

# AR(1) Process

- The first-order autoregressive process, AR(1) is

$$y_t = \beta y_{t-1} + e_t$$

where  $e_t$  is  $WN(0, \sigma^2)$

# Conditional Mean and Variance of AR(1)

- Conditional mean:

$$E(y_t | \Omega_{t-1}) = E(\beta y_{t-1} + e_t | \Omega_{t-1}) = \beta y_{t-1}$$

- Conditional variance:

$$\begin{aligned} \text{var}(y_t | \Omega_{t-1}) &= \text{var}(y_t - E(y_t | \Omega_{t-1}) | \Omega_{t-1}) \\ &= \text{var}(e_t | \Omega_{t-1}) \\ &= \sigma^2 \end{aligned}$$

# Autocovariance of AR(1)

- Take the equation

$$y_t = \beta y_{t-1} + e_t$$

- And then multiply both sides by  $y_{t-k}$

$$y_{t-k} y_t = \beta y_{t-k} y_{t-1} + y_{t-k} e_t$$

- Then take expectations. Since  $e_t$  is white noise, it is uncorrelated with

$$E(y_{t-k} y_t) = \beta E(y_{t-k} y_{t-1}) + E(y_{t-k} e_t)$$

or

$$\gamma(k) = \beta \gamma(k-1)$$

# Autocorrelation of AR(1)

- Dividing by the variance, this implies

$$\rho(k) = \beta\rho(k-1)$$

- We know

$$\rho(0) = 1$$

- Then

$$\rho(1) = \beta\rho(0) = \beta$$

$$\rho(2) = \beta\rho(1) = \beta^2$$

⋮

$$\rho(k) = \beta^k$$

# Autocorrelation of AR(1)

- We have derived

$$\rho(k) = \beta^k$$

- The autocorrelation of the stationary AR(1) is a simple geometric decay ( $|\beta| < 1$ )
- If  $\beta$  is small, the autocorrelations decay rapidly to zero with  $k$
- If  $\beta$  is large (close to 1) then the autocorrelations decay moderately
- The AR(1) parameter describes the persistence in the time series

# One-Step-Ahead Forecast

- As we showed earlier

$$E(y_t | \Omega_{t-1}) = \beta y_{t-1}$$

- Thus

$$E(y_{T+1} | \Omega_T) = \beta y_T$$

- The optimal one-step-ahead forecast is a linear function of the final observed value

# 2-step-ahead forecast

- By back-substitution

$$\begin{aligned}y_t &= \beta y_{t-1} + e_t \\ &= e_t + \beta(\beta y_{t-2} + e_{t-1}) \\ &= \beta^2 y_{t-2} + e_t + \beta e_{t-1}\end{aligned}$$

- Thus

$$\begin{aligned}E(y_t | \Omega_{t-2}) &= E(\beta^2 y_{t-2} + e_t + \beta e_{t-1} | \Omega_{t-2}) \\ &= \beta^2 y_{t-2}\end{aligned}$$

- and

$$E(y_{T+2} | \Omega_T) = \beta^2 y_T$$

# 2-step-ahead forecast

- This shows that the optimal 2-step-ahead forecast is also a linear function of the final observed value, but with the coefficient  $\beta^2$ .

$$E(y_{T+2} | \Omega_T) = \beta^2 y_T$$



# h-step-ahead forecast

- Similarly

$$y_t = \beta^h y_{t-h} + e_t + \beta e_{t-1} + \dots + \beta^{h-1} e_{t-h+1}$$

- So

$$\begin{aligned} E(y_t | \Omega_{t-h}) &= E(\beta^h y_{t-h} + e_t + \beta e_{t-1} + \dots + \beta^{h-1} e_{t-h+1} | \Omega_{t-h}) \\ &= \beta^h y_{t-h} \end{aligned}$$

- Optimal forecast:

$$E(y_{T+h} | \Omega_T) = \beta^h y_T$$

# Inversion of AR(1)

- By inverting the lag operator

$$(1 - \beta L)y_t = e_t$$

$$y_t = (1 - \beta L)^{-1} e_t$$

$$= \left( \sum_{i=0}^{\infty} \beta^i L^i \right) e_t$$

$$= \sum_{i=0}^{\infty} \beta^i e_{t-i}$$

- Which is the same as found by back substitution

# Condition for Invertibility

- The operator  $(1-\beta L)$  is invertible when  $|\beta| < 1$
- This is the same as for the MA(1) model
- $\beta$  is the inverse of the root of the polynomial  $1-\beta L$
- The root of a function is the value where it crosses the x-axis
- The root of  $1-\beta L$  is  $1/\beta$ , the inverse of the root is  $\beta$
- Invertibility requires that the inverse of the root be less than one

