

# Learning about Risk and Return: A Simple Model of Bubbles and Crashes

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## Role of Risk in Financial Bubbles:

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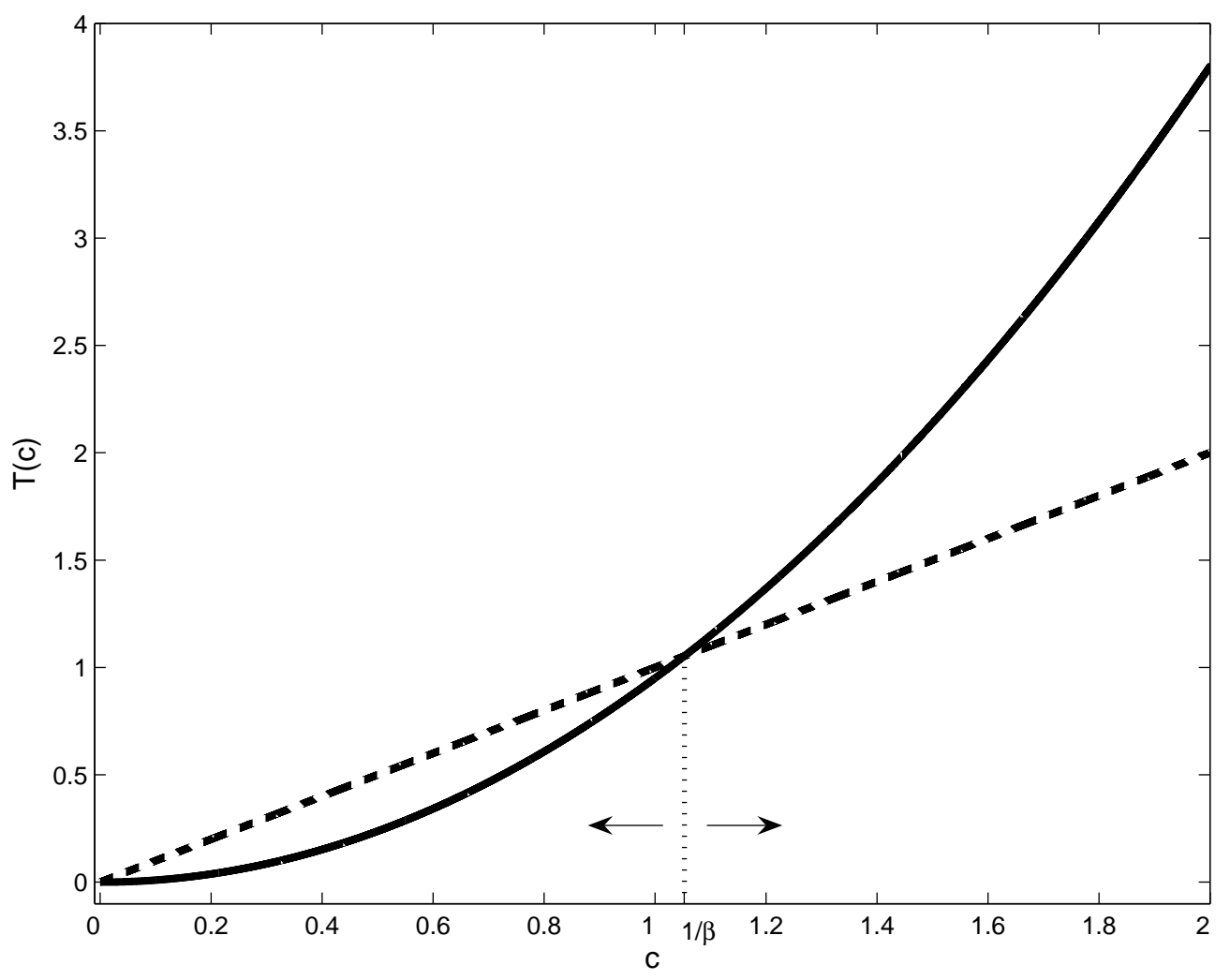
Risk-neutral asset-pricing model:

$$p_t = \alpha + \beta E_t p_{t+1} + \beta d_t$$

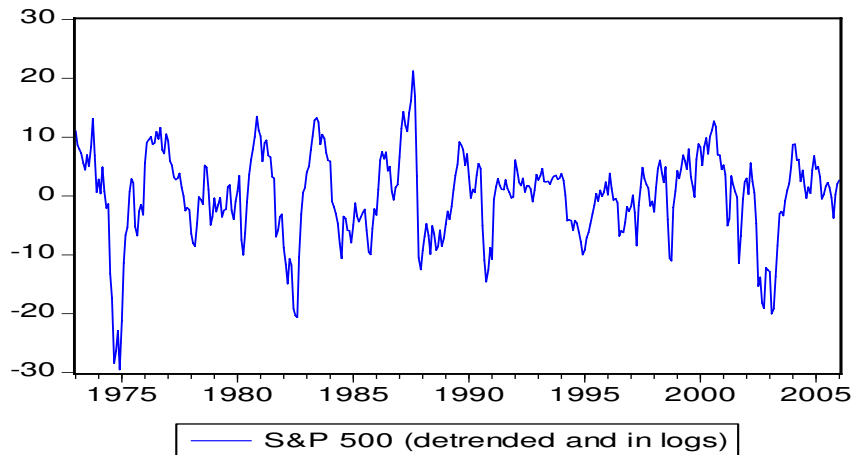
has rational expectations solutions of form:

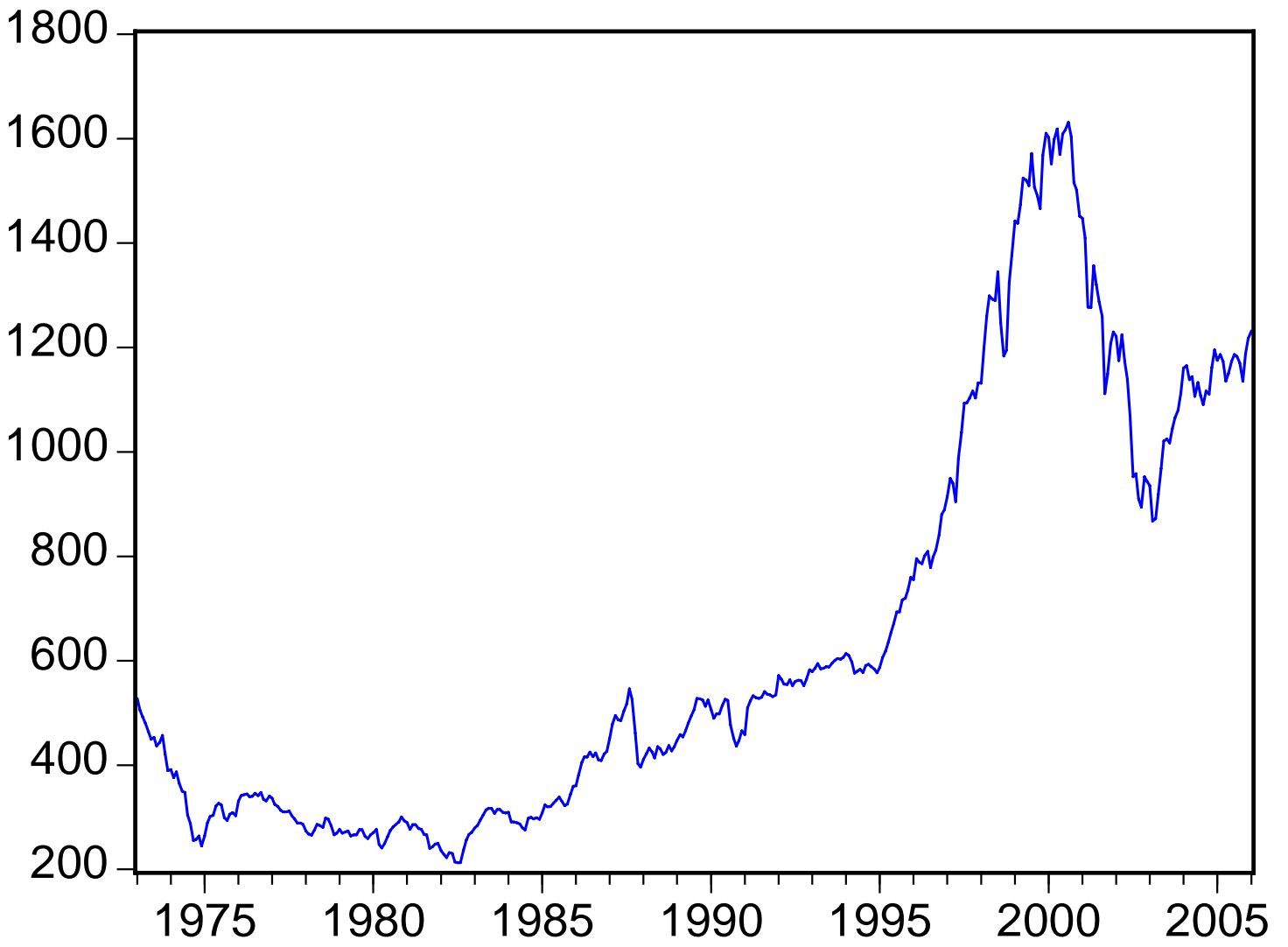
$$p_t = a + b p_{t-1} + c d_t + f \xi_t$$

Fundamentals:  $b = 0, f = 0$  Bubbles:  $b = \beta^{-1} > 1 \Rightarrow$  explosive.

