Economics 144
Economic Forecasting

Lecture 11
VAR and IRF
Examples and Interpretation

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Today's Class

- Two Examples of
  - Vector Autoregressions (VAR)
  - Predicative Causality (Granger-Causality)
  - Impulse-Response Functions (IRF)

VAR(p) Algorithm

- Q: How to determine the order p of the VAR model?
- Solution:

for p=1 to 20,
estimate var

  - Start with p=1, compute VAR(1)
  - Continue with p=2, and keep the one with lowest AIC and BIC

rank by lowest AIC to find best fit model

  - Continue with p= 3, 4, …
  - After a certain value of p, AIC & BIC will worsen, therefore, decide on the model with lowest overall AIC and BIC.

var model shouldn't use high order P - 10 is considered quite high - if p goes to 20/30 - there's not a proper model - the relationship between variables is not that strong.

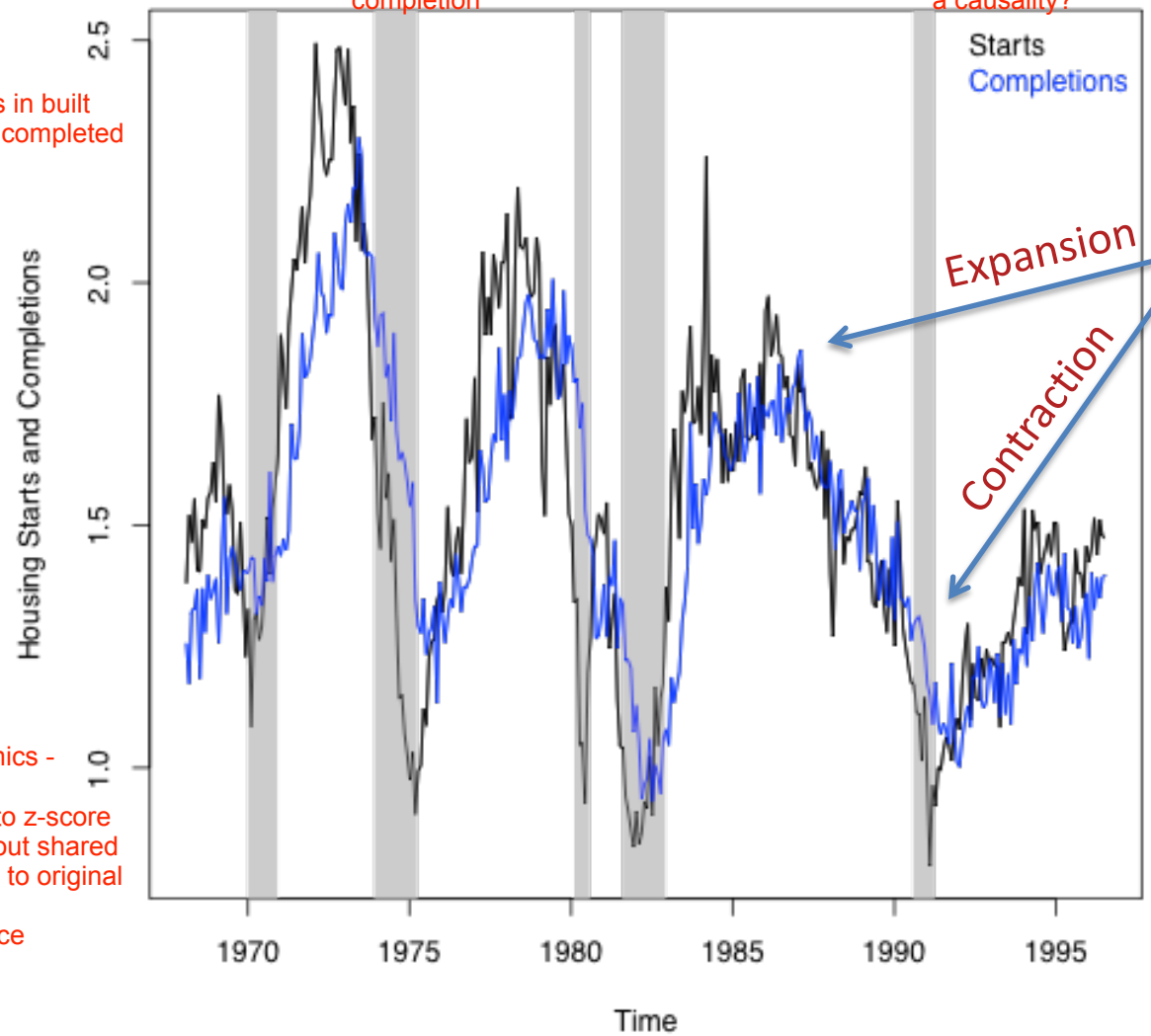
if algorithm does not converge with p goes to 10, it doesn't work - varselect will figure out ocnvergence automatically

