

# Detecting and Forecasting Large Deviations and Bubbles in a Near-Explosive Random Coefficient Model.

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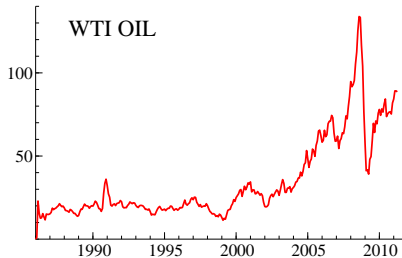
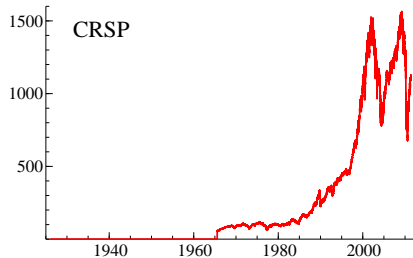
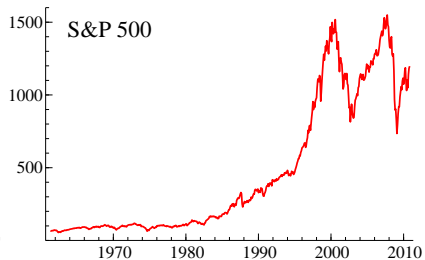
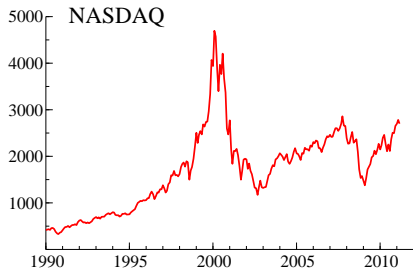
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**CREAR WORKING GROUP ON RISK**

January 8, 2014

# Bubbles?



# Introduction

- Our purpose is to provide a flexible time series model which accommodates periods of sustained growth (*bubbles*)
  - without resorting to (periodic) regime switching or breaks
  - where build-up/burst of bubbles relate to the value of a latent process (stochastic discount factor)
  - where we do not prespecify the *level* reached when the explosion starts and ends
- We design the model to allow for estimation/testing in a classical (non-Bayesian) framework: this is an issue
  - when bubbles (explosiveness) break down asymptotic theorems
  - when some coefficients are very close to some boundaries (unit roots, zero variance)
- The model can be set to match standard present-value models in finance

# Overview

- 1 We revisit the univariate Random Coefficient autoregressive model à la Nicholls & Quinn (1982) and Granger & Swanson (1997) which allows stochastic alternation between mean-reversion and explosiveness
- 2 We follow recent work by PCB Phillips, T Magdalinos, Jun Yu and coauthors introducing local-asymptotic parameterization: the process is local to a random walk, possibly on the explosive side.
  - The combination of 1&2 allows full-sample inference
    - we prove an invariance principle (FCLT) and convergence of OLS estimators
    - we conduct full-sample inference by grid testing (Stock, 1991, Andrews, 1993, Hansen, 1999... Mikusheva, 2012, and Phillips, 2012)
    - we detect bubbles recursively and predict their probabilities.
- 3 We show the model is compatible with standard Present-Value models where growth rates are stochastic (predictability) and can be traced to the value of stochastic discount factor/interest rate; we provide an application to U.S. Housing Prices (Case-Shiller index)

# Outline

- 1 Motivation: Present Value Models and Bubbles
- 2 The NERC model
- 3 Inference, Detection & Forecasting
- 4 Application to U.S. Housing Prices

# Present Value Model

- Campbell and Shiller (1987) model for the price  $P_t$  of a unique asset that generates cash flow  $D_{t+1}$

$$P_t = E_t \left( \frac{P_{t+1} + D_{t+1}}{1 + R_{t+1}} \right) \quad (1)$$

$R_{t+1}$  is discount rate between  $t$  and  $t + 1$ .  $(1 + R_{t+1})^{-1}$  can be understood as (unobserved) stochastic discount factor, pricing kernel.

