

# PLSC 504 – Fall 2022

## Time Series Analysis

October 3, 2022

**Longitudinal Data** = Data reflecting temporal variation.

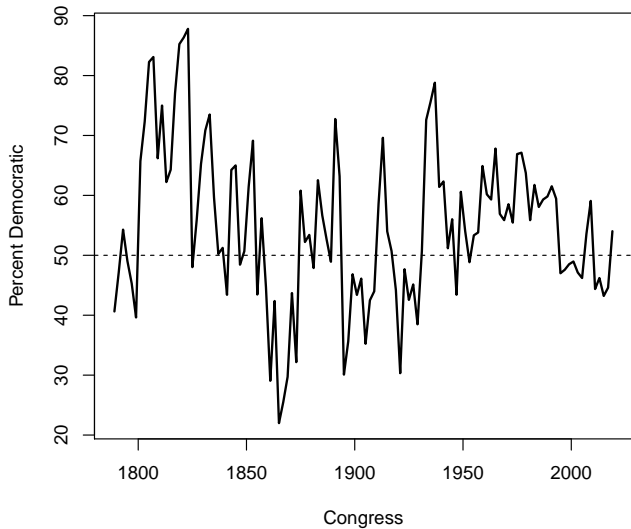
Typically:

- $i \in \{1, 2, \dots, N\}$  indexes cross-sectional units
- $t \in \{1, 2, \dots, T\}$  indexes temporal observations

Terminology:

- Cross-Sectional:  $N$  is large,  $T = 1$
- Time Series:  $T$  is large,  $N = 1$
- Panel:  $N$  is large,  $T$  is small(ish)
- TSCS:  $N \approx T$ , or  $N < T$  (but  $N > 1$ )

# Democratic House Membership, 1789-2019



- **Univariate:** Properties of series, ARIMA, etc.
- **Bivariate:** Pairs of series / regression
  - “Distributed Lag” models
  - Structural breaks / intervention analysis
  - Cointegration / Error Correction
  - Others...
- **Multivariate:** Systems of equations
  - “Seemingly unrelated” regressions
  - Vector Autoregressions (“VARs”) and their variants
- **Higher-moment properties:** ARCH, GARCH, etc.

# Quick Review of Error Correlation

OLS requires:

$$E(u_i, u_j) = 0 \quad \forall i \neq j$$

or...

$$E(\mathbf{u}\mathbf{u}') = \sigma^2 \mathbf{I}$$

Correlated residuals  $\rightarrow$  biased, inconsistent estimates of  $\widehat{\mathbf{V}(\hat{\beta})}$

Example:

$$Y_t = \beta_0 + \beta_1 X_t + u_t$$

$$u_t = \rho u_{t-1} + e_t$$

with  $e_t \sim i.i.d. N(0, \sigma_u^2)$  and  $\rho \in [-1, 1]$  (typically).

→ “First-order autoregressive” (“AR(1)”) errors.

# Serially Correlated Errors and OLS

## Detection

- Plot of residuals vs. lagged residuals
- Runs test (Geary test)
- Durbin-Watson  $d$ 
  - Calculated as:

$$d = \frac{\sum_{t=2}^N (\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^N \hat{u}_t^2}$$

- Non-standard distribution
- Only detects first-order autocorrelation

# Serially Correlated Errors and OLS

## What to do about it?

- GLS, incorporating  $\rho$  /  $\hat{\rho}$  into the equation
- First-difference equations (regressing changes of  $Y$  on changes of  $\mathbf{X}$ )
- Cochrane-Orcutt / Prais-Winsten:
  1. Estimate the basic equation via OLS, and obtain residuals
  2. Use the residuals to consistently estimate  $\hat{\rho}$  (i.e. the empirical correlation between  $u_t$  and  $u_{t-1}$ )
  3. Use this estimate of  $\hat{\rho}$  to estimate the difference equation:

$$(Y_t - \rho Y_{t-1}) = \beta_0(1 - \rho) + \beta_1(X_t - \rho X_{t-1}) + (u_t - \rho u_{t-1})$$

4. Save the residuals, and use them to estimate  $\hat{\rho}$  again
5. Repeat this process until successive estimates of  $\hat{\rho}$  differ by a very small amount



Consider a random series  $\mathbf{Y}$ :

$$\mathbf{Y} = \{Y_0, Y_1, \dots, Y_T\}$$

with moments:

$$\begin{aligned}\mu_t &= E(Y_t) \\ \sigma_t^2 \equiv \text{Var}(Y_t) &= E[(Y_t - \mu_t)^2] \\ \gamma_{t,t-s} \equiv \text{Cov}(Y_t, Y_{t-s}) &= E[(Y_t - \mu_t)(Y_{t-s} - \mu_{t-s})]\end{aligned}$$

Two typical assumptions: stationarity and ergodicity.

**Stationarity**: A constant d.g.p. over time.<sup>1</sup>

Mean stationarity:

$$E(Y_t) = \mu \forall t$$

Variance stationarity:

$$Var(Y_t) = E[(Y_t - \mu)^2] \equiv \sigma_Y^2 \forall t$$

Covariance stationarity:

$$Cov(Y_t, Y_{t-s}) = E[(Y_t - \mu)(Y_{t-s} - \mu)] = \gamma_s \forall s$$

---

<sup>1</sup>A stricter form of stationarity requires that the joint probability distribution (in other words, *all* the moments) of series of observations  $\{Y_1, Y_2, \dots, Y_t\}$  is the same as that for  $\{Y_{1+s}, Y_{2+s}, \dots, Y_{t+s}\}$  for all  $t$  and  $s$ .

**Ergodicity**: Asymptotic (in  $T$ ) independence.

Means that:

$$\text{Cov}(Y_t, Y_{t-s}) = \gamma_s \rightarrow 0 \text{ as } s \rightarrow \infty$$

Stationary ergodic processes:

- are measure-preserving,
- can have their statistical properties inferred/estimated from a sufficiently long observation of the process.

# Autocovariance and Autocorrelation

For a stationary ergodic series:

$$\hat{\mu} = \bar{Y} = T^{-1} \sum_{t=1}^T Y_t$$

$$\hat{\sigma}^2 = T^{-1} \sum_{t=1}^T (Y_t - \bar{Y})^2$$

$$\hat{\gamma}_s = T^{-1} \sum_{t=s+1}^T (Y_t - \bar{Y})(Y_{t-s} - \bar{Y}), \quad s = 1, 2, 3, \dots$$

Autocovariance  $\rightarrow$  Autocorrelation:

$$\hat{\rho}_s = \frac{\hat{\gamma}_s}{\hat{\sigma}^2}, \quad s = 0, \pm 1, \pm 2, \dots$$

# The “ARIMA” Approach

“ARIMA” = Autoregressive Integrated Moving Average...

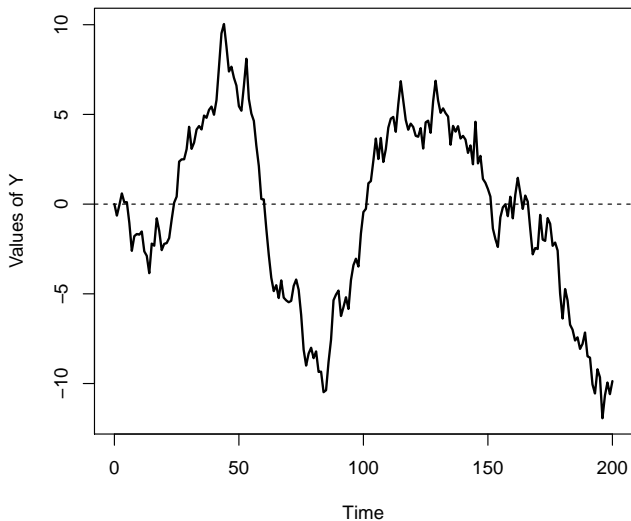
A (first-order) integrated series (“random walk”) is:

$$Y_t = Y_{t-1} + u_t, \quad u_t \sim i.i.d.(0, \sigma_u^2)$$

...a/k/a a “random walk”:

$$\begin{aligned} Y_t &= Y_{t-2} + u_{t-1} + u_t \\ &= Y_{t-3} + u_{t-2} + u_{t-1} + u_t \\ &= \sum_{t=0}^T u_t \end{aligned}$$

I(1) series with  $u_t \sim N(0, 1)$ ,  $T = 200$



**I(1) series are not stationary.**

Variance:

$$\text{Var}(Y_t) \equiv E(Y_t)^2 = t\sigma^2$$

Autocovariance:

$$\text{Cov}(Y_t, Y_{t-s}) = |t - s|\sigma^2.$$

Both depend on  $t$ ...

# I(1) Series: Differencing

For an I(1) series:

$$Y_t - Y_{t-1} = u_t$$

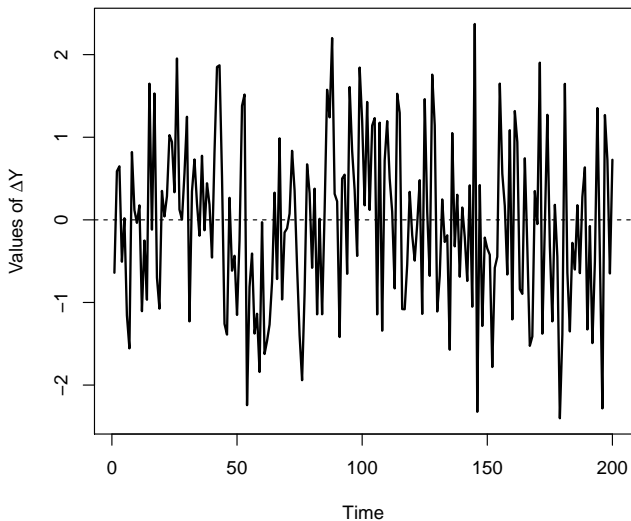
which we often write in terms of the difference operator  $\Delta$  (or sometimes  $\nabla$ ):

$$\Delta Y_t = u_t$$

The differenced series is just the (stationary, ergodic) white-noise process  $u_t$ .



