An econometric analysis of the Blanchard-Watson bubble model

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Søren Johansen and Theis Lange

University of Copenhagen and CREATES

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The paper by Blanchard and Watson (1982) investigates the nature and the presence of bubbles in financial markets and whether the presence of bubbles in a particular market can be detected statistically.

The purpose of the present paper is to analyse a simple bubble model suggested by Blanchard and Watson as a statistical model.

We want

- to find conditions for stationarity and infinite variance of the process
- discuss the behavior of the least squares autoregressive estimator

The question we want to discuss is whether a bubble model can create the long swings, or persistence, which are observed in many macro variables.

Let ho > 1

$$y_t = s_t \rho y_{t-1} + \varepsilon_t, \ t = 1, \ldots, N,$$

 s_t is i.i.d. binary (0, 1) variables with $p = P(s_t = 1) = 1 - q$ ε_t is i.i.d. $(0, \sigma^2)$ and $\{s_t\}$ independent of $\{\varepsilon_t\}$. y_t is explosive when $s_t = 1$ and the bubble bursts when $s_t = 0$ Persistence of y_t is defined to mean that

$$\hat{
ho}_{T} = rac{\sum_{t=1}^{T} y_{t} y_{t-1}}{\sum_{t=1}^{T} y_{t-1}^{2}}$$

is close to one

The question raised by Frydman and Goldberg (2007) is if this model can create long swings, or persistence, when the variance of y_t is infinite. Comments on the model

Plot of bubble process, rho = 1.10, p = 0.95





Figure: Median of 200 simulations of $\hat{\rho}_n$ for N = 10.000 as function of p. For values of $\rho = (1.002, 1.016, 1.032, 1.050)$. For $p < \rho^{-2} = (0.996, 0.968, 0.938, 0.907)$ $\hat{\rho}_n \approx p\rho$. For $p > \rho^2$ the limit is equal to ρ^{-1} , so that $\hat{\rho}_n \xrightarrow{P} \min(p\rho, \rho^{-1})$.

Properties of the process y_t

The model

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

Lemma

Let $\rho > 1$, then y_t is stationary if p < 1.

- If p
 ho < 1, the mean is finite and equal zero
- If $p\rho^2 < 1$ the variance is finite and equal to $\sigma^2/(1-p\rho^2)$.
- If $p\rho^2 > 1$ the variance is infinite.

The proof applies the drift criterion.

Although the process is explosive in the intervals where $s_t = 1$, it collapses to ε_t if $s_t = 0$, and the bubble bursts. It is this repeated collapse that creates a stationary process, which starts each period in a new ε .

But, what happens to the autoregressive estimator?

Description of y_t , its product moments, and the estimator

Burst times are increasing $0 = T_0^* < T_1^* < T_2^* < \cdots < T_n^* \le N$ Burst lengths $T_i = T_i^* - T_{i-1}^*$ have geometric distribution $P(T_i = m) = p^{m-1}q, m = 1, 2, \ldots$ For the first period $t = 0, 1, \ldots, T_1 - 1$ we have

$$y_{t} = \sum_{\nu=0}^{t} \rho^{t-\nu} \varepsilon_{\nu} = \rho^{t} \varepsilon_{0} + \rho^{t-1} \varepsilon_{1} + \dots + \varepsilon_{t} = \rho^{t} \sum_{\nu=0}^{t} \rho^{-\nu} \varepsilon_{\nu}$$
$$y_{t} = \rho^{t} \sum_{\nu=0}^{T_{1}-1} \rho^{-\nu} \varepsilon_{\nu} - \rho^{-1} \sum_{\nu=0}^{T_{1}-t-2} \rho^{-\nu} \varepsilon_{\nu+1+t} = \rho^{t} Z_{1} + \dots$$



Similar expressions can be found for the i'th period leading to an analysis of the estimator

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$$\hat{\rho}_{n} = \frac{\sum_{t=1}^{T_{n}^{*}} y_{t} y_{t-1}}{\sum_{t=1}^{T_{n}^{*}} y_{t-1}^{2}} \approx \frac{\sum_{i=1}^{n} \rho \frac{\rho^{2(T_{i}-1)}-1}{\rho^{2}-1} Z_{i}^{2}}{\sum_{i=1}^{n} \frac{\rho^{2T_{i}}-1}{\rho^{2}-1} Z_{i}^{2}}$$
$$= \rho \frac{\sum_{i=1}^{n} (\rho^{2(T_{i}-1)}-1) Z_{i}^{2}}{\sum_{i=1}^{n} (\rho^{2T_{i}}-1) Z_{i}^{2}} = \rho \frac{\sum_{i=1}^{n} \rho^{2(T_{i}-1)} Z_{i}^{2}}{\sum_{i=1}^{n} \rho^{2T_{i}} Z_{i}^{2}} = \rho^{-1}$$

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The asymptotic properties of $\hat{\rho}_n$

The finite variance case

Theorem

For p<1 (stationarity), $p\rho^2<1$ (variance finite) and $E(\epsilon_t^4)<\infty$ we have

$$\begin{split} \hat{\rho}_n &\xrightarrow{P} p\rho, \\ n^{1/2} (\hat{\rho}_n - p\rho) &\xrightarrow{d} N(0, \Sigma), \end{split}$$

where
$$\Sigma = q([pq\rho^2 E(y_{t-1}^4) + \sigma^2 E(y_{t-1}^2)] / E(y_{t-1}^2)^2$$
.

