Real-time detection of bubbles and crashes

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Introduction

- Asset price bubbles and crashes are a prevalent feature in economic and financial markets.
- The global financial crisis highlighted the impact of asset price bubbles on financial stability.
- Bernanke (2013) - It is unavoidable that there will be bubbles in the financial system and it is crucial that their emergence is taken seriously.
- Emphasised the need for improved econometric techniques to detect bubbles.
- Rational bubble literature: we can model asset bubbles as explosive autoregressive processes - Blanchard and Watson (1982), Campbell and Shiller (1987, 1989).

$$y_t = \phi y_{t-1} + \epsilon_t, \qquad \phi > 1$$

Introduction

- Historical detection of explosive bubble episodes: Phillips, Wu and Yu (2011), Phillips, Shi and Yu (2015), Homm and Breitung (2012), Harvey, Leybourne and Sollis (2015), Whitehouse (2019).

- For empirical researchers and policy-makers, a key area of interest is the detection of ongoing bubbles in a real time monitoring exercise: Astill et al (2017).

- Real time monitoring requires the sequential application of a test as new data becomes available, and is therefore subject to the multiple testing problem whereby the overall size of the procedure is inflated and unknown.

- Astill et al (2018) [AHLST] propose a real time monitoring procedure for bubbles, where the 'false positive rate' of the procedure can be determined at any monitoring horizon.

Introduction

- An equally important problem to real time monitoring of bubbles is monitoring for the subsequent bubble collapse.
- Harvey et al (2016) and Phillips and Shi (2018) model a bubble crash as a stationary process.
- We propose a real time monitoring procedure for stationary crashes, in which crash detection is conditional on having first detected a bubble.
- Our procedure relies on the sequential application of test statistics constructed from the first differences of the price series.
- Our procedure has desirable asymptotic properties in terms of its ability to rapidly detect a crash while never detecting earlier than it occurs.

Bubble and crash DGP

- Consider the following DGP:

$$
\begin{aligned}
y_t &= \mu + u_t \\
u_t &= \begin{cases} u_{t-1} + \epsilon_t & t = 2, ..., \lfloor \tau_1 T \rfloor \\ (1+\delta_1)u_{t-1} + \epsilon_t & t = \lfloor \tau_1 T \rfloor + 1, ..., \lfloor \tau_2 T \rfloor \\ (1-\delta_2)u_{t-1} + \epsilon_t & t = \lfloor \tau_2 T \rfloor + 1, ..., \lfloor \tau_3 T \rfloor \\ u_{t-1} + \epsilon_t & t = \lfloor \tau_3 T \rfloor + 1, ..., T \end{cases}
\end{aligned}
$$

with $\epsilon_t \sim iid(0,1)$, $u_1 = \beta + \epsilon_1$, $0 < \tau_1 \leq \tau_2 \leq \tau_3 \leq 1$, $\delta_1 > 0$ and $0 < \delta_2 < 1$.

- First stage: test for an explosive bubble.

$$H_0^{(1)} : \tau_1 = 1 \quad H_1^{(1)} : \tau_1 < \tau_2 \leq 1$$

- Second stage: test for a stationary crash.

$$H_0^{(2)} : \tau_1 < \tau_2 = 1 \quad H_1^{(2)} : \tau_1 < \tau_2 < 1$$

Explosive Bubble Detection

- We use the AHLST test statistic for explosive bubble detection, computed over rolling sub-sample windows of size k:

$$A_{e,k} = \frac{\sum_{t=e-k+1}^{e} (t-e+k)\Delta y_t}{\sqrt{\sum_{t=e-k+1}^{e} \{(t-e+k)\Delta y_t\}^2}}.$$

where e is the last observation used in the statistic's calculation.

- Motivated by a Taylor series expansion of Δy_t during the explosive regime.

Real Time Monitoring Algorithm

- Suppose that we wish to start monitoring for a bubble at the present time period, $t = T^\dagger$.

- We choose the finite window length, k, and let $t = 1, ..., T^*$ where $T^* = T^\dagger - k$, form an initial training sample.

- We compute the test statistic, $A_{e,k}$, over rolling sub-samples of length k, producing a set of training sample statistics.

- The maximum training sample statistic $A^*_{\max} = \max_{e \in [k+1, T^*]} A_{e,k}$ forms the critical value for explosive bubble detection.

Real Time Monitoring Algorithm

- Monitoring begins at the present time period, $t = T^{\dagger}$, using data from $t = T^{*} + 1, ..., T^{*} + k$.

- Subsequent monitoring statistics are computed as each new observation occurs, rolling forward the window of k observations.

- Detection of an explosive regime is triggered at the first point where a monitoring statistic, $A_{e,k}$, exceeds the critical value, $A^{*}_{\max}$, i.e.

$$\text{Detect } H_1^{(1)} \text{ at time } e \text{ if } A_{e,k} > A^{*}_{\max}.$$

- The time period at which an explosive regime is detected is then denoted $t = T^{\diamond}$.

- We refer to this explosive bubble monitoring procedure as $A_{MAX}(k)$.

Asymptotic Results - Explosive Bubble Monitoring

We can establish the theoretical false positive rate (FPR) of $A_{MAX}(k)$ under $H_0^{(1)}$ for an arbitrary point in the monitoring period $t = T'$.

Theorem 1. *Under $H_0^{(1)}$ and assuming that $\{\varepsilon_t\}$ satisfies the mixing conditions of Ferreira and Scotto, 2002, p. 476, then as $T \to \infty$,*

$$\lim_{T\to\infty} P\left(\max_{e\in[T^*+k,T']} A_{e,k} > \max_{e\in[k+1,T^*]} A_{e,k}\right) = \alpha$$

where

$$\alpha = \lim_{T\to\infty}\left(\frac{T'-T^*-k+1}{T'-2k+1}\right) = \lim_{T\to\infty}\left(\frac{T'-T^*}{T'}\right).$$

Stationary Crash Detection

- If an explosive bubble is detected by $A_{MAX}(k)$, we now want to monitor for the termination of that bubble and the onset of a stationary crash.

- We now motivate a test statistic for distinguishing between $H_0^{(2)}$ and $H_1^{(2)}$.

Stationary Crash Detection

- Consider the DGP expressed in first differences:

$$\Delta y_t = \begin{cases} \varepsilon_t & t = 2, ..., \lfloor \tau_1 T \rfloor \\ \delta_1 u_{t-1} + \varepsilon_t & t = \lfloor \tau_1 T \rfloor + 1, ..., \lfloor \tau_2 T \rfloor \\ -\delta_2 u_{t-1} + \varepsilon_t & t = \lfloor \tau_2 T \rfloor + 1, ..., \lfloor \tau_3 T \rfloor \\ \varepsilon_t & t = \lfloor \tau_3 T \rfloor + 1, ..., T \end{cases} .$$

- We can consider the observations in the immediate neighbourhood of $\lfloor \tau_2 T \rfloor$.

- Specifically, a finite number m of observations on Δy_t up to $\lfloor \tau_2 T \rfloor$, and a finite number n of observations on Δy_t immediately after $\lfloor \tau_2 T \rfloor$.

Stationary Crash Detection

- Given the presence of an explosive regime ($\delta_1 > 0$), the onset of a stationary crash ($\delta_2 > 0$) implies a change in the mean of Δy_t from a positive value β_1 to a negative value β_2 at time $\lfloor \tau_2 T \rfloor + 1$.

- Consider simple OLS estimators of β_1 and β_2 over the two respective sub-samples i.e.:

$$\hat{\beta}_1 = m^{-1} \sum_{t=\lfloor \tau_2 T \rfloor - m + 1}^{\lfloor \tau_2 T \rfloor} \Delta y_t$$

$$\hat{\beta}_2 = n^{-1} \sum_{t=\lfloor \tau_2 T \rfloor + 1}^{\lfloor \tau_2 T \rfloor + n} \Delta y_t$$

- We can motivate a statistic for detecting a change from explosive to stationary crash behaviour at time $\lfloor \tau_2 T \rfloor + 1$ based on the sign of the product $\hat{\beta}_1 \hat{\beta}_2$.