## A Differenced I(1) Series



# Higher-order $I(d)$ Integrated Series

An  $I(d)$  series is one which, differenced  $d$  times, becomes a stationary series.

E.g., the  $I(2)$  series:

$$Y_t = u_t + 2u_{t-1} + 3u_{t-2} + \dots$$

Differencing:

$$\begin{aligned}\Delta Y_t &= [u_t + 2u_{t-1} + 3u_{t-2} + \dots] - [u_{t-1} + 2u_{t-2} + 3u_{t-3} + \dots] \\ &= \sum_{j=0}^T u_{t-j}\end{aligned}$$

Differencing again:

$$\begin{aligned}\Delta^2 Y_t \equiv (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) &= [u_t + u_{t-1} + \dots] - [u_{t-1} + u_{t-2} + \dots] \\ &= u_t\end{aligned}$$

which is stationary / ergodic.

An AR(1) process:

$$Y_t = \phi Y_{t-1} + u_t$$

with  $u_t \sim i.i.d.(0, \sigma_u^2)$ .

Equivalently:

$$Y_t - \phi Y_{t-1} = u_t$$

or:

$$\begin{aligned} Y_t &= \phi[\phi Y_{t-2} + u_{t-1}] + u_t \\ &= \phi^2 Y_{t-2} + \phi u_{t-1} + u_t \\ &= \phi^2[\phi Y_{t-3} + u_{t-2}] + \phi u_{t-1} + u_t \\ &= \phi^3 Y_{t-3} + \phi^2 u_{t-2} + \phi u_{t-1} + u_t \\ &= \dots \\ &= \sum_{j=0}^{T-1} \phi^j u_{t-j} + \phi^T Y_0 \end{aligned}$$

Mean:

$$\begin{aligned} E(Y_t) &= E\left(\sum_{j=0}^{T-1} \phi^j u_{t-j}\right) + E(\phi^T Y_{t-T}) \\ &= \phi^T Y_0 \end{aligned}$$

That means that:

- For  $|\phi| > 1$ ,  $|E(Y_t)|$  is increasing in  $t$
- For  $|\phi| = 1$ ,  $E(Y_t) = Y_0$
- For  $|\phi| < 1$ :
  - the importance of  $Y_0$  decreases over time
  - asymptotically,  $E(Y_t) = 0$

# AR(1) and Stationarity

For an AR(1) series with  $|\phi| < 1$  :

$$Y_t = \sum_{j=0}^{\infty} \phi^j u_{t-j}$$

Means that:

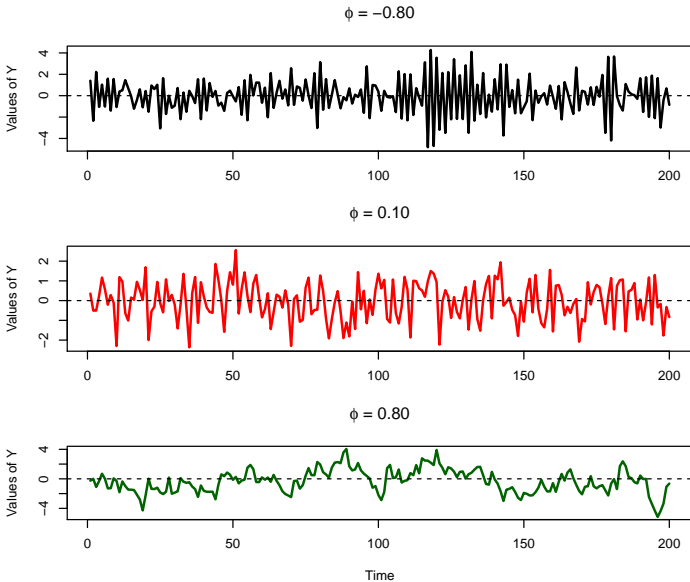
- the effects of a shock *persist* over time; however,
- the *size* of those effects *decay* over time
- In the limit, the effect of any one shock very much later is zero

Similarly:

$$\begin{aligned}\text{Var}(Y_t) \equiv E(Y_t^2) &= E\left(\sum_{j=0}^{\infty} \phi^j u_{t-j}\right)^2 \\ &= \sum_{j=0}^{\infty} \phi^{2j} E(u_{t-j}^2) \\ &= \sigma^2 \sum_{j=0}^{\infty} \phi^{2j} \\ &= \frac{\sigma^2}{1 - \phi^2}\end{aligned}$$

which is stationary iff  $|\phi| < 1$ .

# AR(1) Series, Illustrated



# Notation Digression: The Lag Operator

“Lag operator”  $L$ :

$$LY_t = Y_{t-1}$$

$$L^2 Y_t = Y_{t-2}$$

$$L^s Y_t = Y_{t-s}$$

$$L^0 Y_t = Y_t$$

Means we can write:

$$\begin{aligned}\Delta Y_t &= Y_t - Y_{t-1} \\ &= (1 - L)Y_t\end{aligned}$$

So an AR(1) equation is:

$$(1 - \phi L)Y_t = u_t$$

# Higher-Order AR( $p$ ) Series

An AR( $p$ ) series:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + u_t$$

Equivalently:

$$\begin{aligned} Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \dots - \phi_p Y_{t-p} &= u_t \\ (1 - \phi L - \phi_2 L^2 - \dots - \phi_p L^p) Y_t &= u_t \end{aligned}$$



# Moving Average (MA) Series

MA(1) series:

$$Y_t = u_t + \theta u_{t-1}, \quad t = 1, 2, \dots, T$$

with  $u_t \sim \text{i.i.d.}(0, \sigma_u^2)$ .

Mean:

$$\begin{aligned}\mu &= E(Y_t) \\ &= E(u_t) + \theta E(u_{t-1}) \\ &= 0\end{aligned}$$

Variance:

$$\begin{aligned}\sigma_Y^2 &= E[(u_t + \theta u_{t-1})(u_t + \theta u_{t-1})] \\ &= E(u_t^2) + \theta^2 E(u_{t-1}^2) + 2\theta E(u_t u_{t-1}) \\ &= (1 + \theta^2) \sigma_u^2\end{aligned}$$

Autocovariance at one lag:

$$\begin{aligned}\gamma_1 &= E[(u_t + \theta u_{t-1})(u_{t-1} + \theta u_{t-2})] \\ &= E(u_t u_{t-1}) + \theta E(u_{t-1}^2) + \theta E(u_t u_{t-2}) + \theta^2 E(u_{t-1} u_{t-2}) \\ &= \theta E(u_{t-1}^2) \\ &= \theta \sigma_u^2\end{aligned}$$

Autocovariance at  $s > 1$  lags:

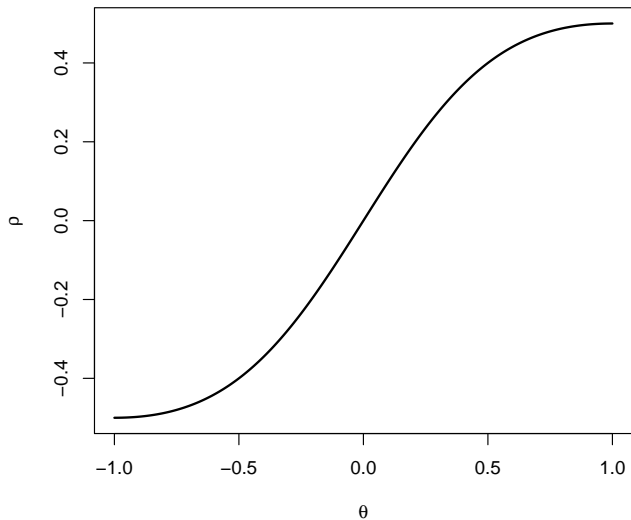
$$\begin{aligned}\gamma_s &= E[(u_t + \theta u_{t-s})(u_{t-1} + \theta u_{t-(s+1)})] \\ &= E(u_t u_{t-s}) + \theta E(u_{t-s}^2) + \theta E(u_t u_{t-(s+1)}) + \theta^2 E(u_{t-s} u_{t-(s+1)}) \\ &= 0\end{aligned}$$

This means that:

- the means, variances and autocovariances are all independent of  $t$ ,
- the ACF is zero for all lags greater than one,
- the ACF at one lag is dependent on the degree of dependence in the moving average process. In particular, since  $\rho = \frac{\gamma}{\sigma^2}$ :

$$\begin{aligned}\rho &= \frac{\theta\sigma_u^2}{(1+\theta^2)\sigma_u^2} \\ &= \frac{\theta}{1+\theta^2}\end{aligned}$$

Relationship between  $\theta$  and  $\rho$  for an MA(1) series



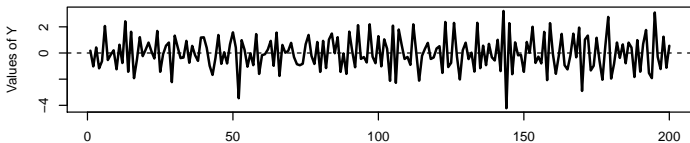
# MA(1) Series Properties

For an MA(1) series:

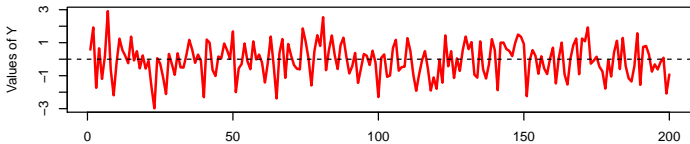
- $\theta = 0 \Leftrightarrow \rho_1 = 0$ , a “white noise” process (no temporal dependence in  $Y_t$ ).
- For  $\theta > 0$ :
  - $\rho_1 > 0$
  - successive values of  $Y_t$  will be *positively* related, and
  - the series will be “smoother” than a white noise series.
- For  $\theta < 0$ :
  - $\rho_1 < 0$
  - successive values of  $Y_t$  will be *negatively* correlated, and
  - the series will be less “smooth” than a white noise sequence.

