Univariate Time Series Analysis

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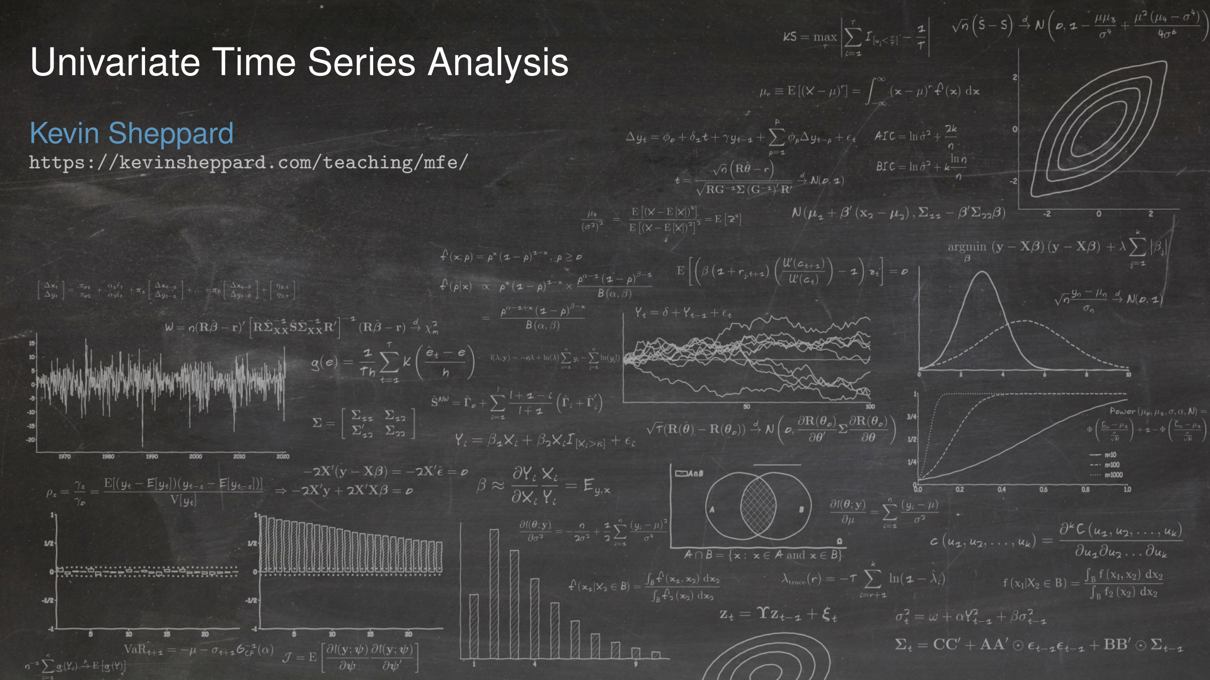
https://kevinsheppard.com/teaching/mfe/



Modules

Overview

- Key Concepts in Time Series Analysis
- Model Components
- Deterministic Processes: Trends and Seasonality
- Cyclical Processes: Autoregressive Moving-Average Processes
- Properties of ARMA Processes
- Autocorrelations and Partial Autocorrelations
- Parameter Estimation
- Model Building and Diagnostics
- Forecasting and Forecast Evaluation
- Cyclical Seasonality and Seasonal Differencing
- Random Walks and Unit Roots
- Non-linear Models for the mean

Course Structure

- Course presented through two overlapping channel:
  1. In-person lectures
  2. Notes that accompany the lecture content
     - Read before or after the lecture or when necessary for additional background
- Slides are primary – material presented during lecturers is examinable
- Notes are secondary and provide more background for the slides
- Slides are derived from notes so there is a strong correspondence

Monitoring Your Progress

- Self assessment
  - Review questions in printer-friendly version of slides
    - Self-assessment
  - Multiple choice questions on Canvas made available each week
    - Answers available immediately
  - Long-form problem distributed each week
    - Answers presented in a subsequent class
- Marked Assessment
  - Empirical projects applying the material in the lectures
  - Each empirical assignment will have a written and code component

Stochastic Processes

Stochastic Processes

Definition (Stochastic Process)

A stochastic process is a collection of random variables $\{Y_t\}$ defined on a common probability space indexed by a set $\mathcal{T}$ usually defined as $\mathbb{N}$ for discrete time processes or $[0, \infty)$ for continuous time processes.

Basic Example: An i.i.d. time series

$$Y_t \overset{\text{i.i.d.}}{\sim} N(0, 1)$$

More Complex Examples

- **Random Walk**

$$Y_t = Y_{t-1} + \epsilon_t,\ \ \epsilon_t \overset{\text{i.i.d.}}{\sim} N\left(0, \sigma^2\right)$$

- **ARMA(1,1)**

$$Y_t = \phi_1 Y_{t-1} + \theta \epsilon_{t-1} + \epsilon_t$$

  - Series focuses on ARMA

- **GARCH(1,1)**

$$Y_t \sim N(0, \sigma_t^2)$$

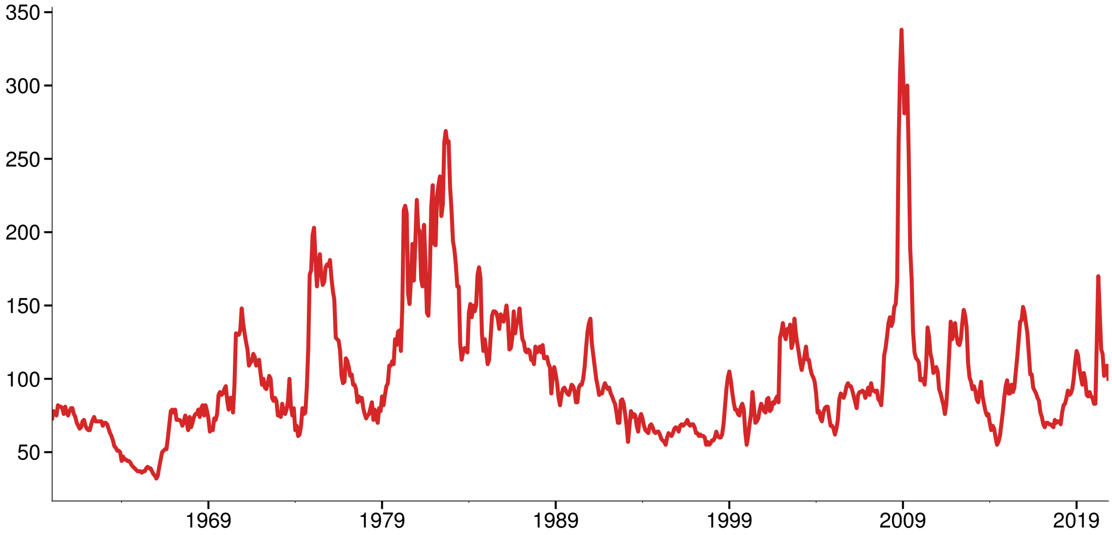
$$\sigma_t^2 = \omega + \alpha Y_{t-1}^2 + \beta \sigma_{t-1}^2$$

  - GARCH and other non-linear processes later

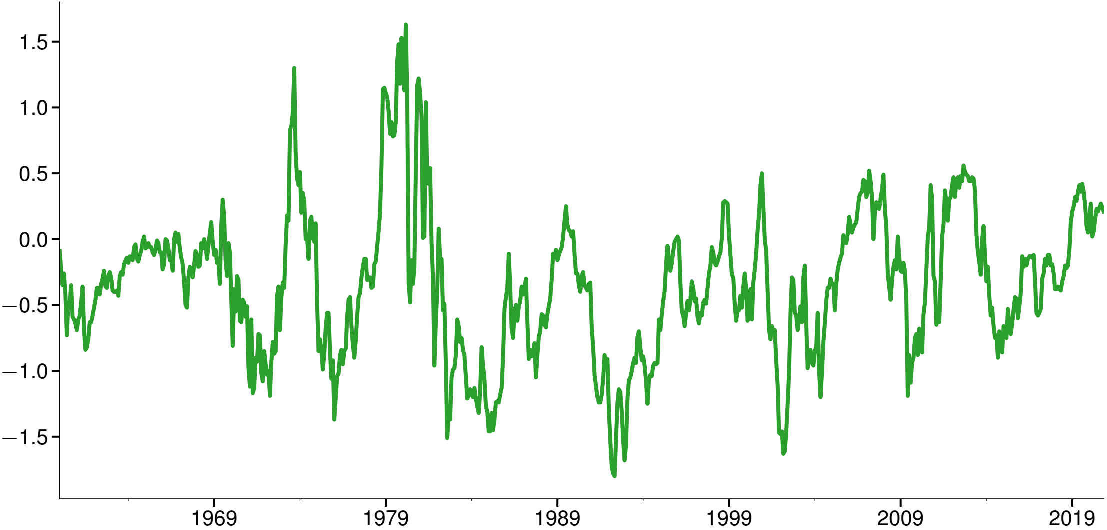
- **Ornstein-Uhlenbeck Process**

$$Y\left(t\right) = e^{-\beta t} Y\left(0\right) + \sigma \int_0^t e^{-\beta(t-s)} \mathrm{d}W\left(s\right)$$

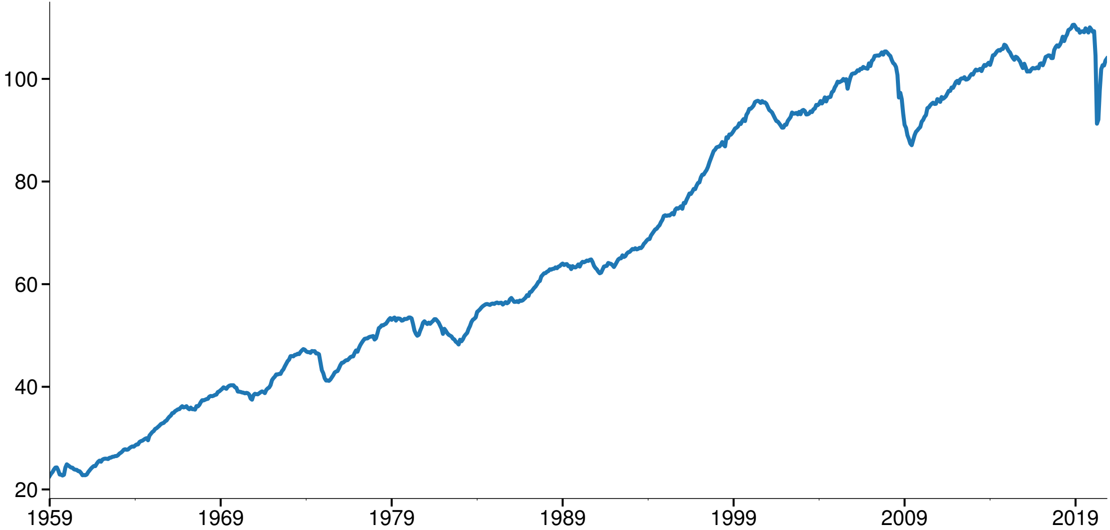
The Default Premium



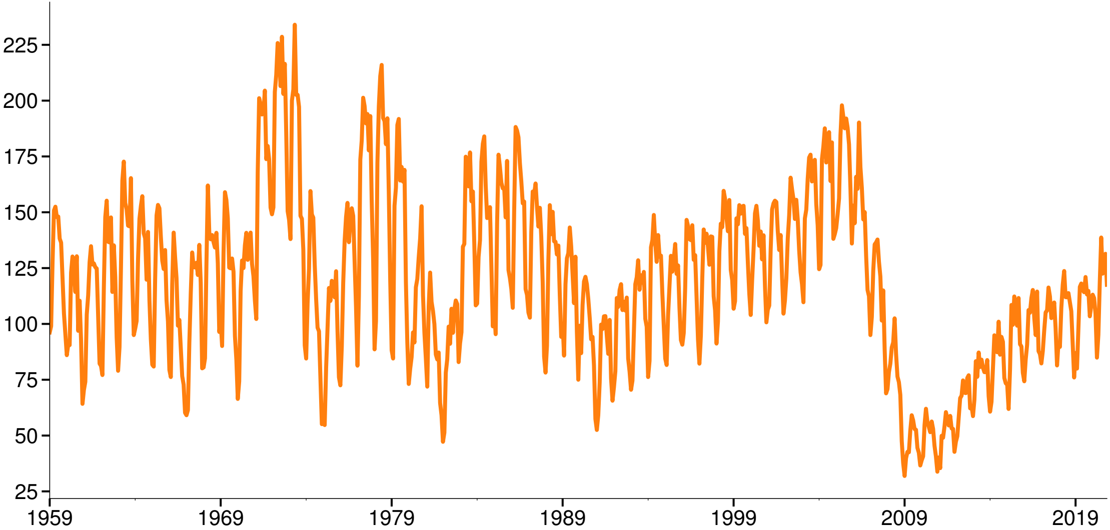
Curvature of Yield Curve



Industrial Production



Housing Starts



Autocovariance

Autocovariance

Definition (Autocovariance)

The autocovariance of a covariance stationary scalar process $\{Y_t\}$ is defined

$$\gamma_s = \mathrm{E}\left[(Y_t - \mu)(Y_{t-s} - \mu)\right]$$

where $\mu = \mathrm{E}\left[Y_t\right]$. Note that $\gamma_0 = \mathrm{E}\left[(Y_t - \mu)(Y_t - \mu)\right] = \mathrm{V}\left[Y_t\right]$.

- Covariance of a process at different points in time
- Otherwise identical to usual covariance

Stationarity

Key concept

- Stationarity is a statistically meaningful form of regularity
- First type:

Definition (Covariance Stationarity)

A stochastic process $\{Y_t\}$ is covariance stationary if

$$\begin{aligned} \mathrm{E}\left[Y_t\right] &= \mu && \text{for } t = 1, 2, \ldots \\ \mathrm{V}\left[Y_t\right] &= \sigma^2 < \infty && \text{for } t = 1, 2, \ldots \\ \mathrm{E}\left[(Y_t - \mu)(Y_{t-s} - \mu)\right] &= \gamma_s && \text{for } t = 1, 2, \ldots, s = 1, 2, \ldots, t-1 \end{aligned}$$

- *Unconditional* mean, variance and autocovariance do *not* depend on time

Stationarity

Second type (stronger):

Definition (Strict Stationarity)

A stochastic process $\{Y_t\}$ is strictly stationary if the joint distribution of $\{Y_t, Y_{t+1}, \dots, Y_{t+h}\}$ only depends only on h and not on t.

- *Entire joint distribution* does not depend on time.
- Examples of stationary time series:
  - i.i.d. : Always strict, covariance if $\sigma^2 < \infty$
  - i.i.d. sequence of t_2 random variables, strict only
  - Multivariate normal, both
  - AR(1): $Y_t = \phi_1 Y_{t-1} + \epsilon_t$, covariance if $|\phi_1| < 1$ and $\mathrm{V}[\epsilon_t] < \infty$, strict is ϵ_t is i.i.d.
  - ARCH(1): $Y_t \sim N(0, \sigma_t^2)$,$\sigma_t^2 = \omega + \alpha Y_{t-1}^2$ both if $\alpha < 1$.

