

Hypothesis Testing in the CER Model

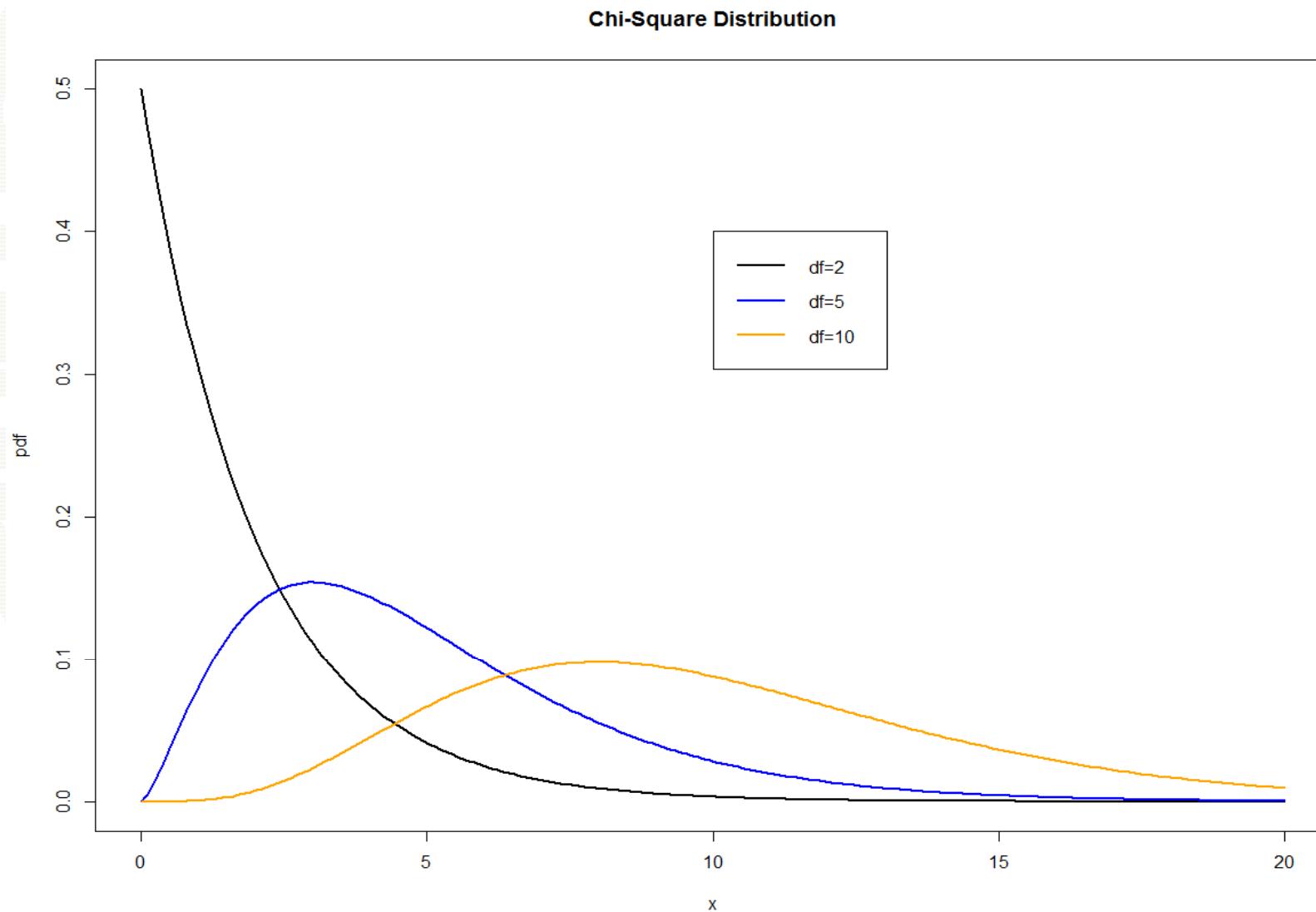
Econ 424/Amath 462

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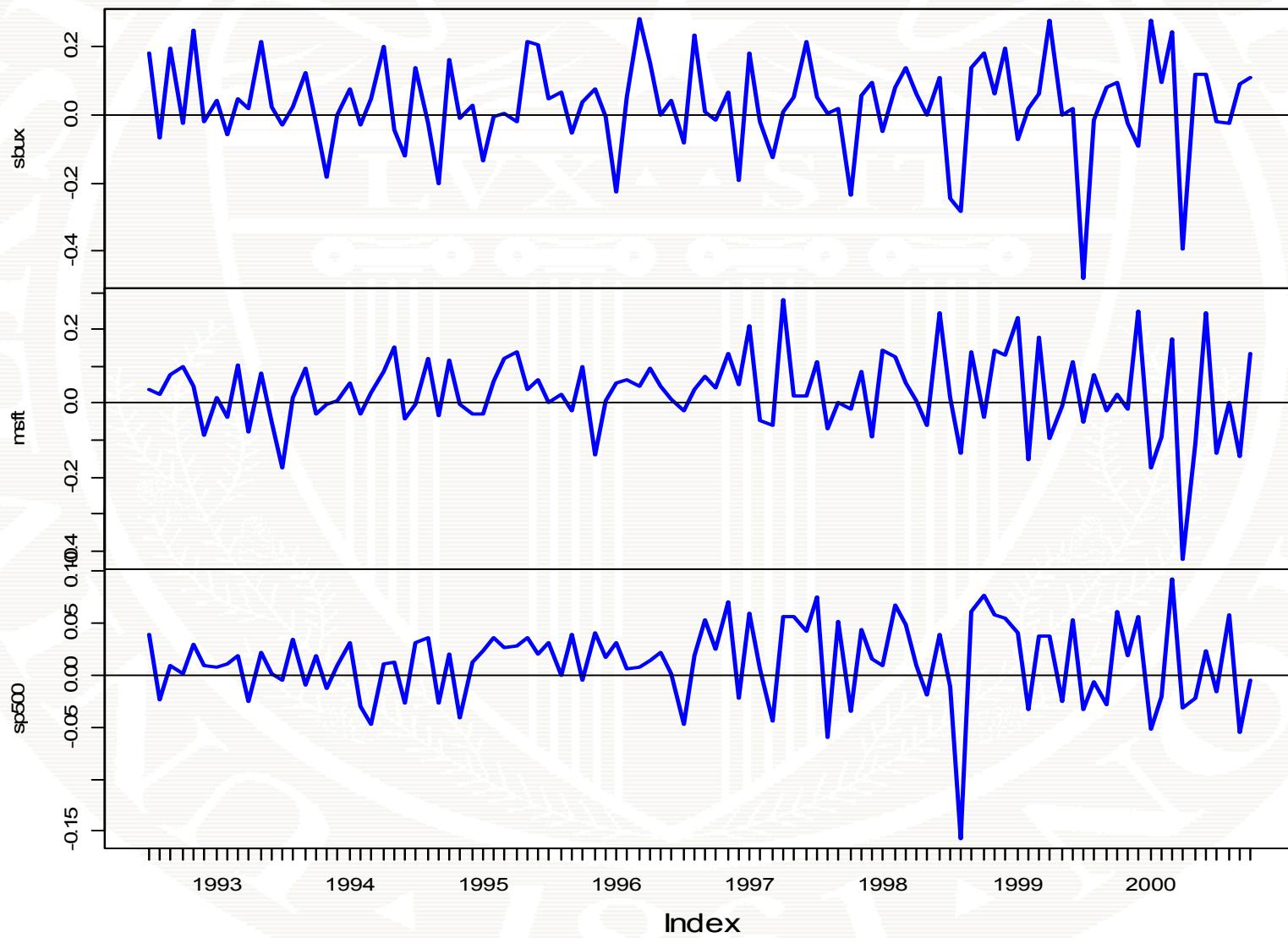
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Chi-Square Distribution



Data for Examples

returns.z

 $T = 100 \text{ months}$

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$H_0: \mu = 0$ vs. $H_1: \mu \neq 0$

```
# construct test by brute force
> nobs = nrow(returns.z)
> muhat.vals = apply(returns.z,2,mean)
> muhat.vals
  sbux    msft    sp500
0.02777 0.02756 0.01253

> sigmahat.vals = apply(returns.z,2,sd)
> se.muhat = sigmahat.vals/sqrt(nobs)
> se.muhat
  sbux    msft    sp500
0.01359 0.01068 0.003785
> t.stats = muhat.vals/se.muhat
> abs(t.stats)
  sbux    msft    sp500
2.044  2.58   3.312
```