Stationary Crash Detection

- We therefore propose the new crash detection statistic:

$$S_{e,m,n} = \frac{\sum_{t=e-n-m+1}^{e-n} \Delta y_t \sum_{t=e-n+1}^{e} \Delta y_t}{\sqrt{\sum_{t=e-n-m+1}^{e-n} \hat{\varepsilon}_t^2 \sum_{t=e-n+1}^{e} (\Delta y_t)^2}}.$$

where the $\hat{\varepsilon}_t^2$ are OLS residuals obtained from a regression of Δy_t on a constant and y_{t-1}.

Real Time Monitoring Algorithm

- The real time monitoring for stationary crash procedure we propose proceeds as follows:

- The $S_{e,m,n}$ statistic is computed over the training sample $t = 1, ..., T^*$ for rolling sub-samples of length $m + n$. The critical value used is the minimum of these training sample statistics, denoted $S^*_{\min}$.

- If the $A_{MAX}(k)$ procedure has signalled the presence of an explosive regime at some time period $t = T^\diamond$, we then switch to monitoring for a crash by computing $S_{e,m,n}$ for $e = T^\diamond + 1, T^\diamond + 2, T^\diamond + 3, ...$

- Detection of a crash is triggered at the first point where the monitoring statistic falls below the critical value, i.e.

$$\text{Detect } H_1^{(2)} \text{ at time } e \text{ if } S_{e,m,n} < S^*_{\min}.$$

- We refer to this stationary collapse monitoring procedure as $S_{MIN}(m, n)$.

Asymptotic Results - Stationary Crash Monitoring

Theorem 2. *Under $H_1^{(2)}$ and assuming that $\{\varepsilon_t\}$ satisfies the mixing conditions of Ferreira and Scotto, 2002, p. 476, then as $T \to \infty$:*

(a) If $e \leq \lfloor \tau_2 T \rfloor$

$$\lim_{T\to\infty} \Pr(S_{e,m,n} < S^*_{\min}) = 0.$$

(b) If $e = \lfloor \tau_2 T \rfloor + j$ *with* $j = 1, ..., n-1$,

$$\lim_{T\to\infty} \Pr(S_{e,m,n} < S^*_{\min}) = \begin{cases} 0 & (1-\delta_2)^j > (1+\delta_1)^{j-n} \\ \in \{0,1\} & (1-\delta_2)^j = (1+\delta_1)^{j-n} \\ 1 & (1-\delta_2)^j < (1+\delta_1)^{j-n} \end{cases}.$$

(c) If $e = \lfloor \tau_2 T \rfloor + n$,

$$\lim_{T\to\infty} \Pr(S_{e,m,n} < S^*_{\min}) = 1.$$

Finite Sample Simulations

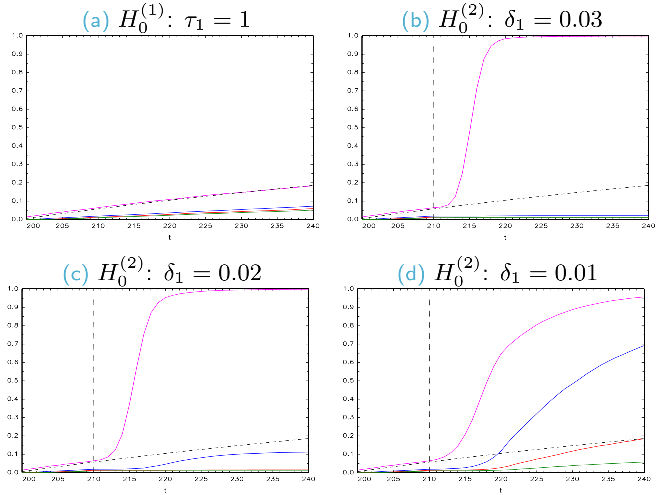
- As before, we consider

$$
\begin{aligned}
y_t &= \mu + u_t \\
u_t &= \begin{cases} u_{t-1} + v_t & t = 2, ..., \lfloor \tau_1 T \rfloor \\ (1+\delta_1)u_{t-1} + v_t & t = \lfloor \tau_1 T \rfloor + 1, ..., \lfloor \tau_2 T \rfloor \\ (1+\delta_2)u_{t-1} + v_t & t = \lfloor \tau_2 T \rfloor + 1, ..., \lfloor \tau_3 T \rfloor \\ u_{t-1} + v_t & t = \lfloor \tau_3 T \rfloor + 1, ..., T \end{cases}
\end{aligned}
$$

  with $v_t \sim iid(0,1)$ and $u_1 = \beta + v_1$. We set $\beta = 100$ to ensure upwards explosive regimes are generated.

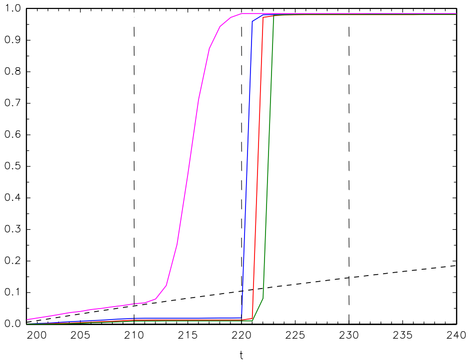
- We evaluate the performance of the $A_{MAX}(k)$ and $S_{MIN}(m,n)$ procedures, using 10,000 Monte Carlo replications for $m = k = 10$ and $T^* + m = 200$.

Rejection frequencies under $H_0^{(1)}$ and $H_0^{(2)}$



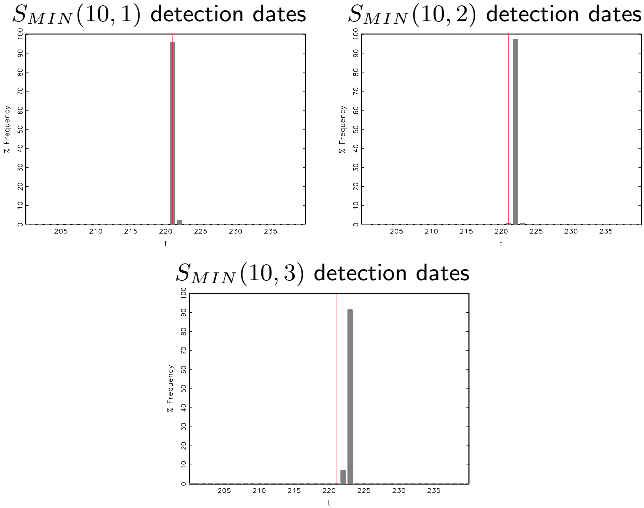
— $A_{MAX}(k)$, — $S_{MIN}(m, 1)$, — $S_{MIN}(m, 2)$, — $S_{MIN}(m, 3)$, - - FPR,
– – $\lfloor \tau_1 T \rfloor$

Rejection frequencies under $H_1^{(2)}$: $\delta_1 = 0.03$, $\delta_2 = 0.015$



— $A_{MAX}(k)$, — $S_{MIN}(m,1)$, — $S_{MIN}(m,2)$, — $S_{MIN}(m,3)$, - - FPR,
– – $\lfloor \tau_1 T \rfloor$, $\lfloor \tau_2 T \rfloor$, $\lfloor \tau_3 T \rfloor$

Detection dates: $\delta_1 = 0.03$, $\delta_2 = 0.015$



— $\lfloor \tau_2 T \rfloor + 1$

Empirical application - US house prices

$T^* + m$ Bubble Crash End

- The sub-prime crisis and subsequent financial distress of the late 2000s has led to increased scrutiny of the dynamics of the housing market.

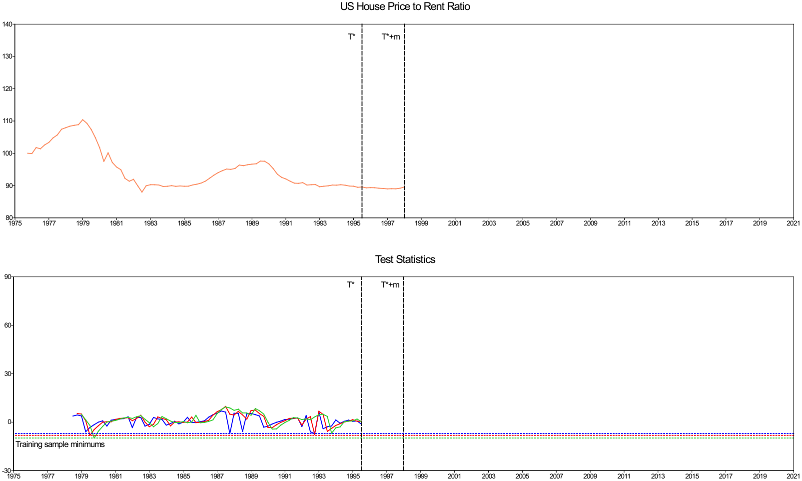
- In the early 2000s there was no consensus on the presence of an asset price bubble in US housing. Greenspan, 2002: "even if a bubble were to develop in a local market, it would not necessarily have implications for the nation as a whole".