# MA(1) Series Illustrated

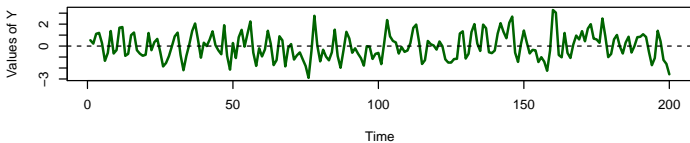
$\theta = -0.80$



$\theta = 0.10$



$\theta = 0.80$



Rewriting our MA(1) series:

$$\begin{aligned}
 Y_t &= u_t + \theta u_{t-1} \\
 &= u_t + \theta(Y_{t-1} - \theta u_{t-2}) \\
 &= u_t + \theta Y_{t-1} - \theta^2 u_{t-2} \\
 &= u_t + \theta Y_{t-1} - \theta^2(Y_{t-2} - \theta u_{t-3}) \\
 &= u_t + \theta Y_{t-1} - \theta^2 Y_{t-2} + \theta^3 u_{t-3} \\
 &= \dots \\
 &= u_t + \theta Y_{t-1} - \theta^2 Y_{t-2} + \theta^3 Y_{t-3} - \dots - (-\theta)^{(T-1)} Y_{t-(T-1)} - (-\theta)^T u_0
 \end{aligned}$$

As  $T \rightarrow \infty$ :

$$Y_t = - \sum_{j=1}^{\infty} (-\theta)^j Y_{t-j} + u_t$$

# The Wold Decomposition Theorem

**Any weakly stationary, purely nondeterministic stochastic process can be written as a linear combination of a sequence of uncorrelated random variables.**

that is, as:

$$Y_t = \sum_{j=0}^{\infty} \psi_j u_{t-j}$$

with  $\sum_{j=0}^{\infty} \psi_j^2 < \infty$ .



MA( $q$ ) model:

$$Y_t = u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \dots + \theta_q u_{t-q}$$

MA( $q$ ) models are:

- always stationary,
- invertable if the AR( $p$ ) form of the model satisfies the stationarity conditions above.

# ARMA / ARIMA Models

A general ARMA( $p, q$ ) model is:

$$Y_t = \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + u_t + \theta_1 u_{t-1} + \dots + \theta_q u_{t-q}$$

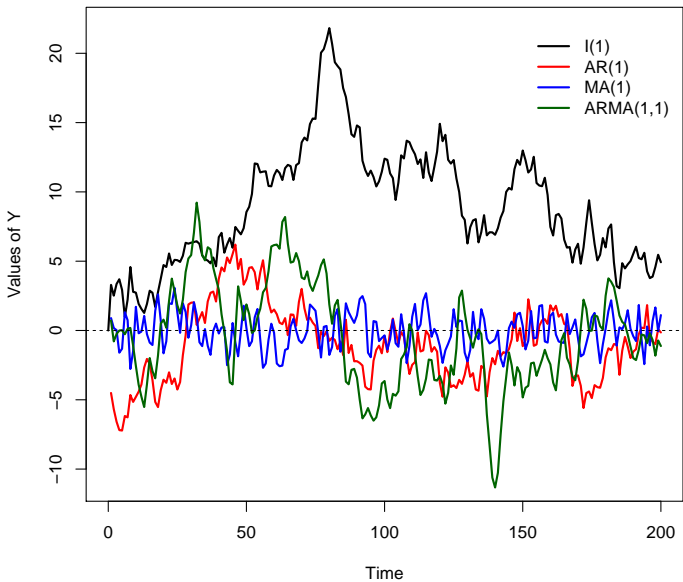
Equivalently:

$$(1 - \phi L - \phi_2 L^2 - \dots - \phi_p L^p) Y_t = (1 + \theta L + \theta_2 L^2 + \dots + \theta_q L^q) u_t$$

If the model also requires  $d$ th-order differencing in order to achieve stationarity, we call it an ARIMA( $p, d, q$ ) model; e.g., the ARIMA( $p, 1, q$ ) model:

$$\Delta Y_t = \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + u_t + \theta_1 u_{t-1} + \dots + \theta_q u_{t-q}$$

# ARIMA Series: A Comparison ( $\phi = \theta = 0.9$ )



# Series Characteristics: ACFs and PACFs

Autocorrelation function (ACF):

$$\hat{\rho}_s = \frac{\hat{\gamma}_s}{\hat{\sigma}^2}, \quad s = 0, \pm 1, \pm 2, \dots$$

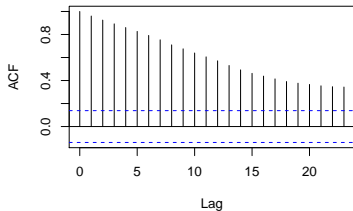
The partial autocorrelation function (PACF) is the correlation between  $Y_t$  and  $Y_{t-s}$  after controlling for (“partialling out”) the the common linear effects of the intermediate lags.<sup>2</sup>

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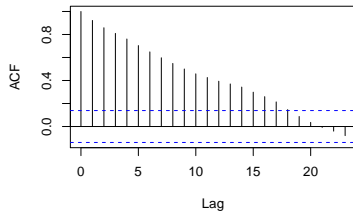
<sup>2</sup>The PACF is estimated from a solution to the Yule-Walker system of equations. A good mathematical treatment of this is in Box et al. 1994, pp. 64-69

# ARIMA Series: ACFs

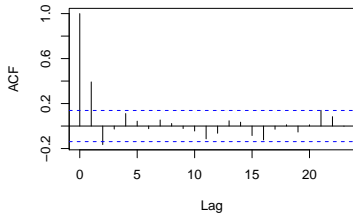
**I(1) series**



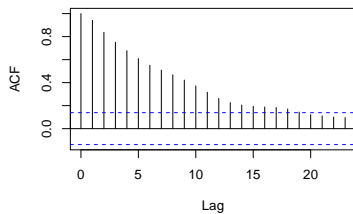
**AR(1) series**



**MA(1) series**

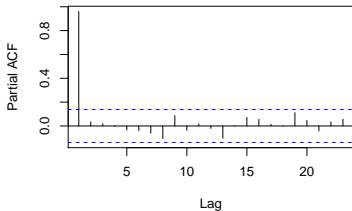


**ARMA(1,1) series**

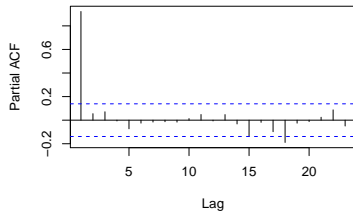


# ARIMA Series: PACFs

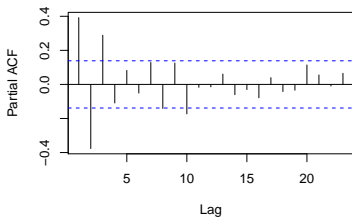
**I(1) series**



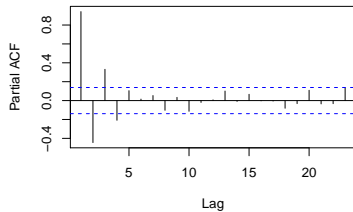
**AR(1) series**



**MA(1) series**



**ARMA(1,1) series**



# ARIMA Modeling: Intuition

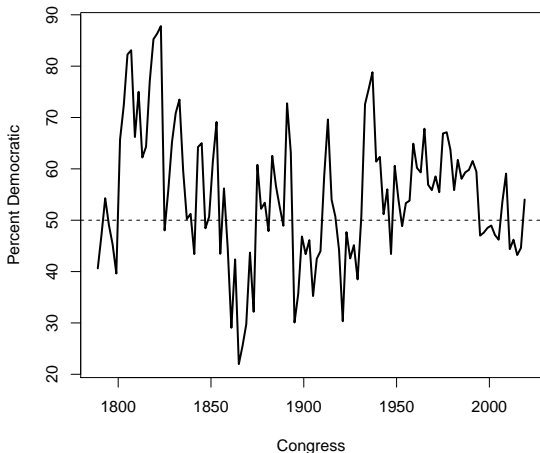
*Identification*  $\rightarrow$  *Estimation*  $\rightarrow$  *Diagnostics*

In general:

1. Determine if the series is stationary. If so, proceed to (3).
2. If not, difference the series until it is.
3. Examine the ACFs and PACFs of the stationary series, in order to determine the data generating process (AR, MA, or some combination thereof).
4. Fit a model – starting simple – using ARIMA/MLE.
5. Examine and test the residuals to determine if they are white noise. If they are, proceed to (7).
6. If they are not, go back to (3) and try again.
7. Proceed with inference, hypothesis testing, forecasting, and the like.

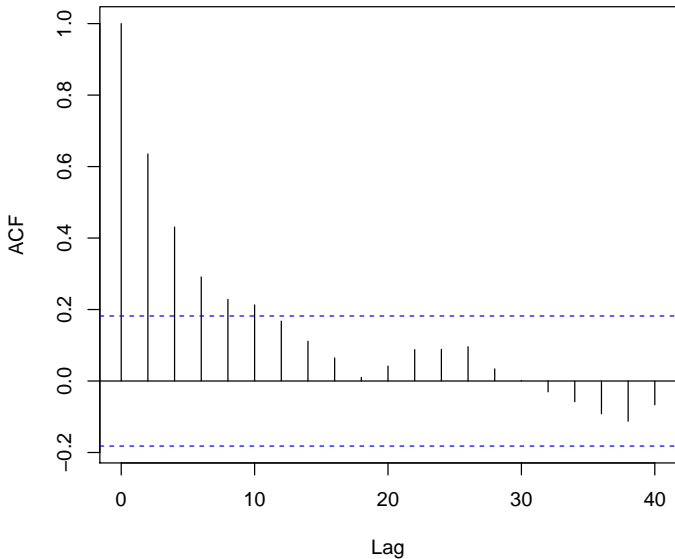
## Example: Democratic House Membership

$Y$  = percentage of U.S. House members identifying with the Democratic party, by Congress, 1789-2019.