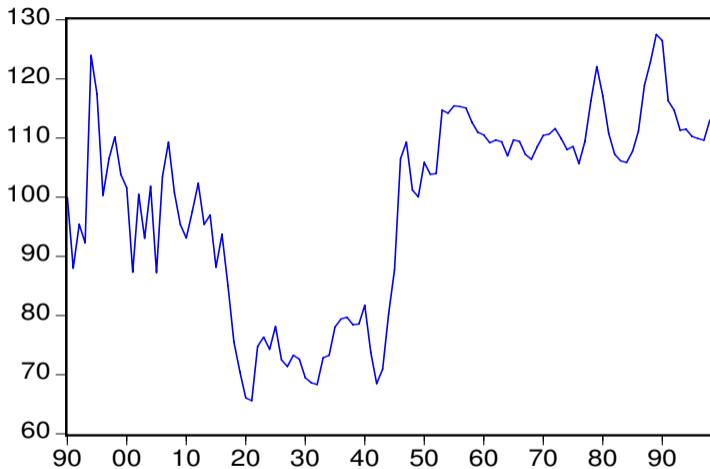


But, bubbles seem to exist...(?)

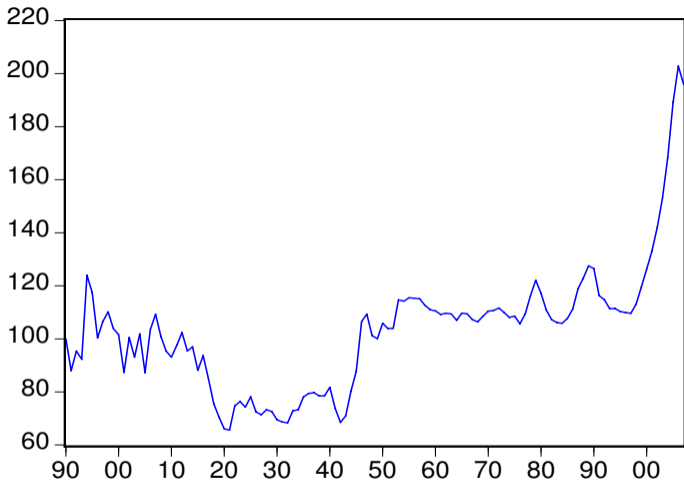




— S&P 500

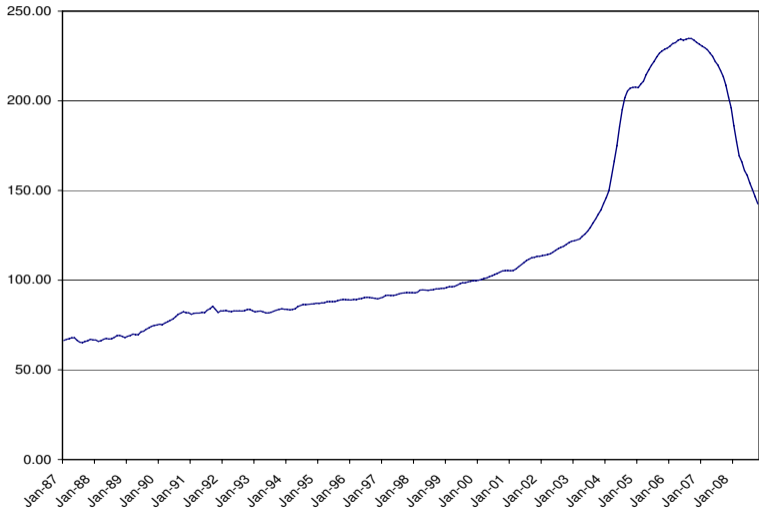


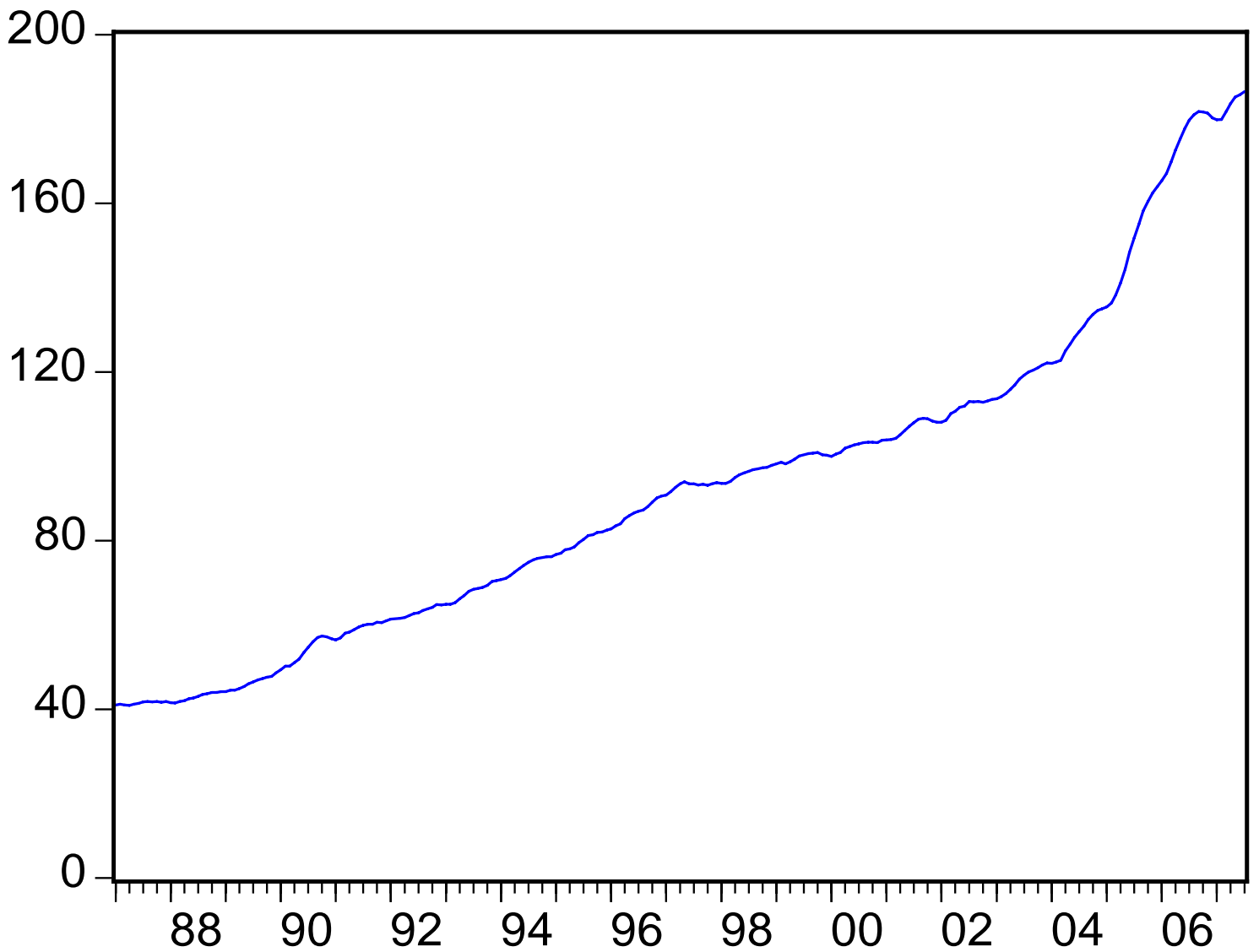
— (real) U.S. home prices 1870-1998



— REALPRICE

Las Vegas Home Prices





— Portland, OR Home Prices (Case-Shiller)

## This paper:

- ▶ Takes a simple asset pricing model with linear demand for the risky asset and risk-aversion.
- ▶ Risk-aversion implies asset price depends on expected conditional variance of net returns. But, bubbles REE is still unstable under least squares learning.
- ▶ Constant gain learning version of the model:
  - ▶ creates drift that causes agents' to occasionally believe stock prices follow a random walk: perceive shocks to be permanent;
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- ▶ Our story: risk, combined with adaptive learning, leads to recurring bubbles and crashes.

# Model

- ▶ Risky asset yields dividends  $\{y_t\}$ , trades at price  $p_t$ .
- ▶ Risk free asset pays  $R = \beta^{-1} > 1$ .
- ▶ Mean-variance setting yields demand for risky asset