# AR(1) with Intercept

- An AR(1) with intercept is

$$y_t = \alpha + \beta y_{t-1} + e_t$$

Taking expectations

$$E(y_t) = \alpha + \beta E(y_{t-1}) + E(e_t)$$

- Thus

$$\mu = \alpha + \beta \mu$$

- and

$$\mu = \frac{\alpha}{1 - \beta}$$

# Best Linear Predictor

- A linear predictor of  $y_t$  given  $y_{t-1}$  is

$$\alpha + \beta y_{t-1}$$

- The forecast error is

$$e_t = y_t - \alpha - \beta y_{t-1}$$

- The linear predictor which minimizes the expected squared forecast error solves

$$\min_{\alpha, \beta} E(y_t - \alpha - \beta y_{t-1})^2$$

# Least-Squares

- The estimate of the expected squared linear forecast error is the sum of squared errors
- The least squares estimate

$$y_t = \hat{\alpha} + \hat{\beta}y_{t-1} + \hat{e}_t$$

minimizes the sum of squared errors, so is the estimate of the best linear predictor

- This is a linear regression, treating  $y_{t-1}$  as a regressor.

# Unemployment Rate

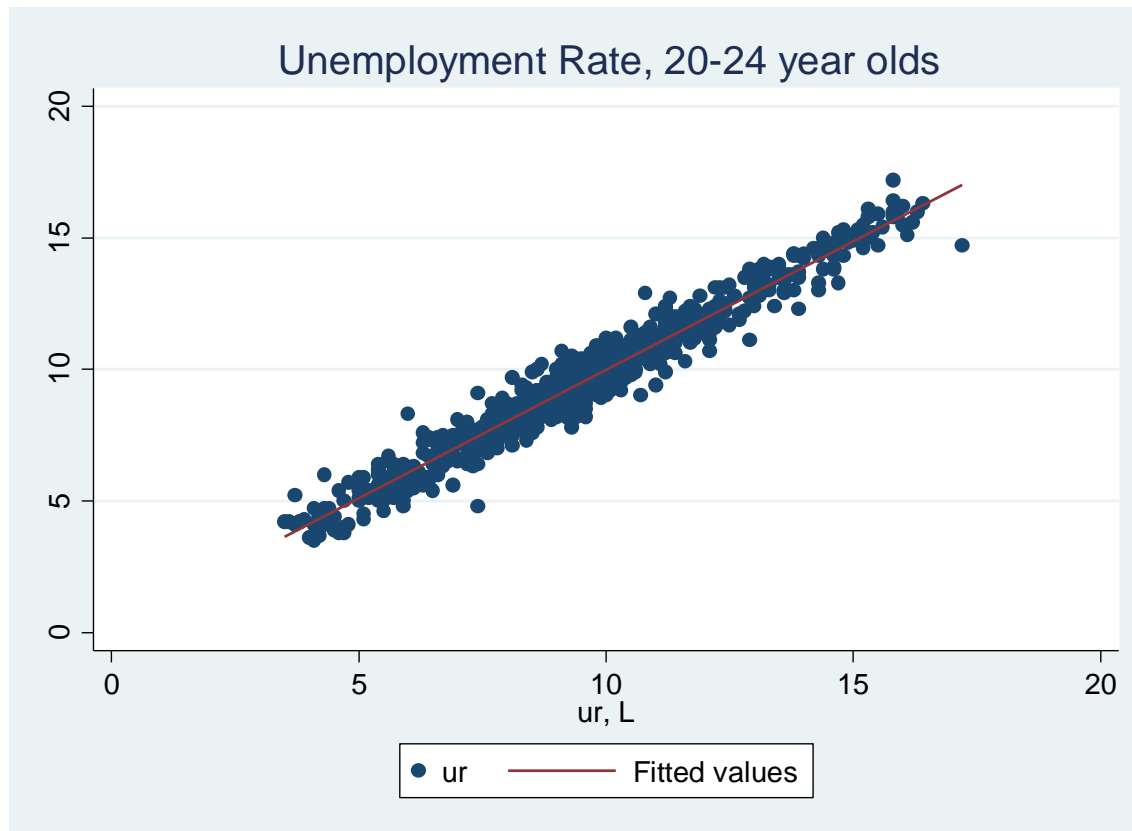
```
. regress ur L.ur
```

Source	SS	df	MS	Number of obs	=	828
Model	5337.15724	1	5337.15724	F(1, 826)	=	17943.11
Residual	245.69276	826	.297448861	Prob > F	=	0.0000
Total	5582.85	827	6.75072551	R-squared	=	0.9560
				Adj R-squared	=	0.9559
				Root MSE	=	.54539