Nonstationarity defined

- Any series which is not stationary is nonstationary
- Four major types
  - Seasonality
    - Only slightly problematic
    - Can often be analyzed using standard tools and Box-Jenkins
  - Deterministic trends: growth over time
    - Linear
    - Polynomial
    - Exponential
  - Random walks or unit roots
  - Structural breaks

What processes are not stationary?

Nonstationary time series

- Seasonalities, Diurnality, Hebdomadality: $Y_t = \mu + \beta I_{[\text{Quarter}(t) = Q1]} + \epsilon_t$
  - $\text{E}[Y_t]$ is different in Q1 than in other quarters
- Time trends: $Y_t = t + \epsilon_t$
  - $\text{E}[Y_t] = t$
- Random walks: $Y_t = Y_{t-1} + \epsilon_t$
  - $\text{V}[Y_t] = t\sigma^2$
- Processes with structural breaks: $Y_t = \mu_1 + \epsilon_t$ if $t < 1974$, $Y_t = \mu_2 + \epsilon_t$, $t \geq 1974$.
  - $\text{E}[Y_t] = \mu_1 + (\mu_2 - \mu_1)(1 - I_{t<1974})$

White Noise

White noise

Essential Building Block of Time Series

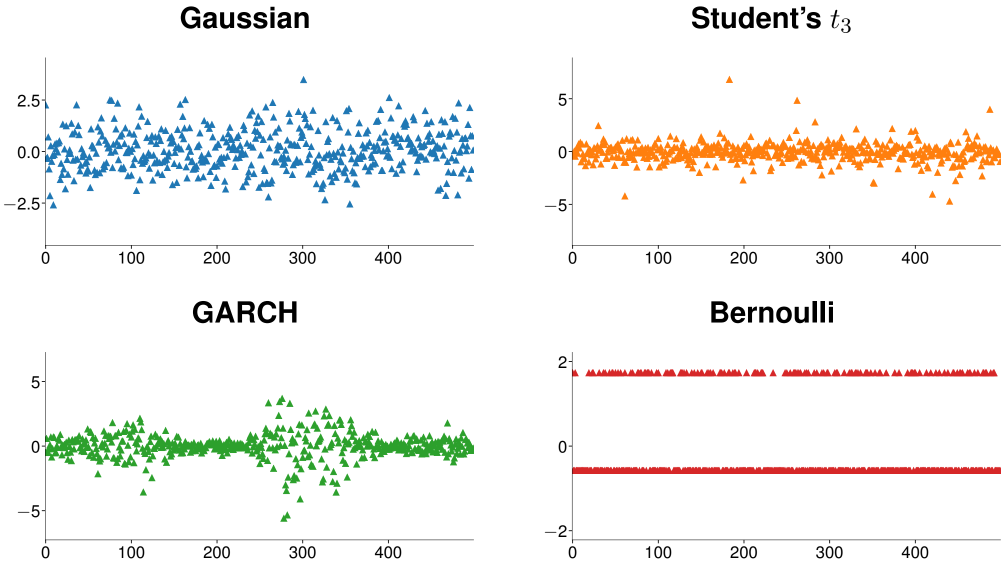
Definition (White Noise)

A process $\{\epsilon_t\}$ is known as white noise if

$$\begin{aligned} \mathrm{E}\left[\epsilon_t\right] &= 0 && \text{for } t = 1, 2, \ldots \\ \mathrm{V}\left[\epsilon_t\right] &= \sigma^2 < \infty && \text{for } t = 1, 2, \ldots \\ \mathrm{E}\left[\epsilon_t \epsilon_{t-j}\right] &= 0 && \text{for } t = 1, 2, \ldots, \; j \neq 0 \end{aligned}$$

- Not necessarily independent
  - ARCH(1) process $Y_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \omega + \alpha Y_{t-1}^2$
  - **Variance** is dependent, mean is not

White noise


Gaussian
2.5
0.0
−2.5
0
100
200
300
400
Student's t_3
5
0
−5
0
100
200
300
400
GARCH
5
0
−5
0
100
200
300
400
Bernoulli
2
0
−2
0
100
200
300
400

Linear Time Series Processes

Linear Time-series Processes

Standard tool of time-series analysis

- *Linear* time series process can always be expressed as

$$Y_t = \delta_t + Y_0 + \sum_{i=0}^{t} \theta_i \epsilon_{t-i}$$

  - Linear in the errors
  - δ_t is a purely deterministic process
  - $\{\epsilon_t\}$ is a White Noise process
- Example of non-linear processes
  - GARCH(1,1)

$$Y_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \omega + \alpha Y_{t-1}^2 + \beta \sigma_{t-1}^2$$

  - Threshold Autoregression

$$Y_t = \phi_s Y_{t-1} + \epsilon_t, \; \phi_s = 1 \text{ if } L < Y_{t-1} < U \text{ otherwise } 0.9$$

Model Components

Component View of a Time Series

$$Y_t = \underbrace{\text{Trend} + \text{Seasonal} + \text{Cyclical}}_{\text{Predictable}} + \underbrace{\text{Noise}}_{\text{Unpredictable}}$$

Trend

- Linear, Quadratic
- Exponential
  - Linear in the log
- *Deterministic* - depends on the time period t

Seasonal

- Seasonal Summies
- Fourier Series
- *Deterministic* - depends on the time period t

Cyclical

- Autoregressive Moving Average Processes
- *Stochastic* - depends on past shocks

Deterministic trends

- Two key types
  - Polynomial

$$Y_t = \phi_0 + \delta_1 t + \delta_2 t^2 + \ldots + \delta_o t^o + \epsilon_t$$

    - Linear (important special case)

$$Y_t = \phi_0 + \delta_1 t + \epsilon_t$$

    - Exponential

$$\ln Y_t = \phi_0 + \delta_1 t + \epsilon_t$$

- *Mean depends on time*

$$Y_t = \phi_0 + \delta_1 t + \epsilon_t \Rightarrow \mathrm{E}\left[Y_t\right] = \phi_0 + \delta_1 t$$

Deterministic Seasonality

Seasonal dummy variables

$$Y_t = \sum_{j=0}^{s-1} \beta_j I_{[t \mod s=j]} + \epsilon_t$$

Seasonal Fourier series

$$Y_t = \sum_{j=0}^{k} \lambda_j \sin\left(2\pi j \frac{t}{s}\right) + \kappa_j \cos\left(2\pi j \frac{t}{s}\right) + \epsilon_t$$

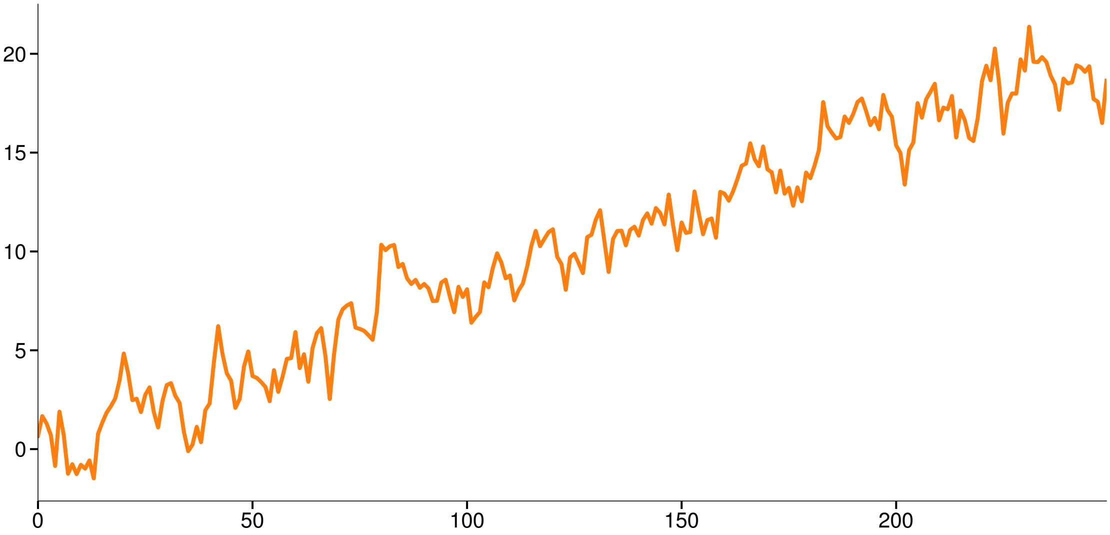
- Capture seasonal patterns using fewer terms
  - $k = 2$ in monthly data
  - 4 rather than 12 parameters
- Multiple fourier terms with different s capture additional determinstic patterms
  - Electricity: day of year, day of week, hour of day

Detrending

$$Y_t = \phi_0 + \delta_1 t + \ldots + \delta_o t^o + \sum_{i=0}^{s-1} \beta_i I_{[t \mod s = i]} + \sum_{j=0}^{k} \lambda_j \sin\left(2\pi j \frac{t}{s}\right) + \kappa_j \cos\left(2\pi j \frac{t}{s}\right) + \epsilon_t$$

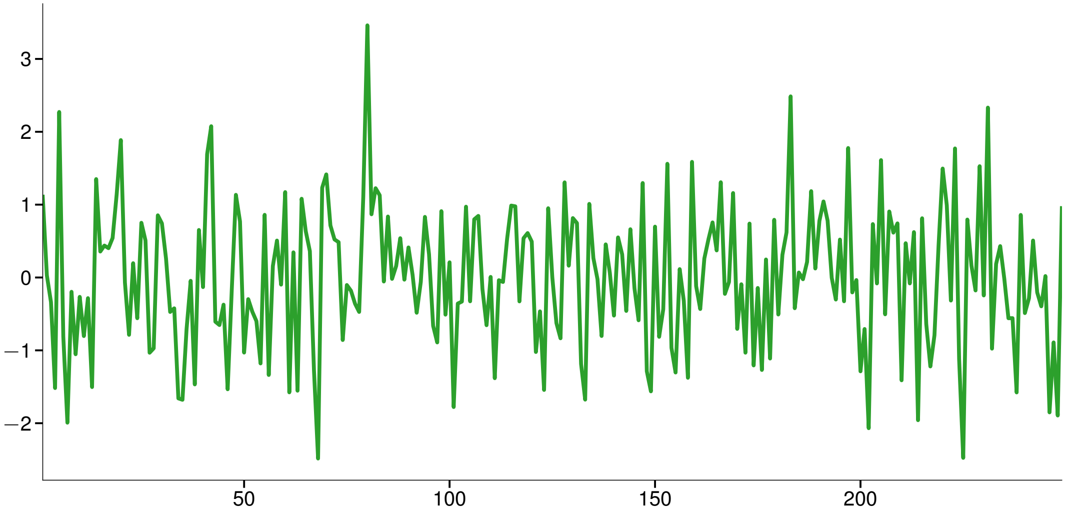
- Detrended series is a stationary process
- Detrending depends only on time t
- Incorporate trends with ARMA models to capture predictable component
- Parameter estimation using OLS
- **Key problem** - most trending economic time series contains *unit roots*
  - Still not stationary even after detrending
  - Alternative: transform to remove the determinstic effects
  - More later

Trending Time Series



Detrended Residuals

$\hat{\epsilon}_t = Y_t - \hat{\phi}_0 - \hat{\delta}_1 t$



Autoregressive-Moving Average Processes

ARMA Processes

- Inclusive class of all linear time-series processes

Definition (Autoregressive-Moving Average Process)

An Autoregressive Moving Average process with orders P and Q, abbreviated ARMA(P,Q), has dynamics which follow

$$Y_t = \phi_0 + \sum_{p=1}^{P} \phi_p Y_{t-p} + \sum_{q=1}^{Q} \theta_q \epsilon_{t-q} + \epsilon_t$$

where ϵ_t is a white noise process with the additional property that $E_{t-1}[\epsilon_t] = 0$.

- ARMA(1,1)

$$Y_t = \phi_1 Y_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t$$

Special case: Moving Average

- ARMA family compromises two sub-classes

Definition (Moving Average Process of Order Q)

A Moving Average process of order Q, abbreviated MA(Q), has dynamics which follow

$$Y_t = \phi_0 + \sum_{q=1}^{Q} \theta_q \epsilon_{t-q} + \epsilon_t$$

where ϵ_t is white noise series with the additional property that $E_{t-1}[\epsilon_t] = 0$.

- 1st order Moving Average (MA(1))

$$Y_t = \phi_0 + \theta_1 \epsilon_{t-1} + \epsilon_t$$

- Simplest non-degenerate time series process

Special cases of ARMA processes: Autoregression

- Other sub-class of ARMA

Definition (Autoregressive Process of Order P)

An Autoregressive process of order P, abbreviated AR(P), has dynamics which follow

$$Y_t = \phi_0 + \sum_{p=1}^{P} \phi_p Y_{t-p} + \epsilon_t$$

where ϵ_t is white noise series with the additional property that $E_{t-1}\left[\epsilon_t\right] = 0$.