$$z_{dt} = \frac{E_t^* (p_{t+1} + y_{t+1}) - \beta^{-1} p_t}{a\sigma_t^2}$$

where  $\sigma_t^2$  is agents' cond'l expect. of  $p_{t+1} + y_{t+1}$ .

## Model (cont.)

In equilibrium,  $z_{st} = z_{dt}$ , implies

$$p_t = \beta \hat{E}_t (p_{t+1} + y_{t+1}) - \beta a \sigma^2 z_{st} \quad (1)$$

Assume

$$\begin{aligned} y_t &= y_0 + u_t \\ z_{st} &= \{\min(s_0, \Phi p_t)\} \cdot (1 + v_t) \\ \sigma^2 &= \hat{Var}_t (p_{t+1} + y_{t+1} - R p_t) \end{aligned}$$

where  $v_t, u_t$  uncorrelated white noise shocks,  $\Phi = 10s_0/\bar{p}$ .

$z_{st}$  is share supply which is:

- ▶ exogenous (constant plus white noise);
- ▶ or, endogenous when price falls to 10% of its fundamental value

**Definition.** A *Rational Expectations Equilibrium* is a solution to (1).

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# Stability under learning

- ▶ To study E-stability, posit a perceived law of motion (PLM)

$$p_t = k + cp_{t-1} + \varepsilon_t$$

Forming  $E_t p_{t+1} = k(1+c) + c^2 p_{t-1}$  leads to the actual law of motion (ALM)

$$p_t = T(k, c)'(1, p_{t-1})' - \beta a \sigma^2 v_t, \quad s_0 \leq \Phi p_t$$

where  $T(k, c) = (\beta[y_0 + k(1+c) - a\sigma^2 s_0], \beta c^2)'$ .