ur	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ur L1.	.9767288	.0072916	133.95	0.000	.9624165	.9910411
_cons	.2213102	.0709754	3.12	0.002	.0819969	.3606236

# Fitted AR(1)

- To plot a scatter and fitted regression,
  - `twoway scatter ur L.ur || lfit ur L.ur, title("Unemployment Rate, 20-24 year olds")`





# GDP Growth Rates

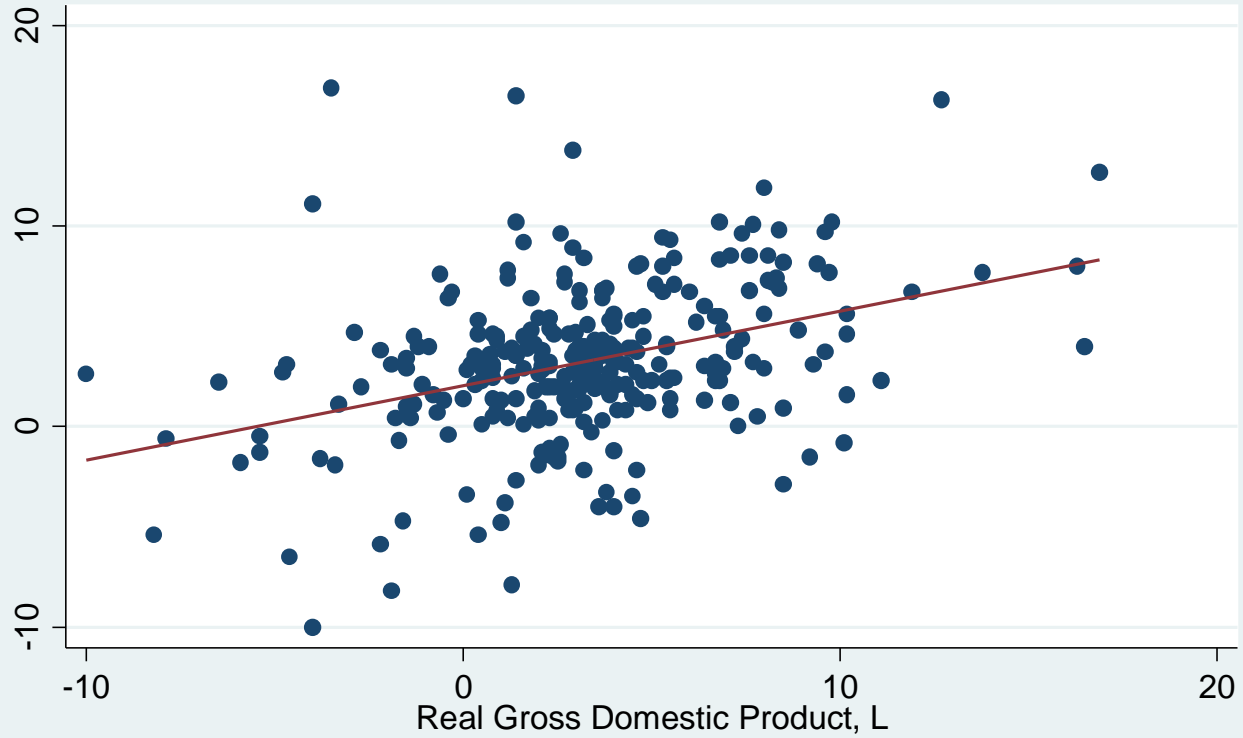
```
. regress gdp L.gdp
```

Source	SS	df	MS	Number of obs	=	278
Model	585.172068	1	585.172068	F(1, 276)	=	44.32
Residual	3643.98246	276	13.202835	Prob > F	=	0.0000
Total	4229.15453	277	15.2677059	R-squared	=	0.1384
				Adj R-squared	=	0.1352
				Root MSE	=	3.6336

gdp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
gdp L1.	.3714752	.0557984	6.66	0.000	.2616307	.4813197
_cons	2.036509	.2826904	7.20	0.000	1.480006	2.593013