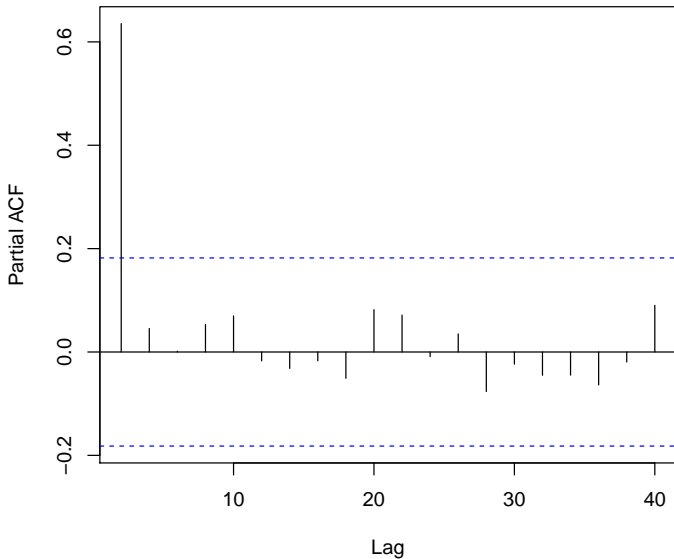




# Democratic House Membership: ACF



# Democratic House Membership: PACF



# ARIMA Model Fitting

```
> DH.AR1 <- arima(DH.TS,order=c(1,0,0),method="ML") # AR(1)
> summary(DH.AR1)
```

Coefficients:

	ar1	intercept
	0.636	54.53
s.e.	0.071	2.53

sigma<sup>2</sup> estimated as 101: log likelihood = -432.6, aic = 871.2

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.1038	10.06	7.951	-3.858	16.03	0.9476	-0.03006

```
> DH.ARMA11 <- arima(DH.TS,order=c(1,0,1),method="ML") # ARMA(1,1)
> summary(DH.ARMA11)
```

Coefficients:

	ar1	ma1	intercept
	0.679	-0.072	54.495
s.e.	0.107	0.148	2.651

sigma<sup>2</sup> estimated as 101: log likelihood = -432.5, aic = 873

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.1123	10.04	7.915	-3.824	15.94	0.9434	-0.001164

# ARIMA Model Selection

```
> # Model selection via LR test:
```

```
>
```

```
> lrtest(DH.AR1,DH.ARMA11)
```

Likelihood ratio test

```
Model 1: arima(x = DH.TS, order = c(1, 0, 0), method = "ML")
```

```
Model 2: arima(x = DH.TS, order = c(1, 0, 1), method = "ML")
```

```
  #Df LogLik Df Chisq Pr(>Chisq)
```

```
1   3   -433
```

```
2   4   -432  1  0.24      0.62
```

```
> # Automated version:
```

```
>
```

```
> DH.robot <- auto.arima(DH.TS)
```

```
> summary(DH.robot)
```

Series: DH.TS

ARIMA(1,0,0) with non-zero mean

Coefficients:

```
    ar1    mean
```

```
  0.636  54.53
```

```
s.e.  0.071  2.53
```

sigma<sup>2</sup> estimated as 103: log likelihood=-432.6

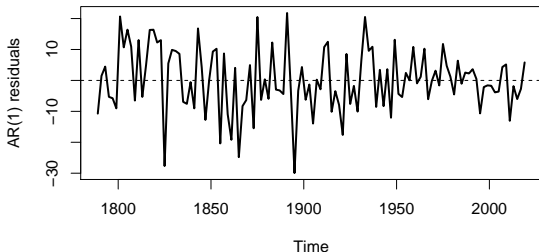
AIC=871.2 AICc=871.4 BIC=879.5

Training set error measures:

```
      ME  RMSE  MAE  MPE  MAPE  MASE  ACF1
```

```
Training set 0.1037 10.06 7.951 -3.858 16.03 0.1452 -0.03005
```

# ARIMA: Residuals Analysis



Box-Pierce and Ljung-Box tests:

```
> Box.test(DH.AR1$residuals)
```

Box-Pierce test

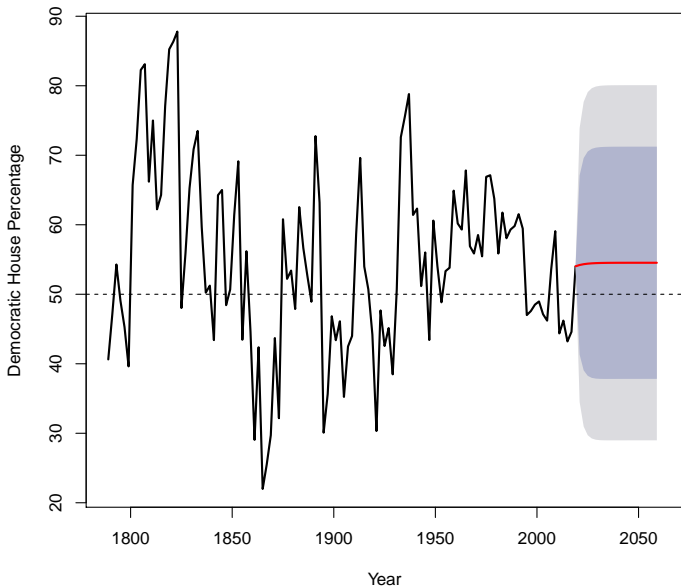
```
data: DH.AR1$residuals  
X-squared = 0.1, df = 1, p-value = 0.7
```

```
> Box.test(DH.AR1$residuals,type="Ljung")
```

Box-Ljung test

```
data: DH.AR1$residuals  
X-squared = 0.11, df = 1, p-value = 0.7
```

# ARIMA: Forecasting (40-Year Window)



# Unit Roots, (Co)Integration, and Error Correction

A basic  $I(1)$  series is:

$$Y_t = Y_{t-1} + u_t$$

Special case of AR(1):

$$Y_t = \rho Y_{t-1} + u_t$$

where  $\rho = 1$ .

Recall:

- $|\rho| < 1.0 \leftrightarrow$  stationary series
- $|\rho| = 1.0 \leftrightarrow$  non-stationary series



## Other Non-Stationary Series

Trending series:

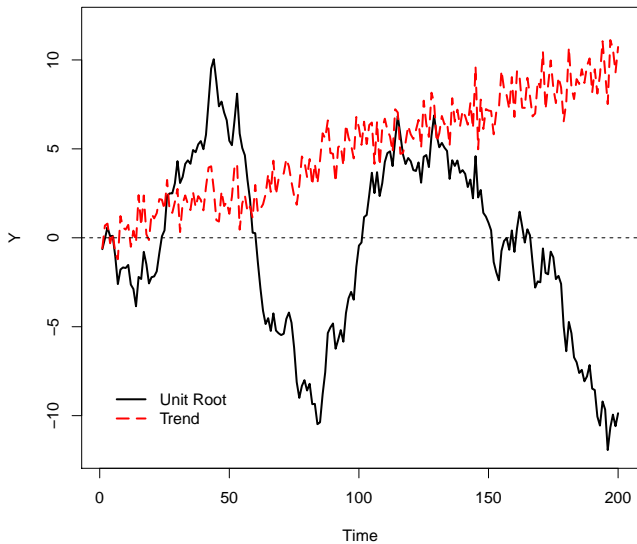
$$Y_t = \beta t + u_t$$

Means:

$$\begin{aligned}\Delta Y_t \equiv Y_t - Y_{t-1} &= \beta t + u_t - Y_{t-1} \\ &= \beta(t) + u_t - \beta(t-1) - u_{t-1} \\ &= \beta(t - t + 1) + u_t - u_{t-1} \\ &= \beta + \Delta u_t\end{aligned}$$

which is also stationary.

# Unit Root vs. Trend



Key: Examine

$$Y_t = \rho Y_{t-1} + \beta t + u_t$$

and test for  $H_0 : \hat{\beta} = 0$ :

- Cannot reject  $\hat{\beta} = 0 \leftrightarrow$  “random walk” without a trend;
- Reject  $\hat{\beta} = 0 \leftrightarrow$  series has a deterministic trend.

- $|\rho| > 1$ 
  - Series is nonstationary / *explosive*
  - Past shocks have a greater impact than current ones
  - Uncommon
- $|\rho| < 1$ 
  - *Stationary* series
  - Effects of shocks die out exponentially according to  $\rho$
  - Is mean-reverting
- $|\rho| = 1$ 
  - Nonstationary series
  - Shocks persist at full force
  - Not mean-reverting; variance increases with  $t$

Basic idea:

$$Y_t = \rho Y_{t-1} + u_t$$

and test for  $\hat{\rho} = 1$ .

Issues:

- $\hat{\rho} = \frac{\sum Y_t Y_{t-1}}{\sum Y_{t-1}^2}$  is consistent for  $\rho$ , but
- the distribution of  $\hat{\rho}$  is not  $t$ ...
  - $T(\hat{\rho} - 1) \rightarrow \frac{\int_0^1 W(r) dW(r)}{\int_0^1 W(r)^2 dr}$ , so
  - $t \equiv \frac{\hat{\rho}}{s.e.(\hat{\rho})} = \frac{\frac{1}{2}[W(1)^2 - 1]}{[\int_0^1 W(r)^2 dr]^{\frac{1}{2}}}$

This is:

- Right-skewed (so t-statistics will tend to be large and negative),
- $\rightarrow$  tend to *overreject* the null hypothesis if we use the standard t-distribution.

# The Dickey-Fuller Test

1. Estimate  $\hat{\rho}$ ,
2. Test  $H_0 : \hat{\rho} = 1$  using a non-standard set of critical values,
3. Ensure that  $\hat{u}$  are white noise.

