=13 in mean and trend case, similar to Nyblom (1989) and KPSS (1992)

Discrimination Between Models?

- Quantify the difficulty using Total Variation Distance
 - The total variation distance between to probability measures P_f and P_g is

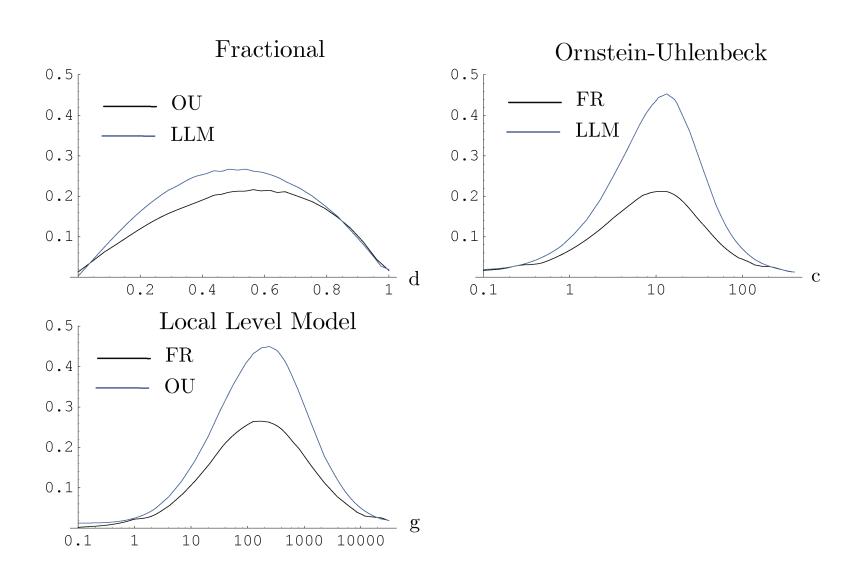
$$TVD(f,g) = \sup_{A} |P_f(A) - P_g(A)|$$

over all Borel sets A.

– If f and g are two densities with respect to a common dominating measure μ , then

$$TVD(f,g) = \int \mathbf{1}[f < g](g - f)d\mu$$
$$= \int \mathbf{1}[\frac{f}{g} < \mathbf{1}](\mathbf{1} - \frac{f}{g})gd\mu$$

TVD Between Models for q = 14, mean case



Empirical Analysis

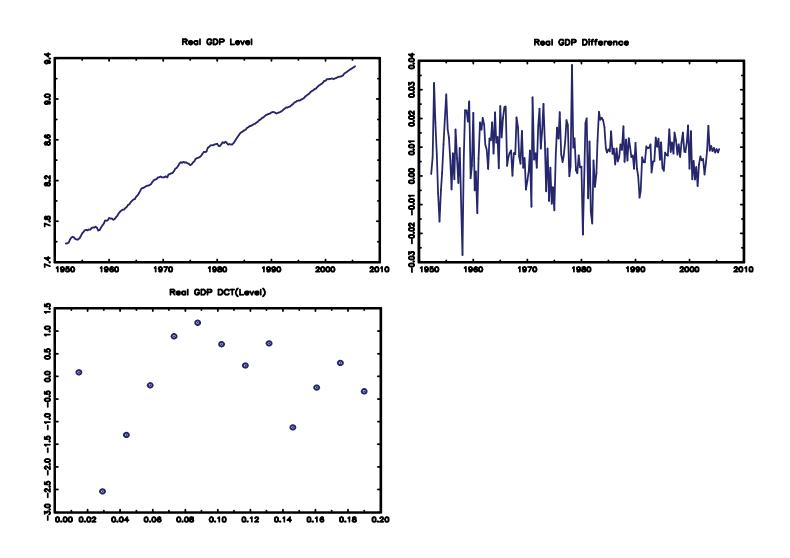
We consider 21 US macroeconomic and financial data series