VAR Example 1
Housing Starts and Completions

starts come first, and then completion

which comes first? Is there a causality?

Black - number of homes in built
Blue - number of homes completed



Business Cycles

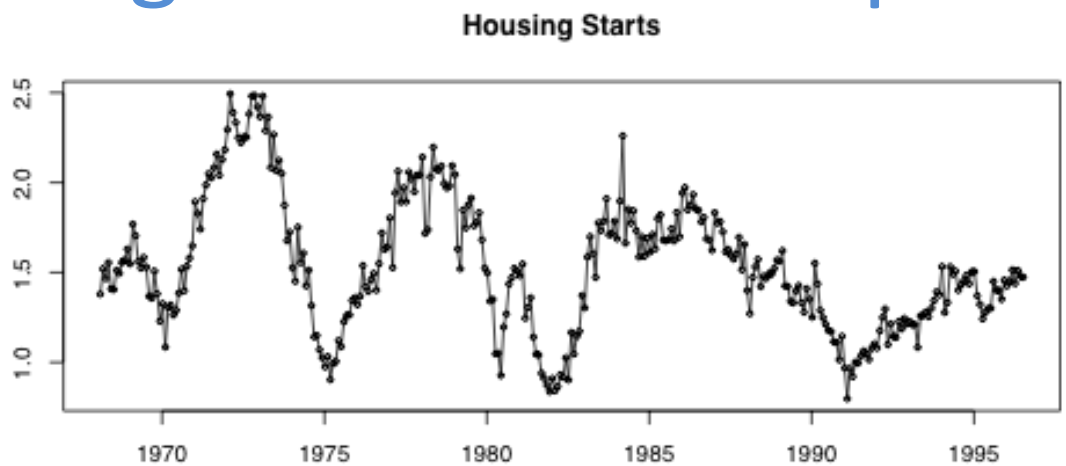
Expansion

Contraction

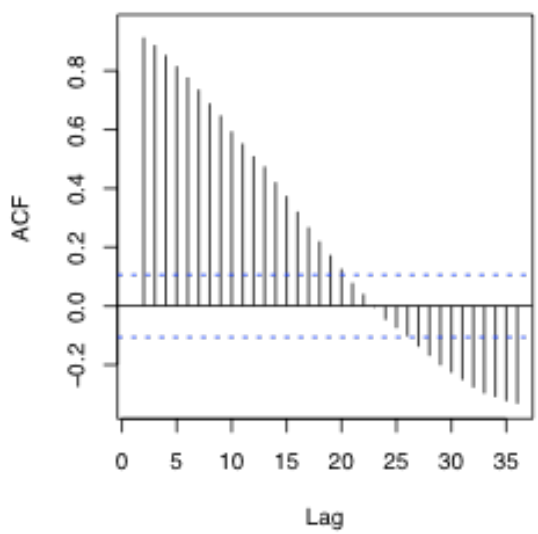
bands - contraction bands

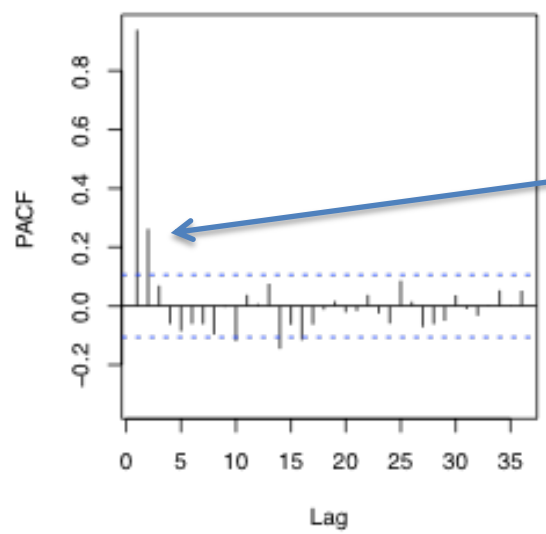
Picking data: shared dynamics - different units
1. take two series, convert to z-score - now they overlap - figure out shared dynamics - work them back to original units
2. They should be covariance stationary