- ▶ But,  $\sigma^2$  is an equilibrium object. Thus, also need to pin down

$$\sigma^2 = E_t (p_{t+1} - E_t p_{t+1} + y_{t+1} - E_t y_{t+1})^2$$

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# Stability of REE

Define  $\theta_t = (k_t, c_t)'$ ,  $X_t = (1, p_{t-1})$ . We assume learning takes place via the recursive algorithm

$$\theta_t = \theta_{t-1} + \gamma_{1,t} R_t^{-1} X_t (p_t - \theta'_{t-1} X_t)$$

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$\gamma_{1,t}, \gamma_{2,t}$  are gain sequences, usually  $\gamma_t > 0, \sum_{t \geq 0} \gamma_t = \infty$ .

Question of interest: what is the asymptotic behavior of  $\theta_t, \sigma_t$ ?

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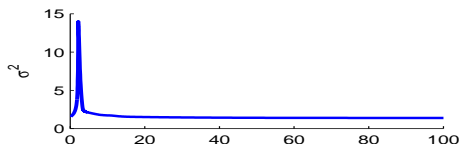
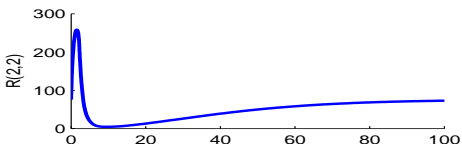
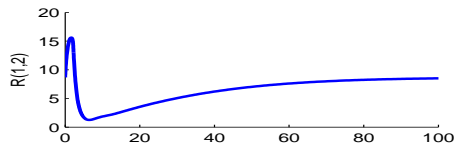
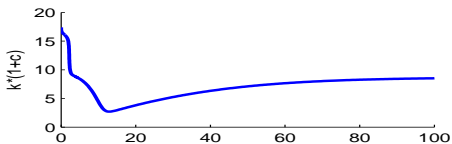
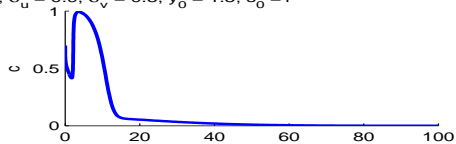
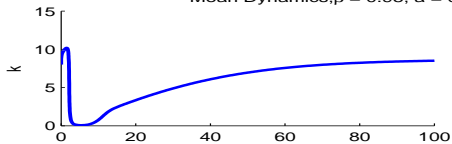
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## REE Stability Result

1. The fundamentals REE is stable under adaptive learning provided  $0 < \beta < 1$  and  $0 < \sigma^2 < 1/2\beta a\sigma_v^2$ . The bubbles REE is unstable under adaptive learning.
2. As  $\gamma \rightarrow 0$ , constant gain learning dynamics weakly converge to the solution of the ODE.

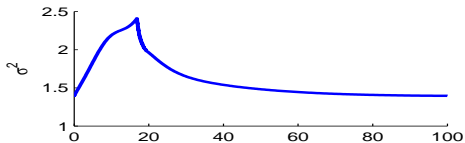
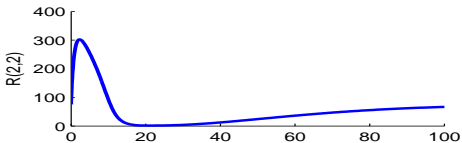
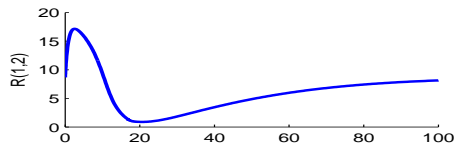
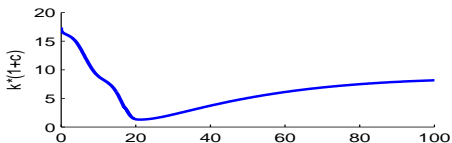
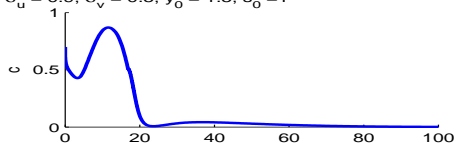
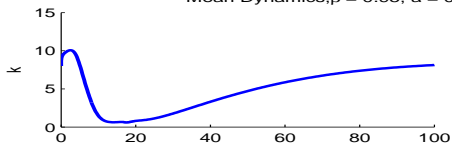
# Mean Dynamics suggest occasional escapes to random walk like behavior:

Mean Dynamics,  $\beta = 0.95$ ,  $a = 0.75$ ,  $\sigma_u^2 = 0.9$ ,  $\sigma_v^2 = 0.5$ ,  $y_0 = 1.5$ ,  $s_0 = 1$