- Postwar quarterly macroeconomic series (GDP, interest rates, inflation, income/consumption)
- Annual long series (GNP, inflation, real exchange rates, price/earnings ratio)
- Daily S&P500 absolute returns 1928-2005

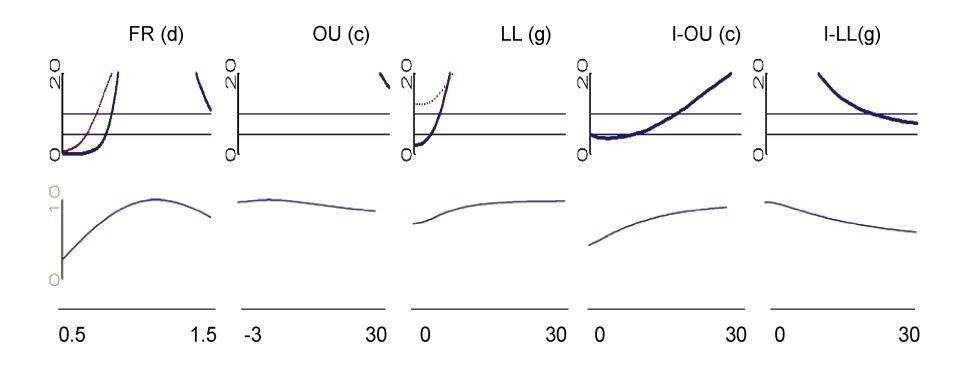
Four questions

- 1. Is the unit root model (d=1 in fractional model, c=0 in OU model, g=0 in integrated LLM) consistent with data?
- 2. Is the I(0) model (d=0 in fractional model, g=0 in LLM) consistent with the data?
- 3. Are there entire classes of models that are rejected?
- 4. How do the results of this analysis compare to results obtained from standard methods?

Postwar Real GDP (q = 13)



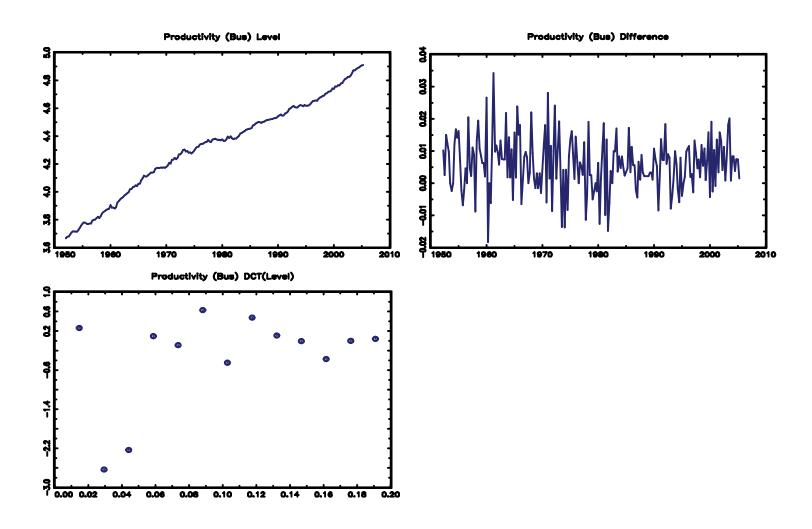
Postwar Real GDP (q = 13)



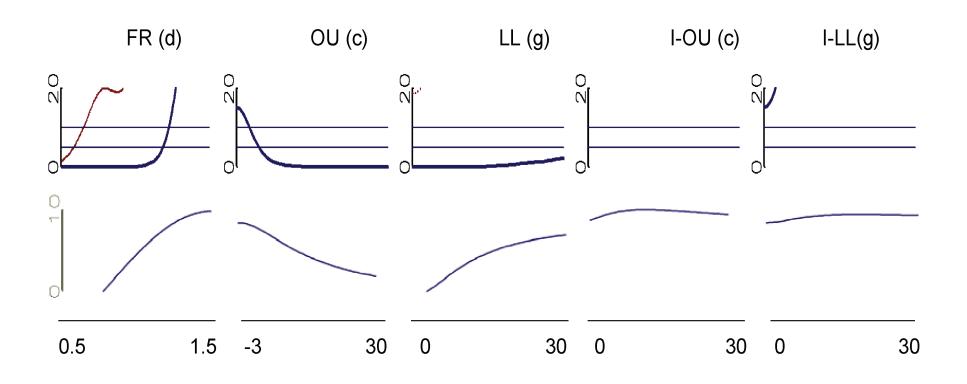
	LFUR	LFST	DF-GLS	KPSS
p-value	0.34	0.01	0.16	0.00