- We construct a US house price to fundamental ratio using rent as a proxy for housing fundamentals. Quarterly data obtained from the OECD from 1975:Q4 - 2021:Q1 ($T = 182$).

- We apply the $A_{MAX}(k)$ and $S_{MIN}(m, n)$ procedure, setting $T^* = 80$ and $k = m = 10$.

Empirical application - US house prices

Back Bubble Crash End



— $S_{MIN}(10,1)$, — $S_{MIN}(10,2)$, — $S_{MIN}(10,3)$, - - $A_{MAX}(10)$ bubble date,
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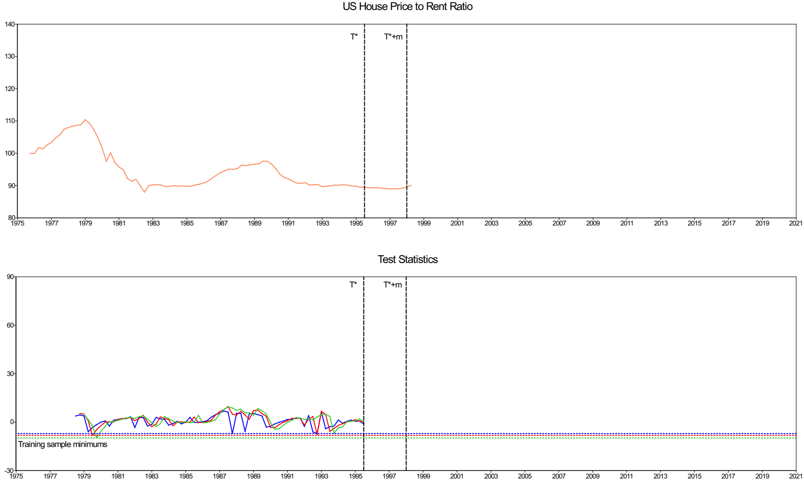
Empirical application - US house prices



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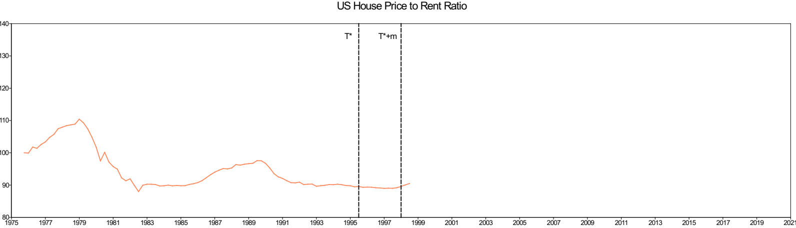
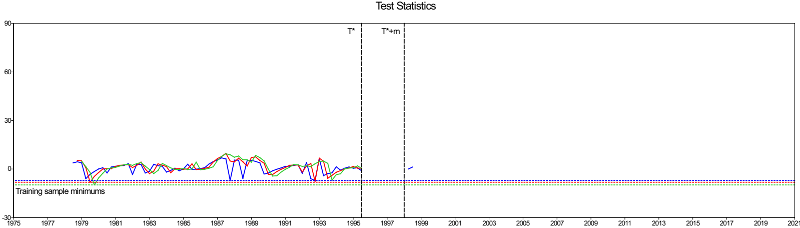
Empirical application - US house prices





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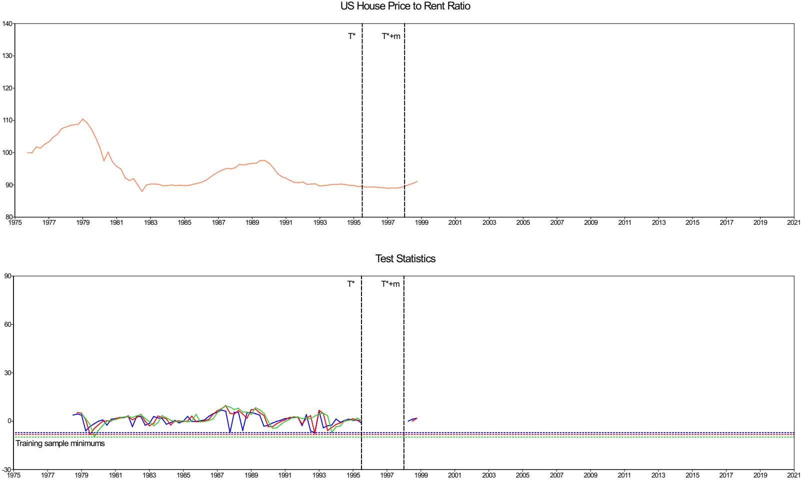
Empirical application - US house prices



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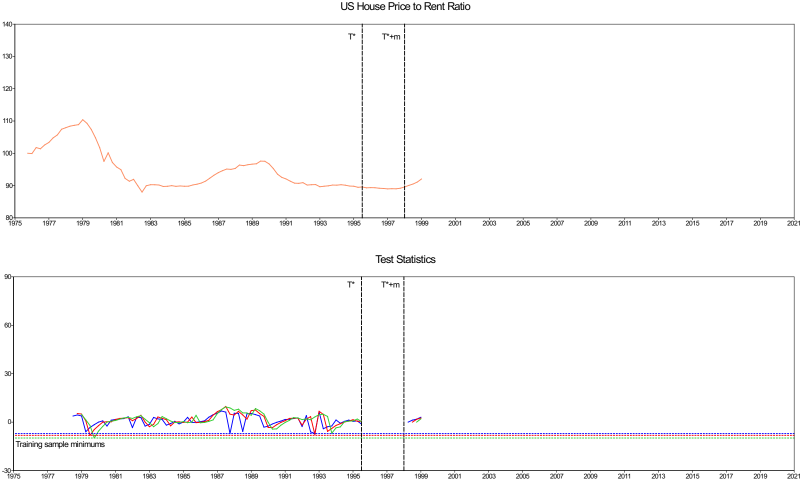
Empirical application - US house prices



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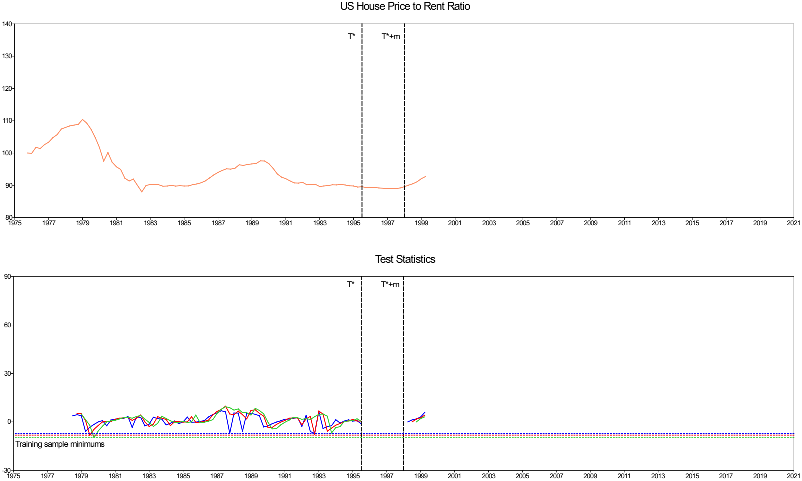
Empirical application - US house prices



