

Lecture 8a: Spurious Regression

Old Stuff

- The traditional statistical theory holds when we run regression using stationary variables.
- For example, when we regress one stationary series onto another stationary series, the coefficient will be close to zero and insignificant if the two series are independent.
- That is NOT the case when we regress one random walk onto another independent random walk, a nonstationary series.

Spurious Regression

- The regression is spurious when we regress one random walk onto another independent random walk. It is spurious because the regression will most likely indicate a non-existing relationship:
 1. The coefficient estimate will not converge toward zero (the true value). Instead, in the limit the coefficient estimate will follow a non-degenerate distribution
 2. The t value most often is significant.
 3. R^2 is typically very high.

Simulation

```
# by construction y and x are two independent random walks
y = rep(0,n)
x = rep(0,n)
ey = rnorm(n)
ex = rnorm(n)
rhoy = 1
rhex = 1
for (i in 2:n) {
y[i] = rhoy*y[i-1] + ey[i]
x[i] = rhex*x[i-1] + ex[i]
}
```

Result of Spurious Regression

```
lm(formula = y ~ x)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-3.43193	0.31671	-10.836	< 2e-16	***
x	0.31607	0.08013	3.944	0.000111	***

The estimated coefficient of x is 0.31607, and is significant, despite that the true coefficient is zero. This result mistakenly indicates that y and x are related; actually they are independent of each other.

Red Flags for Spurious Regression

1. The residual is highly persistent. In theory, the residual of a spurious regression has unit root.
2. The result changes dramatically after the lagged dependent variable is added as new regressor. The previously significant coefficient will become insignificant.
3. Before we had a similar situation. In HW4, when we regress GDP onto trend, the coefficient of trend is significant (model A). However, it becomes insignificant when lagged value of GDP is added as regressor (model B). Back then we showed that the residual has unit root in model A, but is stationary in model B. In short, model A indicates spurious trend.

Lesson: always check the stationarity of the residual. The regression is spurious if the residual is nonstationary (cannot reject the null hypothesis of the unit root test)

What causes the spurious regression?

Loosely speaking, because a nonstationary series contains “stochastic” trend

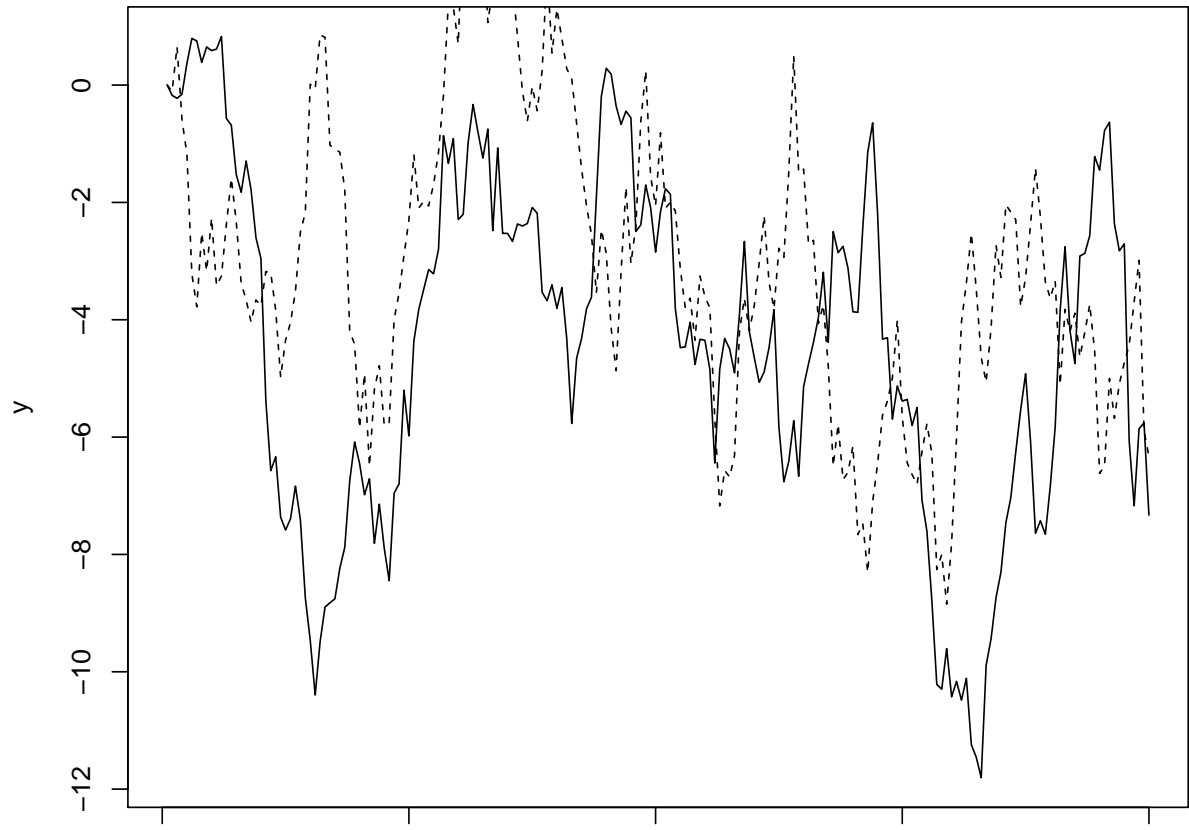
1. For a random walk $y_t = y_{t-1} + u_t$ we can show its MA representation is

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

2. The stochastic trend $u_t + u_{t-1} + u_{t-2} + \dots$ causes the series to appear trending (locally).
3. Spurious regression happens when there are similar local trends.

Time Series Plot of Simulated Data

The solid line is y and dotted line is x . Sometimes their local trends are similar, giving rise to the spurious regression.



Lessons: (I) Just because two series move together does not mean they are related! (II) Use extra caution when you run regression using nonstationary variables; be aware of the possibility of spurious regression! Check whether the residual is nonstationary.

Lecture 8b: Cointegration

Definition

y and x are cointegrated if both of following are true

1. y is nonstationary; x is nonstationary
2. There exists a linear combination of y and x that is stationary

In short, two series are cointegrated if they are nonstationary and related.

Economic Theory

Many economic theories imply cointegration. Two examples are

1. $\text{consumption} = a + b \times \text{income} + e$

2. $\text{nominal interest rate} = \text{inflation rate} + \text{real interest rate}$

Exercise: can you think of another example?

OLS Estimator is Superconsistent

Unlike the spurious regression, when y and x are cointegrated, regressing y onto x makes super sense. “Super” because the coefficient estimate will converge to the true value (which is nonzero) super fast (at rate of T^{-1} instead of $T^{-1/2}$).

Simulation