- 1st order Autoregression (AR(1))

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \epsilon_t$$

Conditional Moments

Moments and Autocovariances

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \epsilon_t$$

- ***Unconditional*** Mean

$$\mathrm{E}\left[Y_t\right]$$

- ***Unconditional*** Variance

$$\gamma_0 = \mathrm{V}\left[Y_t\right]$$

- Autocovariance

$$\gamma_s = \mathrm{E}\left[\left(Y_t - \mathrm{E}\left[Y_t\right]\right)\left(Y_{t-s} - \mathrm{E}\left[Y_{t-s}\right]\right)\right]$$

- ***Conditional*** Mean

$$\mathrm{E}_t[Y_{t+1}] = \mathrm{E}[Y_{t+1}|\mathcal{F}_t]$$

- ***Conditional*** Variance

$$\mathrm{V}_t[Y_{t+1}] = \mathrm{E}_t[(Y_{t+1} - \mathrm{E}_t[Y_{t+1}])^2]$$

Moments of an AR(1) Process

How to work with ARMA processes: AR(1)

The MA(∞) Representation

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \epsilon_t$$

- Use backward substitution (assume $|\phi_1| < 1$)

$$\begin{aligned}
Y_t &= \phi_0 + \phi_1 Y_{t-1} + \epsilon_t \\
&= \phi_0 + \phi_1(\phi_0 + \phi_1 Y_{t-2} + \epsilon_{t-1}) + \epsilon_t \\
&= \phi_0 + \phi_1\phi_0 + \phi_1^2 Y_{t-2} + \phi_1\epsilon_{t-1} + \epsilon_t \\
&= \phi_0 + \phi_1\phi_0 + \phi_1^2(\phi_0 + \phi_1 Y_{t-3} + \epsilon_{t-2}) + \phi_1\epsilon_{t-1} + \epsilon_t \\
&= \phi_0 \sum_{j=0}^{\infty} \phi_1^j + \sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i} \\
&= \frac{\phi_0}{1-\phi_1} + \sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i}
\end{aligned}$$

- $\lim_{s\to\infty} \sum_{i=0}^{s} \phi_1^i = 1/(1-\phi_1)$

Properties of an AR(1)

$$
\begin{aligned}
\mathrm{E}[Y_t] &= \mathrm{E}\left[\frac{\phi_0}{1-\phi_1} + \sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i}\right] \\
&= \frac{\phi_0}{1-\phi_1} + \sum_{i=0}^{\infty} \phi_1^i \mathrm{E}\left[\epsilon_{t-i}\right] \\
&= \frac{\phi_0}{1-\phi_1} + \sum_{i=0}^{\infty} \phi_1^i 0 \\
&= \frac{\phi_0}{1-\phi_1}
\end{aligned}
$$

- In general AR(P): $\mathrm{E}[Y_t] = \frac{\phi_0}{1-\phi_1-\phi_2-...-\phi_P}$
- Only sensible if $\phi_1 + \phi_2 + \ldots + \phi_P < 1$
- Variance can be shown in same manner
  - AR(1): $\mathrm{V}[Y_t] = \frac{\sigma^2}{1-\phi_1^2}$
  - AR(P): $\mathrm{V}[Y_t] = \frac{\sigma^2}{1-\rho_1\phi_1-\rho_2\phi_2-...-\rho_P\phi_P}$
    - ρs are autocorrelations

Autocovariance of an AR(1)

$$
\begin{aligned}
\mathrm{E}\left[(Y_t - \mathrm{E}[Y_t])(Y_{t-s} - \mathrm{E}[Y_{t-s}])\right] &= \mathrm{E}\left[\left(\sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i}\right)\left(\sum_{j=0}^{\infty} \phi_1^j \epsilon_{t-s-j}\right)\right] \\
&= \mathrm{E}\left[\left(\underbrace{\sum_{i=0}^{s-1} \phi_1^i \epsilon_{t-i}}_{\text{After} t-s} + \underbrace{\sum_{k=s}^{\infty} \phi_1^k \epsilon_{t-k}}_{t-s \text{ and later}}\right)\left(\sum_{j=0}^{\infty} \phi_1^j \epsilon_{t-s-j}\right)\right] \\
&= \phi_1^s \frac{\sigma^2}{1-\phi_1^2}
\end{aligned}
$$

- Full details in notes
- The autocovariance *function*

$$
\gamma_s = \phi_1^{|s|}\left\{\frac{\sigma^2}{1-\phi_1^2}\right\}
$$

- Autocovariance declines geometrically with the lag length
- Requires $\phi_1^2 < 1$ to exist
  - Same condition as the mean

Stationarity of AR Processes

Stationarity of ARMA processes

- Primarily interested in covariance stationarity
- Stationarity depends on parameters of *AR* portion
- AR(0) or finite order MA: always stationary
- AR(1) or ARMA(1,Q): $Y_t = \phi_1 Y_{t-1} + \text{MA} + \epsilon_t$
  - $|\phi_1| < 1$
- AR(P) or ARMA(P,Q) $Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_P Y_{t-P} + \text{MA} + \epsilon_t$
- Rewrite $Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \ldots - \phi_P Y_{t-P} = \text{MA} + \epsilon_t$
- Easy to determine using the characteristic equation and corresponding characteristic roots

The characteristic equation

Definition (Characteristic Equation)

Let Y_t follow a Pth order linear difference equation

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_P Y_{t-P} + x_t$$

which can be rewritten as

$$Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \ldots - \phi_P Y_{t-P} = \phi_0 + x_t$$
$$(1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_P L^P) Y_t = \phi_0 + x_t$$

The characteristic equation of this process is

$$z^P - \phi_1 z^{P-1} - \phi_2 z^{P-2} - \ldots - \phi_{P-1} z - \phi_P = 0$$

- Key is in the forming of the characteristic equation and its roots
- L is known as “lag operator”

Characteristic roots

Definition (Characteristic Root)

Let

$$z^P - \phi_1 z^{P-1} - \phi_2 z^{P-2} - \ldots - \phi_{P-1} z - \phi_P = 0$$

be the characteristic polynomial associated with some Pth order linear difference equation. The P characteristic roots, $c_1, c_2, \ldots, c_P$ are defined as the solution to this polynomial

$$(z - c_1)(z - c_2) \ldots (z - c_P) = 0.$$

- The roots are c_1, c_2, . . . , c_P
- AR(P) or ARMA(P,Q) is covariance stationary if $|c_j| < 1$ for all j
- If complex, $|c_j| = |a_j + b_j i| = \sqrt{a^2 + b^2}$ (complex modulus)

Characteristic roots example

- Difficult to determine by inspection

Example 1

$$Y_t = .1Y_{t-1} + .7Y_{t-2} + .2Y_{t-3} + \epsilon_t$$

- Characteristic equation

$$z^3 - .1z^2 - .7z^1 - .2$$

- Roots: 1, $-.5$, and $-.4 \Rightarrow$ nonstationary

Example 2

$$Y_t = 1.7Y_{t-1} - .72Y_{t-2} + \epsilon_t$$

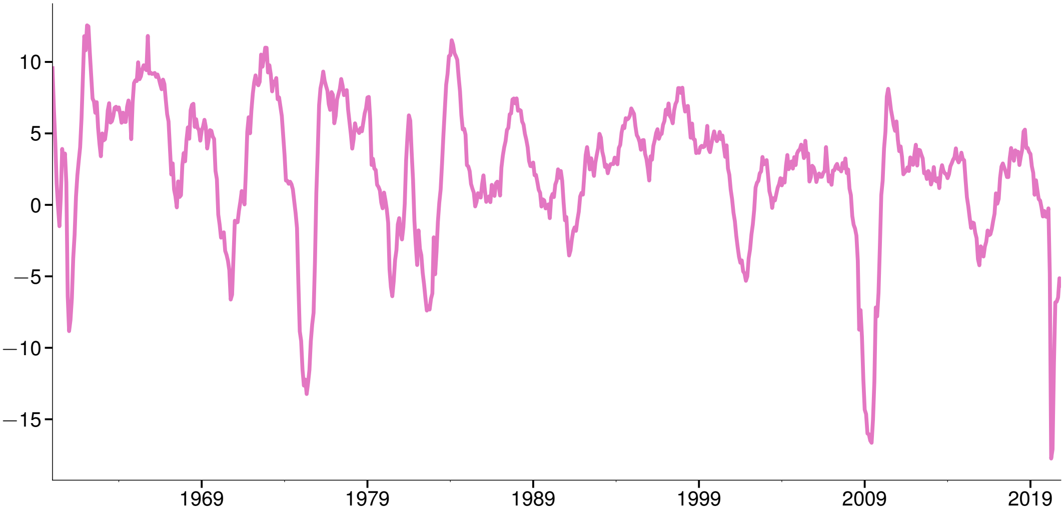
- Characteristic equation

$$z^2 - 1.7z^1 + .72$$

- Roots: $.9$ and $.8 \Rightarrow$ stationary

Fitting a Basic ARMA

YoY % change in Industrial Production



Parameter Estimates

AR2

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \epsilon_2$$

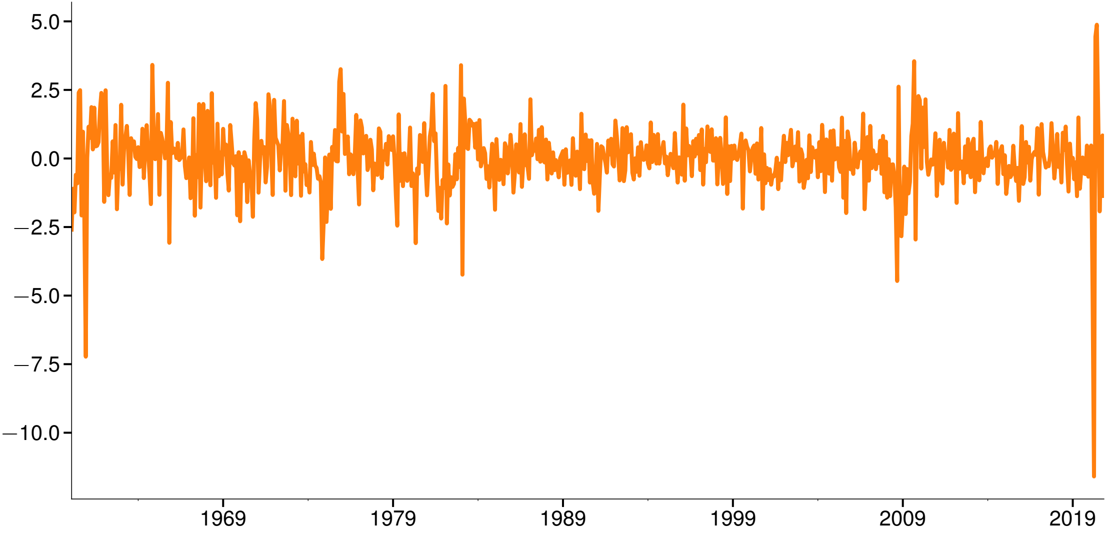
Parameter Estimates

	Estimate	s.e.	Z	p-value
ϕ_0	0.1106	0.045	2.453	0.014
ϕ_1	1.3187	0.017	79.114	0.000
ϕ_2	-0.3643	0.018	-20.624	0.000
σ^2	1.3635	0.028	48.775	0.000

Roots of Characteristic Polynomial

c_1	c_2
0.924852	0.39388

Residuals



Autocorrelations and Partial Autocorrelations

Autocorrelations and the ACF

- Autocorrelations are a key element of model building

Definition (Autocorrelation)

The autocorrelation of a covariance stationary scalar process is defined

$$\rho_s = \frac{\gamma_s}{\gamma_0}$$

where $\gamma_s = \mathrm{E}\left[(Y_t - \mu)(Y_{t-s} - \mu)\right]$.

- Measures the correlation of a process at different points in time
- AR(1):

$$\rho_s = \phi_1^s$$

- One of two possibilities
  - Decay geometrically if $0 < \phi_1 < 1$
  - Oscillate and decay $-1 < \phi_1 < 0$

Partial Autocorrelations (PACF)

- Partial Autocorrelation is the other key element of model building
- More complicated than autocorrelations:
- Regression interpretation of s^th partial autocorrelation:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_{s-1} Y_{t-s+1} + \varphi_s Y_{t-s} + \epsilon_t$$

- φ_s is the s^th partial autocorrelation
  - Population (not sample) value of φ_s
- AR(1):

$$\varphi_s = \begin{cases} \phi_1^{|s|} \text{ for s} = -1, 0, 1 \\ 0 \text{ otherwise} \end{cases}$$

- Partial autocorrelation function maps the parameters of a process to the s^th autocorrelation, $\varphi(s)$

Autocorrelations Structure of ARMA Processes

Using the ACF and PACF to categorize processes

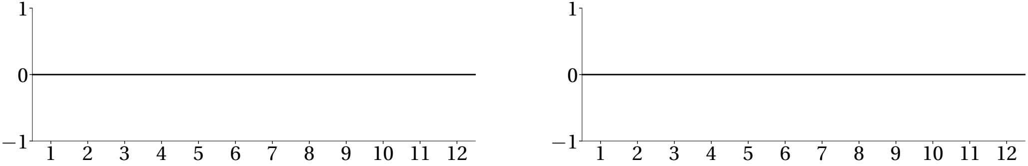
- ACF and PACF are useful when choosing models

Process	ACF	PACF
White Noise	All 0	All 0
AR(1)	$\rho_s = \phi_1^s$	0 beyond lag 2
AR(P)	Decays toward zero exponentially	Non-zero through lag P, 0 thereafter
MA(1)	$\rho_1 \neq 0$, $\rho_s = 0$, $s > 0$	Decays toward zero exponentially
MA(Q)	$\rho_s \neq 0$ $s \leq Q$, $\rho_s = 0$, $s > Q$	Decays toward zero exponentially, possible oscillating
ARMA(P,Q)	Exponential Decay	Exponential Decay

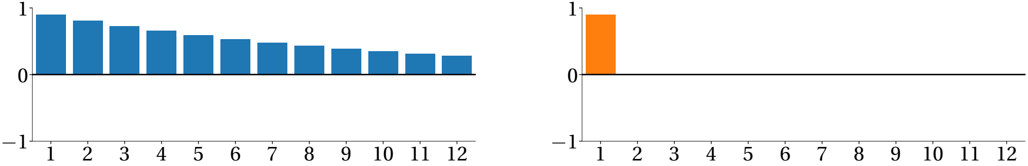
Autocorrelation for ARMA processes

ACF PACF

White Noise



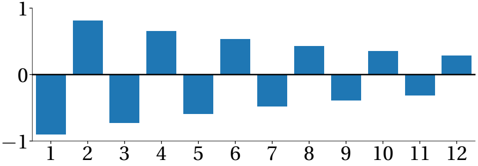
AR(1), $\phi_1 = 0.9$

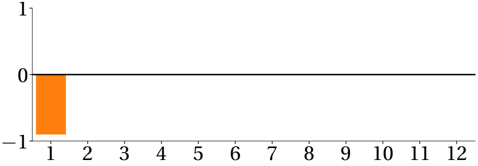


Autocorrelation for ARMA processes

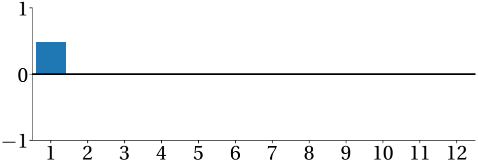
ACF | PACF

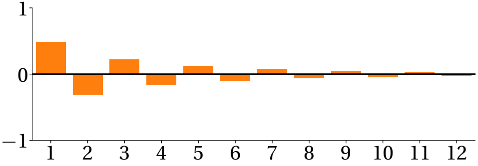
AR(1), $\phi_1 = -0.9$





MA(1), $\theta_1 = 0.8$

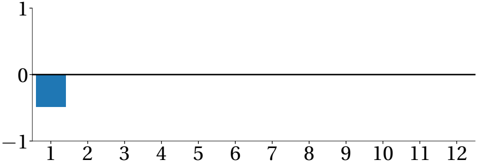


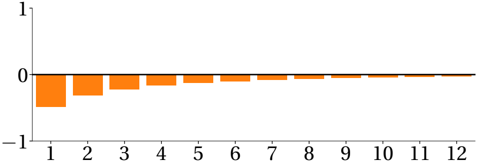


Autocorrelation for ARMA processes

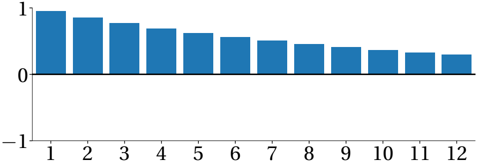
ACF PACF

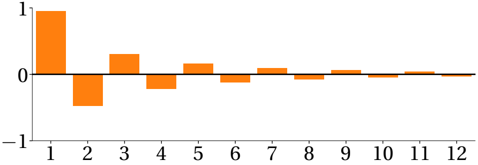
MA(1), $\theta_1 = -0.8$



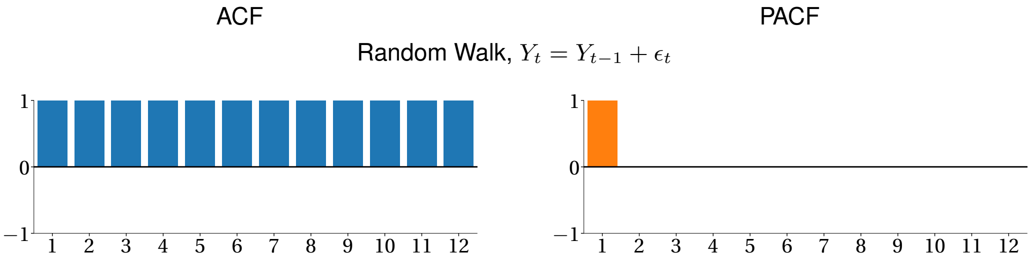


ARMA(1,1), $\phi_1 = 0.9$, $\theta_1 = -0.8$





Autocorrelation for ARMA processes



Estimating Autocorrelations and Partial Auocorreations

Sample ACF and PACF

- Sample autocorrelations

$$\hat{\rho}_s = \frac{\sum_{t=s+1}^{T} Y_t^* Y_{t-s}^*}{\sum_{t=1}^{T} Y_t^{*2}} = \frac{\hat{\gamma}_s}{\hat{\gamma}_0}$$