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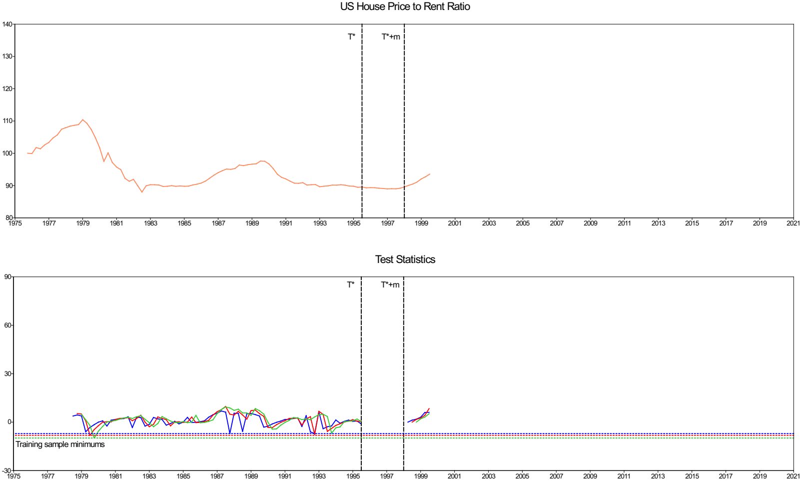
Empirical application - US house prices



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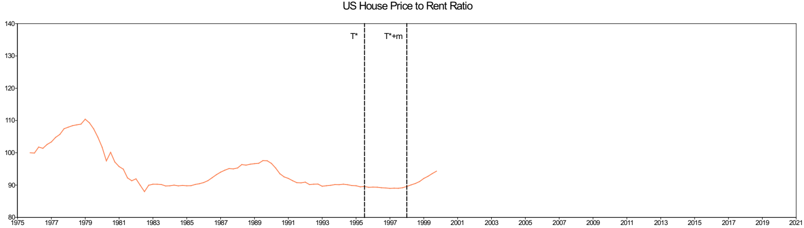
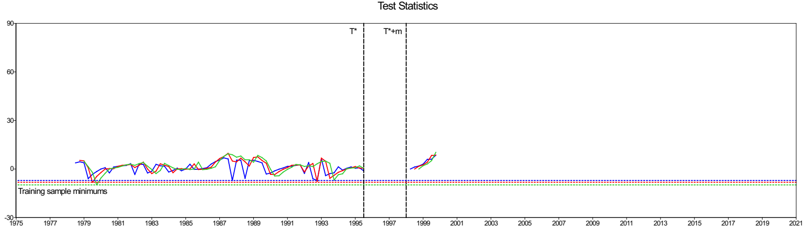
Empirical application - US house prices





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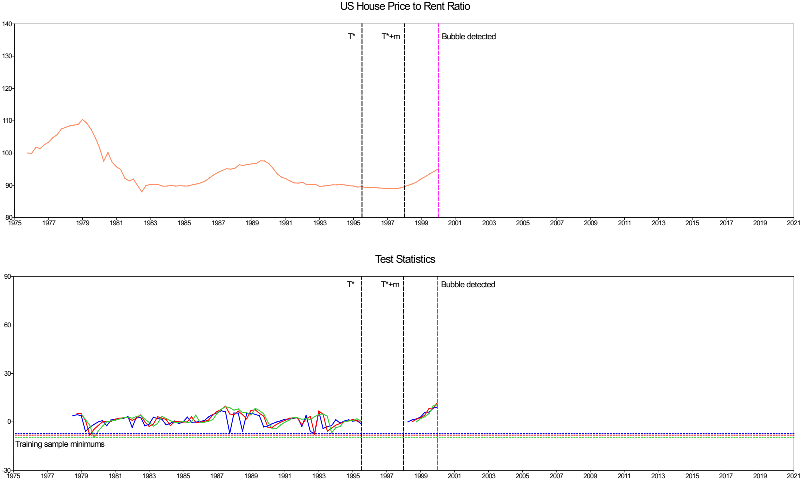
Empirical application - US house prices



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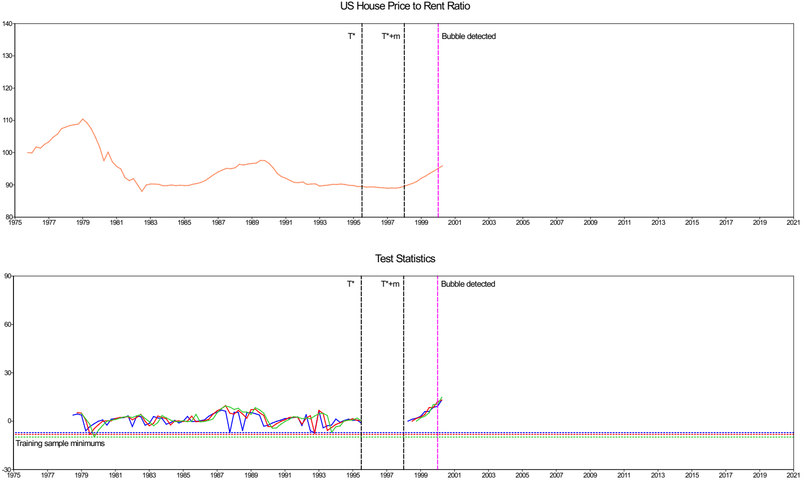
Empirical application - US house prices

Back | $T^* + m$ | Crash | End



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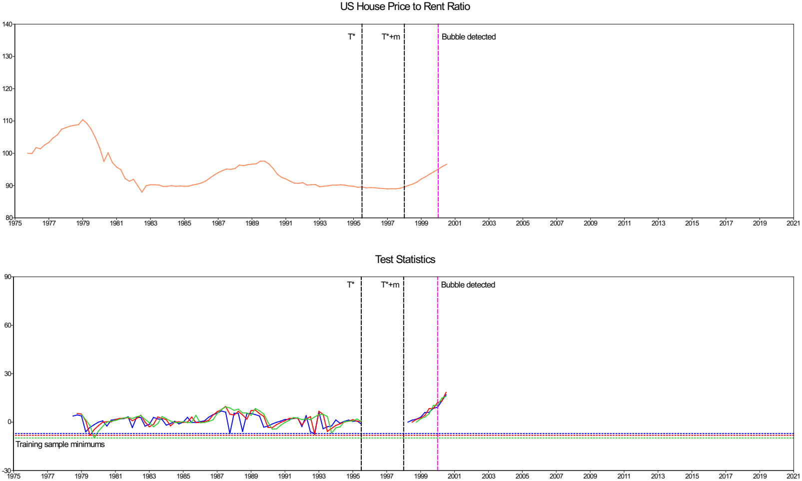
Empirical application - US house prices



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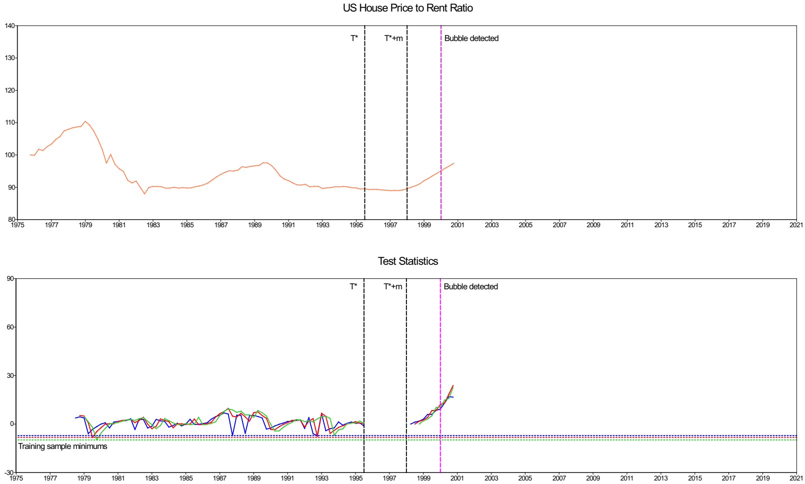
Empirical application - US house prices