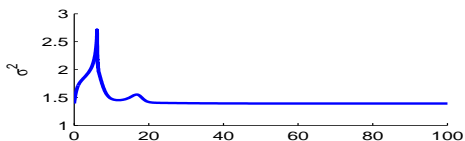
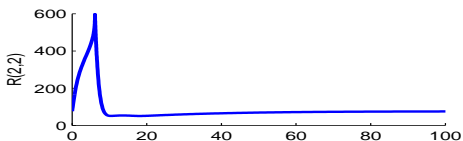
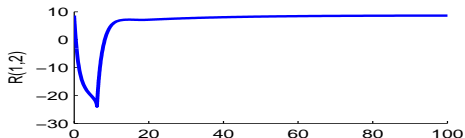
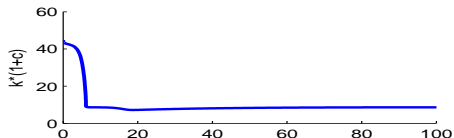
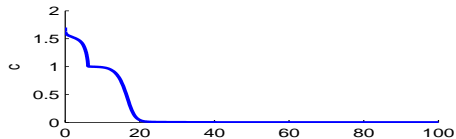
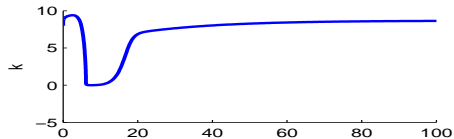
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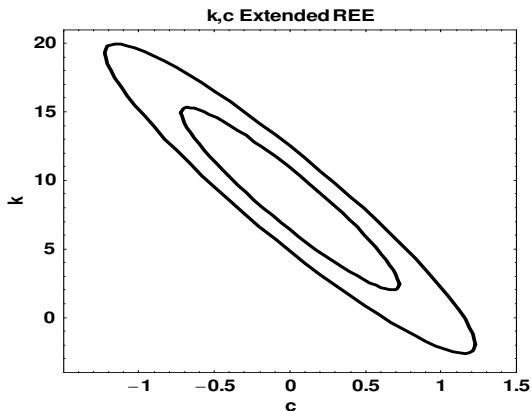
# Endogenous Projection Facility:

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## Intuition for escapes I.

Confidence ellipses around fundamentals REE are pointed toward a random walk:



## Intuition for escapes II.

- ▶ Random walk beliefs, lag coeff  $\rightarrow 1$ , implies PLM:

$$p_t = \frac{1}{1-L}\varepsilon_t \equiv g(L)\varepsilon_t$$

- ▶ So ALM becomes

$$p_t = \mu + f(L)\nu_t,$$

$$f(L) = \beta a \sigma^2 (1 - \beta L)^{-1}.$$

- ▶ As Sargent notes:
  1. Random walk beliefs introduce serial correlation.
  2. Random walk beliefs track constants well, so use higher-order moments to track low frequency movements.  
Risk induces drift in constant.
- ▶ Mean dynamics show that  $\sigma^2$  triggers “escapes”

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# Numerical Simulations

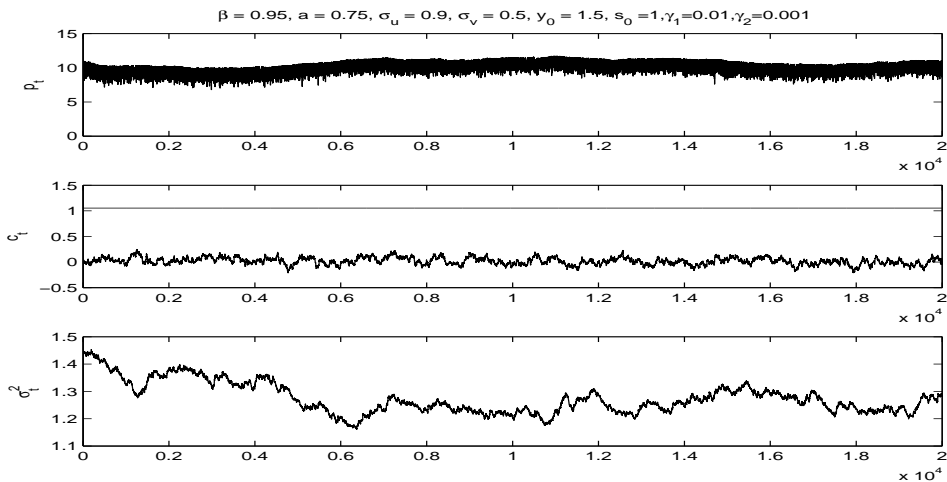
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- ▶ Choose parameters  
 $\beta = .95, a = .75, \sigma_v^2 = .5, \sigma_u^2 = 0.9, y_0 = 1.5, s_0 = 1.$