 \Rightarrow I(0) model rejected, unit root not rejected

Postwar Labor Productivity (q = 13)



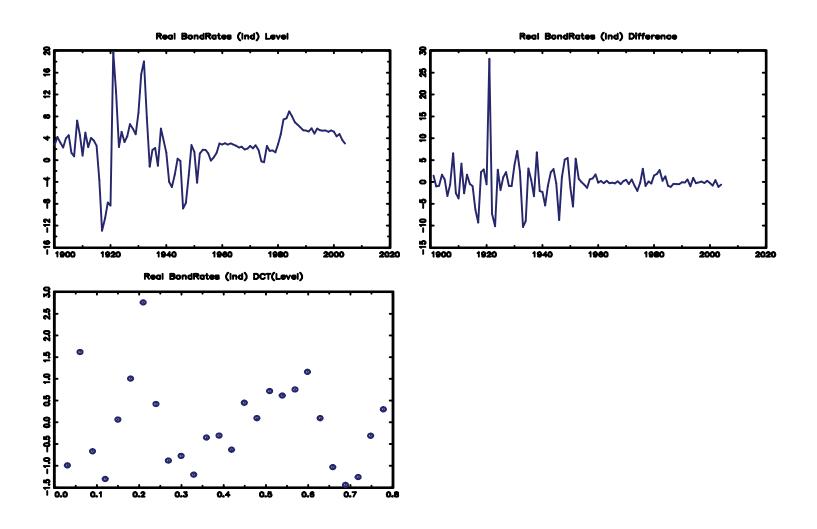
Postwar Labor Productivity (q = 13)



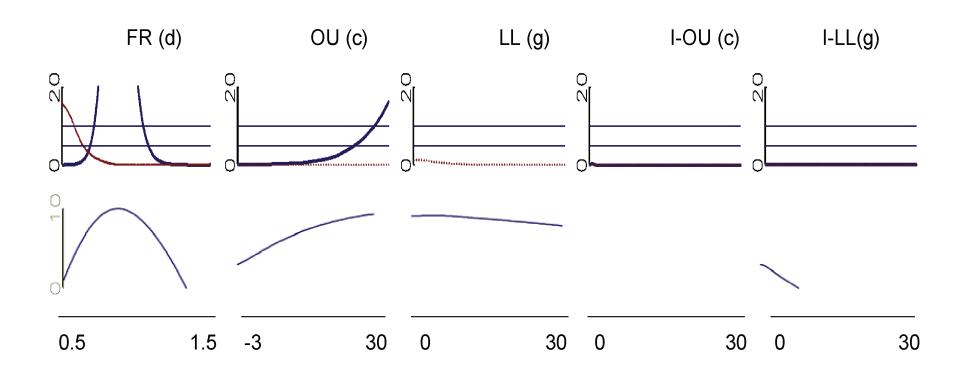
	LFUR	LFST	DF-GLS	KPSS
p-value	0.94	0.00	0.84	0.00

 \Rightarrow More persistence than I(1) model

Real Bond Rates 1900-2004 (q = 26)