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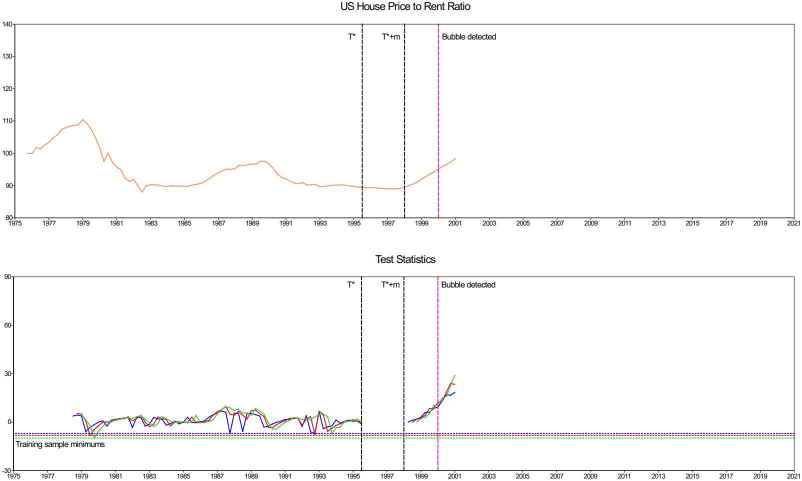
Empirical application - US house prices



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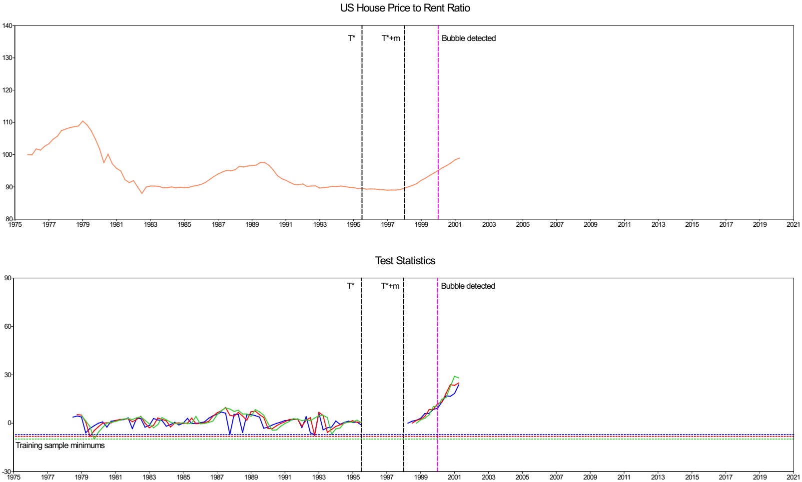
Empirical application - US house prices



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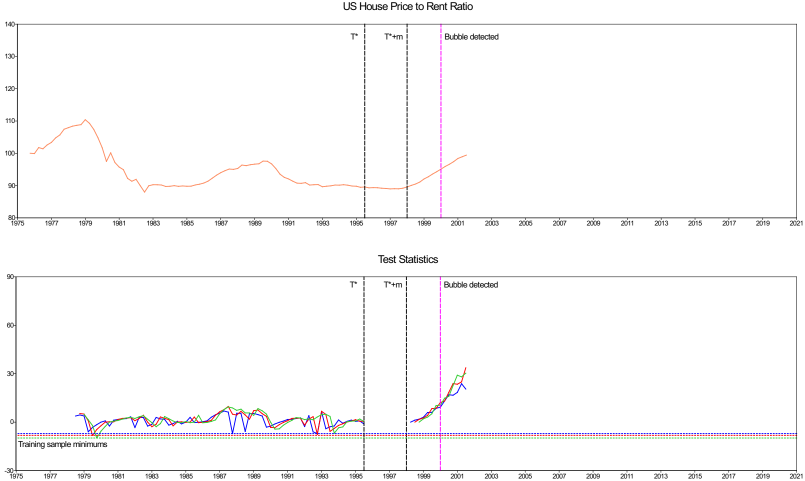
Empirical application - US house prices



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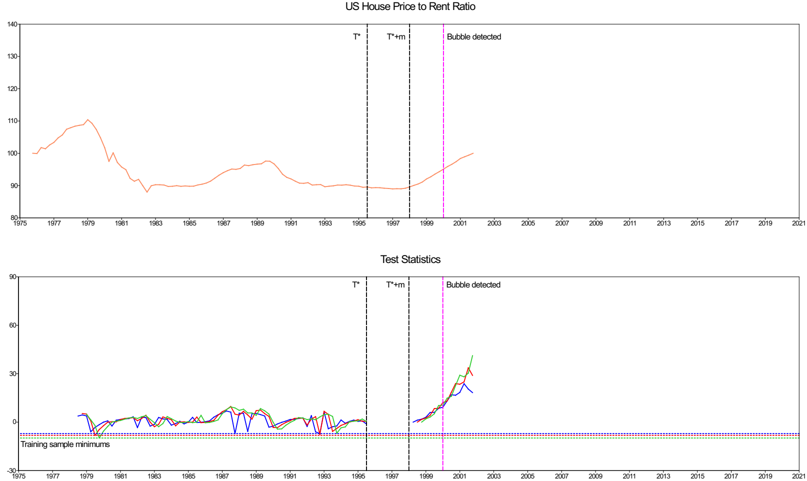
Empirical application - US house prices



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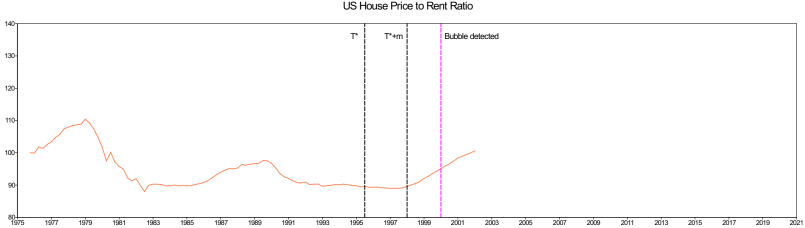
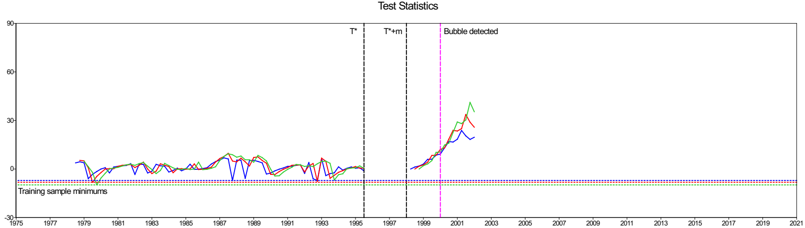
Empirical application - US house prices





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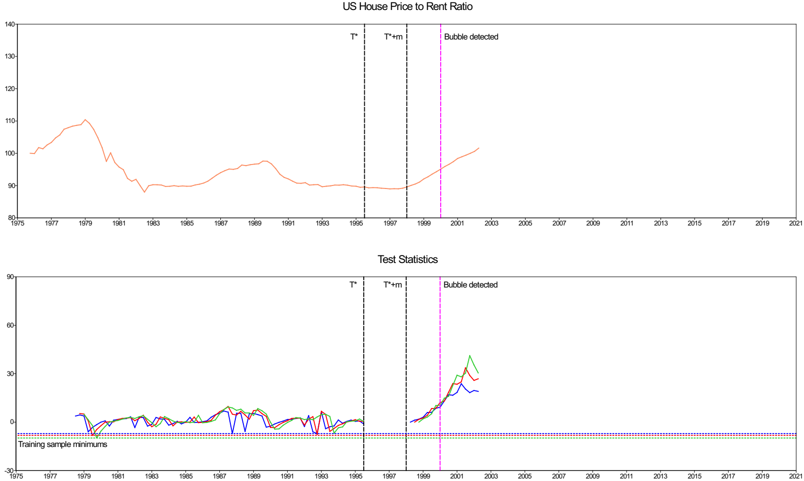
Empirical application - US house prices



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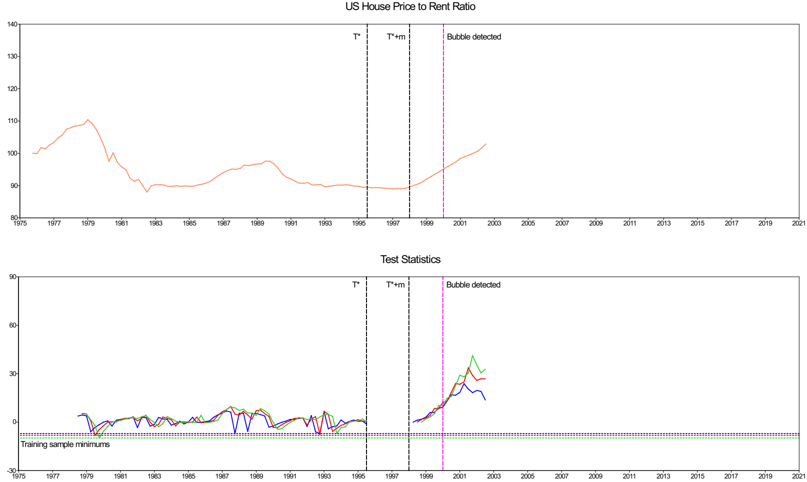
Empirical application - US house prices