```
# y and x are nonstationary but related (cointegrated)
y = rep(0,n)
x = rep(0,n)
ey = rnorm(n)
ex = rnorm(n)
beta = 4
rhox = 1
for (i in 2:n) {
  x[i] = rhox*x[i-1] + ex[i]
  y[i] = beta*x[i] + ey[i]
}
```


Result of Cointegration Regression

```
> co.reg = lm(y~x)
> summary(co.reg)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.10698	0.11219	-0.954	0.341
x	3.99101	0.01061	375.991	<2e-16 ***

The coefficient of x is 3.99101, very close to the true value 4. This result makes super sense (however, the t value does not follow standard t or normal distribution! More on this issue later).

Residual is stationary for cointegrated series

```
> co.res = co.reg$res  
> adf.test(co.res, k = 1)
```

Augmented Dickey-Fuller Test

```
data: co.res  
Dickey-Fuller = -10.4398, Lag order = 1, p-value = 0.01  
alternative hypothesis: stationary
```

The p-value is less than 0.05, so rejects the null hypothesis of unit root (rigorously speaking, the p-value is wrong here because it is based on the Dickey-Fuller distribution. More on this issue later).

Engle-Granger Test for Cointegration

The Engle-Granger cointegration test (1987, Econometrica) is essentially the unit root test applied to the residual of cointegration regression

1. The series are cointegrated if the residual has no unit root
2. The series are not cointegrated (and the regression is spurious) if the residual has unit root

The null hypothesis is that the series are NOT cointegrated.