  - $Y_t^* = Y_t - \bar{Y}$ where $\bar{Y} = T^{-1} \sum_{t=1}^{T} Y_t$
- Some prefer the small-sample-size corrected version

$$\hat{\rho}_s = \frac{\sum_{t=s+1}^{T} Y_t^* Y_{t-s}^*}{\sqrt{\sum_{t=s+1}^{T} Y_t^{*2} \sum_{t=1}^{T-s} Y_t^{*2}}}.$$

- Sample partial autocorrelations
  - Run regression to estimate $\hat{\varphi}_s$

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \varphi_s Y_{t-s} + \epsilon_t$$

- More efficient ways to compute PACF using Yule-Walker (see notes)

Testing Autocorrelations and Partial Auocorreations

Testing autocorrelations and partial ACs

- Inference on autocorrelations:

$$\begin{aligned} \mathrm{V}[\hat{\rho}_s] &= T^{-1} && \text{for } s = 1 \\ &= T^{-1}(1 + 2\sum_{j=1}^{s-1} \hat{\rho}_j^2) && \text{for } s > 1 \end{aligned}$$

- Standard t-stats

$$\frac{\hat{\rho}_s}{\sqrt{\mathrm{V}[\hat{\rho}_s]}} \overset{A}{\sim} N(0,1).$$

- Inference on partial autocorrelations:

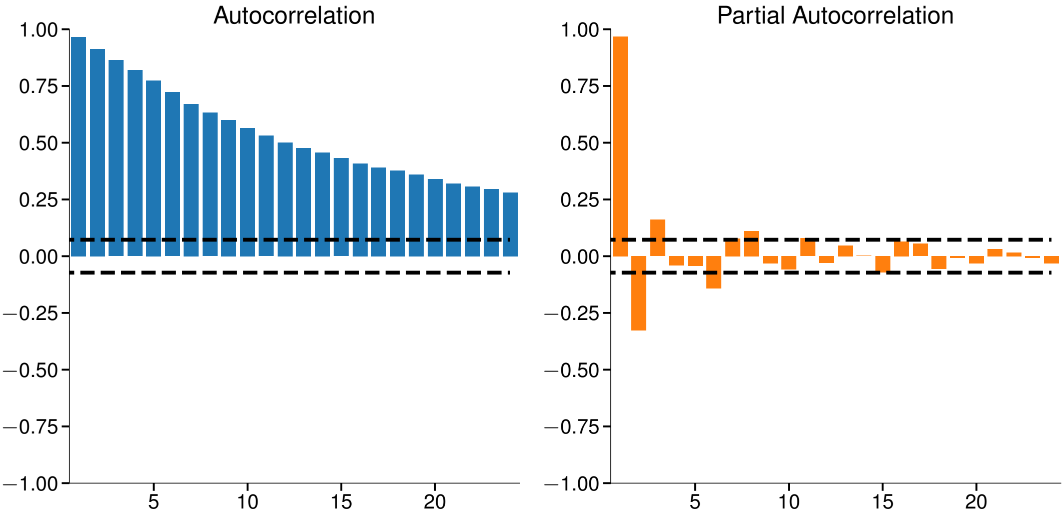
$$\mathrm{V}[\hat{\varphi}_s] \approx T^{-1}$$

- Standard t-stats

$$T^{\frac{1}{2}} \hat{\varphi}_s \overset{A}{\sim} N(0,1)$$

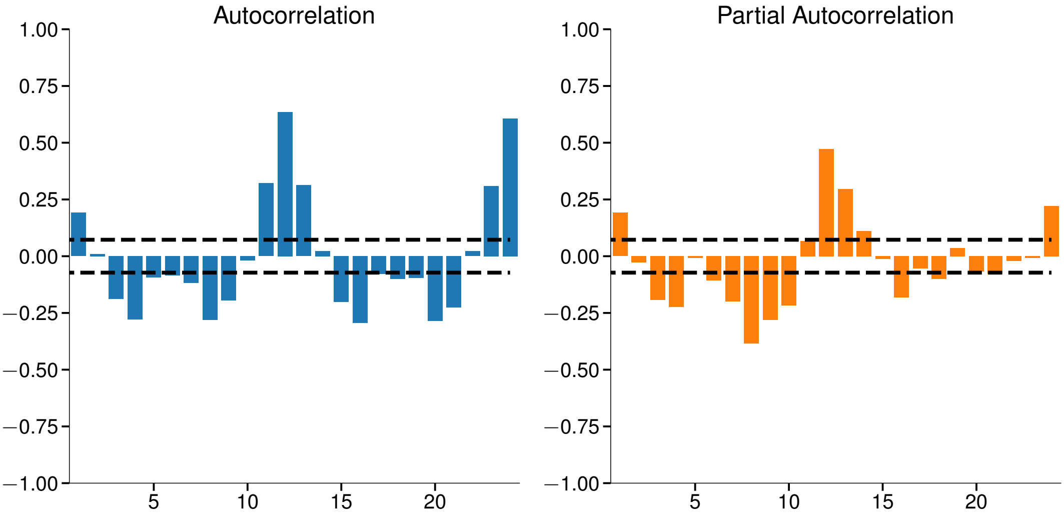
Autocorrelations

The Default Premium



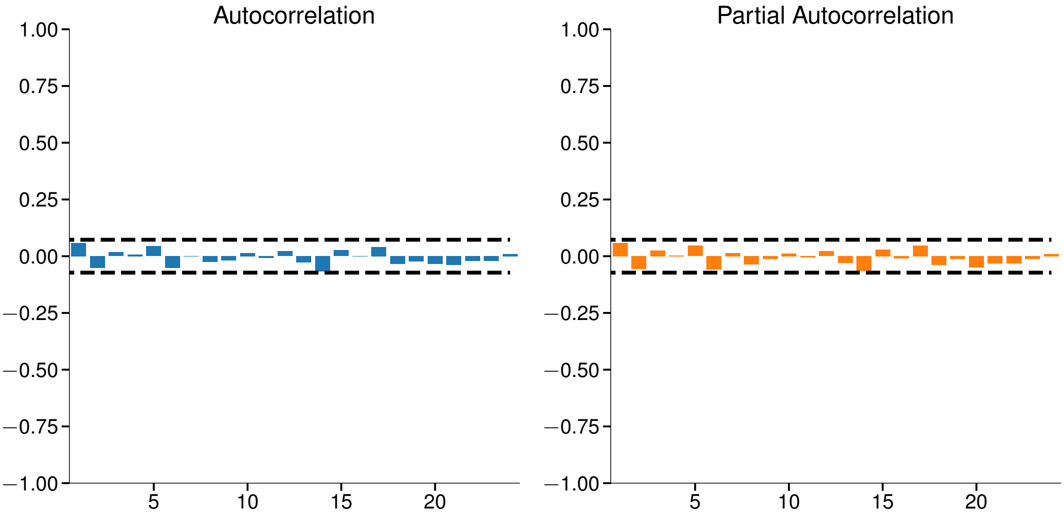
Autocorrelations

Monthly Housing Start Growth Rate



Autocorrelations

Value Weighted Market Return



Testing multiple autocorrelations

- Testing multiple autocorrelations: Ljung-Box Q, $H_0 : \rho_1 = \ldots = \rho_s = 0$

$$Q = T(T+2)\sum_{k=1}^{s}\frac{\hat{\rho}_k^2}{T-k} \sim \chi^2_s$$

- Note: Not heteroskedasticity robust, use LM test for serial correlation

Definition (LM test for serial correlation)

Under the null, $\mathrm{E}[Y_t^* Y_{t-j}^*] = 0$ for $1 \leq j \leq s$. The LM-test for serial correlation is constructed by defining the score vector $\mathbf{s}_t = Y_t^* \left[Y_{t-1}^* \, Y_{t-2}^* \ldots Y_{t-s}^*\right]'$,

$$LM = T\bar{\mathbf{s}}'\hat{\mathbf{S}}^{-1}\bar{\mathbf{s}} \xrightarrow{d} \chi^2_s$$

where $\bar{\mathbf{s}} = T^{-1}\sum_{t=1}^{T}\mathbf{s}_t$, $\hat{\mathbf{S}} = T^{-1}\sum_{t=1}^{T}\mathbf{s}_t\mathbf{s}_t'$ and $Y_t^* = Y_t - \bar{Y}$ where $\bar{Y} = T^{-1}\sum_{t=1}^{T} Y_t$.

Parameter Estimation

Conditional MLE

- Conditional MLE assuming distribution of $Y_t|Y_{t-1},\epsilon_{t-1},Y_{t-2},\epsilon_{t-2},\ldots$ is $N\left(0,\sigma^2\right)$
- If $\epsilon_{t-1},\epsilon_{t-2},...,\epsilon_{t-Q}$ are observable, identical to least squares

$$\underset{\boldsymbol{\phi},\boldsymbol{\theta}}{\operatorname{argmin}} \sum_{t=P+1}^{T} \left(Y_t-\phi_0-\phi_1 Y_{t-1}-\ldots-\phi_P Y_{t-P}-\theta_1\epsilon_{t-1}-\ldots-\theta_Q\epsilon_{t-Q}\right)^2$$

- Ignore distribution of $Y_1,\ldots Y_P$ in fit
  - Finite sample effects, asymptotically irrelevant
- If $\epsilon_{P-1},\ldots,\epsilon_{P-Q}$ are observable, can recursively compute $\epsilon_P.\ldots,\epsilon_T$ for a set of parameters $\boldsymbol{\phi},\boldsymbol{\theta}$
- Overcome missing initial shocks by assuming $\epsilon_{P-1}=\ldots=\epsilon_{P-Q}=0$

Ordinary Least Squares

- If $Q = 0$, conditional MLE simplifies

$$\underset{\boldsymbol{\phi}}{\operatorname{argmin}} \sum_{t=P+1}^{T} \left(Y_t - \phi_0 - \phi_1 Y_{t-1} - \ldots - \phi_P Y_{t-P}\right)^2$$

- Conditional MLE is identical to OLS
- Inference is identical
- Use classical or White's covariance estimator as appropriate
- Can also incorporate deterministic terms such as time trends while maintaining simplicity of OLS

Exact MLE

- Define the vector of data

$$\mathbf{y} = [Y_1, Y_2, \ldots, Y_{T-1}\, Y_T]'$$

- $\mathbf{\Gamma}$ be the T by T covariance matrix of $\mathbf{y}$

$$\mathbf{\Gamma} = \begin{bmatrix} \gamma_0 & \gamma_1 & \gamma_2 & \gamma_3 & \cdots & \gamma_{T-2} & \gamma_{T-1} \\ \gamma_1 & \gamma_0 & \gamma_1 & \gamma_2 & \cdots & \gamma_{T-3} & \gamma_{T-2} \\ \gamma_2 & \gamma_1 & \gamma_0 & \gamma_1 & \cdots & \gamma_{T-4} & \gamma_{T-3} \\ \vdots & \vdots & \vdots & \vdots & \ldots & \vdots & \vdots \\ \gamma_{T-2} & \gamma_{T-3} & \gamma_{T-4} & \gamma_{T-5} & \cdots & \gamma_0 & \gamma_1 \\ \gamma_{T-1} & \gamma_{T-2} & \gamma_{T-3} & \gamma_{T-4} & \cdots & \gamma_1 & \gamma_0 \end{bmatrix}$$

- The joint likelihood of $\mathbf{y}$

$$f(\mathbf{y}|\boldsymbol{\phi}, \boldsymbol{\theta}, \sigma^2) = (2\pi)^{-\frac{T}{2}} |\mathbf{\Gamma}|^{-\frac{T}{2}} \exp\left(-\frac{\mathbf{y}'\mathbf{\Gamma}^{-1}\mathbf{y}}{2}\right)$$

- Log-likelihood

$$l(\boldsymbol{\phi}, \boldsymbol{\theta}, \sigma^2; \mathbf{y}) = -\frac{T}{2}\ln(2\pi) - \frac{T}{2}\ln|\mathbf{\Gamma}| - \frac{1}{2}\mathbf{y}'\mathbf{\Gamma}^{-1}\mathbf{y}$$

Model Building

Model building the Box-Jenkins way

- Model building is similar to cross-section regression
- Can use same techniques
  - General to Specific or Specific to General
  - Information criteria: AIC, BIC
- Box-Jenkins is dominant methodology, 2-steps
  - Identification: Use ACF and PACF to choose model
  - Estimation: Estimate model and do diagnostic checks
- Two principles
  - Parsimony
  - Invertibility

Strategies

- General to Specific
  - Fit largest specification
  - Drop regressor with largest p-value
  - Refit
  - Stop if all p-values indicate significance using a size of α
    - α is the econometrician's choice
- Specific to General
  - Fit all specifications with a single variable
  - Retail variable with smallest p-value
  - Extend this model adding on additional variables one at a time
  - Stop if the p-values of all excluded variables are larger than α

Information Criteria

- Information Criteria
  - Akaike Information Criterion (AIC)

$$AIC = \ln \hat{\sigma}^2 + k\frac{2}{T}$$

  - Schwartz (Bayesian) Information Criterion (SIC/BIC)

$$BIC = \ln \hat{\sigma}^2 + k\frac{\ln T}{T}$$

- Both have versions suitable for likelihood based estimation
- Reward for better fit: Reduce $\ln \hat{\sigma}^2$
- Penalty for more parameters: $k\frac{2}{T}$ or $k\frac{\ln T}{T}$
- Choose model with smallest IC
  - AIC has fixed penalty $\Rightarrow$ inclusion of extraneous variables
  - BIC has larger penalty if $\ln T > 2$ ($T > 7$)

Model Building: Specific-to-General

The Default Premium

AR(1)