VAR Example 1
Housing Starts and Completions



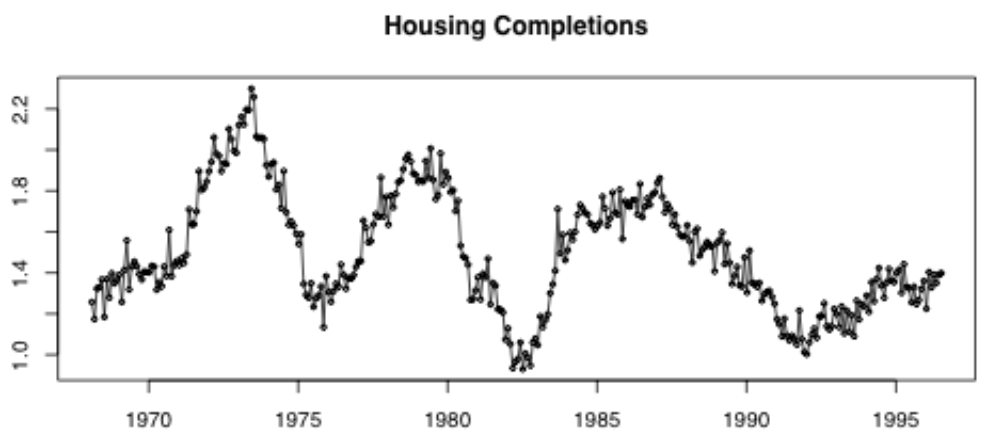
ACF → 0 (slowly)





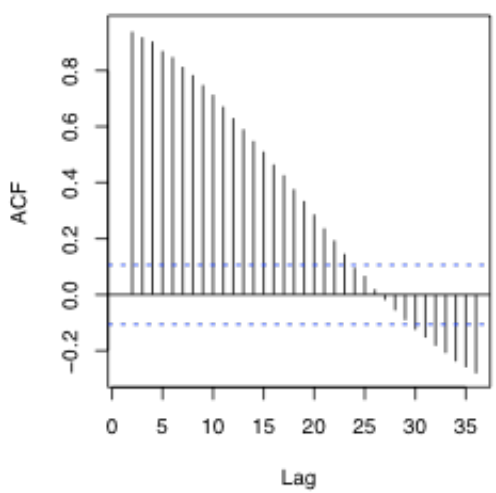
PACF has a Sharp cut off at lag =2.

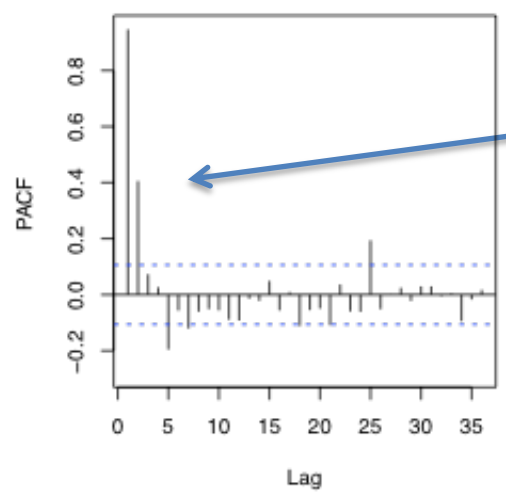
VAR Example 1
Housing Starts and Completions



Additional spikes - some dynamic in completion series than hoursing starts series

ACF → 0 (slowly)





PACF has a Sharp cut off at lag =2.