Equivalent:

$$\begin{aligned}\Delta Y_t &= (\rho - 1)Y_{t-1} + u_t \\ &= \delta Y_{t-1} + u_t\end{aligned}$$

and test for  $\hat{\delta} = 0$ .

“Drift”:

$$Y_t = \alpha + \rho Y_{t-1} + u_t$$

which is also:

$$Y_t = Y_0 + \alpha t + \sum_{t=1}^T u_t$$

This requires testing both  $\hat{\rho} = 1$  and  $\hat{\alpha} = 0$ .

“Trend”:

$$Y_t = \alpha + \beta t + \rho Y_{t-1} + u_t$$

- $\alpha$  is now a “constant”.
- Requires a (slightly) different set of critical values,
- Also: F-tests on the joint nulls:  $\rho = 1$  and  $\beta = 0$

In general, it's worse to *omit* a drift / trend from a model when the data generating process has one, than it is to *include* one where the DGP is driftless / trendless.



Suppose we have:

$$\Delta Y_t = \sum_{i=1}^p d_i \Delta Y_{t-i} + u_t$$

This yields:

$$Y_t = Y_{t-1} + \sum_{i=1}^p d_i \Delta Y_{t-i} + u_t$$

If this is true, a standard D.F. test:

$$Y_t = \hat{\rho} Y_{t-1} + u_t$$

will have AR(1) errors / residuals...

## “Augmented” D-F Tests

Estimate:

$$\Delta Y_t = \rho Y_{t-1} + \sum_{i=1}^p d_i \Delta Y_{t-i} + u_t$$

or:

$$\Delta Y_t = \alpha + \beta t + \rho Y_{t-1} + \sum_{i=1}^p d_i \Delta Y_{t-i} + u_t$$

Choosing  $p$  via AIC/BIC, etc. until we are certain that the residuals  $\hat{u}$  are uncorrelated / white noise.

For:

$$\Delta Y_t = \alpha + \rho Y_{t-1} + u_t$$

The distribution of  $\hat{\rho}$  depends on  $\frac{\sigma^2}{\sigma_e^2}$ , where

- $\sigma^2 = \text{Var}(u)$  and
- $\sigma_e^2 = \lim_{T \rightarrow \infty} T^{-1} \sum_{j=1}^T E[(\sum_{i=1}^t u_i)_j^2]$ .

“Phillips-Perron”:

1. Estimate  $\hat{\rho}$ , then
2. use an empirical estimate of  $\sigma^2$  and  $\sigma_e^2$  to adjust the statistic (“ $Z_\rho$ ” and “ $Z_\tau$ ”).

## Other Unit Root Tests: KPSS

Kwiatkowski et al. (“KPSS”):

$$LM = \sum_{t=1}^T \frac{S_t^2}{\hat{\sigma}_\epsilon^2}$$

where  $S_t^2 = \sum_{i=1}^t \hat{u}_i$  and  $\hat{\sigma}_\epsilon^2$  is  $\widehat{\text{Var}(\epsilon_t)}$  from:

$$Y_t = \alpha + \epsilon_t$$

or:

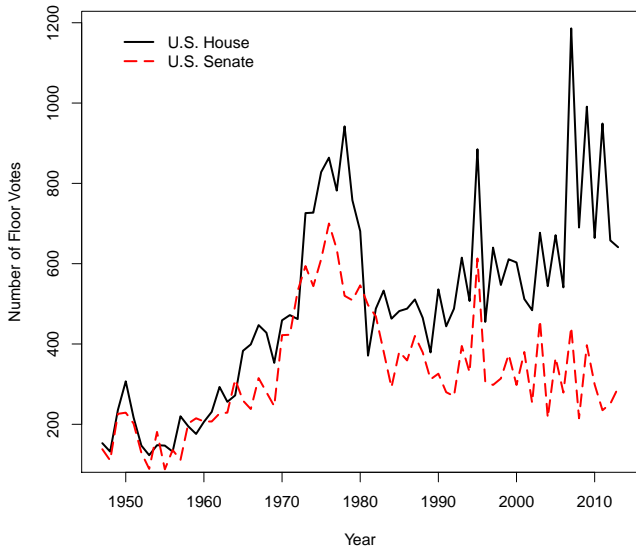
$$Y_t = \alpha + \beta t + \epsilon_t$$

- Idea: if a series is stationary, the variance of the series is not increasing over time.
- Intuition: Compare the variance of a subset of the data “early” in the series with a similarly-sized subset “later” in the process. E.g.,

$$\hat{\rho} = \frac{1}{T} \sum \frac{[\sum(Y)^2]}{\sum(Y^2)}$$

- References: Hamilton (p. 531-32), Cochrane (1988), Lo and McKinlay (1988), Cecchetti and Lam (1991), etc.

# House and Senate Votes, 1946-2013



# Dickey-Fuller Tests

```
> HDF<-ur.df(HVotes.TS,type="none",lags=0)
> summary(HDF)

#####
# Augmented Dickey-Fuller Test Unit Root Test #
#####

Test regression none

Call:
lm(formula = z.diff ~ z.lag.1 - 1)

Residuals:
    Min       1Q   Median       3Q      Max
-449.76  -48.99   25.39   91.19  666.09

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
z.lag.1 -0.03899     0.03846  -1.014   0.315

Residual standard error: 170.5 on 65 degrees of freedom
Multiple R-squared:  0.01556, Adjusted R-squared:  0.0004131
F-statistic: 1.027 on 1 and 65 DF,  p-value: 0.3146

Value of test-statistic is: -1.0135

Critical values for test statistics:
    1pct  5pct 10pct
tau1 -2.6 -1.95 -1.61
```

# Dickey-Fuller Tests (continued)

```
> HDF.D<-ur.df(HVotes.TS,type="drift",lags=0)
> summary(HDF.D)
```

```
#####
# Augmented Dickey-Fuller Test Unit Root Test #
#####
```

Value of test-statistic is: -3.2294 5.2847

Critical values for test statistics:

	1pct	5pct	10pct
tau2	-3.51	-2.89	-2.58
phi1	6.70	4.71	3.86

```
> HDF.T<-ur.df(HVotes.TS,type="trend",lags=0)
> summary(HDF.T)
```

```
#####
# Augmented Dickey-Fuller Test Unit Root Test #
#####
```

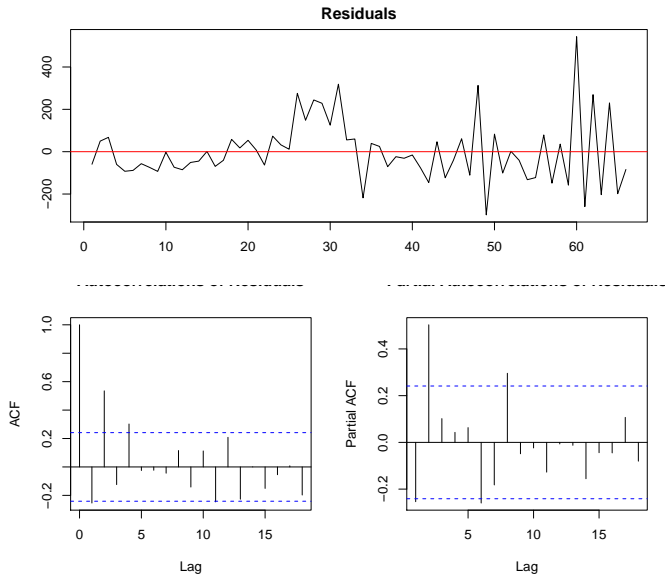
Value of test-statistic is: -4.7424 7.576 11.2834

Critical values for test statistics:

	1pct	5pct	10pct
tau3	-4.04	-3.45	-3.15
phi2	6.50	4.88	4.16
phi3	8.73	6.49	5.47



# Plotting...



# Augmented D-F Tests

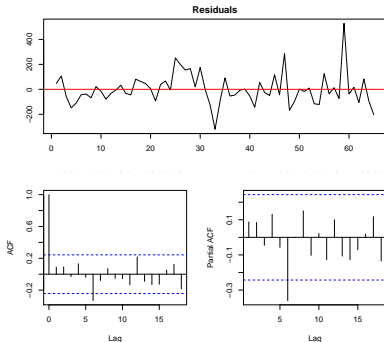
```
> HADF.T1<-ur.df(HVotes.TS,type="trend",lags=1)
> summary(HADF.T1)
```

```
#####
# Augmented Dickey-Fuller Test Unit Root Test #
#####
```

Value of test-statistic is: -2.112 1.8218 2.3959

Critical values for test statistics:

	1pct	5pct	10pct
tau3	-4.04	-3.45	-3.15
phi2	6.50	4.88	4.16
phi3	8.73	6.49	5.47



# ADF Tests, continued...

```
> HADF.BIC<-ur.df(HVotes.TS,type="trend",selectlags="BIC")
> summary(HADF.BIC)
```

```
#####
# Augmented Dickey-Fuller Test Unit Root Test #
#####
```

```
Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-320.30	-68.08	-15.52	48.23	528.75

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	72.1790	38.4963	1.875	0.0656 .
z.lag.1	-0.2368	0.1121	-2.112	0.0388 *
tt	1.6859	1.3295	1.268	0.2096
z.diff.lag	-0.5465	0.1081	-5.055	4.19e-06 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 127.5 on 61 degrees of freedom  
Multiple R-squared: 0.4823, Adjusted R-squared: 0.4568  
F-statistic: 18.94 on 3 and 61 DF, p-value: 8.484e-09

Value of test-statistic is: -2.112 1.8218 2.3959

Critical values for test statistics:

	1pct	5pct	10pct
tau3	-4.04	-3.45	-3.15
phi2	6.50	4.88	4.16
phi3	8.73	6.49	5.47

# Phillips-Perron Test

```
> HPP <- ur.pp(HVotes.TS, type="Z-tau",model="trend",lags="short")
> summary(HPP)
```