	Estimate	s.e.	Z	p-value
ϕ_0	3.4827	1.205	2.891	0.004
ϕ_1	0.9652	0.007	139.901	0.000

MA(1)

	Estimate	s.e.	Z	p-value
ϕ_0	101.2112	2.446	41.378	0.000
θ_1	0.9218	0.008	118.011	0.000

Model Building: Specific-to-General

The Default Premium

AR(2)

	Estimate	s.e.	Z	p-value
ϕ_0	4.5373	1.171	3.874	0.000
ϕ_1	1.2718	0.021	61.901	0.000
ϕ_2	-0.3169	0.020	-15.506	0.000

ARMA(1,1)

	Estimate	s.e.	Z	p-value
ϕ_0	5.7953	1.587	3.652	0.000
ϕ_1	0.9423	0.009	99.314	0.000
θ_1	0.3911	0.021	18.501	0.000

Model Building: Specific-to-General

The Default Premium

ARMA(2,1)

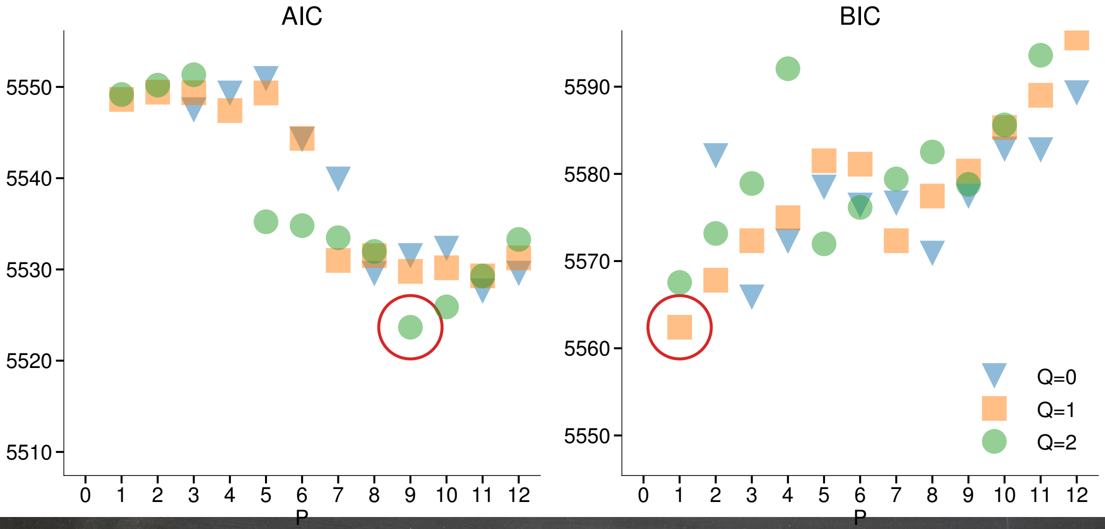
	Estimate	s.e.	Z	p-value
ϕ_0	5.8678	1.631	3.597	0.000
ϕ_1	0.8930	0.057	15.715	0.000
ϕ_2	0.0486	0.056	0.873	0.383
θ_1	0.4337	0.052	8.412	0.000

ARMA(1,2)

	Estimate	s.e.	Z	p-value
ϕ_0	5.5511	1.590	3.491	0.000
ϕ_1	0.9447	0.010	96.942	0.000
θ_1	0.3814	0.024	16.024	0.000
θ_2	-0.0217	0.023	-0.949	0.343

Model Building: Information Criteria

The Default Premium



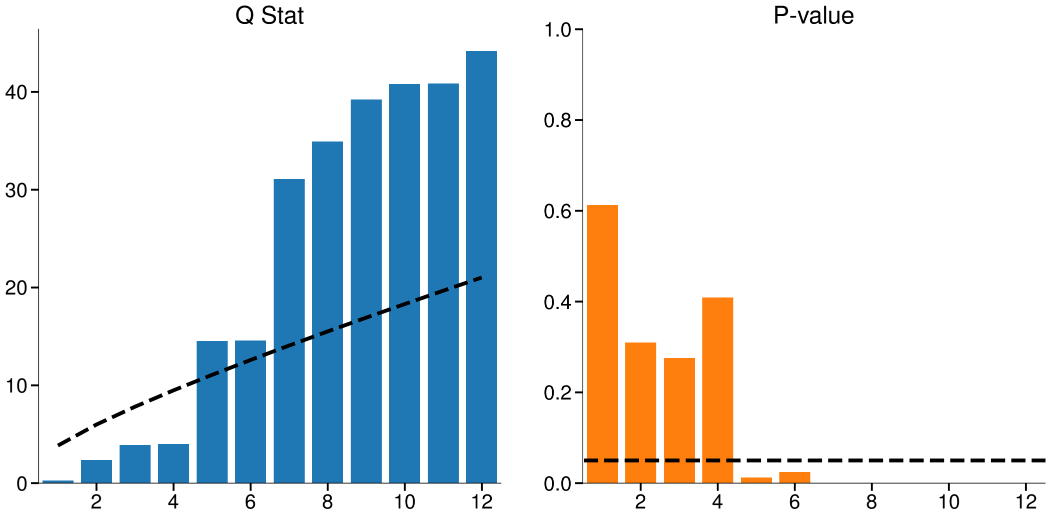
Model Diagnostics

Model Diagnostics

- Important to assess whether your model "fits"
  - Are the residuals white noise?
    - Eye-ball test
    - Ljung-Box Q stat or LM serial correlation test of $H_0 : \rho_1 = \ldots = \rho_s = 0$.
    - SACF/SPACF of the residuals
  - Are there any large outliers?
    - Eye-ball test
- What to do if there are problems?
  - Use SPACF/SACF to repeat Box-Jenkins and augment your model with correct dynamics to pick up problem
  - Repeat diagnostics
- Concern: Repeated testing may render critical values misleading

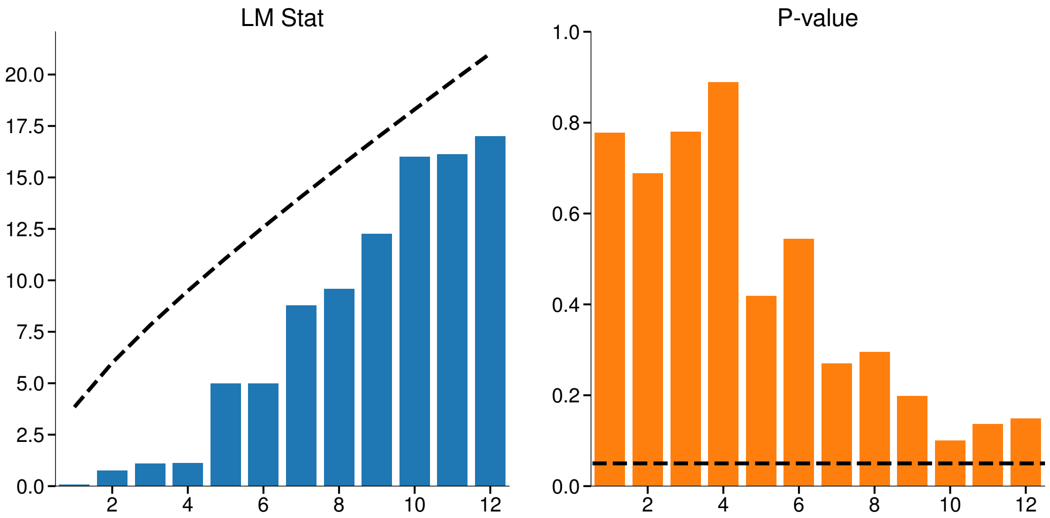
Ljung-Box on Residuals

ARMA(1,1)



LM test for Serial Correlation on Residuals

ARMA(1,1)



The Information Set

The information set and the law of iterated expectations

- Information set: $\mathcal{F}_t$
- Contains a lot of information!
  - Every time t *measurable* event
  - Observed variables: prices, returns, GDP, interest rates, FX rates
  - Functions of these
  - Excludes variables which are latent: volatility
- Conditional expectation:

$$\mathrm{E}[Y_{t+1}|\mathcal{F}_t]$$

  Conditional Variance

$$\mathrm{V}[Y_{t+1}|\mathcal{F}_t]$$

  - Shorthand $\mathrm{E}_t[Y_{t+1}]$ and $\mathrm{V}_t[Y_{t+1}]$
- Law of Iterated Expectation (LIE):

$$E_t[E_{t+1}[Y_{t+2}]] = E_t[Y_{t+2}]$$

  - Monday's belief about what Tuesday's belief about Wednesday is the same as Monday's belief of Wednesday

Loss Functions

Forecasting

- A $h-$step ahead forecast, $\hat{Y}_{t+h|t}$, is designed to minimize a loss function
  - MSE: $(Y_{t+h} - \hat{Y}_{t+h|t})^2$
  - MAD: $|Y_{t+h} - \hat{Y}_{t+h|t}|$
  - Quad-Quad: $\alpha_1(Y_{t+h} - \hat{Y}_{t+h|t})^2 + \alpha_2 I_{[Y_{t+h} - \hat{Y}_{t+h|t} < 0]}(Y_{t+h} - \hat{Y}_{t+h|t})^2$
    - Asymmetric if $\alpha_1 \neq \alpha_2$

The MSE Optimal Forecast is the conditional mean

- Let $Y^*_{t+h} = \mathrm{E}_t[Y_{t+h}]$
- Let $\tilde{Y}_{t+h}$ be any other value

$$\begin{aligned}
\mathrm{E}_t[(Y_{t+h} - \tilde{Y}_{t+h})^2] &= \mathrm{E}_t[\left(\left(Y_{t+h} - Y^*_{t+h}\right) + \left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)\right)^2] \\
&= \mathrm{E}_t[\left(Y_{t+h} - Y^*_{t+h}\right)^2 + 2\left(Y_{t+h} - Y^*_{t+h}\right)\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right) + \left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)^2] \\
&= \mathrm{V}_t[Y_{t+h}] + 2\mathrm{E}_t[\left(Y_{t+h} - Y^*_{t+h}\right)\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)] + \mathrm{E}_t[\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)^2] \\
&= \mathrm{V}_t[Y_{t+h}] + 2\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)\mathrm{E}_t[\left(Y_{t+h} - Y^*_{t+h}\right)] + \mathrm{E}_t[\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)^2] \\
&= \mathrm{V}_t[Y_{t+h}] + 2\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)\cdot 0 + \mathrm{E}_t[\left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)^2] \\
&= \mathrm{V}_t[Y_{t+h}] + \left(Y^*_{t+h} - \tilde{Y}_{t+h}\right)^2
\end{aligned}$$

Forecasting

Forecasting

- MSE optimal forecast for an AR(1):

$$Y_t = \phi_1 Y_{t-1} + \epsilon_t$$

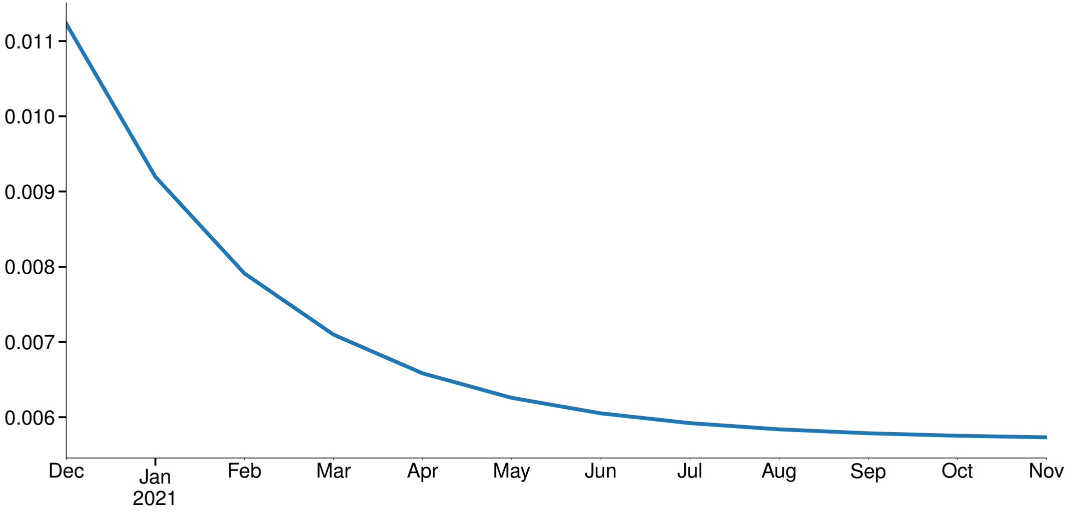
$$\begin{aligned} \mathrm{E}_t[Y_{t+1}] &= \mathrm{E}_t[\phi_1 Y_t + \epsilon_{t+1}] \\ &= \phi_1 \mathrm{E}_t[Y_t] + \mathrm{E}_t[\epsilon_{t+1}] \\ &= \phi_1 Y_t + 0 \end{aligned}$$

$$\begin{aligned} \mathrm{E}_t[Y_{t+2}] &= \mathrm{E}_t[\phi_1 Y_{t+1} + \epsilon_{t+2}] \\ &= \phi_1 \mathrm{E}_t[Y_{t+1}] + \mathrm{E}_t[\epsilon_{t+2}] \\ &= \phi_1 \left(\phi_1 Y_t\right) + 0 \\ &= \phi_1^2 Y_t + 0 \end{aligned}$$

Note: Long-run forecast is always $\mathrm{E}\left[Y_t\right]$ for a covariance stationary process

Forecasting

AR(1) for M2 Growth



Forecast Errors

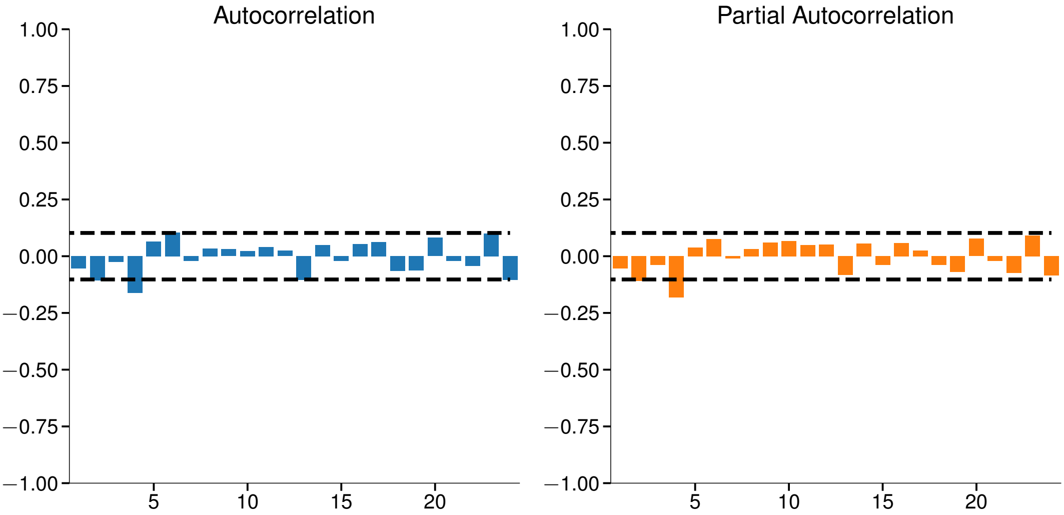
$$
\begin{aligned}
\mathrm{V}_t[Y_{t+1}] &= \mathrm{E}_t\left[\left(Y_{t+1} - \mathrm{E}_t\left[Y_{t+1}\right]\right)^2\right] \\
&= \mathrm{E}_t\left[\left(\phi Y_t + \epsilon_{t+1} - \phi Y_t\right)^2\right] \\
&= \mathrm{E}_t\left[\epsilon_{t+1}^2\right] = \sigma^2 \text{ if homoskedastic}
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{V}_t[Y_{t+2}] &= \mathrm{E}_t\left[\left(Y_{t+2} - \mathrm{E}_t\left[Y_{t+2}\right]\right)^2\right] \\
&= \mathrm{E}_t\left[\left(\phi^2 Y_t + \phi\epsilon_{t+1} + \epsilon_{t+2} - \phi^2 Y_t\right)^2\right] \\
&= \mathrm{E}_t\left[\left(\phi\epsilon_{t+1} + \epsilon_{t+2}\right)^2\right] \\
&= \phi^2 \mathrm{E}_t\left[\epsilon_{t+1}^2\right] + \mathrm{E}_t\left[\epsilon_{t+2}^2\right] = \left(1 + \phi^2\right)\sigma^2 \text{ if homoskedastic}
\end{aligned}
$$