## GDP Growth Rates



● Real Gross Domestic Product — Fitted values

# One-Step-Ahead Forecast

- The optimal forecast for  $T+1$  given  $T$  is

$$\hat{y}_{T+1|T} = \alpha + \beta y_T$$

- The forecast using the estimates is

$$\hat{y}_{T+1|T} = \hat{\alpha} + \hat{\beta} y_T$$

# Unemployment Rate, 20-24 year olds

- The estimates were

ur	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ur L1.	.9767288	.0072916	133.95	0.000	.9624165 .9910411
_cons	.2213102	.0709754	3.12	0.002	.0819969 .3606236

$$y_t = 0.22 + 0.977 y_{t-1} + \hat{e}_t$$

- The value for Jan 2016 is 8.3%, so

$$\hat{y}_{2017:2} = 0.22 + 0.977 \times 8.3 = 8.3$$

- Point forecast is 8.3% (unchanged from current)

- `list time ur L.ur p if time>=tm(2016m1)`

	time	ur	L. ur	p
817.	2016m1	8.2	9.4	9.402561
818.	2016m2	8.6	8.2	8.230487
819.	2016m3	8.4	8.6	8.621178
820.	2016m4	8.8	8.4	8.425833
821.	2016m5	8.3	8.8	8.816524
822.	2016m6	8.6	8.3	8.328159
823.	2016m7	8.9	8.6	8.621178
824.	2016m8	8.1	8.9	8.914197
825.	2016m9	8.2	8.1	8.132813
826.	2016m10	8.4	8.2	8.230487
827.	2016m11	8.1	8.4	8.425833
828.	2016m12	8.2	8.1	8.132813
829.	2017m1	8.3	8.2	8.230487
830.	2017m2	.	8.3	8.328159

# Example – GDP Growth

- The estimates were

gdp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gdp L1.	.3714752	.0557984	6.66	0.000	.2616307 .4813197
_cons	2.036509	.2826904	7.20	0.000	1.480006 2.593013

$$y_t = 2.04 + 0.371y_{t-1} + \hat{e}_t$$

- The value for 4<sup>th</sup> quarter 2016 is 1.9%, so

$$\hat{y}_{2017:1} = 2.04 + 0.371 \times 1.9 = 2.7\%$$

# GDP Growth

	time	gdp	L. gdp	p
272.	2015q1	2	2.3	2.890902
273.	2015q2	2.6	2	2.77946
274.	2015q3	2	2.6	3.002345
275.	2015q4	.9	2	2.77946
276.	2016q1	.8	.9	2.370837
277.	2016q2	1.4	.8	2.333689
278.	2016q3	3.5	1.4	2.556575
279.	2016q4	1.9	3.5	3.336673
280.	2017q1	.	1.9	2.742312

# One-Step-Ahead Forecast Error

- The forecast error is

$$\begin{aligned}y_{T+1} - \hat{y}_{T+1|T} &= \alpha + \beta y_T + e_{T+1} - (\alpha + \beta y_T) \\ &= e_{T+1}\end{aligned}$$