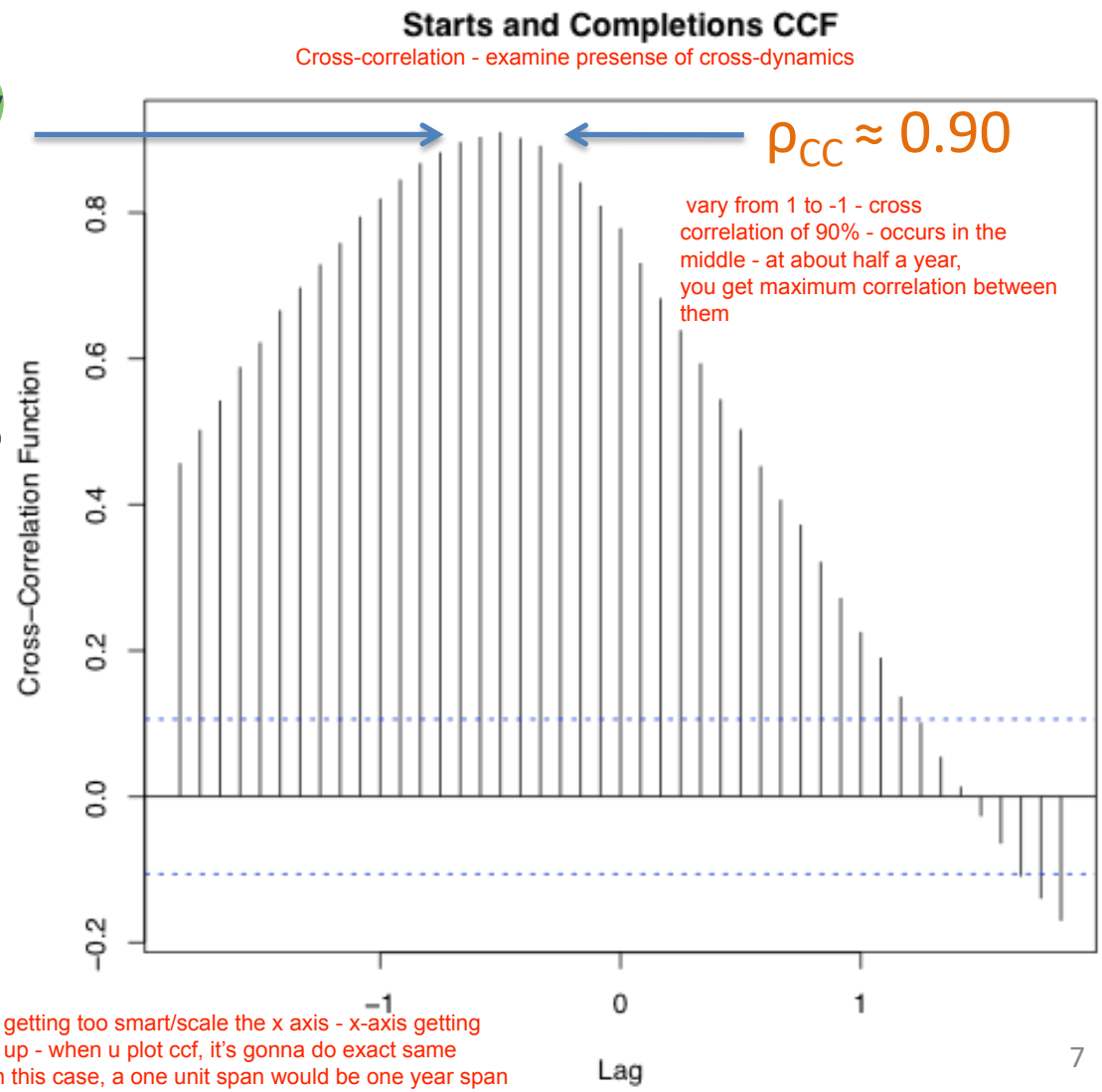
VAR Example 1
Housing Starts and Completions

tsdisplay or acf/pacf

Completions are maximally correlated with starts lagged by 6-12 months.

Q: Do comps depend of starts, or do starts depend on comps?