- The expression solves as

$$P_t = F_t + B_t$$

The **fundamental price**  $F_t$  satisfies transversality condition

$$\lim_{k \rightarrow \infty} E_t F_{t+k} \prod_{j=1}^k (1 + R_{t+j})^{-1} = 0 :$$

$$F_t = E_t \sum_{j=1}^{\infty} \frac{D_{t+j}}{(1 + R_{t+1}) \dots (1 + R_{t+j})}$$

- $B_t$  denotes any process that exhibits “**conditional exuberance**”:

$$B_t = E_t \frac{B_{t+1}}{1 + R_{t+1}} \quad (2)$$

There exist solutions to (2) where  $B_t$  exhibits exponential growth and is labeled “bubble”, see inter alia Blanchard (1979), Blanchard and Watson (1982), Hamilton (1986), Abreu and Brunnermeier (2003)... see Lansing (2010) for an overview.

- Standard example is Blanchard (1979) for  $R_t = R$  constant:

$$B_t = \begin{cases} \frac{1+R}{\pi} B_{t-1} + \zeta_t & w.p. \pi \in (0, 1) \\ \zeta_t & w.p. 1 - \pi \end{cases}$$

studied by Johansen and Lange (2013).

## Testing for bubbles

- West (1987) and Diba & Grossman (1988): prices and dividends are integrated-cointegrated only in the absence of a bubble: when  $D_t$  is a random walk and  $R_t$  constant

$$D_t = D_{t-1} + \zeta_t, \quad F_t = \sum_{j=1}^{\infty} \frac{E_t D_{t+j}}{(1+R)^j} = \frac{1}{R} D_t$$

- Evans (1991): this approach has low power in the case of periodically collapsing bubbles
- Recent proposal of Phillips, Wu & Yu (2009), Phillips & Yu (2009,10), Phillips, Shi & Yu (2011,12) who build on the local explosive roots of Phillips and Madgalinos (2007, 2009) to propose an extension of

$$y_t = y_{t-1} 1\{t < t_1 \text{ or } t > t_2\} + \delta_T y_{t-1} 1\{t_1 \leq t \leq t_2\} + \varepsilon_t$$
$$\delta_T = 1 + \frac{c}{T^\alpha}, \quad c > 0, \alpha \in (0, 1)$$

the autoregressive root experiences deterministic breaks at the inception  $t_1$  and burst  $t_2$  of the bubble.

sup-Sequential ADF tests with finite sample corrections are used to test the presence of a bubble and ex-post estimation of  $(t_1, t_2)$ .



# Discussion of the proposal by Phillips, Yu and coauthors

## ■ Benefits:

- univariate: no need for cointegration
- simple: null of a unit-root process, rejection indicates bubble
- local-asymptotics to improve power of the ADF test
- subsample estimation: look at the  $\sup ADF$  statistic over subsamples (under explosiveness)

## ■ Drawbacks:

- models with deterministic breaks need burn-in/out periods
- deterministic breaks are unforecastable
- for consistent estimation of break dates, require long(ish) bubbles duration of at least  $O(\log T)$  and diverging critical values

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# An explosive Random coefficient AR model

- Nicholls & Quinn (1982), Granger & Swanson (1997) Random Coefficient AR(1) (RCA):

$$y_t = \rho_t y_{t-1} + \eta_t, \quad t = 1, \dots, T,$$

with  $y_0 = 0$ .  $\rho_t$  and  $\eta_t$  are *i.i.d* and independent.

- Nicholls & Quinn (1982), Aue, Horváth & Steinebach (2006) show  $y_t$  admits a strictly non-anticipatory **stationary solution** if and only if

$$E \left[ \log \rho_t^2 \right] < 0 \quad (3)$$

a **covariance stationary** solution if

$$\log E \left[ \rho_t^2 \right] < 0. \quad (4)$$

with the possibility of **Fat tails**: if

$$E \left[ \log \rho_t^2 \right] < 0 \leq \log E \left[ \rho_t^2 \right]$$

- RCA generates ARCH, let  $\rho_t \sim iid \left( \rho, \sigma_\rho^2 \right)$

$$E [y_t | y_{t-1}] = \rho y_{t-1}, \quad \text{Var} [y_t | y_{t-1}] = \sigma_\rho^2 y_{t-1}^2 + \sigma_\eta^2$$

# Local Asymptotics

- We specify

$$\log \rho_t = \frac{\phi + \lambda T^{\alpha/2} u_t}{T^\alpha},$$

for  $(\phi, \lambda) \in \mathbb{R} \times \mathbb{R}_+$ ,  $\alpha \in (0, 1)$ , and  $(u_t) \perp (\eta_t)$ . (see also Phillips & Magdalinos, 2007).