```
#####
# Phillips-Perron Unit Root Test #
#####
```

Call:

```
lm(formula = y ~ y.l1 + trend)
```

Residuals:

Min	1Q	Median	3Q	Max
-298.55	-84.95	-27.39	57.55	543.23

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	265.9933	57.5321	4.623	1.92e-05 ***
y.l1	0.4682	0.1121	4.176	9.30e-05 **
trend	4.5726	1.4060	3.252	0.00184 **

---

Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 149.6 on 63 degrees of freedom

Multiple R-squared: 0.6157, Adjusted R-squared: 0.6035

F-statistic: 50.47 on 2 and 63 DF, p-value: 8.267e-14

Value of test-statistic, type: Z-tau is: -4.8552

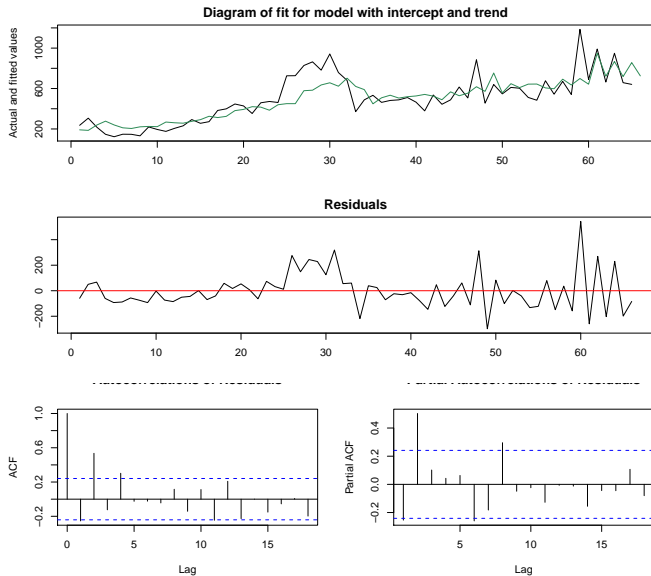
aux. Z statistics

Z-tau-mu	4.122
Z-tau-beta	3.356

Critical values for Z statistics:

	1pct	5pct	10pct
critical values	-4.101251	-3.47789	-3.166276

# Plotting...



## KPSS Test (null = stationarity)

```
> HKPSS <- ur.kpss(HVotes.TS,type="tau",lags="short")  
> summary(HKPSS)
```

```
#####  
# KPSS Unit Root Test #  
#####
```

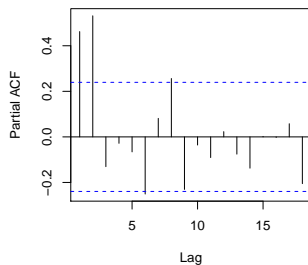
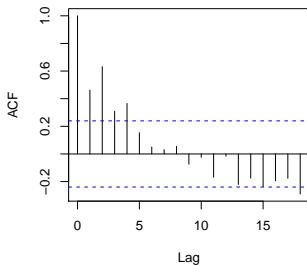
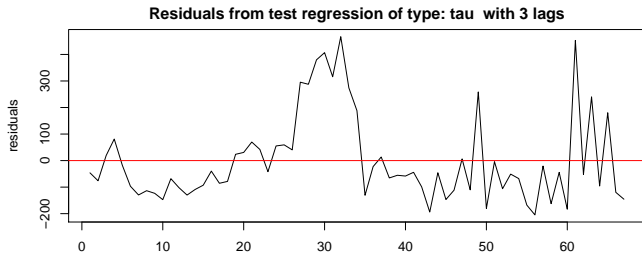
Test is of type: tau with 3 lags.

Value of test-statistic is: 0.1568

Critical value for a significance level of:

	10pct	5pct	2.5pct	1pct
critical values	0.119	0.146	0.176	0.216

# Plotting...



## Variance-Ratio Test

```
> library(egcm)

> H.VRatio <- bvr.test(HVotes.TS, detrend=TRUE)

> H.VRatio
```

Breitung Variance Ratio Test for a Unit Root

```
data:  HVotes.TS
rho = 0.0058012, p-value = 0.1872
alternative hypothesis: stationary
```



- Choosing Lag Lengths...
- “Knife-Edge” Tests and Bayesians vs. Frequentists...
- Why bother? Differencing...

## Packages:

- `tseries`
- `uroot` (including seasonality)
- `urca`
- `egcm`
- `CADFtest`

Consider:

$$Y_t = \rho Y_{t-1} + u_t$$

Properties:

1. Linear transformations of  $Y_t$  preserve the level of integration.
2. For two  $I(0)$  series  $X_t$  and  $Y_t$ ,  $aX_t + bY_t + c$  is also  $I(0)$ .
3. For two  $I(1)$  series  $X_t$  and  $Y_t$ ,  $aX_t + bY_t + c$  is *generally*  $I(1)$  as well.
4. If  $X_t$  is  $I(0)$  and  $Y_t$  is  $I(1)$ , then  $aX_t + bY_t + c$  is  $I(1)$  (*integration dominates stationarity*).

Now consider:

$$\begin{aligned}X_t &= W_t + u_{Xt} \\Y_t &= AW_t + u_{Yt}, \\W_t &\sim I(1), \\u_{Xt}, u_{Yt} &\sim I(0)\end{aligned}$$

Here, both  $X_t$  and  $Y_t$  will be  $I(1)$ , but:

$$\begin{aligned}Z_t &= Y_t - AX_t \\&= [AW_t + u_{Yt}] - A[W_t + u_{Xt}] \\&= AW_t + u_{Yt} - AW_t - Au_{Xt} \\&= u_{Yt} - Au_{Xt}\end{aligned}$$

is  $I(0)$ .

**If there exist two  $I(1)$  series  $X_t, Y_t$  such that  $Z_t = \mu + aX_t + bY_t$  is  $I(0)$ , then  $X_t$  and  $Y_t$  are said to be cointegrated.**

Intuition:

- The nonstationarity in  $X$  and  $Y$  arises from a *common component* ( $W_t$ ) which is  $I(1)$ .
- Combining  $X$  and  $Y$  cancels out the common part, leaving  $I(0)$  “residuals.”

# Cointegration as an Attractor

Above:

$$X_t = AY_t$$

means that:

$$Z_t = X_t - AY_t \sim \text{i.i.d.}(0, \sigma_Z^2)$$

Examples:

1. Murray (1994): Drunks and puppies...
2. Regional commodity prices...

# Cointegration in Practice

First: Assess whether  $X$  and  $Y$  are  $I(1)$ .

Then rewrite:

$$Z_t = X_t - \alpha Y_t$$

as the cointegrating regression:

$$X_t = \alpha Y_t + Z_t.$$

Cointegration implies:

$$\begin{aligned} Z_t &\sim I(0), \text{ and} \\ \text{Var}(Z_t) &< \infty. \end{aligned}$$

# Cointegration: A Roadmap

1. Determine that the two series are  $I(1)$ ,
2. Estimate  $X_t = \hat{\alpha} Y_t + Z_t$  using OLS,
3. Examine  $\hat{Z}_t$  for stationarity, using
  - a Durbin-Watson test (“CRDW”), and/or
  - standard unit root tests (DF, ADF, KPSS, etc.)



# Wait, What? OLS???

Recall that for cointegrated  $X_t$  and  $Y_t$ ,  $\text{Var}(Z_t) < \infty$ .

Suppose we (incorrectly) estimate  $\delta$ :

$$\tilde{Z}_t = X_t - \delta Y_t$$

Then  $\tilde{Z}_t$  is  $I(1)$ , and  $\lim_{T \rightarrow \infty} [\text{Var}(\tilde{Z}_t)] = \infty$ , while in finite samples:

$$\text{Var}(\tilde{Z}_t) > \text{Var}(\hat{Z}_t),$$

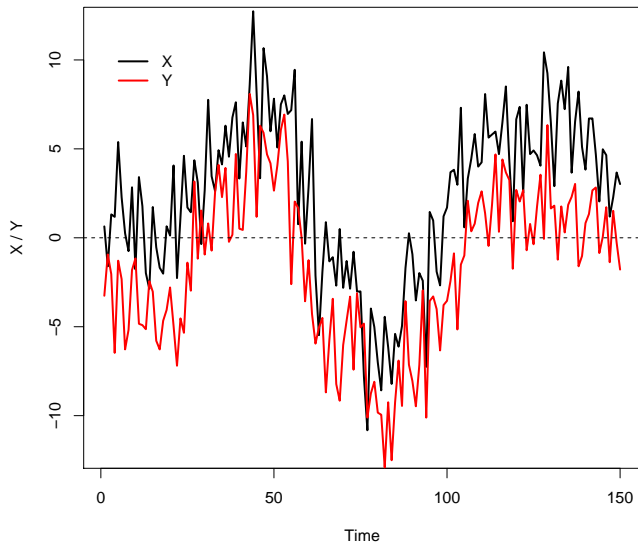
Thus:

- OLS minimizes residual variance  $\rightarrow$
- OLS makes  $\hat{Z}_t$  stationary [and makes  $\text{Var}(Z_t)$  finite]  $\rightarrow$
- $\hat{\alpha}_{OLS} \rightarrow \alpha$  as  $T \rightarrow \infty$  (“superconsistent”).

## A Simulated Example

```
> T <- 150
>
> set.seed(7222009)
>
> W <- cumsum(rnorm(T)) # I(1)
> X <- 2 + 0.8*W + 2*rnorm(T)
> Y <- -2 + 0.8*W + 2*rnorm(T)
>
> W.TS <- ts(W,start=1,end=T) # time series objects
> X.TS <- ts(X,start=1,end=T)
> Y.TS <- ts(Y,start=1,end=T)
```

# Our Series



# Unit Root Tests