Def: Cross-Correlation = ACF for the multivariate case



acf/pacf getting too smart/scale the x axis - x-axis getting messed up - when u plot ccf, it's gonna do exact same thing - in this case, a one unit span would be one year span

Regression Results

VAR(4) Model

Equation 1:

```
> summary(y_model)

VAR Estimation Results:
=========================
Endogenous variables: starts, comps
Deterministic variables: const
Sample size: 338
Log Likelihood: 673.885
Roots of the characteristic polynomial:
0.9585 0.9585 0.6156 0.5913 0.5913 0.3472 0.3472 0.08024
Call:
VAR(y = y_tot, p = 4)
```

keep them in the model

$$\text{starts} = c + \text{starts}_{t-k} + \text{comps}_{t-k}$$

modeled as lags for starts+lags for completions

```
Estimation results for equation starts:
=======================================
starts = starts.l1 + comps.l1 + starts.l2 + comps.l2 + starts.l3 + comps.l3 + starts.l4 + comps.l4 + const
```

which lag you're in

const = intercept

```
          Estimate Std. Error t value Pr(>|t|)
starts.l1  0.655743   0.056076  11.694  < 2e-16 ***
comps.l1   0.007276   0.091906   0.079 0.936948
starts.l2  0.235371   0.066386   3.546 0.000449 ***
comps.l2  -0.118989   0.092478  -1.287 0.199116
starts.l3  0.138673   0.066452   2.087 0.037675 *
comps.l3  -0.021141   0.089701  -0.236 0.813828
starts.l4  0.011877   0.060330   0.197 0.844053
comps.l4   0.002711   0.083819   0.032 0.974218
const      0.131220   0.036749   3.571 0.000409 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.1189 on 329 degrees of freedom
Multiple R-Squared: 0.8959, Adjusted R-squared: 0.8934
F-statistic: 353.9 on 8 and 329 DF,  p-value: < 2.2e-16
```

completion do not seem to cause starts

what happens in starts explain starts

not gonna get rid of these terms - need integrity - estimate it as a whole
estimate fitted values with all these terms present

good R^2

```
Estimation results for equation comps:
======================================
comps = starts.l1 + comps.l1 + starts.l2 + comps.l2 + starts.l3 + comps.l3 + starts.l4 + comps.l4 + const

         Estimate Std. Error t value Pr(>|t|)
starts.l1  0.06802    0.03310   2.055 0.040676 *
comps.l1   0.20486    0.05425   3.776 0.000189 ***
starts.l2  0.05966    0.03919   1.523 0.128817
comps.l2   0.21775    0.05459   3.989 8.18e-05 ***
starts.l3  0.03358    0.03922   0.856 0.392592
comps.l3   0.10504    0.05295   1.984 0.048114 *
starts.l4  0.09309    0.03561   2.614 0.009356 **
comps.l4   0.18231    0.04948   3.685 0.000267 ***
const      0.04524    0.02169   2.086 0.037793 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.07016 on 329 degrees of freedom
Multiple R-Squared: 0.9411, Adjusted R-squared: 0.9396
F-statistic: 656.6 on 8 and 329 DF,  p-value: < 2.2e-16


Covariance matrix of residuals:
         starts    comps
starts 0.014129 0.001564
comps  0.001564 0.004923

Correlation matrix of residuals:
       starts  comps
starts 1.0000 0.1875
comps  0.1875 1.0000
```

Regression Results VAR(4) Model Equation 2:

lags of starts are statistically significant - they help explain compeltion

R^2 improved

$$comps = c + starts_{t-k} + comps_{t-k}$$

A: It appears that comps depend on starts

Ask R which one is it?

VAR Example 1
Housing Starts and Completions

Predicative Causality (Granger-Causality)

- Q: Do comps 'Granger-cause' starts?

```
library(lmtest)
Grangertest(starts~comps,order=4)
```

ordering of var - asking if competion is going to cause starts

order depends on AIC/BIC

R commands

Looking at big picture of what R is doing - test the null hypothesis that if completion cause starts/starts cause completions

```
Granger causality test
```

H_0: comps do not cause starts

Default: no causation

```
Model 1: starts ~ Lags(starts, 1:4) + Lags(comps, 1:4)
Model 2: starts ~ Lags(starts, 1:4)
  Res.Df Df      F  Pr(>F)
1    329
2    333 -4 2.3066 0.05801 .
--
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
  1
```

compare to 5%, this is larger - fail to reject

A:Fail to reject H_0 → No!