- This is a nonlinear state-space model. So far, we assume  $u_t \sim iid(0, 1)$ ,  
 $\eta_t \sim iid(0, \sigma_\eta^2)$ .

- near unit root: as  $T \rightarrow \infty$

$$(E[\rho_T], V[\rho_T]) \rightarrow (1, 0)$$

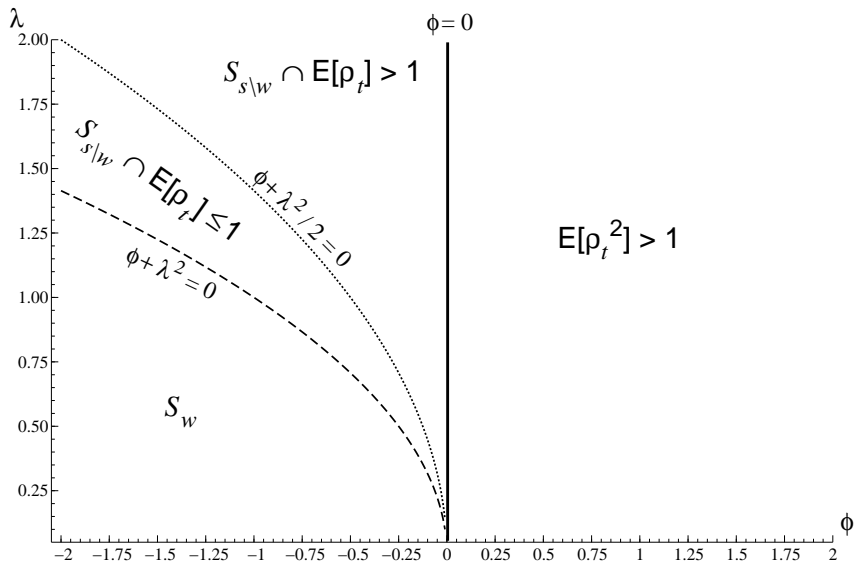
- Strict & weak stationarity conditions:

$$E[\log \rho_t^2] = \frac{2\phi}{T^\alpha} < 0 \Leftrightarrow \phi < 0$$

$$E[\rho_t^2] \sim \exp\left\{2\frac{\phi + \lambda^2}{T^\alpha}\right\} < 1 \Leftrightarrow \phi + \lambda^2 < 0$$

also notice  $E[\rho_t] < 1 \Leftrightarrow \phi + \frac{1}{2}\lambda^2 < 0$

# Parameter Set



# The NERC may generate temporary bubbles

- near stochastic unit root

$$\rho_t = \left( 1 + \frac{\phi + \frac{1}{2}\lambda^2}{T^\alpha} \right) + \frac{\lambda}{T^{\alpha/2}} u_t + \frac{\lambda^2}{2T^\alpha} (u_t^2 - 1) + O_p(T^{-2\alpha})$$

with the possibility that  $E(\rho_t) = 1$  when  $\phi + \frac{1}{2}\lambda^2 = 0$

$u_t > 0$  : temporary explosive root

$u_t < 0$  : temporary stationary root

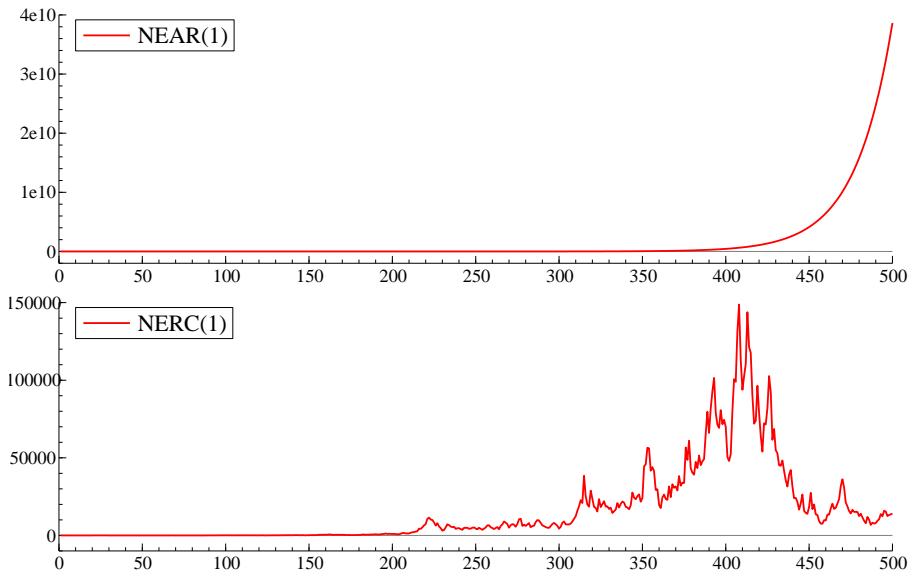
but the sign needs to be sustained for a bubble to appear