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# Small Gains

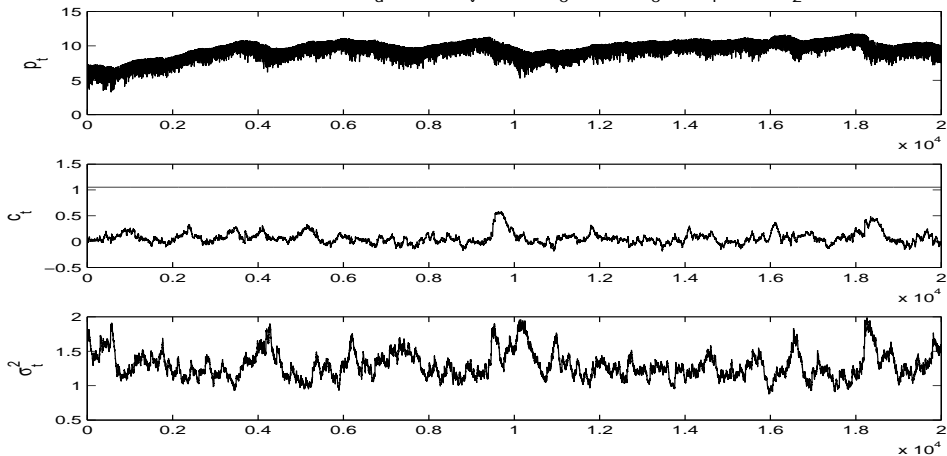
Figure: Constant gain learning with  $\gamma_1 = .01, \gamma_2 = .001$ .



# Start to see serial correlation

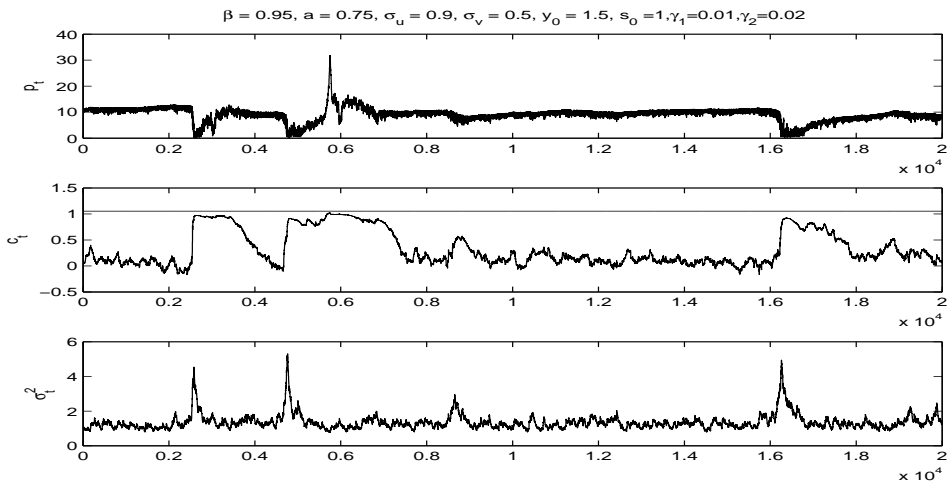
Figure: Constant gain learning with  $\gamma_1 = \gamma_2 = .01$ .

$\beta = 0.95, a = 0.75, \sigma_u = 0.9, \sigma_v = 0.5, y_0 = 1.5, s_0 = 1, \gamma_1 = 0.01, \gamma_2 = 0.01$



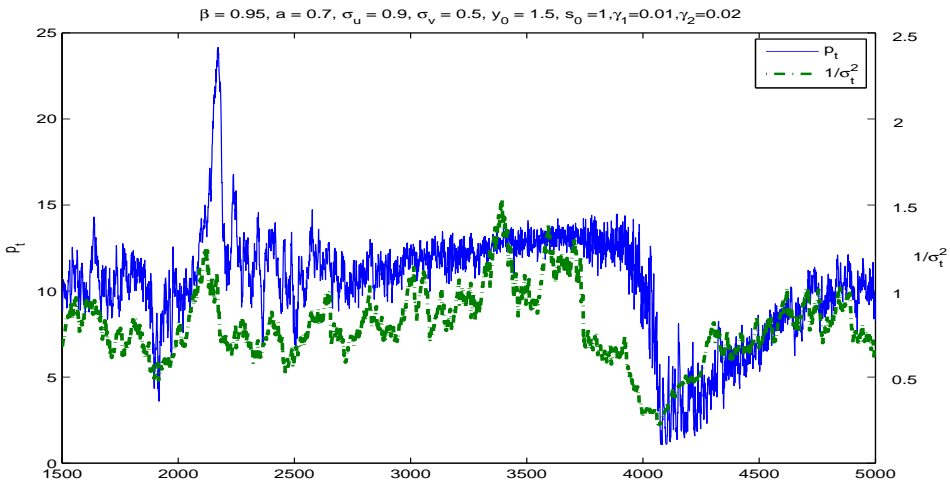
# Bubbles and Crashes

Figure: Constant gain learning with  $\gamma_1 = .01, \gamma_2 = .02$ .