|t-stats| > 2 => we should
reject $H_0: \mu = 0$

$H_0: \mu = 0$ vs. $H_1: \mu \neq 0$

```
# compute 2-sided 5% critical values
> cv.2sided = qt(0.975, df=nobs-1)
> cv.2sided
[1] 1.984
> abs(t.stats) > cv.2sided
  sbux msft sp500
    T      T      T

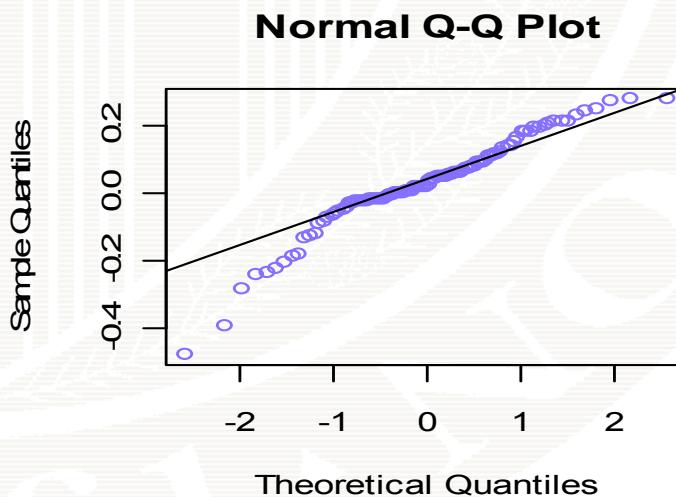
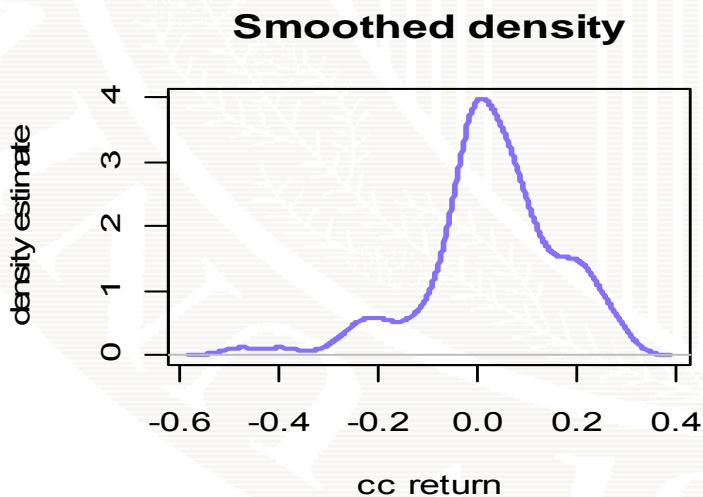
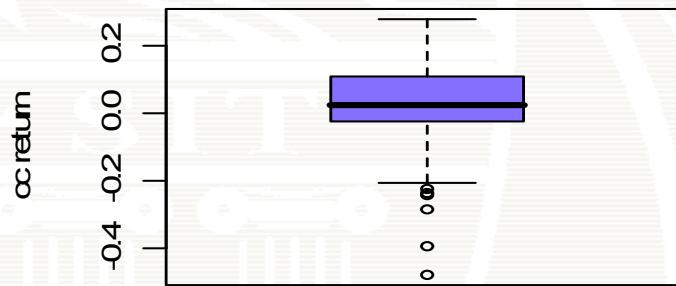
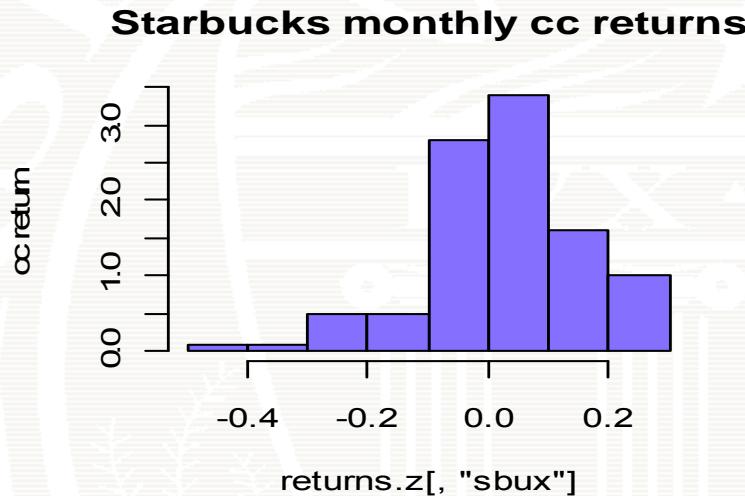
# compute 2-sided p-values
> 2*(1-pt(abs(t.stats),df=nobs-1))
  sbux      msft      sp500
0.04363 0.01134 0.001295
```

R t.test() function

```
# Test H0: mu = 0 for msft
> t.test.msft = t.test(returns.z[, "msft"],
+                         alternative="two.sided",
+                         mu=0, conf.level=0.95)
> class(t.test.msft)
[1] "htest"
> t.test.msft
One Sample t-test
data: returns.z[, "msft"]
t = 2.580, df = 99, p-value = 0.01134
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
0.006368 0.048760
sample estimates:
mean of x
0.02756
```

$\mu = 0$ does not lie in 95% CI so we reject $H_0 \mu=0$ at 5% level

Test for Normal Distribution



Jarque-Bera Test for Normality

```
> sbux.skew = skewness(returns.z[, "sbux"])
> sbux.ekurt= kurtosis(returns.z[, "sbux"])
> sbux.skew
[1] -0.8272737
> sbux.ekurt
[1] 1.761706
> JB = nobs*(sbux.skew^2 + 0.25*sbux.ekurt^2)/6
> JB
[1] 24.33806 ← JB = 24.34 > 6 so we reject H0:
   returns on sbux are normally
   distributed at the 5% level
> p.value = 1 - pchisq(JB, df = 2)
> p.value
[1] 5.188691e-06
```

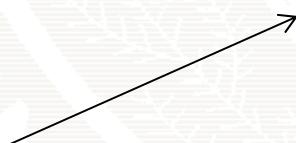
tseries function `jarque.bera.test()`

```
> library(tseries)  
> jarque.bera.test(returns.z[, "sbux"])
```