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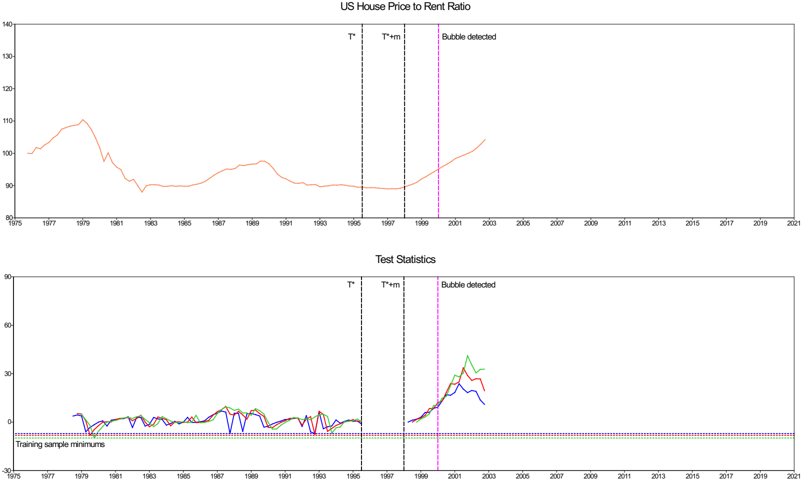
Empirical application - US house prices



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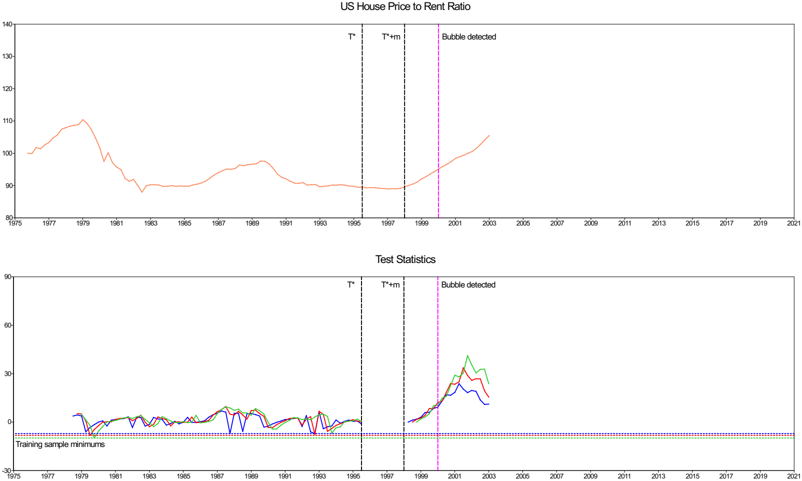
Empirical application - US house prices



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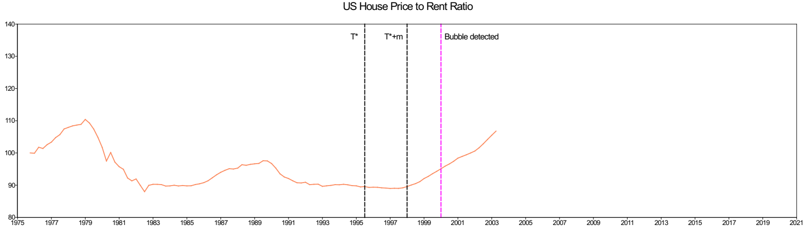
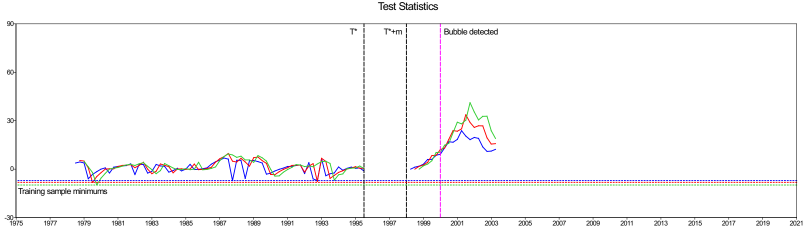
Empirical application - US house prices





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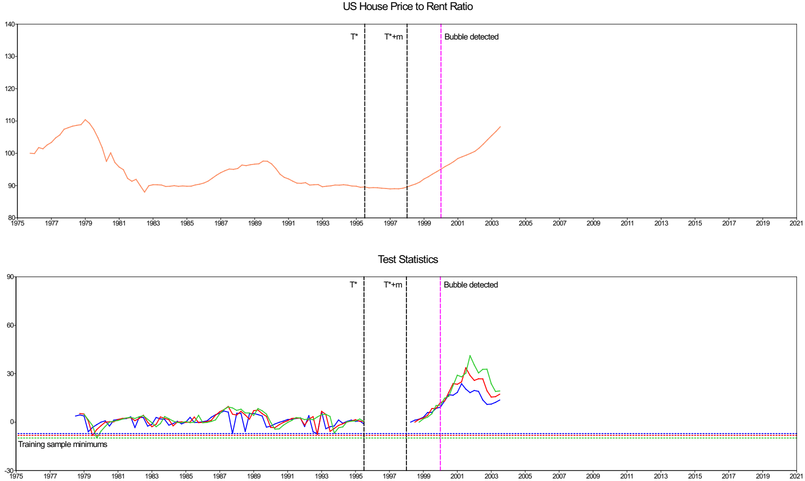
Empirical application - US house prices



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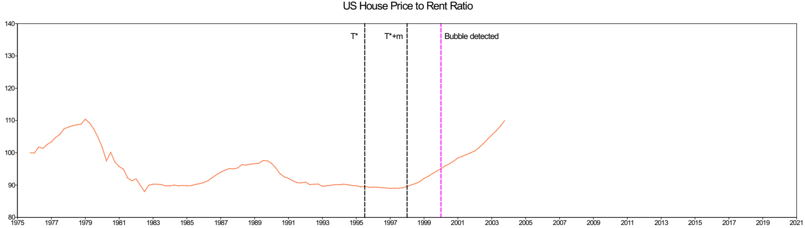
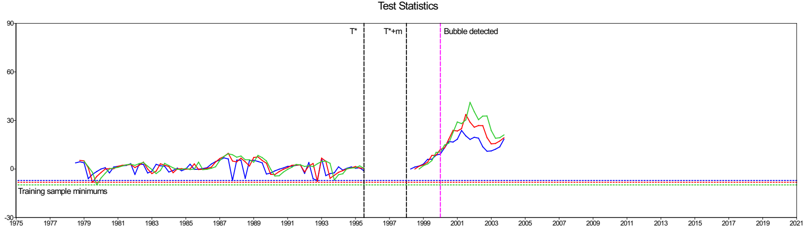
Empirical application - US house prices





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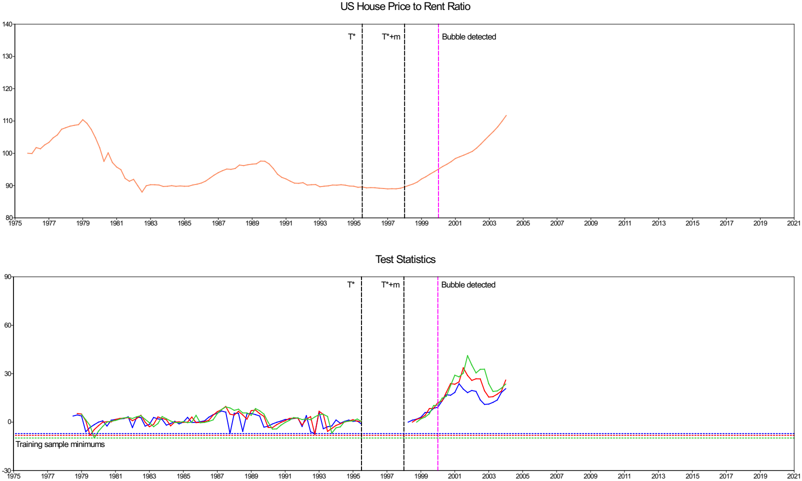
Empirical application - US house prices