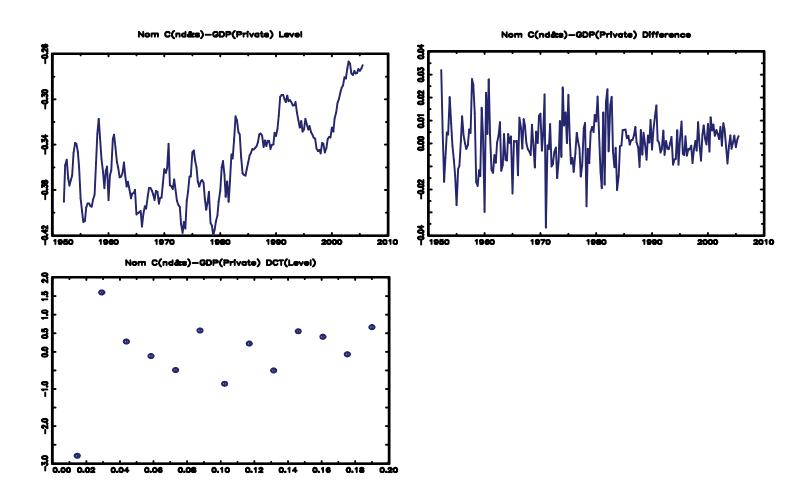
Real Bond Rates 1900-2004 (q = 26)



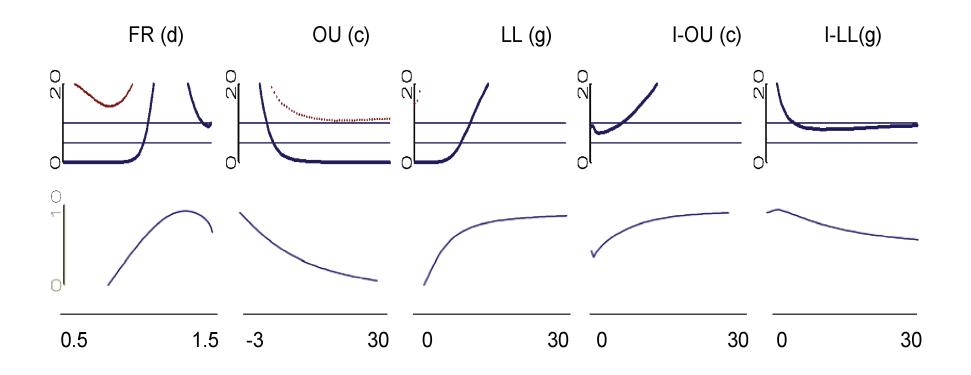
	LFUR	LFST	DF-GLS	KPSS
p-value	0.00	0.16	0.00	0.21

⇒ All models rejected due to second moment instability

Postwar Consumption/Income Ratio (q = 13)



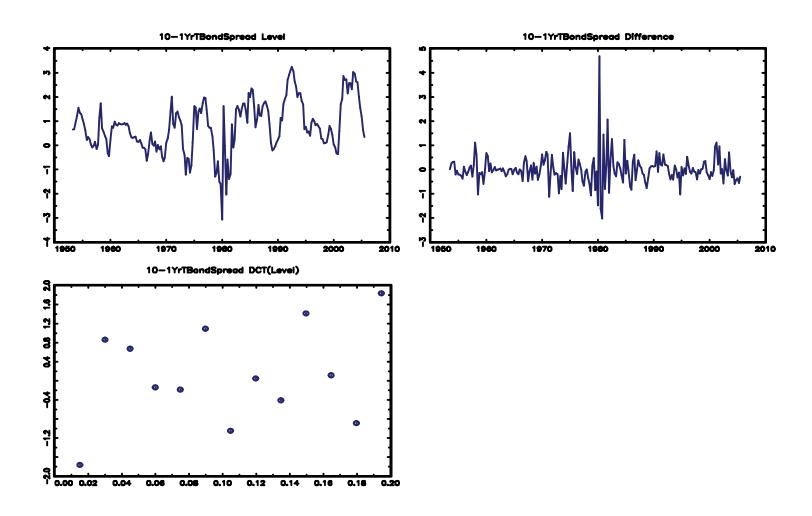
Postwar Consumption/Income Ratio (q = 13)