Distribution of Engle-Granger Test

- You may think that Engle-Granger test follows the Dickey-Fuller distribution. But that is true only when the coefficient β is known *a priori*.
- When β is unknown and estimated by sample, the distribution changes, as shown by Phillips and Ouliaris (1990, Econometrica).
- For example, when there is no trend in the cointegration regression, the 5% critical value of the Engle-Granger test is -3.34, rather than -2.86 (the critical value for the Dickey-Fuller unit root test).

Simulation

Step 1: we need to generate y and x under the null hypothesis, i.e., they are not cointegrated

Step 2: then we regress y onto x , and save the residual

Step 3: we regress the differenced residual onto its first lag. The t value of the first lagged residual is the Engle-Granger test

Step 4: we repeat Steps 1,2,3 many times. The 5% percentile of the distribution of the t values is the 5% critical value for the Engle-Granger test

Lesson: make sure you are using the correct critical values when running the cointegration test.

Another Technical Issue

Consider the cointegration regression

$$y_t = \beta_0 + \beta_1 x_t + e_t \quad (1)$$

The superconsistency means

$$T(\hat{\beta}_1 - \beta_1) \Rightarrow \text{Nonstandard Distribution}$$

So we cannot conduct the hypothesis testing using the normal distribution.

Example

For the consumption-income relationship, we may test the null hypothesis that the marginal propensity to consume is unity, ie.,

$$H_0 : \beta_1 = 1$$

We can construct the t test as usual. However, we cannot compare it to the critical values of t distribution or normal distribution.

Dynamic OLS (DOLS) Estimator

Stock and Watson (1993, Econometrica) suggest adding the leads and lags of Δx_t as new regressors

$$y_t = \beta_0 + \beta_1 x_t + \sum_{i=-p}^p c_i \Delta x_{t-i} + e_t \quad (2)$$

Now $\hat{\beta}_1$ is called dynamic OLS estimator, and the t-value is asymptotically normally distributed.

Lesson: use DOLS estimator so that the normal distribution can be used in hypothesis testing

Lecture 8c: Vector Error Correction Model (VECM)

Big Picture of Multivariate Model

1. We can apply VAR if series are stationary
2. We can apply VAR to differenced series if they are nonstationary and not cointegrated
3. We need to apply vector error correction model if series are nonstationary and cointegrated

Error Correction Model

Consider a VAR(1): $z_t = \phi z_{t-1} + w_t$, which can be rewritten as

$$\Delta z_t = (\phi - I)z_{t-1} + w_t.$$

If z_t is cointegrated, then the eigenvalues for ϕ are $\lambda_1 = 1, |\lambda_2| < 1$. It can be shown that the eigenvalues for $\phi - I$ are $\lambda_1 - 1, \lambda_2 - 1$ or $0, \lambda_2 - 1$, respectively. The eigenvectors remain unchanged. Now apply the spectral decomposition to $\phi - I$ we can show that

$$\Delta z_t = C \tilde{\Lambda} C^{-1} z_{t-1}, \quad \tilde{\Lambda} = \text{diag}(0, \lambda_2 - 1) \quad (3)$$

$$= (\lambda_2 - 1) c_2 c^{-2} z_t \quad (4)$$

where c_2 is the second column of C , and c^{-2} is the second row of C^{-1} . Basically, the cointegrating vector is c^{-2} , and the error correction term is $\eta_{2t} \equiv c^{-2} z_t$. More generally, letting $\gamma = (\lambda_2 - 1) c_2$, an error correction model is

$$\Delta z_t = \gamma \eta_{2t} + \sum_{j=1}^p \alpha_j \Delta z_{t-j} + w_t \quad (5)$$

Example

Consider a bivariate series y_t and x_t . Suppose they are cointegrated, then the first order vector error correction model is

$$\Delta y_t = \alpha_{01} + \gamma_y \hat{e}_{t-1} + \alpha_{11} \Delta y_{t-1} + \alpha_{12} \Delta x_{t-1} + u_t \quad (6)$$

$$\Delta x_t = \alpha_{02} + \gamma_x \hat{e}_{t-1} + \alpha_{21} \Delta y_{t-1} + \alpha_{22} \Delta x_{t-1} + v_t \quad (7)$$

$$\hat{e}_{t-1} = y_{t-1} - \hat{\beta}_0 - \hat{\beta}_0 x_{t-1} \quad (8)$$

where the residual \hat{e}_t of the cointegration regression is called (estimated) error correction term. It measures the deviation from the long run equilibrium.