- The forecast variance is

$$\text{var}(y_{T+1} - \hat{y}_{T+1|T}) = \text{var}(e_{T+1}) = \sigma^2$$



# Forecast variance estimation

- Average of squared residuals

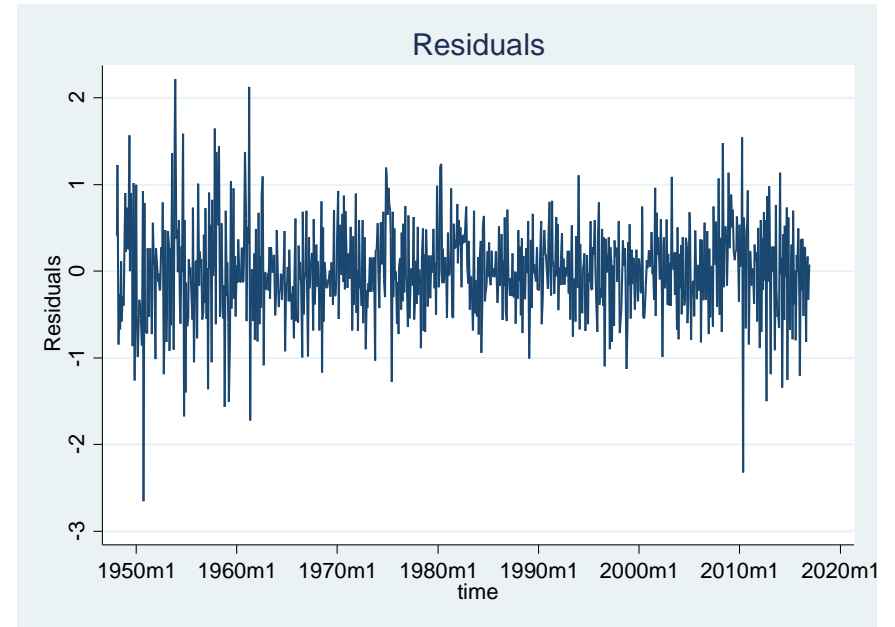
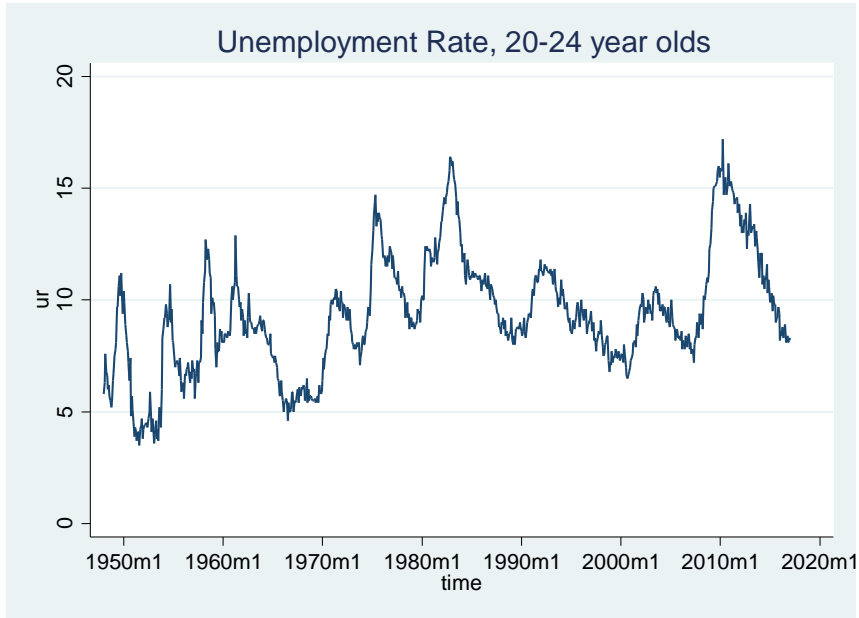
$$\hat{\sigma}^2 = \frac{1}{T} \sum_{t=1}^T \hat{e}_t^2$$