Calculation

$$\begin{array}{lcl} E(y_{t}y_{t-1}) & = & E((s_{t}\rho y_{t-1} + \varepsilon_{t})y_{t-1}) = p\rho E(y_{t-1}^{2}) \\ \\ \frac{E(y_{t}y_{t-1})}{E(y_{t-1}^{2})} & = & p\rho \end{array}$$

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The infinite variance case

Theorem

For p < 1 (stationarity), $p\rho^2 > 1$ (infinite variance) and $E(\varepsilon_t^4) < \infty$ we have $\hat{\rho}_n \xrightarrow{P} \rho^{-1}$.

Discussion of one difficulty and two tricks

$$\hat{\rho}_n = \frac{\sum_{t=1}^{T_n^*} y_t y_{t-1}}{\sum_{t=1}^{T_n^*} y_{t-1}^2} = \frac{\sum_{i=1}^n \rho \frac{\rho^{2(T_i-1)}-1}{\rho^2-1} Z_i^2 + \dots}{\sum_{i=1}^n \frac{\rho^{2T_i-1}}{\rho^2-1} Z_i^2 + \dots}$$

Difficulty: We want the order of magnitude of the main term $\sum_{i=1}^{n} \rho^{T_i} Z_i^2$.

Introduction of exponential waiting times

Trick 1: Let U_i be an exponential variable with parameter $\lambda = -\log p$ so that $P(U \ge x) = e^{-\lambda x} = p^x$ Define the waiting time $T_i = [U_i] + 1$ then $P(T_i = m) = qp^{m-1}$

$$\sum_{i=1}^{n} \rho^{2U_i} Z_i^2 \leq \sum_{i=1}^{n} \rho^{2T_i} Z_i^2 \leq \rho^2 \sum_{i=1}^{n} \rho^{2U_i} Z_i^2.$$

Let $\alpha = -\log p / \log \rho < 2$. The tail index, $\alpha/2$, of ρ^{2U} is defined by

$$P(\rho^{2U} > x) = e^{-\frac{\lambda \log x}{2\log \rho}} = x^{\frac{\log p}{2\log \rho}} = x^{-\alpha/2}$$

For independent $W>0,~E(W^{\alpha})<\infty,$ the tail index of $\rho^{2U}W^2$ is also $\alpha/2:$

 $P(\rho^{2U}W^2 > x) = E[P(\rho^{2U}W^2 > x)|W)] = E(x/W^2)^{-\alpha/2} = x^{-\alpha/2}E(W^{\alpha})$ and then, Feller (1971, Chapter IX, Section 8),

$$\sum_{i=1}^{n} \rho^{2U_i} W_i^2 = O_P(n^{2/\alpha})$$

Trick 2

Because Z_i is not independent of T_i or U_i we use another idea

$$Z_1 = \sum_{\nu=0}^{T_1-1} \rho^{-\nu} \varepsilon_{\nu} = \sum_{\nu=0}^{\infty} \rho^{-\nu} \varepsilon_{\nu} - \sum_{\nu=T_1}^{\infty} \rho^{-\nu} \varepsilon_{\nu}$$
$$= \sum_{\nu=0}^{\infty} \rho^{-\nu} \varepsilon_{\nu} - \rho^{-T_1} \sum_{\nu=0}^{\infty} \rho^{-\nu} \varepsilon_{\nu+T_1} = Z_1^* + Z_1^{**}$$

because $\sum_{\nu=0}^{\infty} \rho^{-\nu} \varepsilon_{\nu}$ is independent of T_1 and the remainder $O_P(\rho^{-T_1})$. Then the order of magnitude of $\sum_{i=1}^{n} \rho^{2T_i} Z_i$ is the order of magnitude of

$$\sum_{i=1}^n \rho^{2U_i} Z_i^*$$

which is given by Feller (1971, Chapter IX, Section 8) as $n^{2/\alpha}$.

The statistical analysis of the simple bubble model

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

shows two results which appear a bit surprising

- The process y_t is stationary of p < 1
- The autoregressive estimator converges to $\min(p\rho, \rho^{-1})$

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