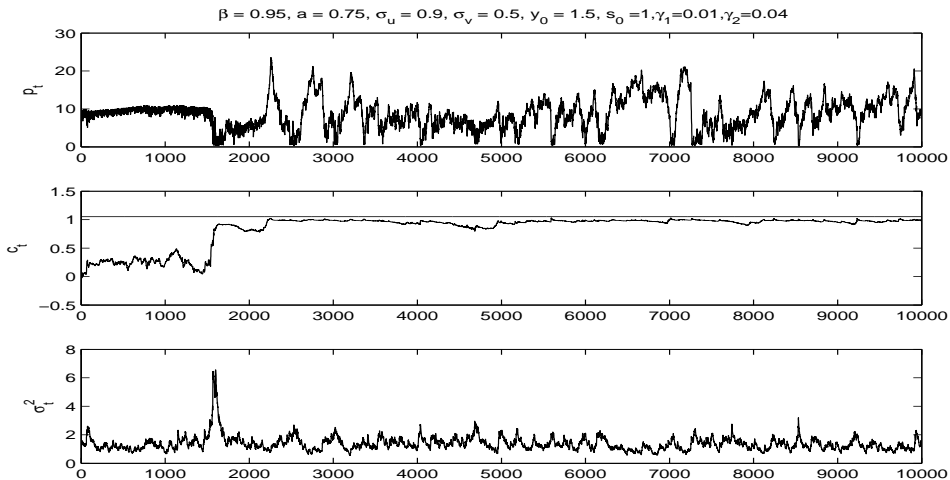
# Bubbles and Crashes: Risk

Figure: Comparing price with inverse of risk,  $1/\sigma_t^2$



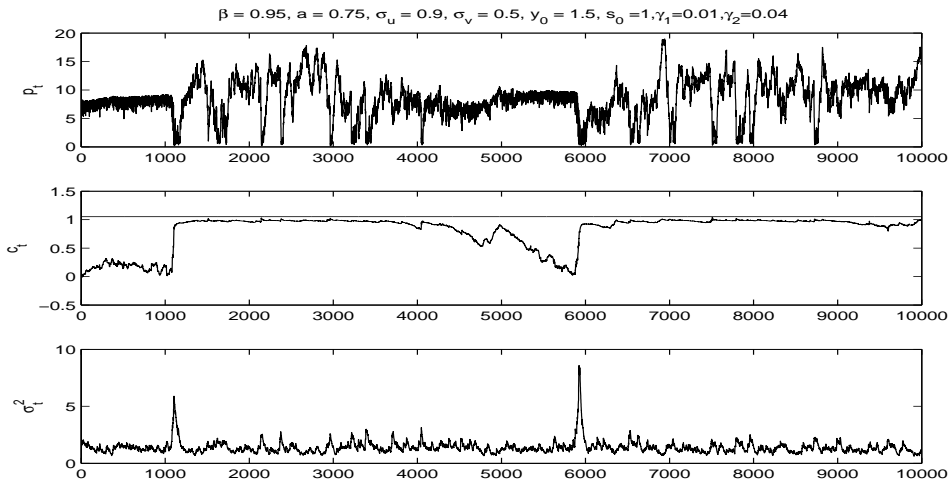
# Bubbles and Crashes

Figure: Constant gain learning with  $\gamma_1 = .01, \gamma_2 = .04$ .



# Bubbles and Crashes

Figure: Constant gain learning with  $\gamma_1 = .01, \gamma_2 = .04$ .



## Detecting Bubbles

- ▶ Literature on testing bubbles work with regressions like

$$p_t = a + by_t + u_t$$

and look for unit roots in the residuals  $u_t$ . Periodically collapsing bubbles, though, will fail unit root tests. (Recursive unit root tests of Phillips, Wu, Yu (2007) an exception.)

- ▶ Recursive Estimates Statistic of Wu and Xiao: Look for exploding segments of time-series:

$$\max_{k=1, \dots, n} \frac{k}{\sqrt{n}} \left| \frac{1}{k} \sum_{t=1}^k \hat{u}_t - \frac{1}{n} \sum_{t=1}^n \hat{u}_t \right|$$

- ▶ Simulate model for 15000 periods, storing last 1000 or 100 periods, estimate Augmented Dickey-Fuller and Recursive Statistic, repeat 1000 times.

Gain Parameters	Simulation Length:			
	1000		100	
	RES	ADF	RES	ADF
$\gamma_1 = .001, \gamma_2 = .001$	0.024	0.000	0.0000	0.000
$\gamma_1 = .01, \gamma_2 = .01$	0.8760	0.0040	0.0220	0.000
$\gamma_1 = .01, \gamma_2 = .04$	0.980	0.0210	0.8340	.0640

## Conclusion:

- ▶ Asset pricing models should incorporate learning about risk and return.
- ▶ Suggests a story for bubbles:
  - ▶ Stock price “usually” near its fundamentals value
  - ▶ Occasional shocks cause agents to lower their risk estimates
  - ▶ This causes them to mistakenly think that recent price innovations are permanent
  - ▶ Bid up stock prices, bubble ensues.
  - ▶ Eventually, though risk estimates increase, thereby crashing the bubble.