$$y_{t+k} = \exp \left\{ \frac{k\phi + \lambda T^{\alpha/2} \sum_{j=1}^k u_{t+j}}{T^\alpha} \right\} y_t + \sum_{i=1}^k e^{\frac{(k-i)\phi + \lambda T^{\alpha/2} \sum_{j=i+1}^k u_{t+j}}{T^\alpha}} \eta_{t+i}$$

$k\phi + \lambda T^{\alpha/2} \sum_{j=1}^k u_{t+j} > 0$  generates explosive patterns over  $t, \dots, t+k$

# Examples of simulated data

above:  $(\phi, \lambda) = (.75, 0)$ , below:  $(\phi, \lambda) = (.5, .5)$  so  $E[\rho_t] = 1.028$



# Discussion of the NERC model

- **Benefits:** same as the local explosive AR(1) with break  
Plus
  - no breaks: a unique model over the whole sample
  - inference on the parameters feasible
  - allows for prediction of emergence/collapse of a bubble (stochastic nature)
  - presence of the bubble related to the stochastic discount factor
- **Drawbacks**
  - $u_t$  must be filtered out (deconvolution/nonlinear Kalman filter)
  - parameters not consistently estimable (local to unity/zero)
  - $u_t$  is iid here, too restrictive



# Asymptotics

- Extending Phillips and Madgalinos (2004, 2007, 2009), an FCLT follows from: for  $r \in [0, T^{1-\alpha}]$  and as  $T \rightarrow \infty$ ,

$$T^{-\alpha/2} y_{[rT^\alpha]} \Rightarrow \int_0^r \exp \{ \phi(r-s) + \lambda (W_r - W_s) \} dB_s \stackrel{\text{def}}{=} K_{\phi, \lambda}(r) \quad (5)$$

where, for  $(s, v) \in [0, 1]^2$ ,  $T^{-1/2} \left( \sum_{t=1}^{[sT]} u_t, \sigma^{-1} \sum_{t=1}^{[vT]} \eta_t \right) \Rightarrow (W_s, B_v)$ .

- Define  $c = \phi + \lambda^2$  such that  $\sqrt{E(\rho_t^2)} = \exp(cT^{-\alpha})$

$$\text{sd}(y_T) = \begin{cases} O_p \left( T^{\frac{\alpha}{2}} \right) & \text{if } c < 0 \\ O_p \left( T^{\frac{1}{2}} \right) & \text{if } c = 0 \\ O_p \left( T^{\frac{\alpha}{2}} e^{cT^{1-\alpha}} \right) & \text{if } c > 0 \end{cases}$$

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# Inference

- Key question: whether  $(\phi, \lambda) \neq (0, 0)$ , or also  $c = 0$ .
- $(\phi, \lambda)$  are localizing parameters; it is well known that such parameters are difficult (at least) to estimate.
- We construct confidence sets by inverting an asymptotic test statistic (Stock, 1991, Andrews, 1993, Hansen, 1999, Elliott and Stock, 2001, Mikusheva, 2008, 2012, Phillips, 2012...), see also the weak instrument literature.
- Assume that a scalar function  $\tau_T$  (a test statistic) of  $\mathcal{Y}_T = (y_1, \dots, y_T)'$  satisfies

$$\tau_{\theta, T}(Y_T) \Rightarrow \mathcal{D}_\theta$$

where here  $\theta = (\phi, \lambda)' \in \Theta$ . Under the null

$$H_0 : \theta = \theta_0$$

Stock (1991) constructs asymptotic  $100(1 - \varphi)\%$  confidence sets as  $\Theta^* \subset \Theta$  consisting of the values  $\theta^*$  which are not rejected by  $\tau_{\theta^*, T}(Y_T)$  at size  $\varphi$ .