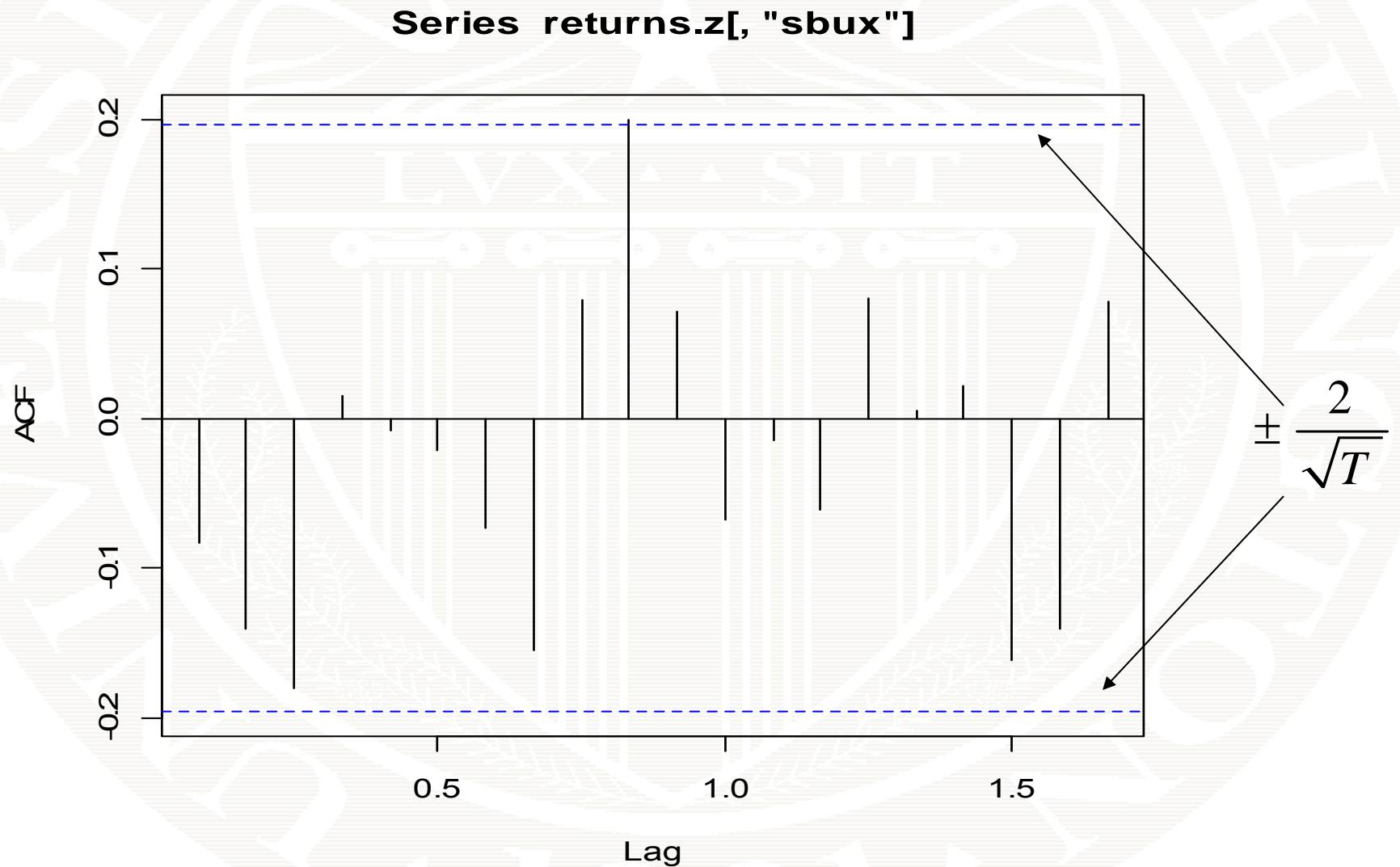
Jarque Bera Test

```
data: returns.z[, "sbux"]  
x-squared = 24.34, df = 2, p-value = 5.189e-06
```