```
> summary(ur.df(X.TS,type="trend",lags=1))  ### ADF
```

```
Value of test-statistic is: -3.2619 3.5655 5.3352
```

```
Critical values for test statistics:
```

```
      1pct  5pct 10pct  
tau3 -3.99 -3.43 -3.13  
phi2  6.22  4.75  4.07  
phi3  8.43  6.49  5.47
```

```
> summary(ur.df(Y.TS,type="trend",lags=1))
```

```
Value of test-statistic is: -2.6832 2.4 3.5999
```

```
Critical values for test statistics:
```

```
      1pct  5pct 10pct  
tau3 -3.99 -3.43 -3.13  
phi2  6.22  4.75  4.07  
phi3  8.43  6.49  5.47
```

```
> summary(ur.kpss(X.TS,type="tau",lags="short"))  ### KPSS
```

```
Value of test-statistic is: 0.3143
```

```
Critical value for a significance level of:
```

```
      10pct  5pct 2.5pct 1pct  
critical values 0.119 0.146 0.176 0.216
```

```
> summary(ur.kpss(Y.TS,type="tau",lags="short"))
```

```
Value of test-statistic is: 0.2913
```

```
Critical value for a significance level of:
```

```
      10pct  5pct 2.5pct 1pct  
critical values 0.119 0.146 0.176 0.216
```

# CI Regression + Residual Check

```
> CI.reg <- lm(X~Y)
> # summary(CI.reg)
>
> Zhats.TS <- ts(CI.reg$residuals,start=1,end=T)
>
> summary(ur.df(Zhats.TS,type="trend",lags=1)) ### ADF
```

Value of test-statistic is: -9.0599 27.3846 41.0621

Critical values for test statistics:

	1pct	5pct	10pct
tau3	-3.99	-3.43	-3.13
phi2	6.22	4.75	4.07
phi3	8.43	6.49	5.47

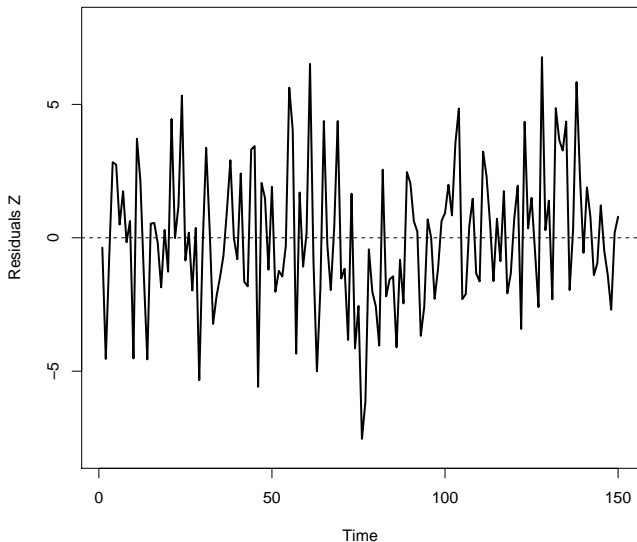
```
> summary(ur.kpss(Zhats.TS,type="tau",lags="short")) ### KPSS
```

Value of test-statistic is: 0.1625

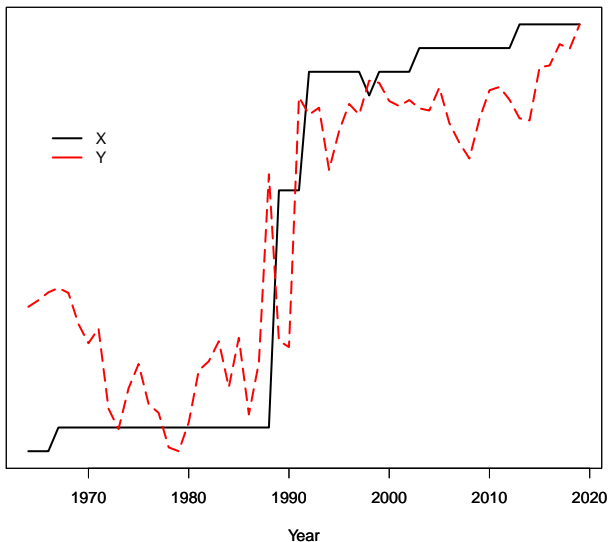
Critical value for a significance level of:

	10pct	5pct	2.5pct	1pct
critical values	0.119	0.146	0.176	0.216

# Residuals from Cointegrating Regression



## Two (More) Series, 1964-2019



```
> summary(lm(Y.TS~X.TS))
```

```
Call:
```

```
lm(formula = Y.TS ~ X.TS)
```

```
Residuals:
```

Min	1Q	Median	3Q	Max
-3751.1	-806.2	108.1	597.6	4657.5

```
Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	21177.78	194.42	108.93	<2e-16 ***
X.TS	403.65	24.97	16.17	<2e-16 ***

```
---
```

```
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
```

```
Residual standard error: 1453 on 54 degrees of freedom
```

```
Multiple R-squared:  0.8288, Adjusted R-squared:  0.8256
```

```
F-statistic: 261.4 on 1 and 54 DF,  p-value: < 2.2e-16
```



## Another Regression (Lagged X)

```
> summary(dyn$lm(Y.TS~lag(X.TS,-1)))   ### Lagged X
```

Call:

```
lm(formula = dyn(Y.TS ~ lag(X.TS, -1)))
```

Residuals:

Min	1Q	Median	3Q	Max
-3864.3	-787.9	138.0	594.6	4613.1

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	21277.22	188.35	112.96	<2e-16 ***
lag(X.TS, -1)	410.54	24.26	16.92	<2e-16 ***

---

Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 1396 on 53 degrees of freedom  
(2 observations deleted due to missingness)

Multiple R-squared: 0.8438, Adjusted R-squared: 0.8409

F-statistic: 286.3 on 1 and 53 DF, p-value: < 2.2e-16



$X$  = Ford Mustang prices, in  
constant \$US



$Y$  = Paraguay's POLITY IV  
(democracy / autocracy)  
score

Lagged  $X$ s:

$$Y_t = \alpha + \beta X_{t-1} + u_t$$

often yield autocorrelated errors / spurious regressions.

vs. “difference equations”:

$$\Delta Y_t = \alpha + \beta \Delta X_{t-1} + u_t$$

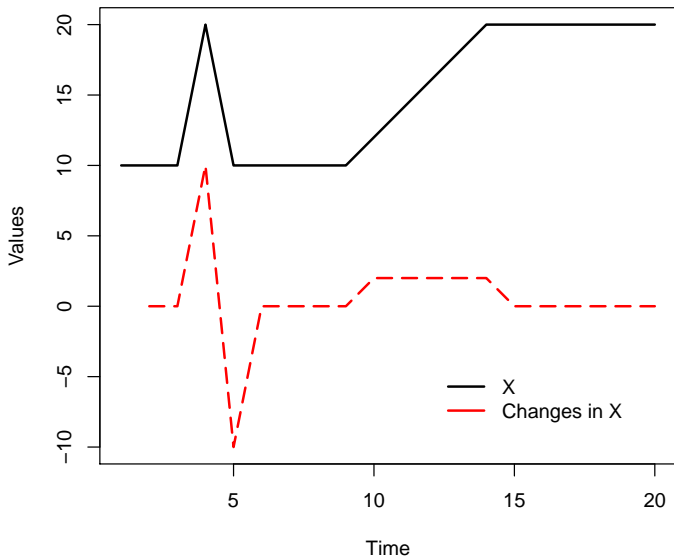
where all effects are “short term.”

$$\Delta Y_t = \beta \Delta X_{t-1} + \rho(Y_{t-1} - \alpha - \gamma X_{t-1})$$

## Terms:

- $\hat{\beta} \rightarrow$  short-term relationship between  $X$  and  $Y$ .
- $\hat{\alpha}$  and  $\hat{\gamma} \rightarrow$  long-term relationship between  $X$  and  $Y$  (the “attractor” – the equilibrium distance between  $X$  and  $Y$ ).
- $\hat{\rho} \rightarrow$  the rate at which the model “reequilibrates”  
(formally, the proportion of the disequilibrium which is corrected with each period)

# ECM: Toy Example



## Two Cointegrated Series

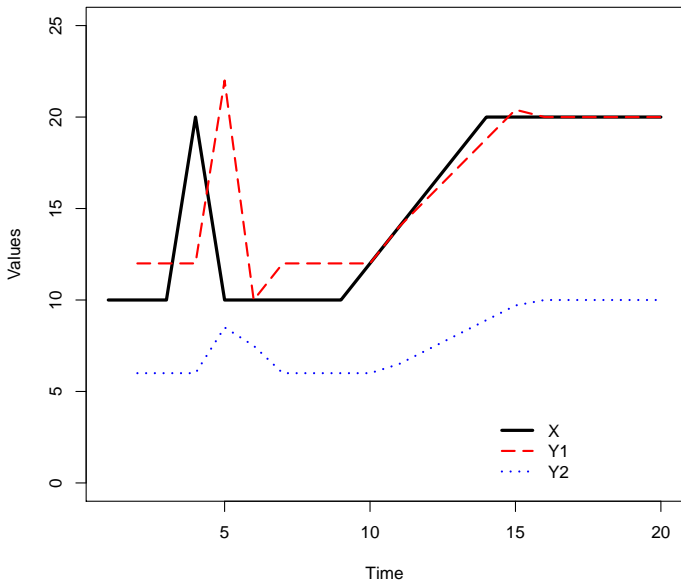
Two examples:

$$\Delta Y_{1t} = 1.0\Delta X_{t-1} - 0.8(Y_{1t-1} - 5.0 - 1.0X_{t-1})$$

$$\Delta Y_{2t} = 0.25\Delta X_{t-1} - 0.2(Y_{2t-1} - 10.0 - 2.0X_{t-1})$$

Note:

- $\Delta Y_1$  has a larger degree of short-term dependence on  $X$ .
- The “equilibrium distance” for  $\Delta Y_1$  is  $Y_t = 5 + X_t$ ; that in  $\Delta Y_2$  is  $Y_t = 10 + 2X_t$ .
- $Y_1$  reequilibrates at a much faster rate than does  $Y_2$ .