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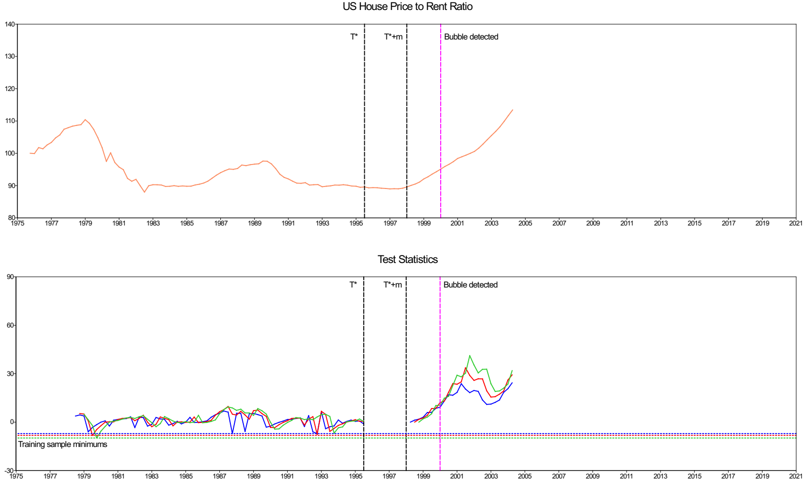
Empirical application - US house prices



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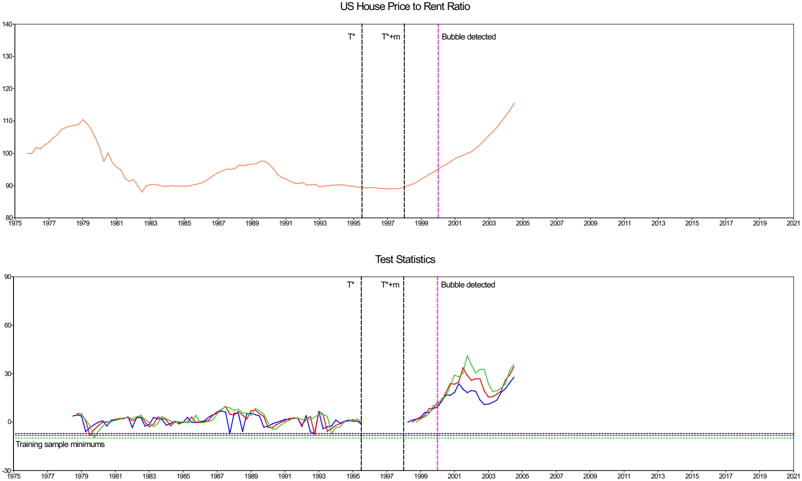
Empirical application - US house prices



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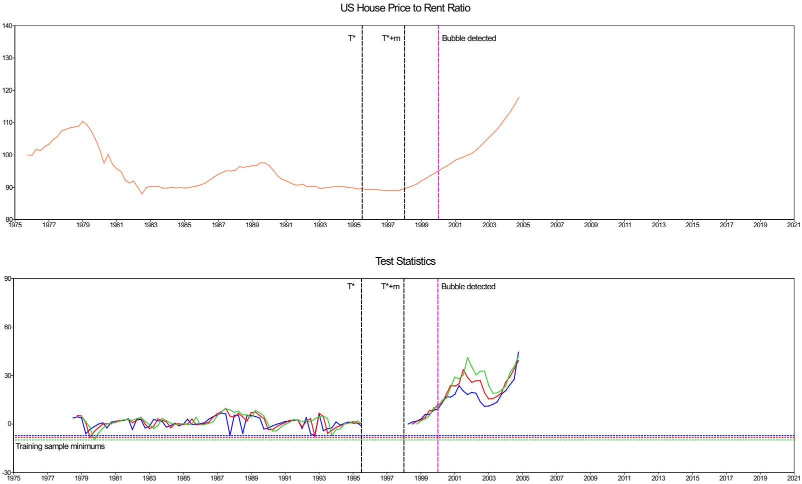
Empirical application - US house prices



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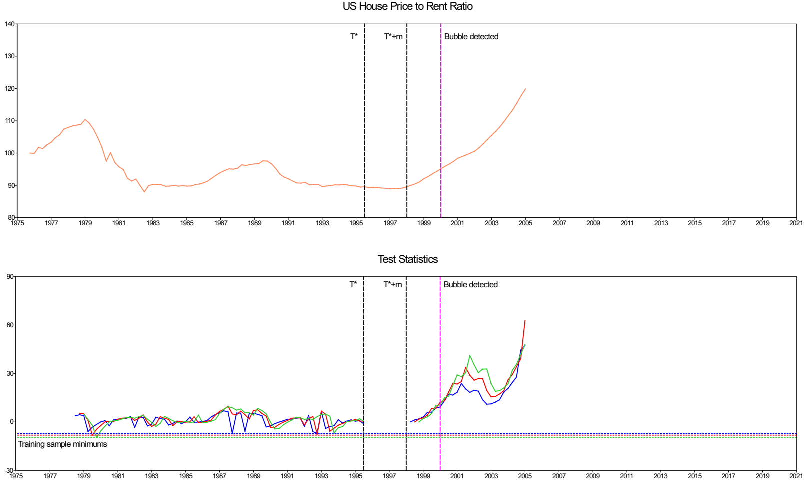
Empirical application - US house prices



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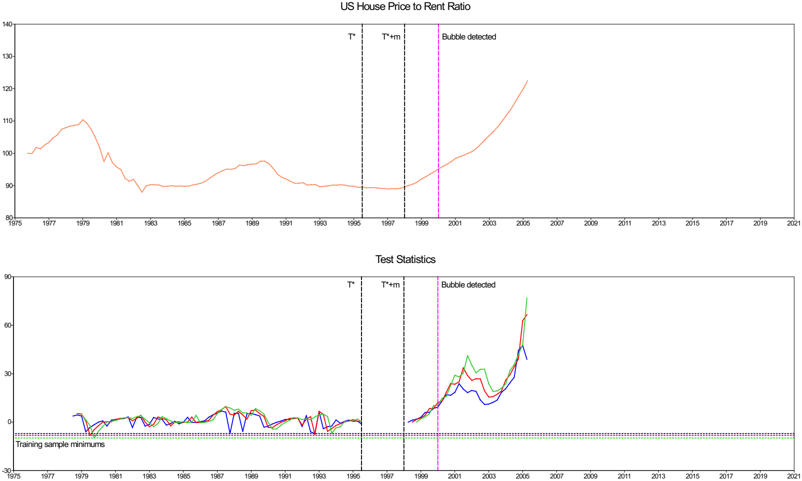
Empirical application - US house prices



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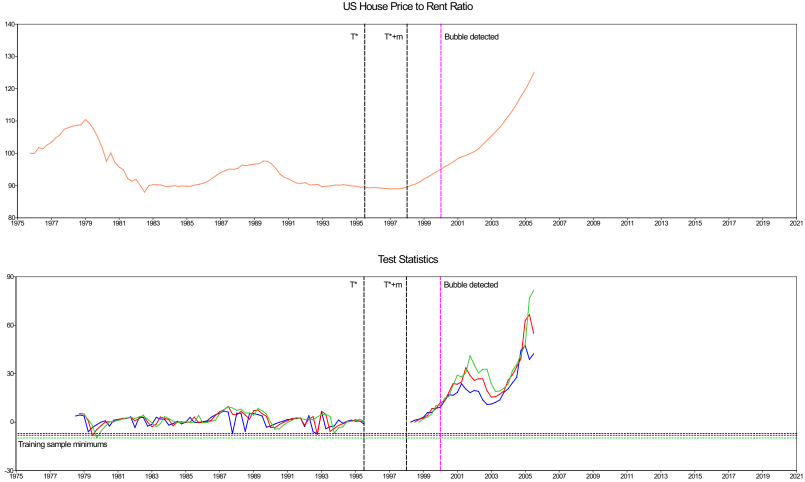
Empirical application - US house prices