JB statistic



Testing for Serial Correlation

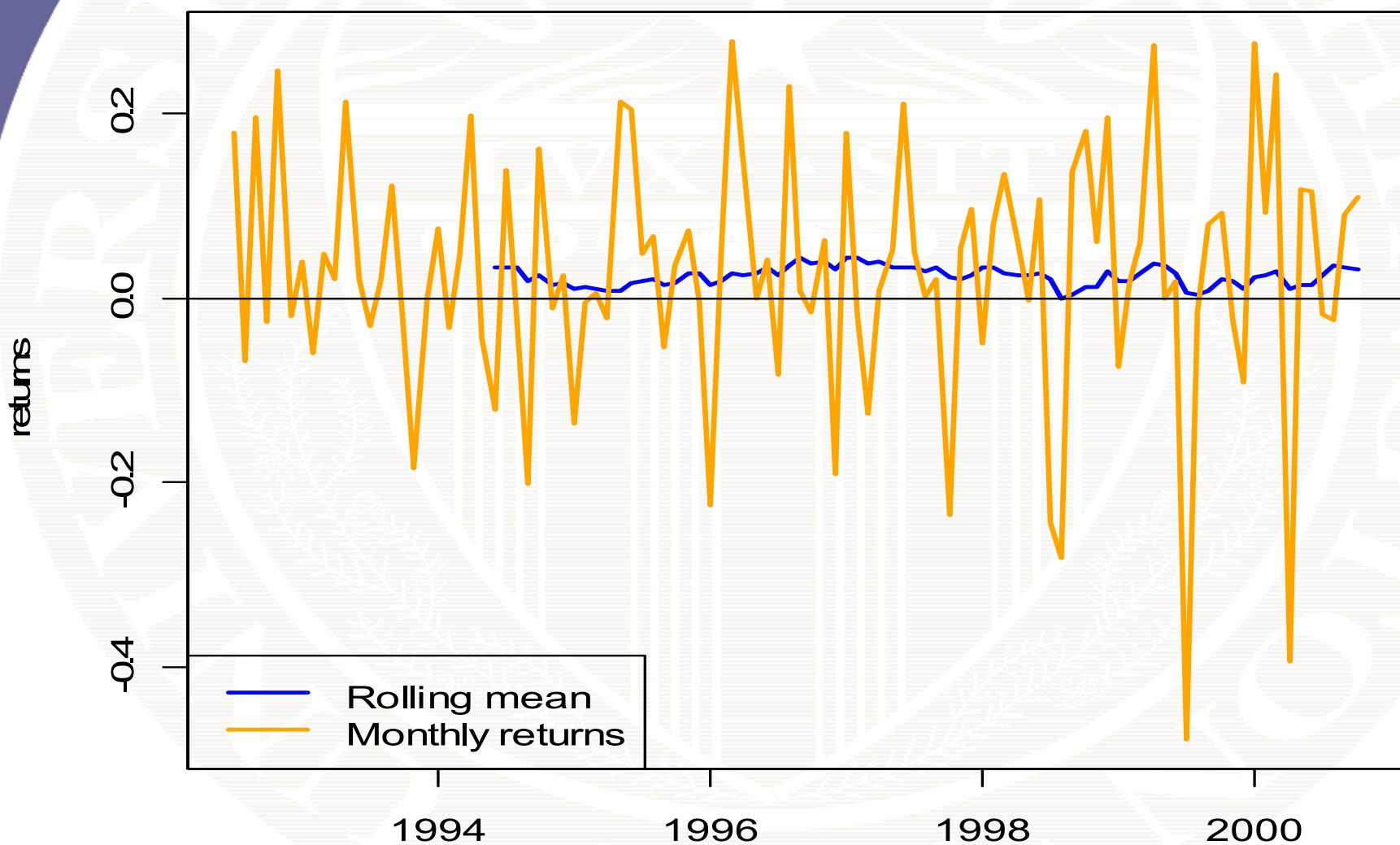


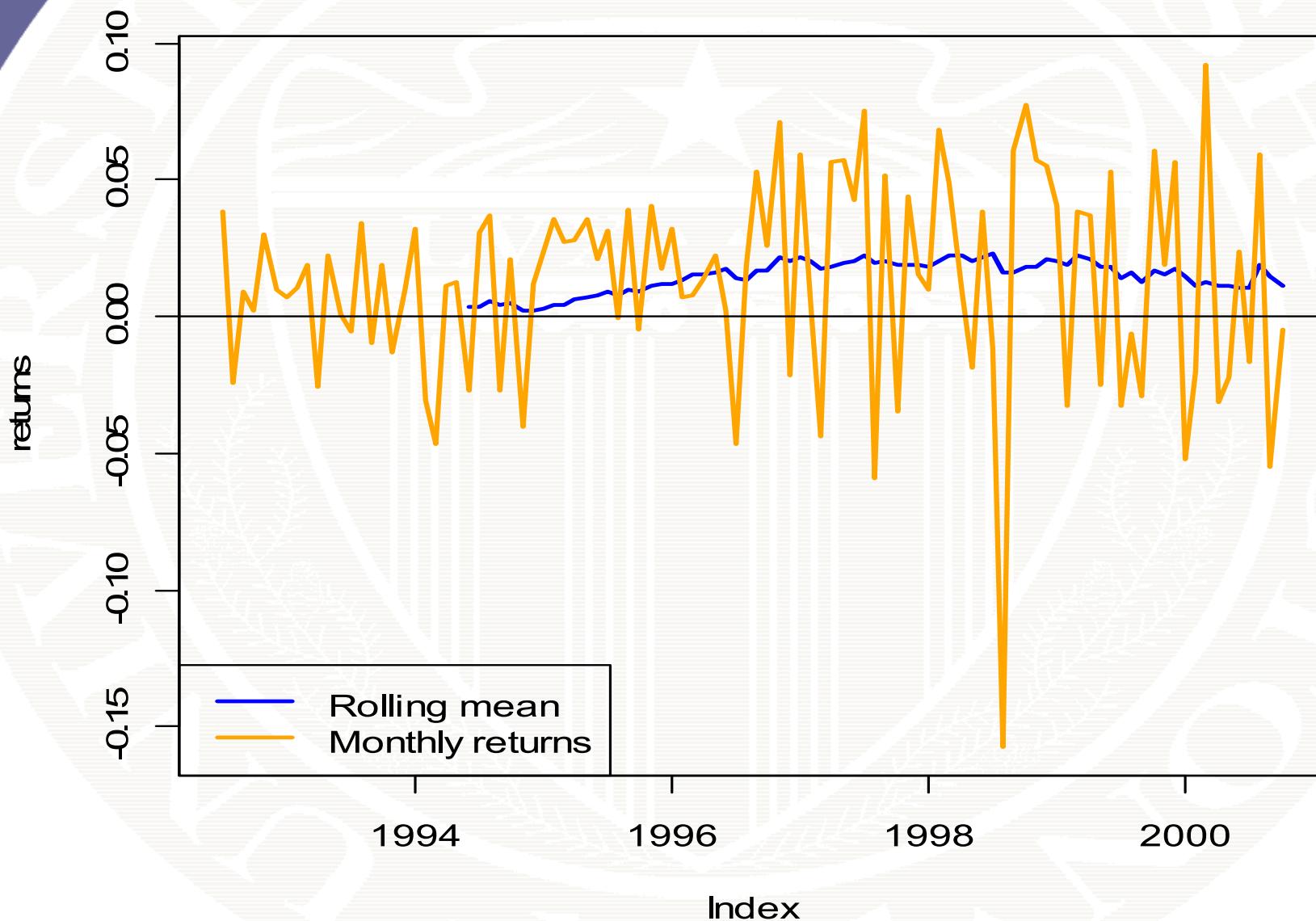
> `acf(returns.ts[, "sbux"])` © Eric Zivot 2006