- Median-Unbiased estimator (locus): (monotonicity conditions)

$$\hat{\theta} = \operatorname{argmin}_\theta \|\tau_{\theta, T}(Y_T) - \operatorname{median}(\tau_\theta(Y))\|$$

- The least rejected parameter  $\theta^*$  constitutes an estimator of  $\theta$ . When  $\tau$  is a continuously-updated GMM statistic,  $\theta^*$  can be seen as the continuously updated estimator (see Stock and Wright, 2000).

# Application to the NERC

- We conduct inference under the null

$$H_0 : (\phi, \lambda) = (\phi_0, \lambda_0)$$

with  $y_t - E_{H_0}(\rho_T) y_{t-1} = (\rho_t - E_{H_0}(\rho_T)) y_{t-1} + \eta_t$ . So using the moment condition:

$$\text{Cov}(y_t - E_{H_0}(\rho_T) y_{t-1}, y_{t-1}) \underset{H_0}{\approx} 0$$

- We derive the distribution of  $\hat{\rho} - E_{H_0}(\rho_T)$ , where  $\hat{\rho}$  OLS estimator of fixed-coefficient AR(1)
- There exist more efficient tests but they suffer from
  - low power against an explosive alternative (LM test in McCabe & Tremayne, 1995, Distaso, 2008, see Nagakura, 2009)
  - nuisance parameters ( $\sigma_\eta^2$  in Berkes et al, 2009)
  - complexity of design (weighted average power, Elliott, Müller & Watson, 2012)

# Asymptotics: OLS

We derive the distribution of  $\hat{\rho}$  in the OLS estimation of

$$y_t = \rho y_{t-1} + v_t$$

**Theorem** there exist  $V \sim N(0, 1)$ ,  $Z \sim (0, 1)$ ,  $V \perp Z$ , s.t.

$$c = \phi + \lambda^2 < 0 : T^{(1+\alpha)/2} (\hat{\rho} - E_{H_0}(\rho_T)) \xrightarrow{L} N(0, 3\lambda^2 - 2c)$$

$$c \geq 0 : T^\alpha (\hat{\rho} - E_{H_0}(\rho_T)) \Rightarrow \lambda \sqrt{c + 2\lambda^2} \frac{V}{Z}$$

- $c < 0$  : similar to Phillips & Magdalinos with additional  $\lambda^2$
- $c \geq 0$  : neither the  $O_p(T^{-1})$  or unit roots or  $O_p(T^{-\alpha} e^{-\phi T^{1-\alpha}})$  of locally explosive models.
  - consistent  $\hat{\rho}$  contrary to non-local explosive models.
  - Similarity w.r.t.  $\alpha \in (0, 1)$  and  $\sigma_\eta^2$ , discontinuity when  $\lambda \rightarrow 0$ .

# Asymptotics: Power

## Corollary

Let the test statistic  $\tau_{0,T}$  for the null  $H_0 : (\phi, \lambda) = (\phi_0, \lambda_0)$  as

$$\tau_{0,T} = \begin{cases} T^{\frac{1+\alpha}{2}} (\hat{\rho} - E_{H_0}(\rho_t)), & \text{if } \phi_0 + \lambda_0^2 < 0; \\ T^\alpha (\hat{\rho} - E_{H_0}(\rho_t)), & \text{if } \phi_0 + \lambda_0^2 \geq 0. \end{cases}$$

Then under  $H_1 : (\phi, \lambda) = (\phi_1, \lambda_1) \neq (\phi_0, \lambda_0)$  and as  $T \rightarrow \infty$

$$\tau_{0,T} \underset{H_1}{=} \begin{cases} O_p \left( T^{\frac{1-\alpha}{2}} \right), & \text{if } \phi_0 + \lambda_0^2 < 0; \\ O_p(1), & \text{if } \phi_0 + \lambda_0^2 \geq 0. \end{cases}$$

Lack of power on the explosive side: an issue of multiple bubbles pointed out by Evans (1991).

# Forecasting

- Most bubble definitions imply some sustain growth  $y_{t+k}/y_t \geq \gamma$ .