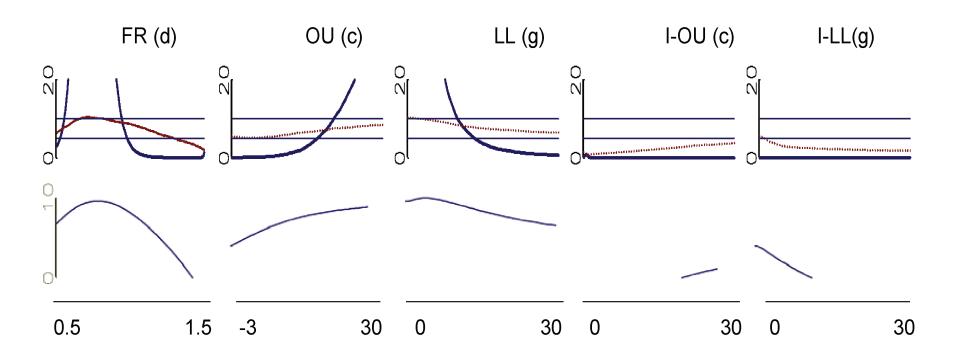
	LFUR	LFST	DF-GLS	KPSS
p-value	0.85	0.00	0.91	0.00

 $\Rightarrow I(0)$ model (=cointegration) rejected

Postwar 10 Year – 1 Year Interest Spread (q = 13)



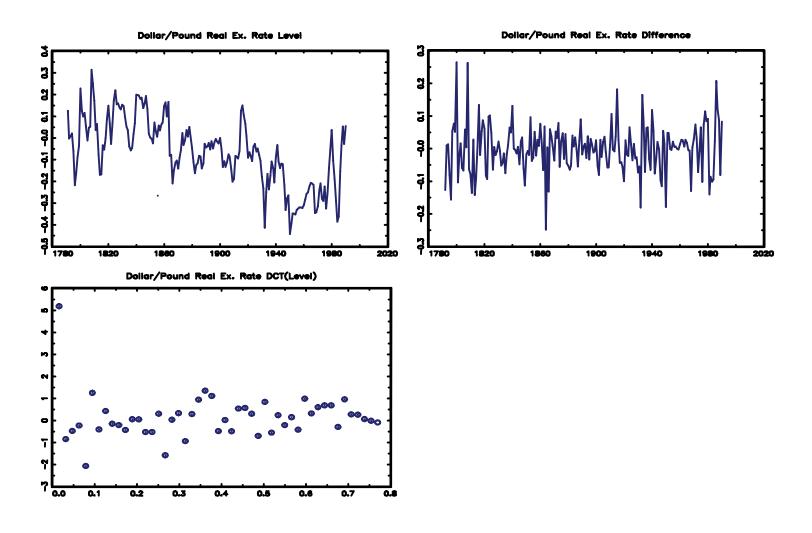
Postwar 10 Year – 1 Year Interest Spread (q = 13)



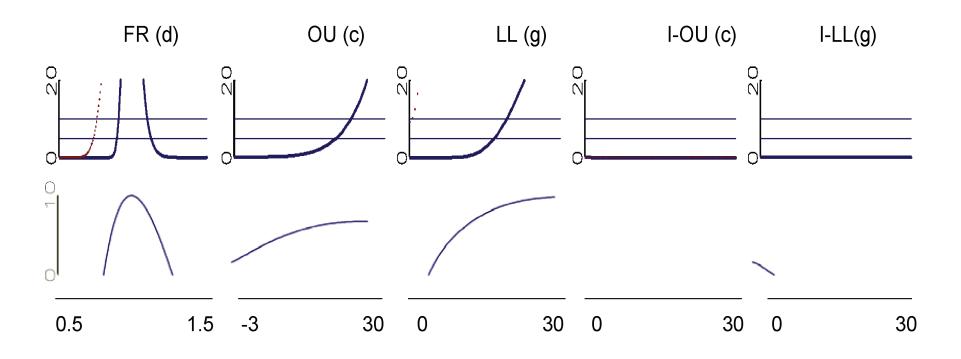
	LFUR	LFST	DF-GLS	KPSS
p-value	0.00	0.19	0.00	0.01