Compute Rolling Means using zoo function `rollapply()`

```
# 24-month rolling means incremented by 1 month
> roll.muhat = rollapply(returns.z[, "sbux"], width=24,
+                         FUN=mean, align="right")
> class(roll.muhat)
[1] "zoo"

> roll.muhat[1:5]
Jun 1994 Jul 1994 Aug 1994 Sep 1994 Oct 1994
0.03415  0.03244  0.03418  0.01758  0.02538
```

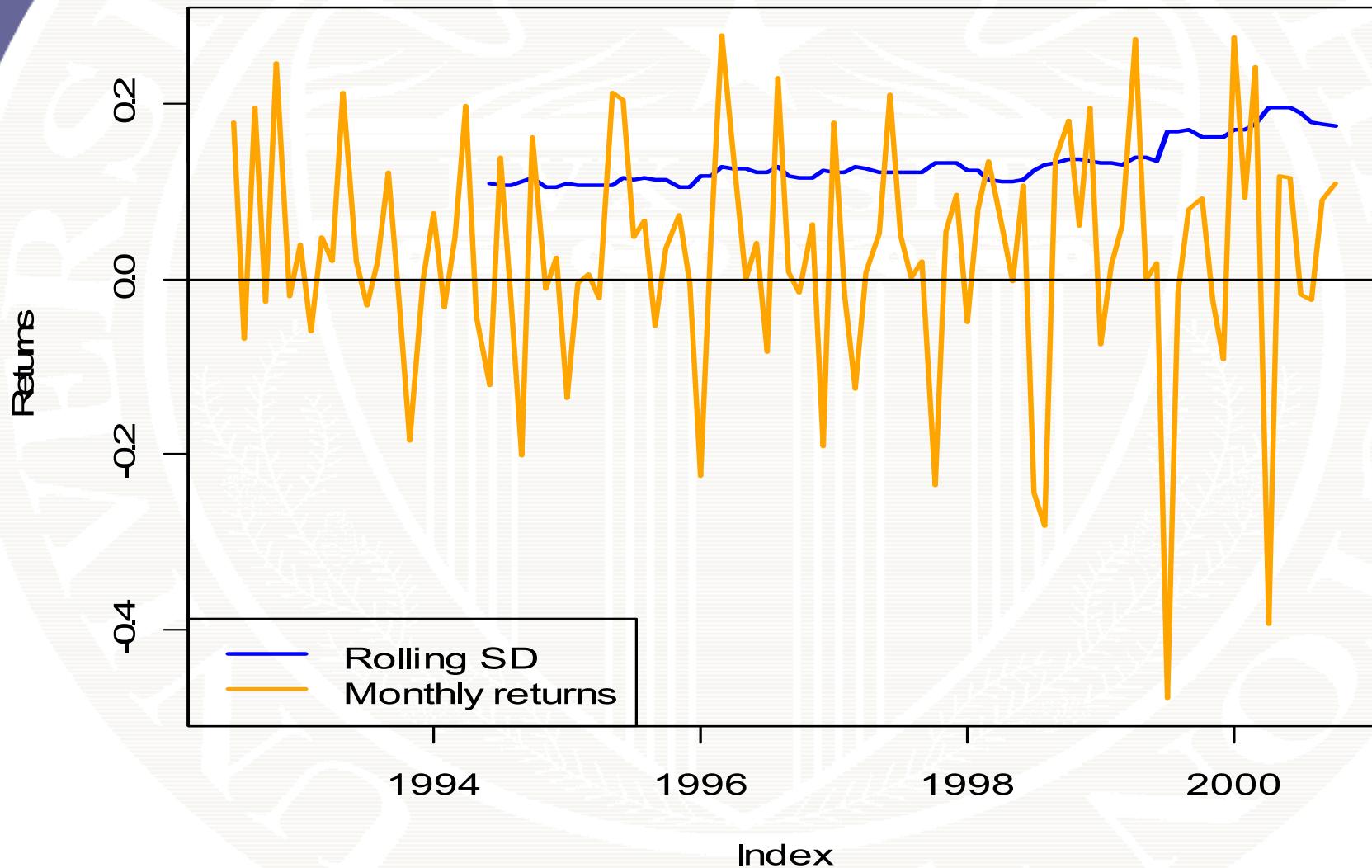
24 month rolling means for SBUX