## Theorem

(i) For  $(r, s) \in [0, T^{1-\alpha}]^2$ , as  $T \rightarrow \infty$

$$\frac{y_{\lfloor T^\alpha(r+s) \rfloor}}{y_{\lfloor T^\alpha r \rfloor}} \Rightarrow \exp\{\phi s + \lambda(W_{r+s} - W_r)\} + \sqrt{\frac{e^{2cs} - 1}{e^{2cr} - 1}} C$$

where  $C$  is a Cauchy variable, and

(ii) if  $c \geq 0$  and  $s = o(r)$ , as  $(T, r) \rightarrow (\infty, \infty)$

$$P\left(\frac{y_{\lfloor T^\alpha(r+s) \rfloor}}{y_{\lfloor T^\alpha r \rfloor}} \geq \gamma\right) \rightarrow \Phi\left(\frac{\phi s - \log \gamma}{\lambda \sqrt{s}}\right), \quad \Phi \text{ std normal cdf}$$

- Construct confidence intervals for  $P\left(\frac{y_{t+k}}{y_t} \geq \gamma\right)$  using  $(\phi, \lambda)$  not rejected at a given size.

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- 4 Monte Carlo
- 5 **Application to U.S. Housing Prices**

## Revisiting Present Value Models

- Standard in the log-linearized Campbell-Shiller (1987) model to consider cointegration in the absence of a bubble:  $\log \frac{P_t}{D_t} \sim I(0)$  but with  $\log \frac{P_t}{D_t}$  explosive under the alternative (West, 1987; Diba & Grossman, 1988; also Gonzalo & Lee, 1999). Phillips and Yu consider – when  $R_t$  varies – the null

$$\frac{P_t}{D_t} \sim I(1)$$

- Alternatively, under the simplifying assumptions,  $D_t = D_{t-1} + \zeta_t$ ,  $R_t, \zeta_t \sim iid$  then the PV relation with constant ex-post (realized) returns admits the solution

$$\Delta P_t = (1 + R + \delta(R_t - R)) \Delta P_{t-1} - \zeta_t$$

for  $\delta \in [0, 1]$ . Compare with NERC:

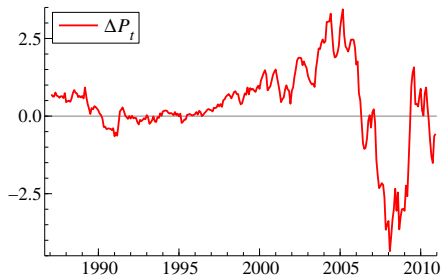
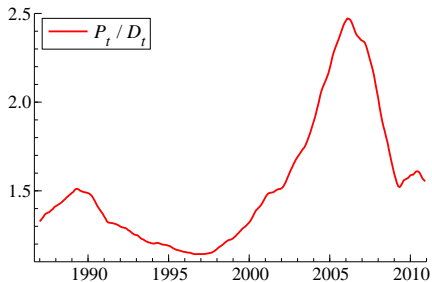
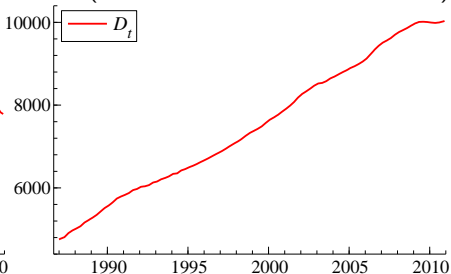
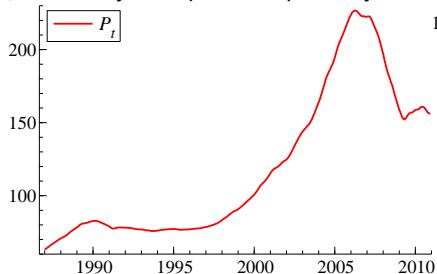
$$\rho_t = 1 + \frac{\phi + \frac{1}{2}\lambda^2}{T^\alpha} + \frac{\lambda}{T^{\alpha/2}} \left( u_t + \lambda \frac{u_t^2 - 1}{2T^{\alpha/2}} \right) + O_p(T^{-2\alpha})$$

here  $\Delta P_t$  can be negative (see Diba and Grossman, 1998).