 \Rightarrow I(0) model (=cointegration) not rejected, but second moment instability

Real Exchange Rates US-UK 1780-1992 (q = 48)



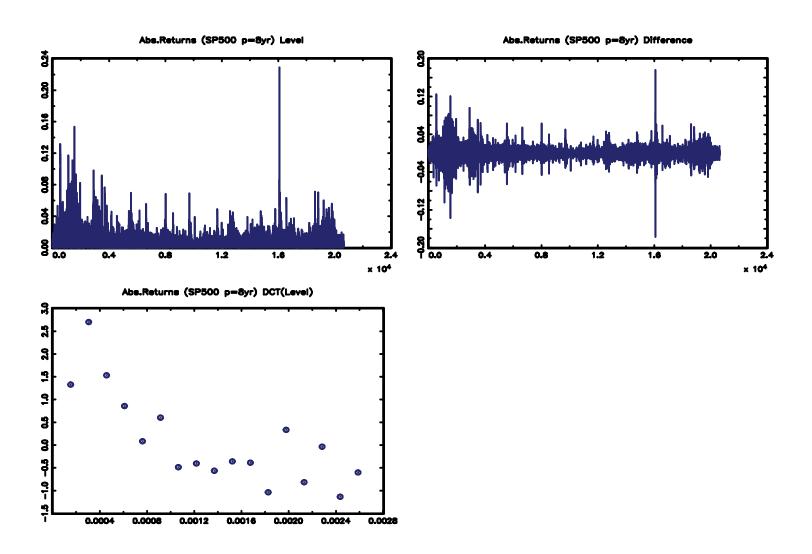
Real Exchange Rates US-UK 1780-1992 (q = 48)



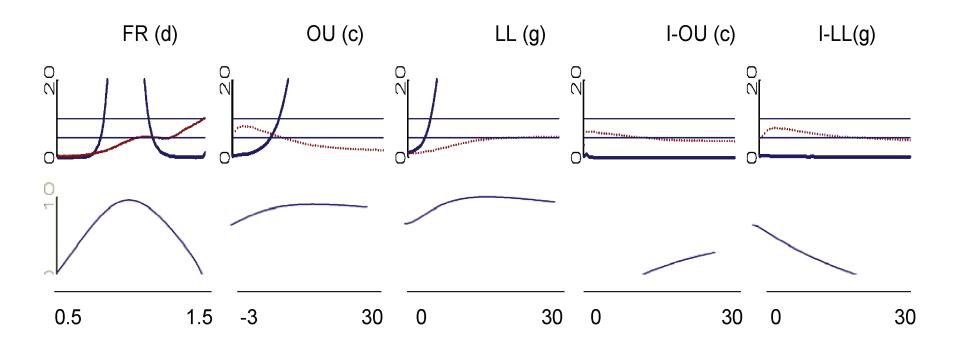
	LFUR	LFST	DF-GLS	KPSS
p-value	0.00	0.00	0.03	0.00

 \Rightarrow I(0) model rejected, unit root rejected, fractional model and local level model fit well

Daily Absolute Returns 1927-2004 (q = 18)



Daily Absolute Returns 1927-2004 (q = 18)



 \Rightarrow I(0) model rejected, unit root model rejected, fractional model and local level model fit best, second moment instability

Conclusions

- Theoretical results
 - 1. Method to assess model fit of standard models at low frequencies
 - 2. Quantification of difficulty of distinguishing low-frequency models
- Empirical results
 - 1. I(0) model is mostly rejected, even for putative cointegration relationships
 - 2. Unit root model fares much better
 - 3. Fractional model fits better for some series that are typically modelled as autoregressions
 - 4. For some series, too much heteroskedasticity in the underlying data for all models