Note: Long-run forecast error variance is always $\mathrm{V}\left[Y_t\right]$ for a covariance stationary process

Forecast Error Autocorrelation

Recursive AR(1) for M2 Growth



Mincer-Zarnowitz Tests

Forecast evaluation

Mincer-Zarnowitz regressions

- Objective Forcecast Evaluation

$$Y_{t+h} = \alpha + \beta \hat{Y}_{t+h|t} + \eta_t$$

- $H_0 : \alpha = 0, \beta = 1,\ H_1 : \alpha \neq 0 \cup \beta \neq 1$
  - Use any test: Wald, LR, LM
- Can be generalized to include any variable available when the forecast was produced

$$Y_{t+h} = \alpha + \beta \hat{Y}_{t+h|t} + \boldsymbol{\gamma} \mathbf{x}_t + \eta_t$$

- $H_0 : \alpha = 0, \beta = 1, \boldsymbol{\gamma} = \mathbf{0},\ ,\ H_1 : \alpha \neq 0 \cup \beta \neq 1 \cup \gamma_j \neq 0$
- $\mathbf{x}_t$ *must* be in the time t information set
- Important when working with macro data

Mincer-Zarnwotz

AR(1) for M2 Grwoth

Standard Form

$$Y_{t+1} = \alpha + \beta \hat{Y}_{t+1|t} + \eta_t$$

	Estimate	s.e.	Z	p-value
α	0.0004	0.000	0.936	0.350
β	0.8481	0.061	13.985	0.000

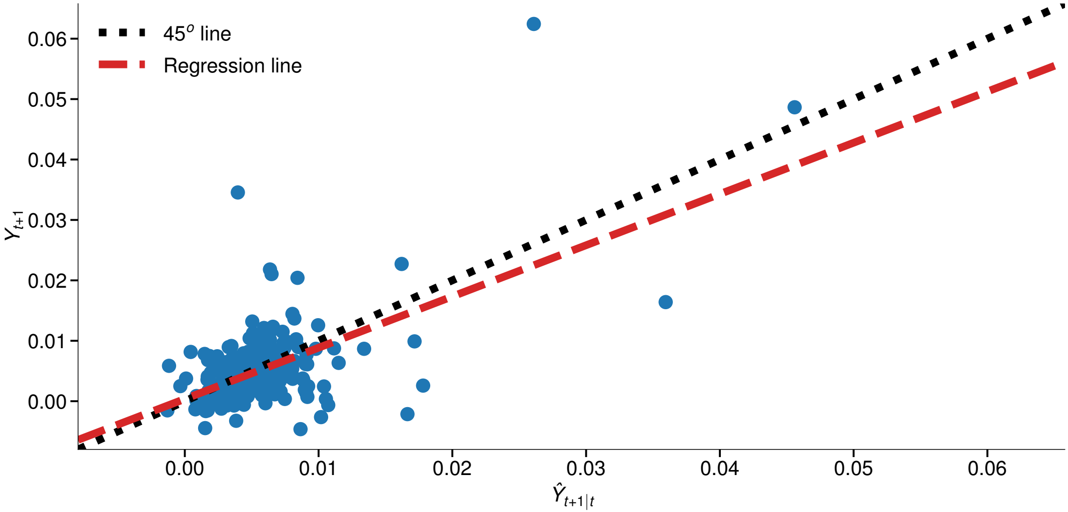
Simplified Form

$$Y_{t+1} - \hat{Y}_{t+1|t} = \alpha + \gamma \hat{Y}_{t+1|t} + \eta_t$$

	Estimate	s.e.	Z	p-value
α	0.0004	0.000	0.936	0.350
γ	-0.1519	0.061	-2.505	0.013

Mincer-Zarnwotz

AR(1) for M2 Grwoth



Diebold-Mariano Tests

Relative evaluation: Diebold-Mariano

- Two forecasts, $\hat{Y}^A_{t+h|t}$ and $\hat{Y}^B_{t+h|t}$
- Two losses, $l^A_t = (Y_{t+h} - \hat{Y}^A_{t+h|t})^2$ and $l^B_t = (Y_{t+h} - \hat{Y}^B_{t+h|t})^2$
  - Losses do not need to be MSE
- If equally good or bad, $\mathrm{E}[l^A_t] = \mathrm{E}[l^B_t]$ or $\mathrm{E}[l^A_t - l^B_t] = 0$
- Define $\delta_t = l^A_t - l^B_t$

Relative evaluation: Diebold-Mariano

- Implemented as a t-test that $\mathrm{E}[\delta_t] = 0$
- $H_0 : \mathrm{E}[\delta_t] = 0$, $H_1^A : \mathrm{E}[\delta_t] < 0$, $H_1^B : \mathrm{E}[\delta_t] > 0$
  - Composite alternative
  - Sign indicates which model is favored

$$DM = \frac{\bar{\delta}}{\sqrt{\widehat{\mathrm{V}[\bar{\delta}]}}} = \frac{T^{-1}\sum_{t=1}^{T}\delta_t}{\sqrt{\frac{\hat{\sigma}^2_{NW}}{T}}}$$

- One complication: $\{\delta_t\}$ cannot be assumed to be uncorrelated, so a more complicated variance estimator is required
- Newey-West covariance estimator:

$$\hat{\sigma}^2_{NW} = \hat{\gamma}_0 + 2\sum_{l=1}^{L}\left[1 - \frac{l}{L+1}\right]\hat{\gamma}_l$$

Implementing a Diebold-Mariano Test

$$DM = \frac{\bar{\delta}}{\sqrt{\widehat{\mathrm{V}[\bar{\delta}]}}}$$

Algorithm (Diebold-Mariano Test)

1. *Using the two forecasts,* $\hat{Y}^A_{t+h|t}$ *and* $\hat{Y}^B_{t+h|t}$*, compute* $\delta_t = l^A_t - l^B_t$
2. *Run the regression*

$$\delta_t = \beta + \eta_t$$

3. *Use a Newey-West covariance estimator (*`cov_type="HAC"`*)*
4. *T-test* $H_0 : \beta = 0$ *against* $H^A_1 : \beta < 0$*, and* $H^B_1 : \beta > 0$
5. *Reject if* $|t| > C_\alpha$ *where* C_α *is the critical value for a 2-sided test using a normal distribution with a size of* α*. If significant, reject in favor of model A if test statistic is negative or in favor of model B if test statistic is positive.*

Diebold-Mariano Testing

M2 Growth: AR(1) vs a Random Walk

Mean Square Error

$$L\left(Y_{t+1}, \hat{Y}_{t+1|t}\right) = \left(Y_{t+1} - \hat{Y}_{t+1|t}\right)^2$$

	Estimate	s.e.	Z	p-value
δ	-4.365×10^{-6}	2.16×10^{-6}	-2.017	0.044

Mean Absolute Error

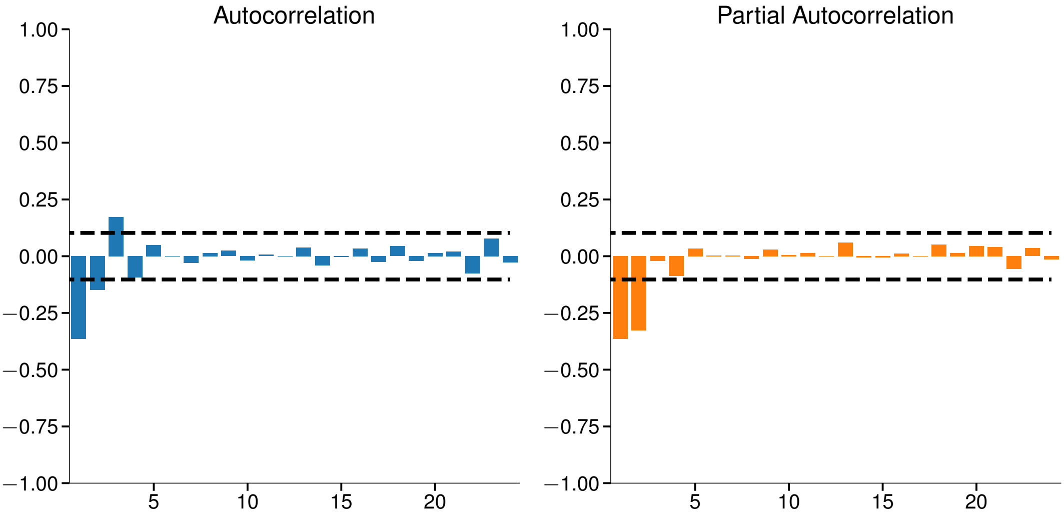
$$L\left(Y_{t+1}, \hat{Y}_{t+1|t}\right) = \left|Y_{t+1} - \hat{Y}_{t+1|t}\right|$$

	Estimate	s.e.	Z	p-value
δ	-0.0003	0.000	-2.358	0.018

- OLS on a constant using Newey-West with $\lfloor T^{1/3} \rfloor$

Autocorrelation of MAE δ_t

M2 Growth: AR(1) vs a Random Walk



The Lag Operator

The Lag Operator

- The Lag Operator is a useful tool in time series
- Simplifies expressing complex models with seasonal dynamics
- Key properties
  1. $LY_t = Y_{t-1}$
  2. $L^2Y_t = LY_{t-1} = L(LY_t) = Y_{t-2}$
  3. $L^aL^b = L^{(a+b)}$
  4. $Lc = c$ where c is a constant

Seasonality

Seasonality

- Seasonality is technically a form of non-stationarity
  - Mean explicitly depends on the quarter, month, day or minute
- Three types:

Definition (Seasonality)

Data are said to be seasonal if they exhibit a non-constant deterministic pattern on an annual basis.

Definition (Hebdomadality)

Data which exhibit day-of-week deterministic effects are said to be hebdomadal.

Definition (Diurnality)

Data which exhibit intra-daily deterministic effects are said to be diurnal.

Seasonality

- Simpler to think of processes with seasonality as having two models
  - Short-run AR and MA dynamics
  - Seasonal AR and MA dynamics
- Model building is standard with these two goals in mind

ARMA Modeling of Seasonality

Univariate Time Series Analysis

ARMA Modeling of Seasonality

Four Components

- Observation AR

$$(1 - \phi_1 L)\, Y_t = \phi_0 + \epsilon_t$$

- Seasonal AR

$$(1 - \phi_s L^s)\, Y_t = \phi_0 + \epsilon_t$$

- Observation MA

$$Y_t = \phi_0 + \left(1 + \theta_1 L^1\right) \epsilon_t$$

- Seasonal MA

$$Y_t = \phi_0 + (1 + \theta_s L^s)\, \epsilon_t$$

- Combined Model

$$(1 - \phi_1 L)(1 - \phi_s L^s)\, Y_t = \left(1 + \theta_1 L^1\right)(1 + \theta_s L^s)\, \epsilon_t$$

$$\begin{aligned} Y_t =& \phi_0 + \phi_1 Y_{t-1} + \phi_s Y_{t-s} - \phi_1 \phi_s Y_{t-s-1} \\ & + \theta_1 \epsilon_{t-1} + \theta_s \epsilon_{t-s} + \theta_1 \theta_s \epsilon_{t-s-1} + \epsilon_t \end{aligned}$$

ARMA Modeling of Seasonality

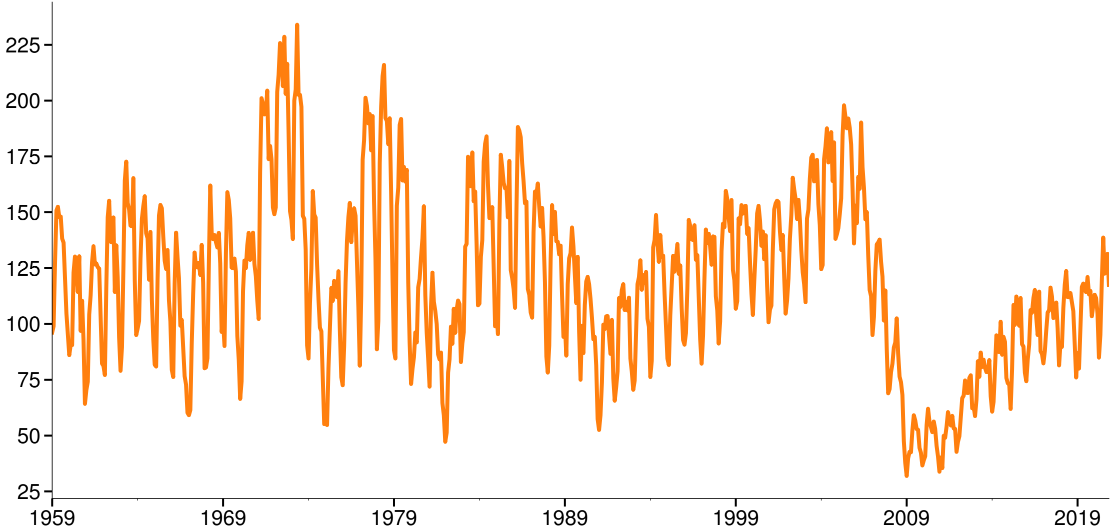
Four Components

- Generalizes to higher orders of each term
- Known as SARIMA$(p, 0, q) \times (P, 0, Q, s)$
- Imposes restrictions on parameters due to multiplication of terms
- Can estimate unrestricted equivalent