# Application: Monthly Case-Shiller Housing price

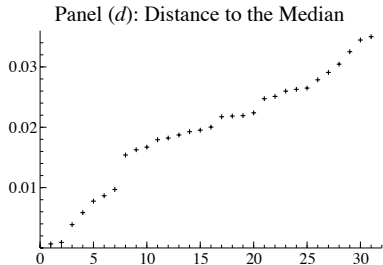
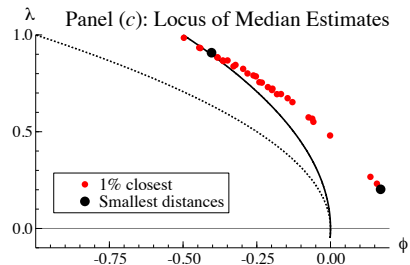
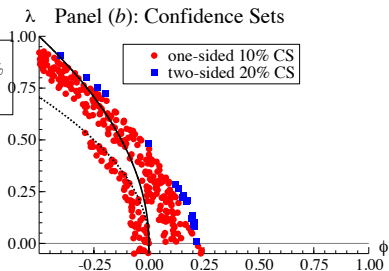
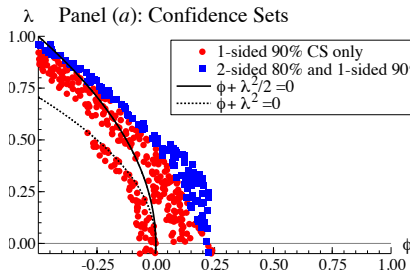
$P_t$  is seasonally adjusted monthly Case-Shiller housing market price

$D_t$  is linearly interpolated quarterly rental data (Davis, Lehnert & Martin, 2008)



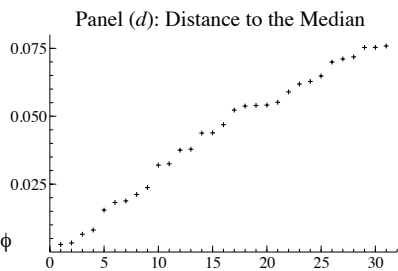
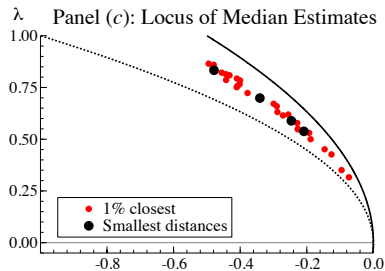
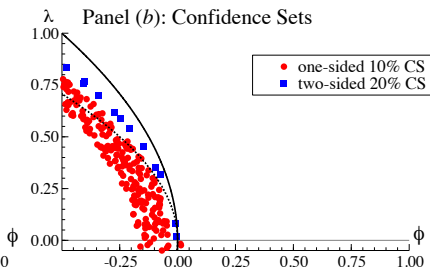
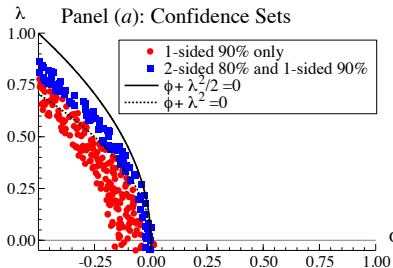
# Inference for $\Delta P$

$$\hat{\rho} = 0.97$$



# Inference for $P/D$

$$\hat{\rho} = 1.00$$



# Inference

two-sided (2S) and one-sided (1S)

2S for GMM-CUE, 1S biased

	Least Rejected $(\phi, \lambda)^*$	Median Estimates $(\phi, \lambda)^+$	Test $(\phi, \lambda) = (0, 0)$ <i>pvalue</i>
$\Delta P_t : \hat{\rho} = 0.97$	1S : $(.05, .01)$ $E[\rho_t^*] = 1.00$	1S : $(.17, .20)$ $E[\rho_t^+] = 1.01$	1S : 0.95
	2S : $(.17, .20)$ $E[\rho_t^*] = 1.01$	2S : $(.17, .20)$ $E[\rho_t^+] = 1.01$	2S : 0.11
$P_t/D_t : \hat{\rho} = 1.00$	1S : $(.51, .02)$ $E[\rho_t^*] = 1.03$	1S : $(-.25, 0.59)$ $E[\rho_t^+] = 1.00$	1S : 0.32
	2S : $(-.25, .59)$ $E[\rho_t^*] = 1.00$	2S : $(-.25, .59)$ $E[\rho_t^+] = 1.00$	2S : 0.64