Intuition

1. Note that the residual \hat{e}_t is stationary when the series are cointegrated. So it makes sense to use it to explain the stationary Δy_t and Δx_t .
2. There will be omitted variable bias if we apply VAR to differenced series when they are cointegrated; the omitted variable is \hat{e}_{t-1}
3. It is called error correction model because it shows how variable adjusts to the deviation from the equilibrium (the error correction term)
4. The speed of error correction is captured by γ_y and γ_x .

Engle-Granger Two Step Procedure

Step 1: Obtain the error correction term, or the residual of the cointegration regression (8).

Step 2: Estimate (6) and (7) using OLS.

In the second step, we can treat the estimated $\hat{\beta}_0$ and $\hat{\beta}_1$ as the true values since they are super-consistent.

Hypothesis Testing

1. All the variables in the error correction models are stationary if the series are cointegrated.
So the t test and f test follow the standard distributions.
2. In particular, we can apply the standard test for Granger Causality:

$$H_0 : \alpha_{12} = 0$$

$$H_0 : \alpha_{21} = 0$$

VECM-based Cointegration Test

1. The vector error correction model (VECM) can also be used to construct a test for cointegration
2. The null hypothesis of no cointegration is

$$H_0 : \gamma_y = 0, \gamma_x = 0$$

3. The test follows nonstandard distribution because under the null hypothesis the series are not cointegrated and \hat{e}_{t-1} is nonstationary.

Weak Exogeneity

1. It is possible that some of variables are error-correcting; others are not.
2. In that case, the variables that are not error correcting are called weakly exogenous. “Exogenous” because they are irresponsive.
3. For example, if x is weakly exogenous, the VECM becomes

$$\Delta y_t = \alpha_{01} + \gamma_y \hat{e}_{t-1} + \alpha_{11} \Delta y_{t-1} + \alpha_{12} \Delta x_{t-1} + u_t$$

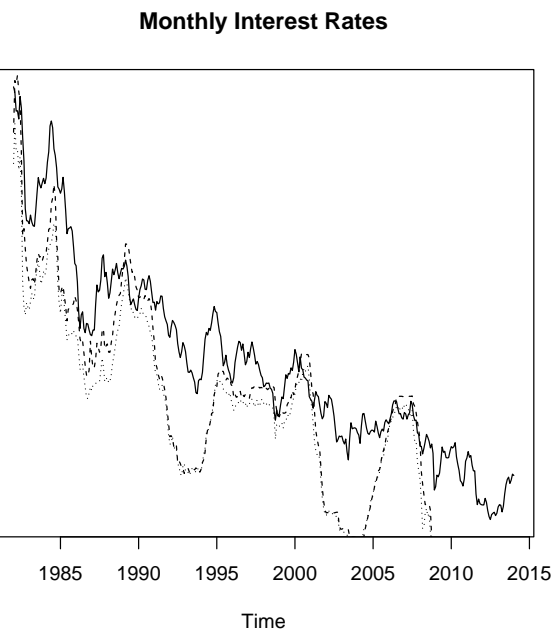
$$\Delta x_t = \alpha_{02} + \alpha_{21} \Delta y_{t-1} + \alpha_{22} \Delta x_{t-1} + v_t$$

Lecture 8d: Empirical Example

Data

- We are interested in the relationship between the federal fund rate (sr), 3-month treasury bill rate (mr) and 10-year treasury bond rate (lr)
- The monthly data from Jan 1982 to Jan 2014 are downloaded from Fred data.