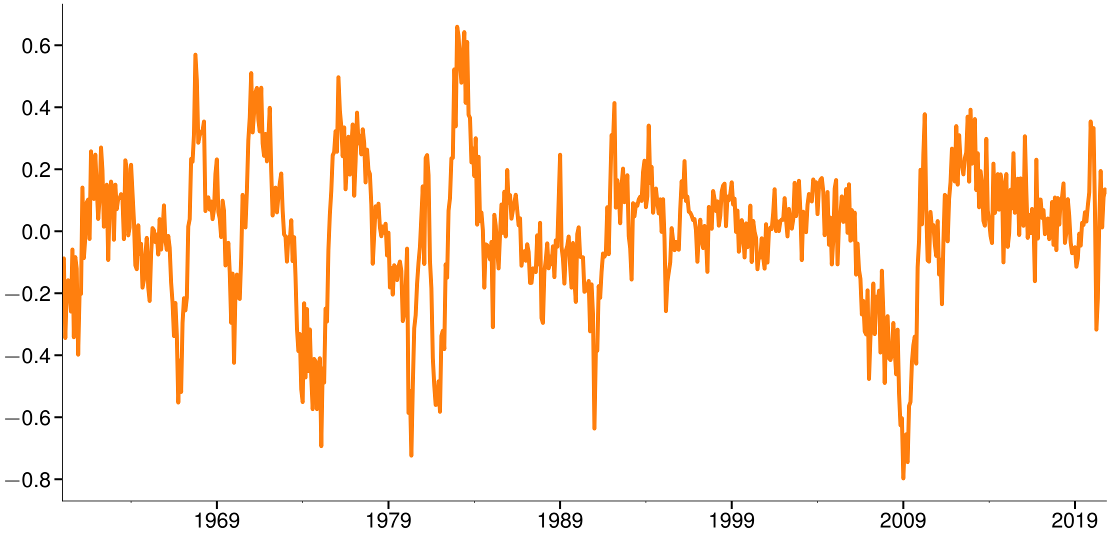
$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_s Y_{t-s} + \phi_{s+1} Y_{t-s-1} + \theta_1 \epsilon_{t-1} + \theta_s \epsilon_{t-s} + \theta_{s+1} \epsilon_{t-s-1} + \epsilon_t$$

- Can test $H_0 : \phi_{s+1} = \phi_1 \phi_s \cap \theta_{s+1} = \theta_1 \theta_s$

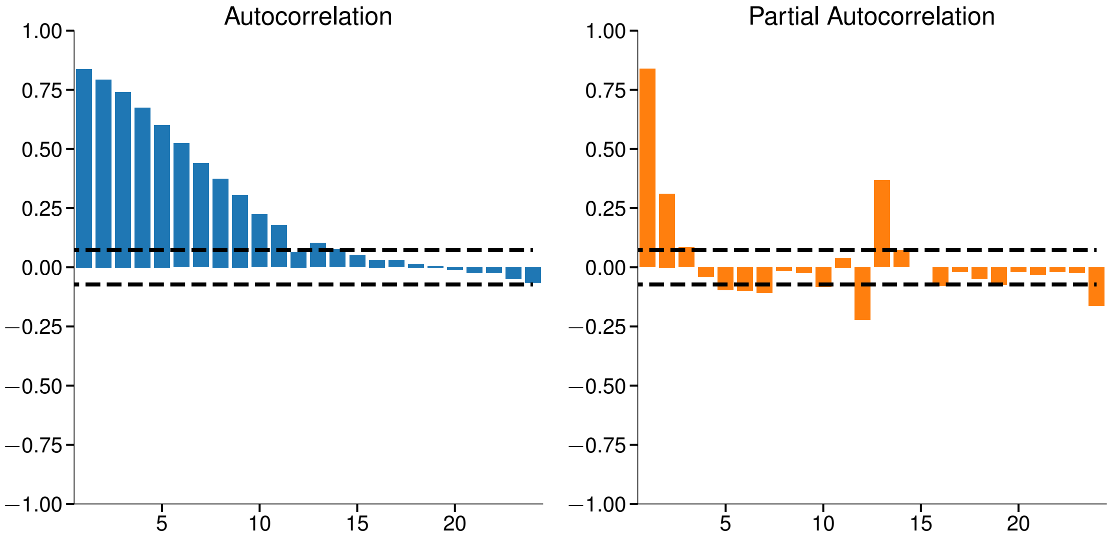
Housing Starts



YoY Growth in Housing Starts

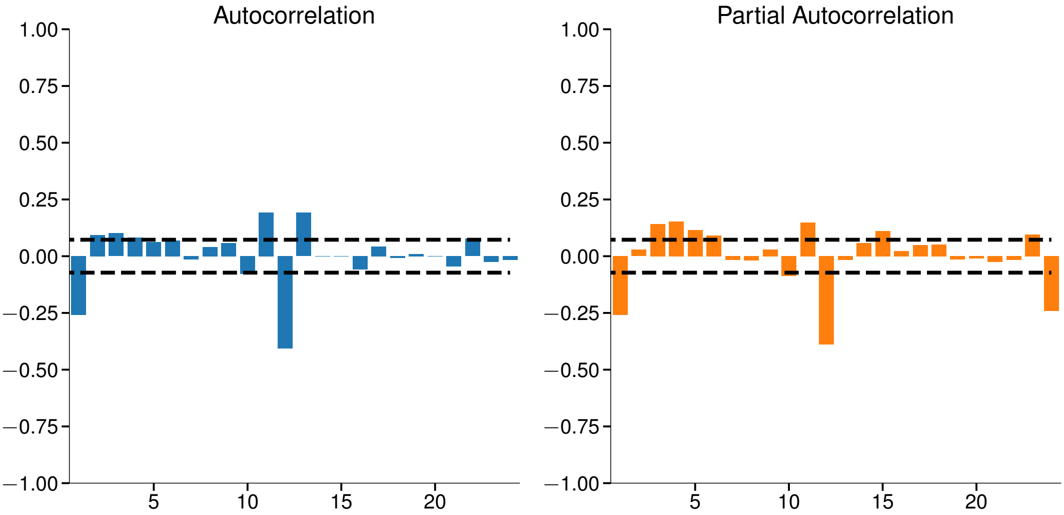


YoY Growth in Housing Starts Autocorrelation



Modeling YoY Growth in Housing Starts

AR(1) Residuals



Modeling Housing Starts

Levels

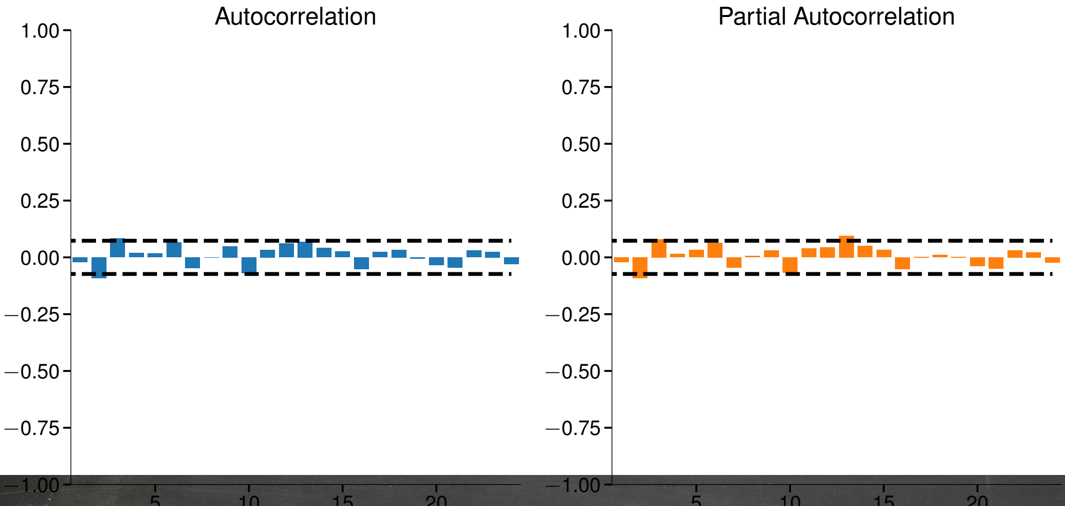
SARIMAX$(2,0,0) \times (0,0,1,12)$

	Estimate	s.e.	Z	p-value
ϕ_1	0.6809	0.034	20.284	0.000
ϕ_2	0.2824	0.034	8.233	0.000
$\theta_{s,12}$	-0.8795	0.017	-50.520	0.000

Modeling Housing Starts

Levels

SARIMAX$(2,0,0) \times (0,0,1,12)$



Modeling Housing Starts

Seasonal DIfferencing

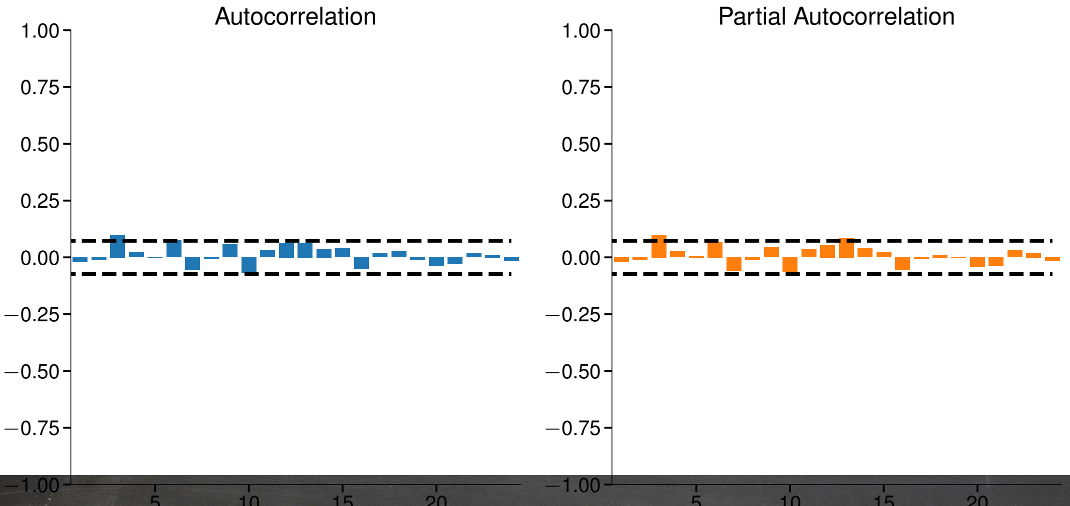
SARIMAX$(1,0,1)\times(0,1,1,12)$

	Estimate	s.e.	Z	p-value
ϕ_1	0.9779	0.008	127.034	0.000
θ_1	-0.3129	0.033	-9.361	0.000
$\theta_{s,12}$	-0.8775	0.018	-48.079	0.000

Modeling Housing Starts

Seasonal DIfferencing

SARIMAX$(1, 0, 1) \times (0, 1, 1, 12)$



Modeling Housing Starts

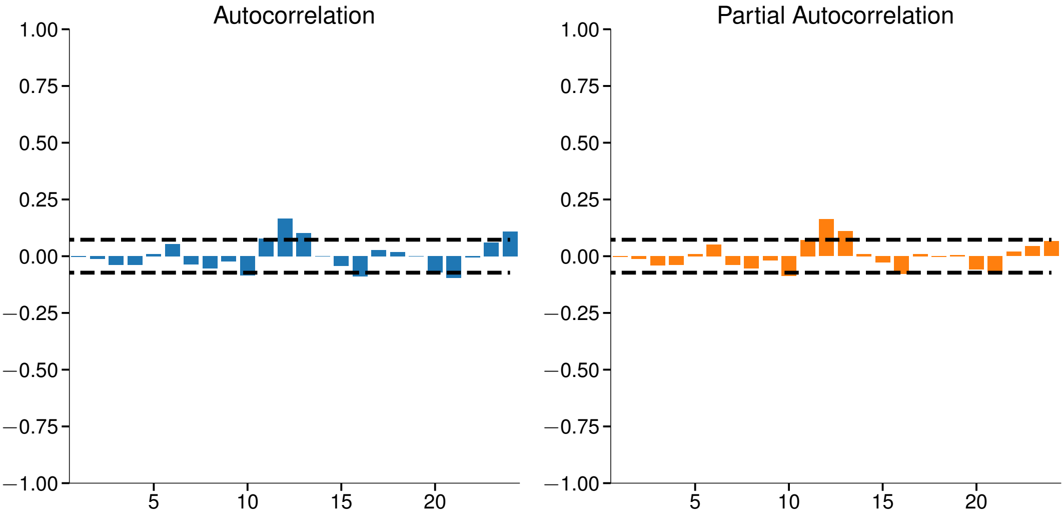
Seasonal Dummies

SARIMAX$(2, 1, 0)$ with Seasonal Dummies

	Estimate	s.e.	Z	p-value
ϕ_0	0.0002	0.004	0.046	0.964
Feb	0.0358	0.012	2.965	0.003
Mar	0.3075	0.012	24.776	0.000
Apr	0.4289	0.015	29.516	0.000
May	0.4669	0.018	26.260	0.000
Jun	0.4697	0.019	25.309	0.000
Jul	0.4328	0.019	23.265	0.000
Aug	0.4117	0.019	22.227	0.000
Sep	0.3657	0.017	21.803	0.000
Oct	0.3921	0.015	26.253	0.000
Nov	0.2169	0.013	16.943	0.000
Dec	0.0502	0.010	5.242	0.000
ϕ_1	-0.2675	0.033	-8.114	0.000
ϕ_2	-0.1107	0.034	-3.276	0.001

Modeling Housing Starts

Seasonal Dummies



Key Concepts

Seasonality, Lag Operator, SARIMA, Deterministic Trend, Exponential Trend

Questions

- How can seasonality be modeled in an ARMA model?
- Define diurnality, hebdomadality and seasonality.
- What are seasonal determinist terms and how do they differ from seasonal AR and MA terms?
- What is an exponential trend?
- What do the orders in a SARIMA mean?
- How could a standard AR be used to model a time series with a seasonal AR component?

Random Walks, Unit Roots and Stochastic Trends

Stochastic trends

- Stochastic trends are similar to deterministic trends
  - Dominant feature of a process

$$Y_t = \text{stochastic trend} + \text{stationary component} + \text{noise}$$

- Most common stochastic trend is a unit root
- There are others (generally non-linear)
- Removed using stochastic detrending (differencing)
  - Meaningfully different that deterministic detrending

Short-run Dynamics in a Unit Root process

- Unit root processes, in the long-run, behave like random walks
- In the short run, can have stationary dynamics

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \epsilon_t$$

- If this process contains a unit root, $\phi_1 + \phi_2 + \phi_3 = 1$
- Can see the SR dynamics by differencing

$$\begin{aligned}
Y_t &= \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-2} - \phi_3 Y_{t-2} + \phi_3 Y_{t-3} + \epsilon_t \\
Y_t &= \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-2} - \phi_3 \Delta Y_{t-2} + \epsilon_t \\
Y_t - Y_{t-1} &= (\phi_1 + \phi_2 + \phi_3 - 1) Y_{t-1} - (\phi_2 + \phi_3) \Delta Y_{t-1} - \phi_3 \Delta Y_{t-2} + \epsilon_t \\
\Delta Y_t &= \pi_1 \Delta Y_{t-1} + \pi_2 \Delta Y_{t-2} + \epsilon_2
\end{aligned}$$

What's the problem with unit roots?