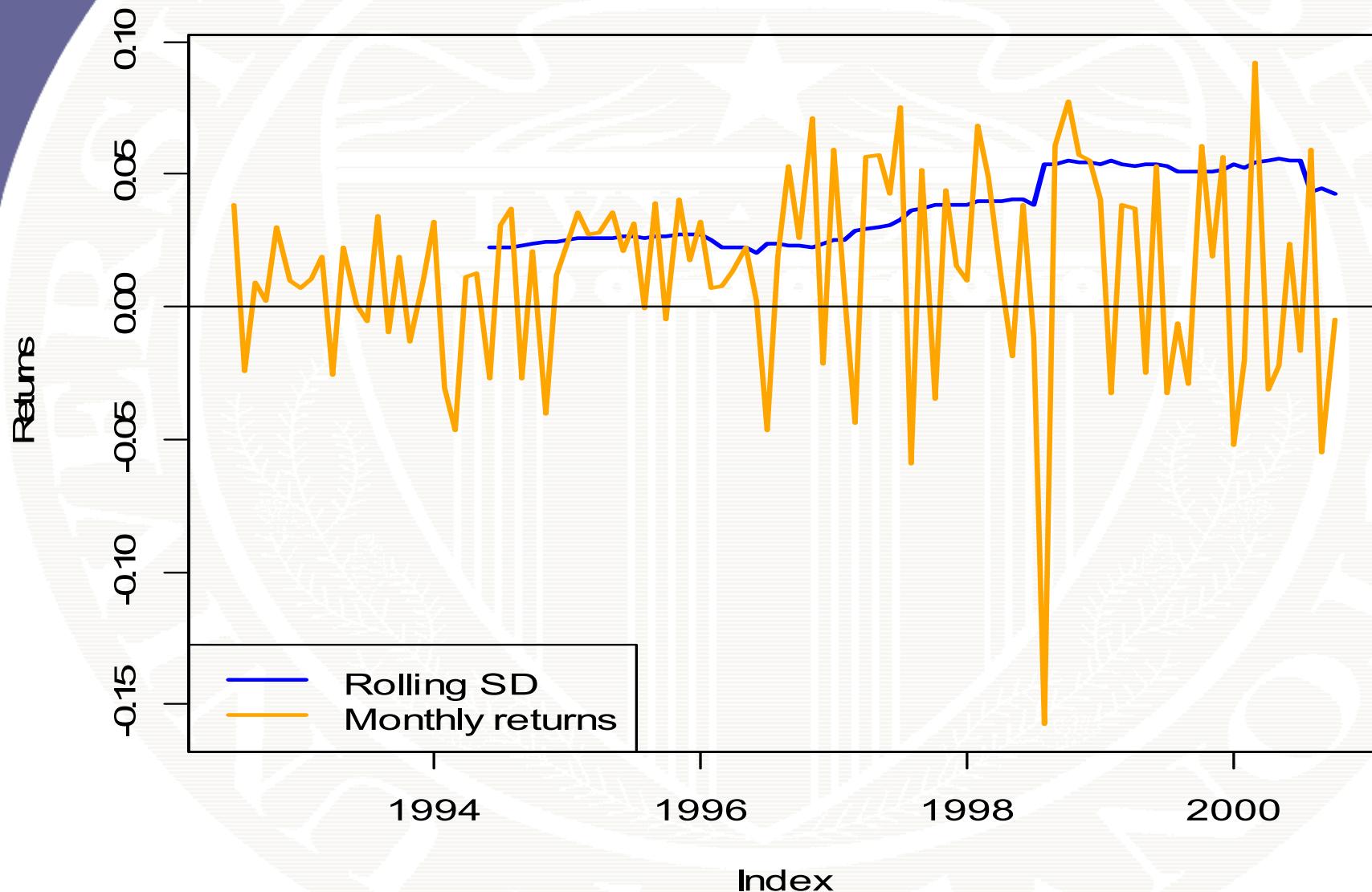
24 month rolling means for SP500

Compute Rolling SDs Using `zoo` Function `rollapply()`

```
# 24-month rolling SD incremented by 1 month
> roll.sigmahat = rollapply(returns.z[, "sbux"], width=24,
+                               FUN=sd, align="right")
> class(roll.sigmahat)
[1] "zooreg" "zoo"

> roll.sigmahat[1:5]
Jun 1994 Jul 1994 Aug 1994 Sep 1994 Oct 1994
 0.1101    0.1080    0.1067    0.1114    0.1148
```