Plot



Remarks

We see overall the three series tend to move together (sr and mr are particularly close). Nevertheless we are not sure the co-movement (or similar local trends) indicates a spurious regression or a cointegration.

Unit Root Test

```
ob = length(lr)
lr.1 = c(NA, lr[1:ob-1])    # first lag
dlr = lr - lr.1             # difference
summary(lm(dlr~lr.1))
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	0.057562	0.034181	1.684	0.09300	.
lr.1	-0.013961	0.004939	-2.827	0.00495	**

The adf test with zero lag is -2.827, greater than the 5% critical value -2.86. So the null hypothesis of unit root cannot be rejected for lr.

Cointegration Regression

```
> co.reg = lm(lr~sr)
> summary(co.reg)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	2.51249	0.10031	25.05	<2e-16	***
sr	0.80281	0.01749	45.89	<2e-16	***

So $\hat{\beta}_0 = 2.51249$, $\hat{\beta}_1 = 0.80281$. Those are super-consistent estimates if the two interest rates are cointegrated.

Error Correction Term

The estimated error correction term is the residual, and is computed as

$$\hat{e}_t = \text{lr}_t - \hat{\beta}_0 - \hat{\beta}_1 \text{sr}_t$$

The R command is

```
ect = co.reg$res
```

Exercise: how to interpret a positive error correction term? How about an extremely negative error correction term?

Engle-Granger Test for lr and sr

```
> ob = length(ect)
> ect.lag1 = c(NA, ect[1:ob-1])
> dect = ect - ect.lag1
> summary(lm(dect~ect.lag1))
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.003084	0.015211	-0.203	0.83945	
ect.lag1	-0.038388	0.013632	-2.816	0.00511	**

The Engle-Granger test is -2.816, greater than the 5% critical value -3.34. So the null hypothesis of no cointegration cannot be rejected.

Remark

This result is not surprising. Basically it says that the relation between the federal fund rate and 10 year rate is very weak (not as strong as cointegration). Given no cointegration, the appropriate multivariate model is VAR in difference.

VAR in difference for lr and sr

```
lm(formula = dsr ~ dlr.1 + dsr.1)
```

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.02046	0.01256	-1.629	0.104110	
dlr.1	0.15746	0.04715	3.340	0.000921	***
dsr.1	0.38339	0.04555	8.417	7.99e-16	***

```
lm(formula = dlr ~ dlr.1 + dsr.1)
```

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.01918	0.01351	-1.420	0.156	
dlr.1	0.32944	0.05072	6.495	2.61e-10	***
dsr.1	0.02825	0.04901	0.577	0.565	

It seems that sr does not Granger cause lr. Does this result make sense?

Engle-Granger Test for mr and sr

```
lm(formula = dect ~ ect.lag1)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.0009721	0.0088427	-0.110	0.913
ect.lag1	-0.2024256	0.0307505	-6.583	1.53e-10 ***

Now the Engle Granger test is -6.583, less than the 5% critical value -3.34. The null hypothesis of no cointegration can be rejected. So unlike lr, mr is cointegrated with sr. The appropriate multivariate model is VECM.

ECM for sr

```
lm(formula = dsr ~ ect.1 + dmr.1 + dsr.1)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.02478	0.01208	-2.050	0.041	*
ect.1	0.25031	0.04626	5.411	1.11e-07	***
dmr.1	0.08862	0.07337	1.208	0.228	
dsr.1	0.31101	0.06649	4.677	4.05e-06	***

So sr is error correcting (t-value for error correction term is 5.411). It seems that mr does not Granger cause sr (t-value for Δmr_{t-1} is 1.208)

ECM for mr

```
lm(formula = dmr ~ ect.1 + dmr.1 + dsr.1)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.01969	0.01251	-1.574	0.1162	
ect.1	-0.01457	0.04788	-0.304	0.7610	
dmr.1	0.17723	0.07594	2.334	0.0201	*
dsr.1	0.28467	0.06881	4.137	4.34e-05	***

mr is weakly exogenous or not error correcting (t-value for error correction term is -0.304). It seems that sr Granger causes mr (t-value for Δsr_{t-1} is 4.137)