$$\hat{\sigma} = \sqrt{\hat{\sigma}^2}$$

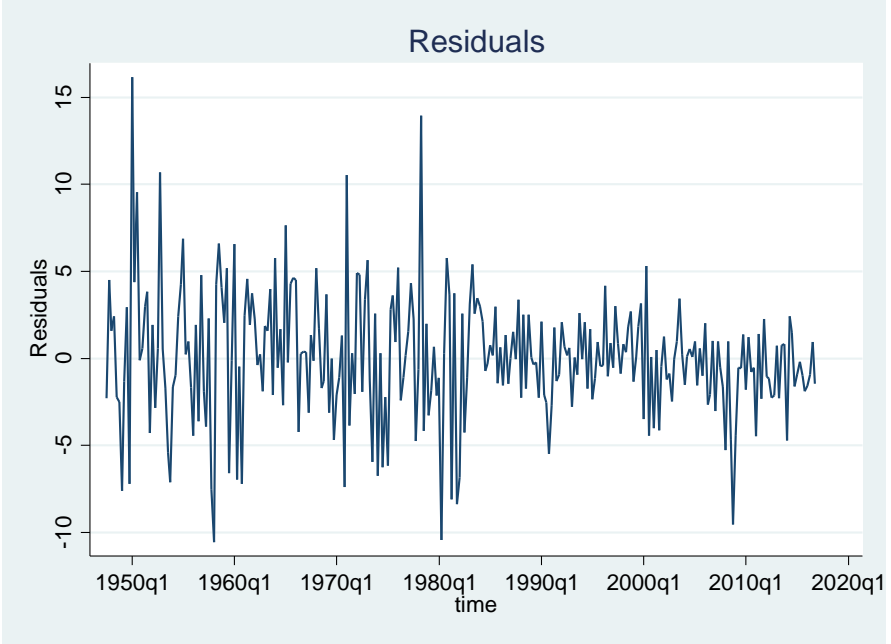
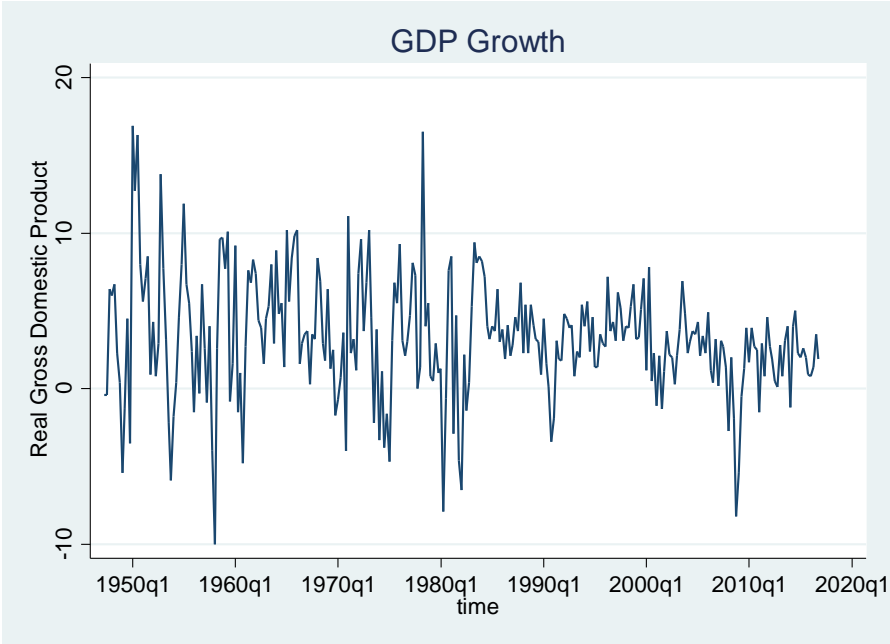
where the least-squares residuals are

$$\hat{e}_t = y_t - \hat{\alpha} - \hat{\beta}y_{t-1}$$

# Unemployment Rate, 20-24 year olds



# GDP Growth



# One-Step-Ahead Intervals

- Normal Method

- Assume forecast error is normally distributed
- Forecast interval is point estimate, plus and minus the *standard deviation of forecast* multiplied by a normal percentile

- For a 95% interval:

$$\hat{y}_{T+1|T} \pm \hat{\sigma} \cdot z_{.025} = \hat{y}_{T+1|T} \pm \hat{\sigma} \cdot 1.96$$

- For a 90% interval

$$\hat{y}_{T+1|T} \pm \hat{\sigma} \cdot z_{.05} = \hat{y}_{T+1|T} \pm \hat{\sigma} \cdot 1.645$$

# Standard Dev of Forecast

- The forecast variance is the variance of the error, plus the variance of the estimate
- The standard deviation of the forecast is its square root
- In most cases the major component of the forecast variance is the variance of the error
- Thus a simple method to estimate the standard deviation of the forecast is to use  $\sigma$ , “root mean squared error”, from the regression estimate
- In STATA, for `stdf` you can use the command  
**predict s, stdf**
- The difference between the rmse and stdf grows when the number of regressors is large relative to the sample size.

# Example: GDP

- The “Root MSE” is 3.63
- The stdf is 3.64, only slightly higher!

```
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```

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# Forecast Interval Construction

- `tsappend, add(1)`
- `predict p`
- `predict s, stdf`
- `gen p1 = p - 1.645*s`
- `gen p2 = p + 1.645*s`
- `list time p1 p p2 s if time>tq(2016q4)`

	time	p1	p	p2	s
280.	2017q1	-3.246891	2.742312	8.731515	3.640853

- Point estimate = 2.7%
- Std = 3.64
- 90% Interval = [-3.2%, 8.7%]

# Assignments

- Read Diebold through Chapter 7
- Problem Set # 5
  - Due Tuesday (2/21)
- Read Chapter 5 from *The Signal and the Noise*
  - Reading Reflection
  - Due Thursday (2/23)