# Detection of Bubbles

- Consider testing

$$H_0 : \phi + \lambda^2/2 = 0 \quad \text{vs} \quad H_1 : \phi + \lambda^2/2 > 0$$

$$H_0 : E[\rho_t] = 1 \quad \text{vs} \quad H_1 : E[\rho_t] > 1$$

- We test the nulls by drawing 5,000 parameter combinations of  $\theta = (\phi, \lambda)$  and compute the **max**  $p$ -value; rejection occurs if

$$\text{max } p\text{-value} < \text{nominal size}$$

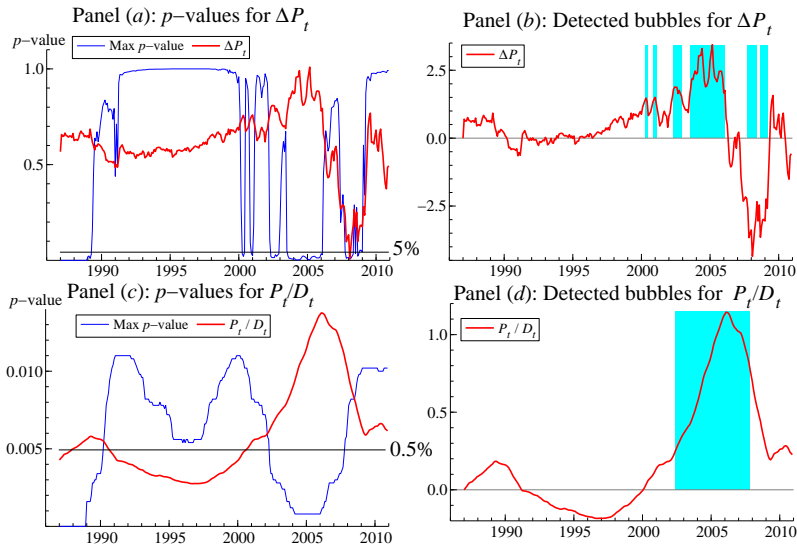
i.e. if there is no  $\theta$  such that  $H_0$  is not rejected.

- We proceed recursively over increasing samples (burn-in of 24 obs). Bonferroni-type size correction for  $P_t/D_t$  as in Phillips-Yu.

# Bubble Detection

$\Delta P_t$ : turning points in 04/2000 and 03/2006; downward bubble 10/2007-11/2008

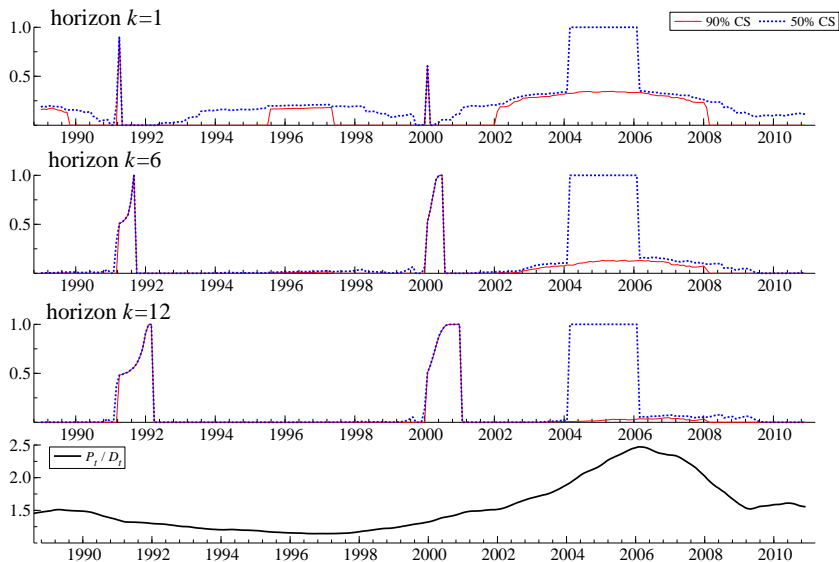
$P_t/D_t$ : 05/2002-11/2007





# Bubble Forecasting

We compute confidence intervals for  $P\left(\frac{y_{t+k}}{y_t} \geq \frac{y_t}{y_{t-k}}\right)$  for horizons  $k \ll t$ .  $\Delta P_t$  too volatile.



# Conclusions

- We used a model for possibly explosive time series
  - flexible random coefficient model that allows multiple bubbles
  - local asymptotics to improve power
  - method of inference that is slightly liberal
  - Application to bubble detections
- Possible Extensions
  - Allow for  $u_t$  non-iid
  - multivariate model for spillovers