- Unit roots cause a number of problems
  - Exploding variance: $\mathrm{V}[Y_t] = t\sigma^2$
  - Parameter estimates converge at different rates
  - Hypothesis tests have non-standard distributions
  - No mean reversion in long-run forecasts
  - Spurious regression
- Crucial to understand whether a process is stationary or contains a unit root
- Often has large economic consequences
  - PPP
  - Covered interest rate parity
  - Carry trades

Testing for Unit Roots

Testing for unit roots

- Dickey-Fuller looks like a standard t-test

$$Y_t = \phi_1 Y_{t-1} + \epsilon_t$$

- $H_0 : \phi_1 = 1$, $H_1 : \phi_1 < 1$
- Impose the null

$$\begin{aligned} Y_t - Y_{t-1} &= \phi_1 Y_{t-1} - Y_{t-1} + \epsilon_t \\ \Delta Y_t &= (\phi_1 - 1) Y_{t-1} + \epsilon_t \\ \Delta Y_t &= \gamma Y_{t-1} + \epsilon_t \end{aligned}$$

- New $H_0 : \gamma = 0$, $H_1 : \gamma < 0$
- Test with t-stat
- Augmented Dickey Fuller (ADF) captures short run dynamics as well

$$\Delta Y_t = \gamma Y_{t-1} + \rho_1 \Delta Y_{t-1} + \rho_2 \Delta Y_{t-2} + \ldots + \rho_P \Delta Y_{t-P} + \epsilon_t$$

- Lags of ΔY_{t-1} needed to ensure $\epsilon_t \sim WN\left(0, \sigma^2\right)$, also reduce variance of residuals

The problem

- t-stat is no longer asymptotically normal
- Requires Dickey-Fuller distribution
  - Most software packages contain the correct critical value
- Many processes with unit roots also contain deterministic components
- Asymptotic distribution depends on choice of model:

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{p=1}^{P} \phi_p \Delta Y_{t-p} + \epsilon_t \qquad \text{(No trend)}$$

$$\Delta Y_t = \delta_0 + \gamma Y_{t-1} + \sum_{p=1}^{P} \phi_p \Delta Y_{t-p} + \epsilon_t \qquad \text{(Constant, linear in } Y_t\text{)}$$

$$\Delta Y_t = \delta_0 + \delta_1 t + \gamma Y_{t-1} + \sum_{p=1}^{P} \phi_p \Delta Y_{t-p} + \epsilon_t \qquad \text{(Constant, quadratic in } Y_t\text{)}$$

- More deterministic regressors lower the critical value
- Reject null of unit root if t-stat of γ is ***negative*** and below the critical value

The Role of The Deterministic Terms

- ADF tests include deterministic terms to remove these effects from Y_{t-1}
- Suppose Y_t is a pure time trend process

$$Y_t = \alpha + \beta t + \epsilon_t$$

- The differenced value is

$$\begin{aligned}\Delta Y_t &= \alpha + \beta t + \epsilon_t - \alpha - \beta (t-1) - \epsilon_{t-1} \\ &= \beta - \epsilon_{t-1} + \epsilon_t\end{aligned}$$

  - MA(1) without a trend
- In an ADF with deterministic regressors

$$\Delta Y_t = \delta_0 + \delta_1 t + \gamma Y_{t-1} + \epsilon_t$$

- The deterministic terms remove determinitic components from Y_{t-1}
- γ depends on

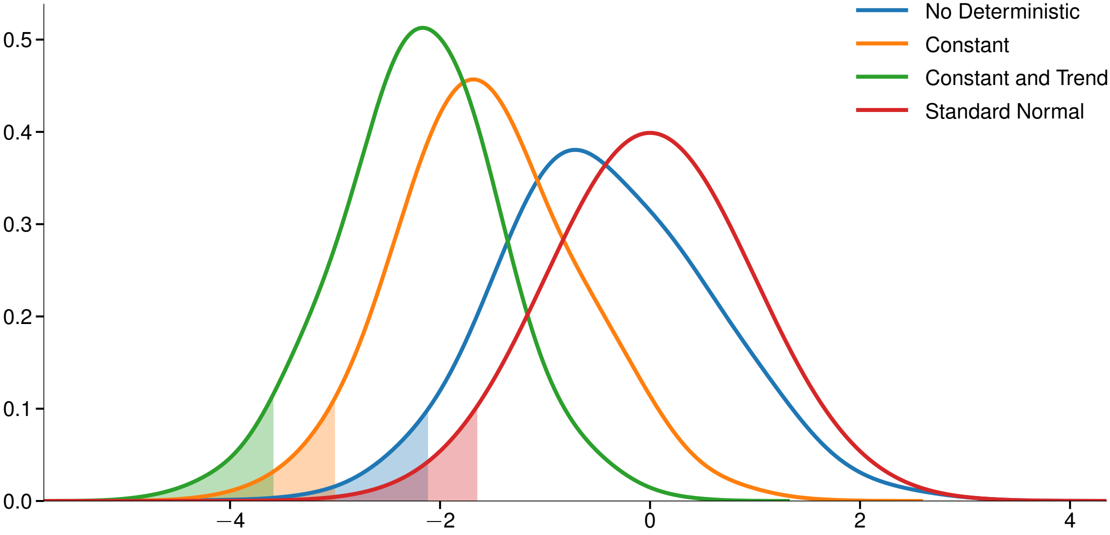
$$\text{Cov}\left[\Delta Y_t, Y_{t-1} - \alpha - \beta (t-1)\right] = \text{Cov}\left[\beta - \epsilon_{t-1} + \epsilon_t, \epsilon_{t-1}\right] = -\sigma^2$$

- Failing to include the deterministic regressors results in γ that depends on

$$\text{Cov}\left[\Delta Y_t, Y_{t-1}\right] = 0$$

  - Time trend dominates the other components of Y_{t-1}

The Dickey-Fuller Distributions



Important considerations

- Unit root tests are well known for having low power
- Power = 1-Pr(type II)
  - Chance you don't reject when alternative is true
- Some suggestions
  - Use a loose model selection when choosing the number of lags of ΔY_{t-j}, e.g. AIC
  - Be conservative in excluding deterministic regressors.
    - Including a constant or time-trend when absent hurts power
    - Excluding a constant or time-trend when present results in no power
  - More powerful tests than the ADF are available: DF-GLS
  - Visually inspect the data and differenced data
  - Use a general-to-specific search
- Number of differences needed is the *order of integration*
  - Integrated of Order 1 or I(1): Y_t is nonstationary but ΔY_t is stationary
  - I(d): Y_t is nonstationary, $\Delta^j Y_t$ also nonstationary when $j < d$, $\Delta^d Y_t$ is stationary

Unit Root Testing

	ADF Statistic	p-value	Lags	Deterministic
Default	-3.866	0.002	10	c
Curvature	-4.412	0.000	19	c
$\ln$ Ind Prod	-2.186	0.211	4	c
	-1.831	0.690	6	ct
	-2.962	0.314	6	ctt
$\Delta \ln$ Ind Prod	-11.945	0.000	3	c

- Lags determined using AIC
- Deterministic order increased when null is not rejected

The Role Of Deterministics

Trend Stationary AR(1)

$$Y_t = 0.025t + 0.7Y_{t-1} + \epsilon_t$$

ADF Statistic	p-value	Lags	Deterministic
1.934	0.988	9	n
-1.146	0.696	9	c
-6.790	0.000	0	ct
-6.885	0.000	0	ctt

- Correct specification uses “ct”

Seasonal Differencing

Seasonal Differencing

- Seasonal series should use seasonal differencing

$$\Delta_s Y_t = Y_t - Y_{t-s}$$

- Complete SARIMA$(P, D, Q) \times (P_s, D_s, Q_s, s)$ model
  - D is order of observational difference
  - D_s is order of seasonal difference
  - P and Q are observational AR and MA orders
  - P_s and Q_s are seasonal AR and MA orders
- Special Cases
  - ARMA(P, Q): $D = D_s = P_s = Q_s = 0$
  - ARIMA(P, D, Q): $D_s = P_s = Q_s = 0$
  - SARMA$(P, Q) \times (P_s, Q_s, s)$: $D = D_s = 0$

Key Concepts

Unit Root, Integrated Process, I(1), Augmented Dickey-Fuller Test, Seasonal Difference

Questions

- What happens if a relevant deterministic term is omitted in a ADF test?
- What is the effect of including an unnecessary deterministic in an ADF test?
- How should you decide how many lags of the differenced variable to include in an ADF test?
- When should you use seasonal differencing?
- What is the relationship between a random walk and a unit root process?
- What are the consequences of ignoring a unit root when modeling a time series?

Self-Exciting Threshold Autoregression

Nonlinear Models for the mean

- *Linear* time series process

$$Y_t = Y_0 + \sum_{i=0}^{t} \theta_i \epsilon_{t-i}$$

- Alternatives
  - Markov Switching Autoregression (MSAR)
  - Threshold Autoregression (TAR) and Self-exciting Threshold Autoregression (SETAR)
  - Many, many others
- Nonlinear models can capture different dynamics
  - *State-dependent parameters*

$$Y_t = \phi_0^{s_t} + \phi_1^{s_t} Y_{t-1} + \sigma^{s_t} \epsilon_t$$

  - Models differ in how s_t evolves

Markov-Switching Models

Markov Switching Example

- Two states, H and L

$$Y_t = \left\{ \begin{array}{c} \phi^H + \epsilon_t \\ \phi^L + \epsilon_t \end{array} \right.$$

- States evolve according to a 1st order Markov Chain

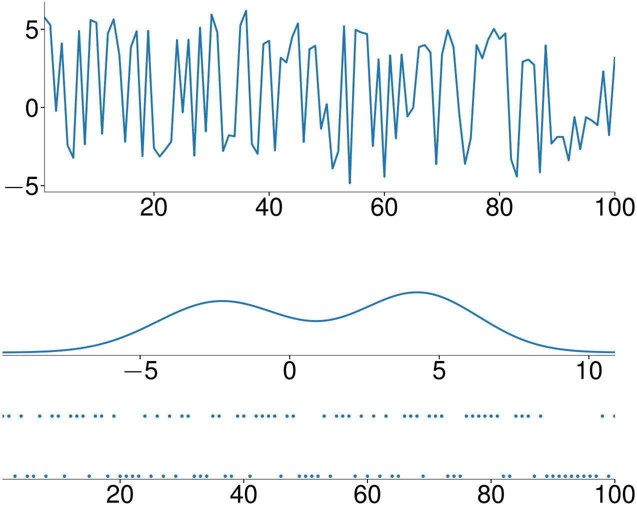
$$\{s_t\} = \{H, H, H, L, L, L, H, L, \ldots\}$$

- Transition Probabilities

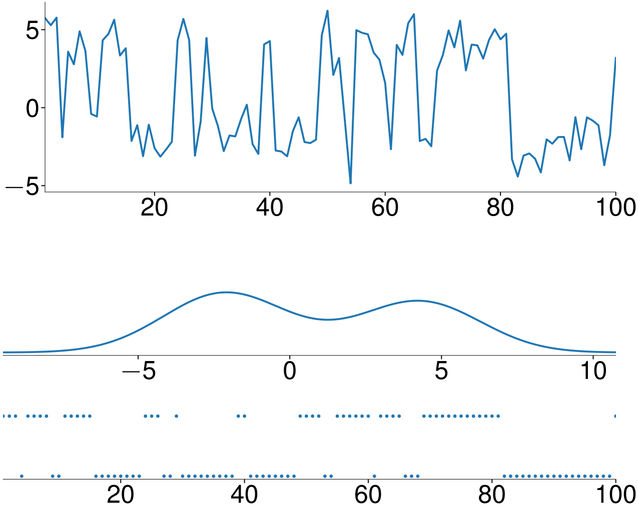
$$\left[\begin{array}{cc} p_{HH} & p_{HL} \\ p_{LH} & p_{LL} \end{array} \right] = \left[\begin{array}{cc} p_{HH} & 1 - p_{LL} \\ 1 - p_{HH} & p_{LL} \end{array} \right]$$

  - p_{HH} is the probability $s_{t+1} = H$ given $s_t = H$.
- Model will switch between a high mean state and a low mean state
- Models like this are very flexible and nest ARMA
  - Successful in financial econometrics for asset allocation, volatility modeling, modeling series with business-cycle length patterns: GDP

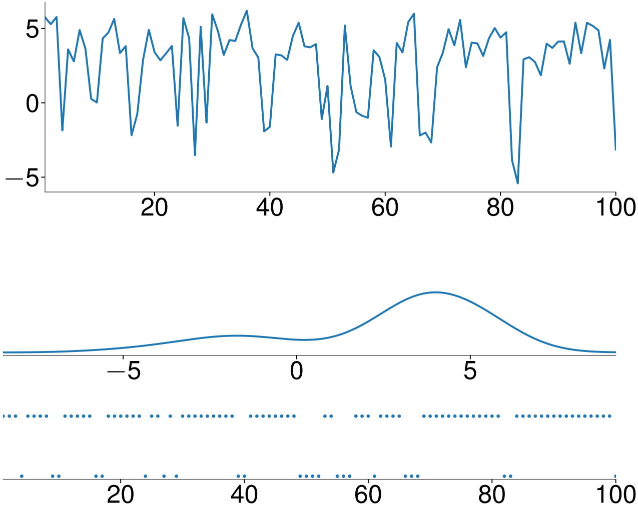
Markov Switching: i.i.d. Mixture



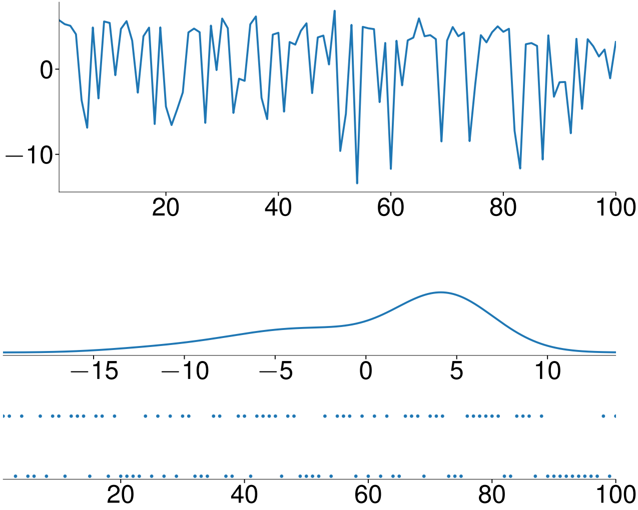
Markov Switching: Symmetric Persistent



Markov Switching: Asymmetric Persistent



Markov Switching: Different Variances



Key Concepts

Self-exciting Threshold Autoregression, Markov Switching Processe

Questions

- It is always necessary to consider nonlinear models to model covariance stationary time series?
- What advantages might a nonlinear model have over a linear model when modeling a covariance stationary time series?