VAR Example 1
Housing Starts and Completions

Predicative Causality (Granger-Causality)

- Q: Do starts 'Granger-cause' completions?

```
library(lmtest)
grangertest(comps~starts,order=4)
```

R commands

```
Granger causality test
```

H_0: starts do not cause comps

What can go wrong - max of 10 in varselect - order of 8-9 - something's gonna go wrong - increase and run it again - crank it to 20 - new order is 15 - stop and look for new dataset

```
Model 1: comps ~ Lags(comps, 1:4) + Lags(starts, 1:4)
Model 2: comps ~ Lags(comps, 1:4)
  Res.Df Df      F    Pr(>F)
1    329
2    333 -4 32.125 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
  1
```

tips of what's gonna go wrong - Steps 1: take any two series that u believe share dynamic - not same scale - plot z-score - overlay and check they're covariance stationary - if not covariance stationary but have shared dynamic - ok - take difference of them - return space - they will be stationary - or take log of difference.

A: Reject H_0 → Yes!

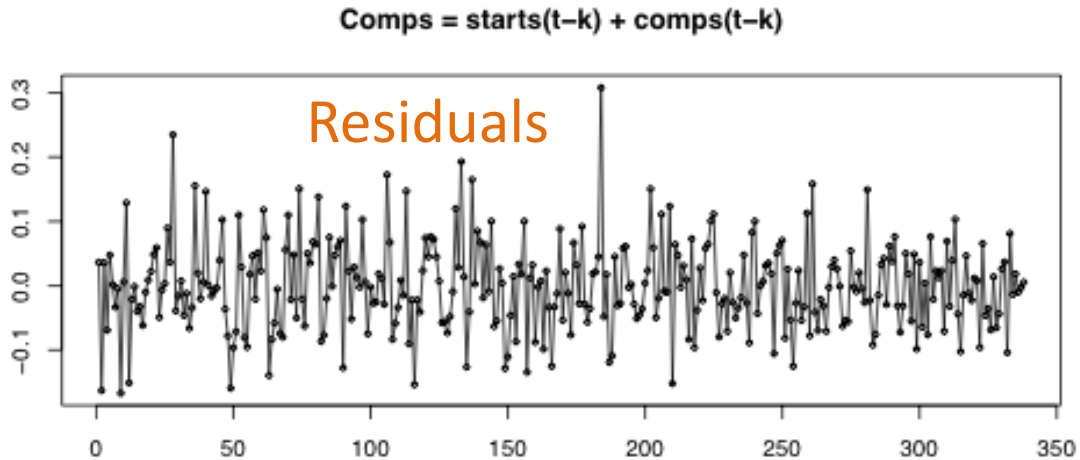
Both of them cause each other - results inconclusive

Step 2: Put them into varselect and run them in grangertest - one direction fail to reject and the other reject - ideal case

other thing - they don't case each other at all - common for dataset

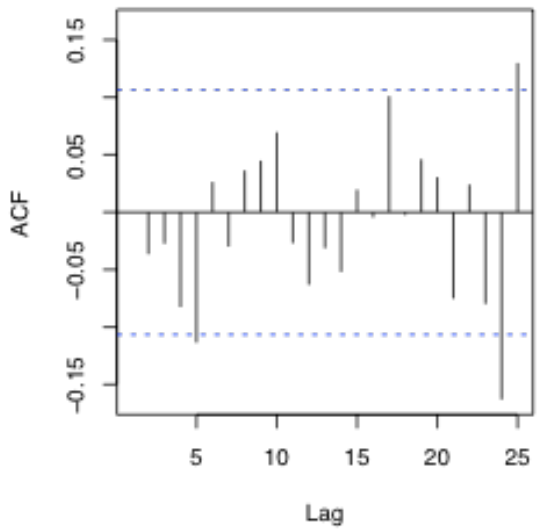
Var model - ar type - vector autoregression - financial data are not good candidates since they mean revert very often - unless u're looking for monthly, it's gonna get too noisy - try to think of economic variables/variables that have classic AR signature