# Estimation and Testing: Two-Steps...

If both  $X_t$  and  $Y_t$  are cointegrated, then a general ECM is:

$$\begin{aligned}\Delta Y_t &= \beta_0 + \beta_1 \Delta X_{t-1} + \beta_2 \Delta X_{t-2} + \dots + \beta_k \Delta X_{t-k} + \rho Z_{t-1} + u_t \\ &= \beta_0 + \beta_1 \Delta X_{t-1} + \beta_2 \Delta X_{t-2} + \dots + \beta_k \Delta X_{t-k} + \rho(X_t - \alpha Y_t) + u_t\end{aligned}$$

where the  $\Delta X$ s capture the short-term dependence between  $X$  and  $Y$ .

## The Engle-Granger Two-Step:

1. Estimate the cointegrating regression  $Y_t = \alpha + \gamma X_t + e_t$ ,
2. From these estimates, generate  $\hat{Z}_t = Y_t - \hat{\alpha} - \hat{\gamma} X_t$ ,
3. Include  $\hat{Z}_{t-1}$  for  $Z_{t-1}$  in the model above.



# The One-Step Approach

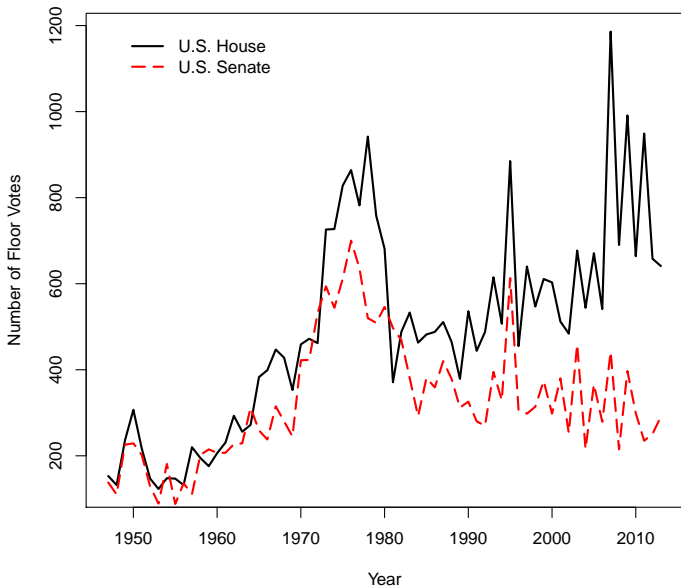
Substituting  $Z_t = X_t - \alpha Y_t$  into the equation above, we get:

$$\begin{aligned}\Delta Y_t &= \beta_0 + \beta_1 \Delta X_{t-1} + \rho(Y_{t-1} - \alpha - \gamma X_{t-1}) + u_t \\ &= (\beta_0 - \rho\alpha) + \beta_1 \Delta X_{t-1} + \rho Y_{t-1} - \rho\gamma X_{t-1} + u_t\end{aligned}$$

Suggests a single equation, where changes in  $Y_t$  are a function of:

- Lagged  $\Delta X$ s,
- $X_{t-1}$ , and
- $Y_{t-1}$ .

# Example: House and Senate Votes, 1946-2013



# Unit Roots? (A: Yes)

```
> summary(ur.df(HVotes.TS,type="trend",lags=1))
```

```
Value of test-statistic is: -2.112 1.8218 2.3959
```

```
> summary(ur.df(SVotes.TS,type="trend",lags=1))
```

```
Value of test-statistic is: -1.6975 1.3998 2.033
```

```
Critical values for test statistics:
```

	1pct	5pct	10pct
tau3	-4.04	-3.45	-3.15
phi2	6.50	4.88	4.16
phi3	8.73	6.49	5.47

```
> summary(ur.kpss(HVotes.TS,type="tau",lags="short"))
```

```
Value of test-statistic is: 0.1568
```

```
Critical value for a significance level of:
```

	10pct	5pct	2.5pct	1pct
critical values	0.119	0.146	0.176	0.216

```
> summary(ur.kpss(SVotes.TS,type="tau",lags="short"))
```

```
Value of test-statistic is: 0.3122
```

```
Critical value for a significance level of:
```

	10pct	5pct	2.5pct	1pct
critical values	0.119	0.146	0.176	0.216

## ECM, Step One

```
> StepOne <- lm(SVotes.TS~HVotes.TS) # CI regression  
> summary(StepOne)
```

Call:

```
lm(formula = SVotes.TS ~ HVotes.TS)
```

Residuals:

Min	1Q	Median	3Q	Max
-287.302	-54.055	-6.071	54.946	220.677

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	118.43749	28.20367	4.199	8.31e-05 ***
HVotes.TS	0.42557	0.05154	8.257	1.02e-11 ***

---

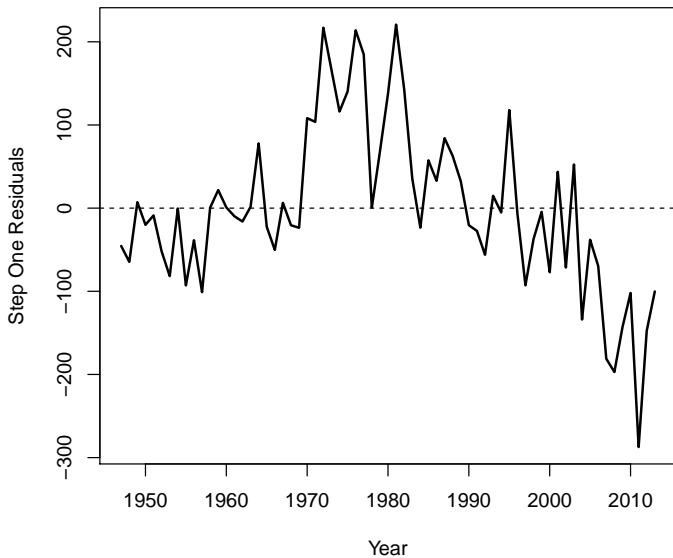
Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 100.3 on 65 degrees of freedom

Multiple R-squared: 0.5119, Adjusted R-squared: 0.5044

F-statistic: 68.18 on 1 and 65 DF, p-value: 1.021e-11

## Step One Residuals...☹



## ECM: Step Two

```
> DSV.TS <- diff(SVotes.TS) # difference Y
> DHVLag.TS <- lag(diff(HVotes.TS),k=-1) # Lag differenced X
> Ztminus1.TS <- lag(Zt.TS,k=-1) # Lag residuals
> df <- ts.intersect(DSV.TS,DHVLag.TS,Ztminus1.TS)

> StepTwo <- lm(DSV.TS ~ DHVLag.TS + Ztminus1.TS,
+               data = df)
> summary(StepTwo)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	5.56516	10.93399	0.509	0.6126
DHVLag.TS	-0.27917	0.06362	-4.388	4.53e-05 ***
Ztminus1.TS	-0.27269	0.10992	-2.481	0.0158 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 88.04 on 62 degrees of freedom  
Multiple R-squared: 0.2875, Adjusted R-squared: 0.2645  
F-statistic: 12.51 on 2 and 62 DF, p-value: 2.734e-05

# What Does That Mean?

The fitted ECM is:

$$\begin{aligned}\Delta \text{Senate Votes}_t = & 5.56 - 0.28\Delta \text{House Votes}_{t-1} \\ & - 0.27[\text{Senate Votes}_{t-1} - 118.4 - 0.43(\text{House Votes}_{t-1})]\end{aligned}$$

This means that:

- The “short term” relationship between Senate and House votes has about 0.28.
- Following a “shock,” the relationship between the two returns to its equilibrium level at a rate of about 27 percent per year.

```
> SVLag.TS <- lag(SVotes.TS,k=-1) # Lag Y
> HVLag.TS <- lag(HVvotes.TS,k=-1) # Lag X
> df2 <- ts.intersect(DSV.TS,DHVLag.TS,SVLag.TS,HVLag.TS)
> OneStep <- lm(DSV.TS~DHVLag.TS+SVLag.TS+HVLag.TS,
+               data=df2)

> summary(OneStep)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	67.79858	29.46161	2.301	0.024808	*
DHVLag.TS	-0.25004	0.06750	-3.704	0.000458	***
SVLag.TS	-0.27186	0.10943	-2.484	0.015744	*
HVLag.TS	0.05466	0.06773	0.807	0.422782	

---

Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 87.64 on 61 degrees of freedom

Multiple R-squared: 0.3052, Adjusted R-squared: 0.2711

F-statistic: 8.933 on 3 and 61 DF, p-value: 5.411e-05



- Distributed lag models
- (“Granger”) Causality
- Intervention analysis, “structural breaks,” and threshold models
- Vector autoregression (VAR) models
- Autoregressive Conditional Heteroscedasticity (ARCH and GARCH) models
- Fractional integration / long-memoried series
- Spectral domain analysis
- Time series models for binary, ordered, event count, etc. outcomes
- Models for spatio-temporal data

Some favorite references:

- Box-Steffensmeier, Janet M., John R. Freeman, Matthew P. Hitt, and Jon C. Pevehouse. 2015. *Time Series Analysis for the Social Sciences*. New York: Cambridge University Press.
- Fuller, W.A. 1996. *Introduction to Statistical Time Series*, 2nd ed. New York: Wiley.
- Pickup, Mark. 2014. *Introduction to Time Series Analysis*. New York: SAGE Publications. Quantitative Applications in the Social Sciences.
- Shumway, Robert H., and David S. Stoffer. 2016. *Time Series Analysis and Its Applications, With R Examples*. New York: Springer.

Syllabi (examples; some also include panel data models):

- [Adolph \(2022\)](#)
- [Enns \(2018\)](#)
- [Mitchell \(2020\)](#)
- [Philips \(2022\)](#)