24 month rolling SDs for SBUX

24 month rolling SDs for SP500

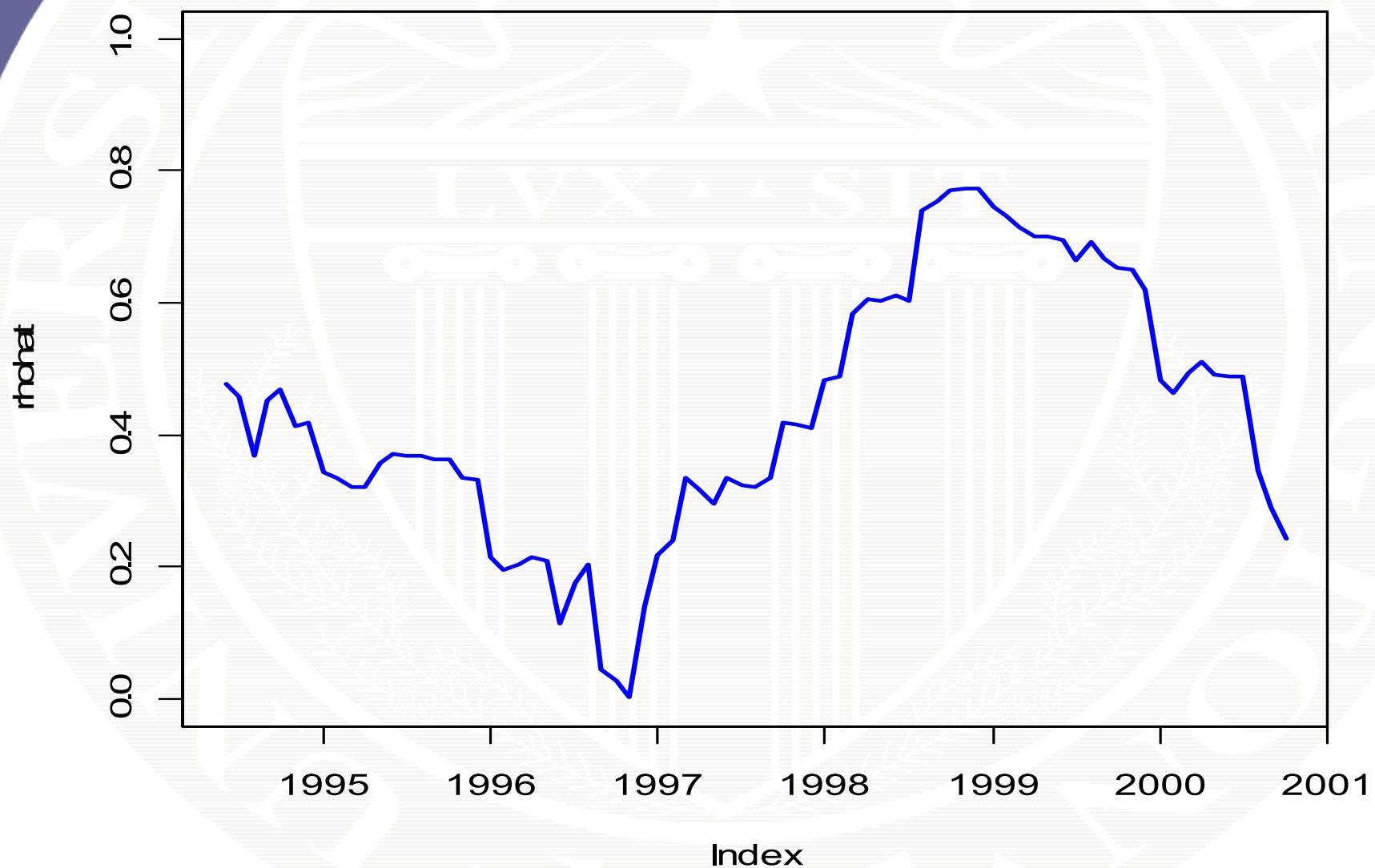
Compute Rolling Correlations Using zoo Function **rollapply()**

```
# compute 24-month rolling correlations between
# sp500 and sbux

# function to compute pairwise correlation
rho_hat = function(x) {
  cor(x)[1,2]
}

> roll.rho_hat = rollapply(returns.z[,c("sp500","sbux")],
+                           width=24,FUN=rho_hat,
+                           by.column=FALSE, align="right")
> class(roll.rho_hat)
[1] "zoo"

> roll.rho_hat[1:5]
Jun 1994 Jul 1994 Aug 1994 Sep 1994 Oct 1994
0.4786    0.4570    0.3694    0.4515    0.4683
```

24 month rolling correlations b/w sbux and sp500

Summary of Hypothesis Testing in CER model

- Hypothesis tests about μ are not very powerful because $SE(\hat{\mu})$ is typically very large
- Can often reject hypothesis that monthly returns are normally distribution
- Typically cannot reject hypothesis that monthly returns are uncorrelated over time
- Rolling window estimates indicate that μ , σ and ρ_{ij} are typically not constant over time
 - Assumption of covariance stationarity is suspect!