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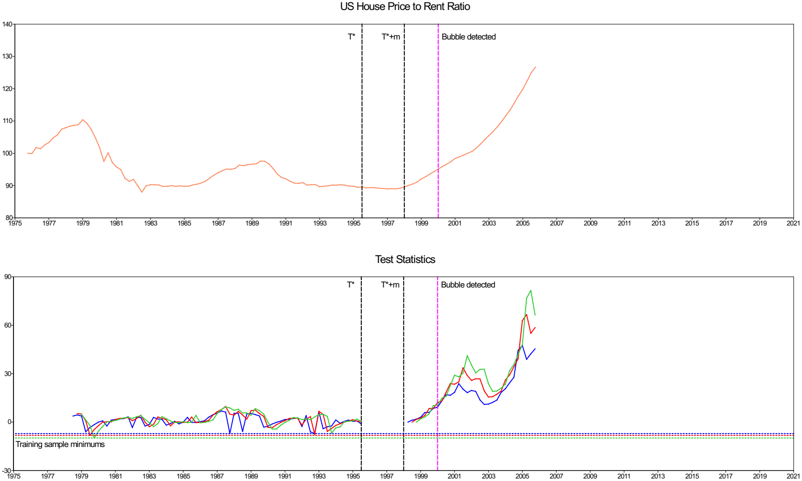
Empirical application - US house prices



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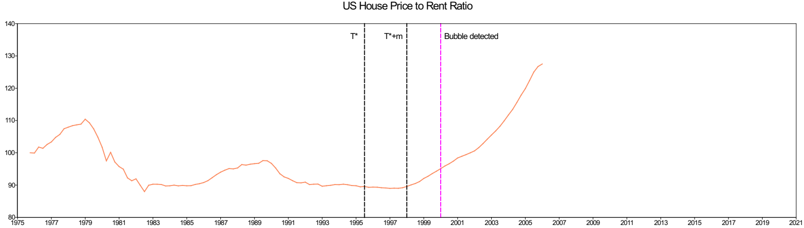
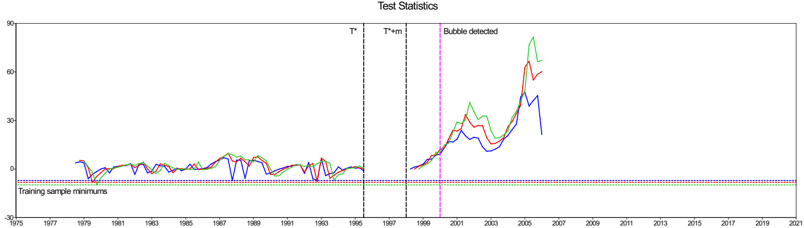
Empirical application - US house prices





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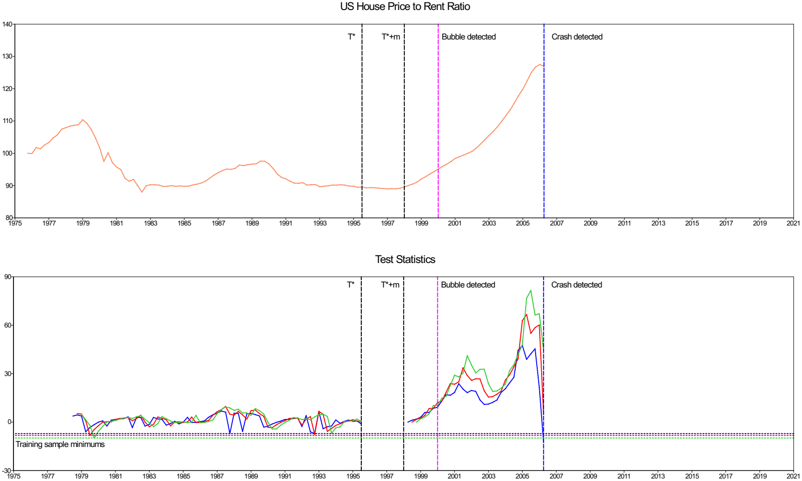
Empirical application - US house prices



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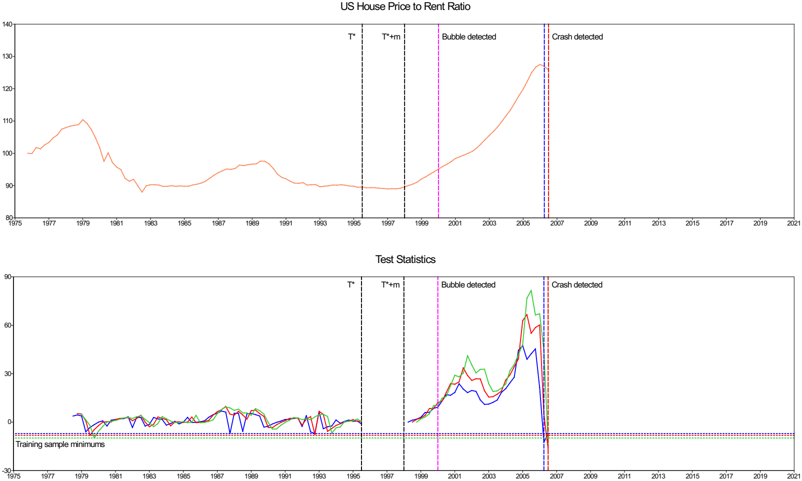
Empirical application - US house prices



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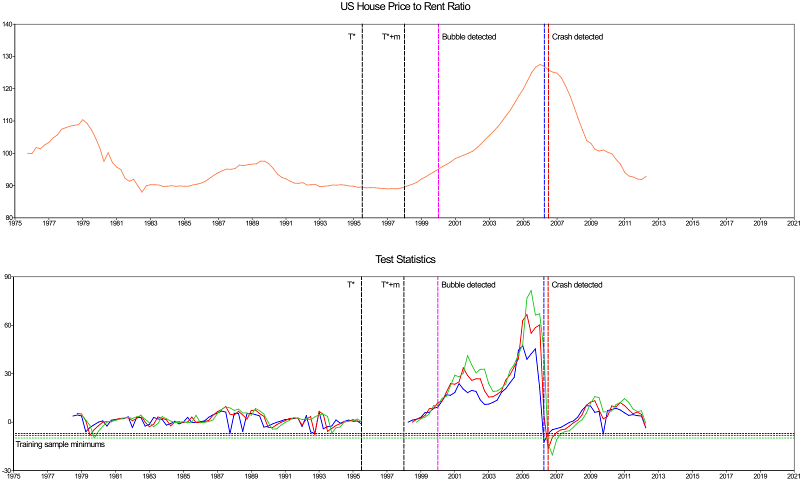
Empirical application - US house prices



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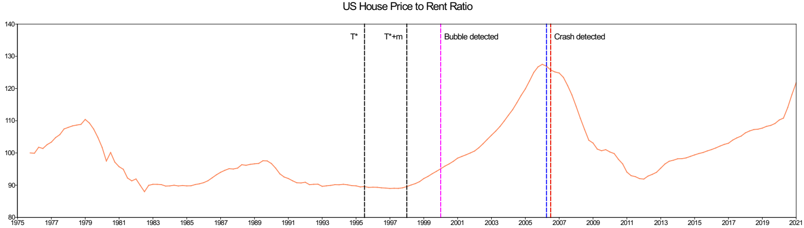
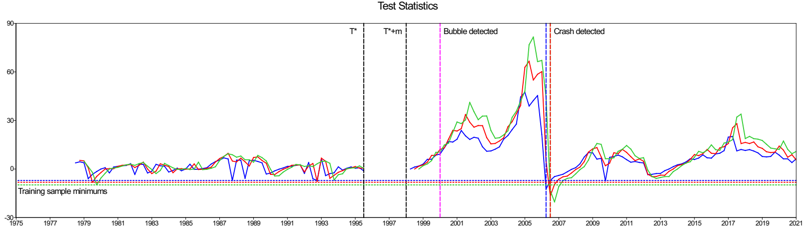
Empirical application - US house prices

Back | $T^* + m$ | Bubble | Crash





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Conclusion

- We propose a real time monitoring procedure for bubbles and crashes, in which a crash is detected conditional on first detecting a bubble.
- The theoretical FPR of the bubble monitoring procedure can be determined at each monitoring horizon, and the crash procedure has desirable asymptotic properties in terms of its ability to rapidly detect a crash.
- Our procedure performs well in finite sample simulations and an application.