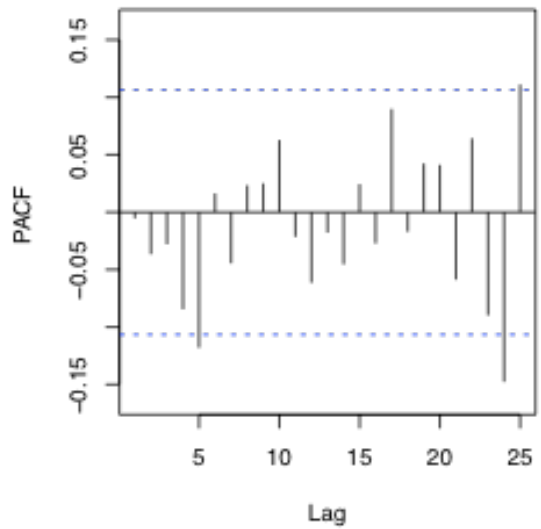
VAR Example 1
Housing Starts and Completions



Decent job for wiping out residual dynamics - for the most part, this suggest model is not doing too bad

Residuals ACF





Residuals PACF

VAR Example 1
Housing Starts and Completions

when plotting it - it knows what we want
customize it - one plot function in R
plot(varobject) - does it all automatically

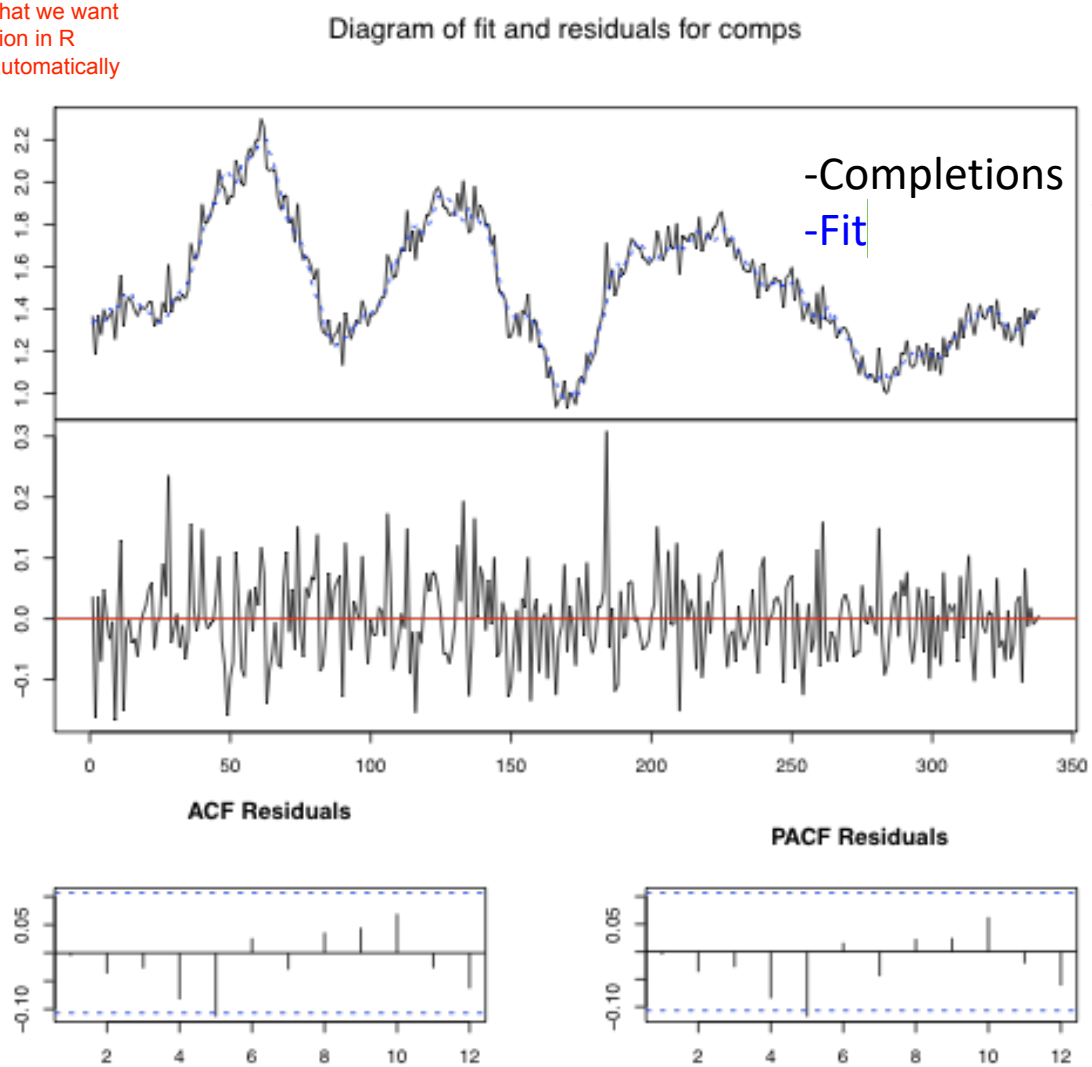
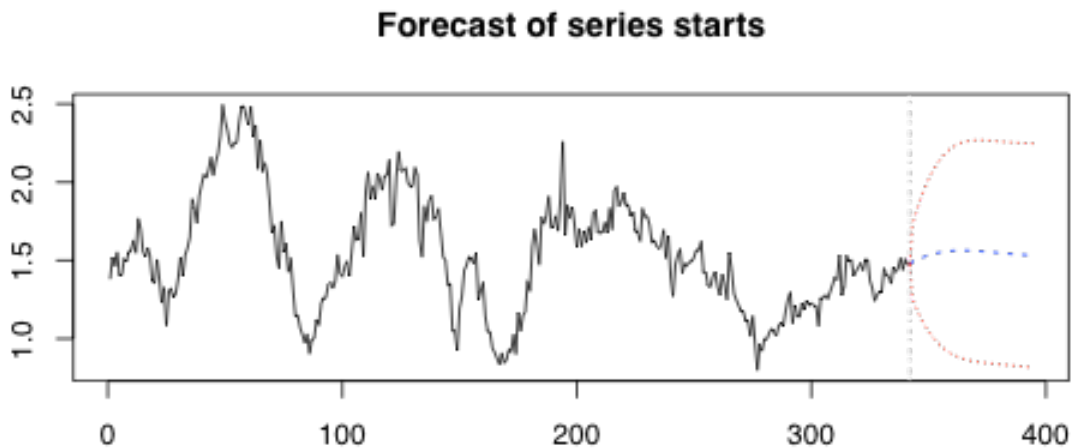
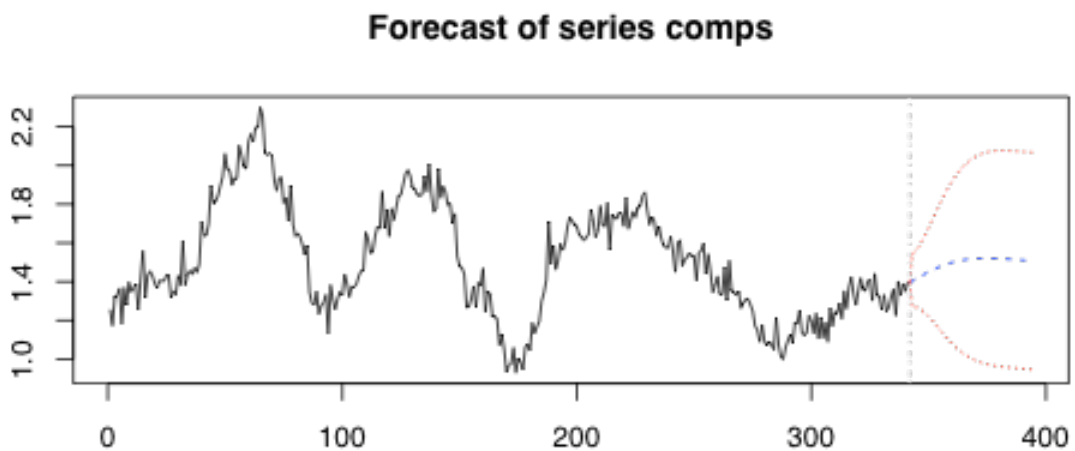


Figure generate
for both series
- toggle between
the two
- key to go to next
one

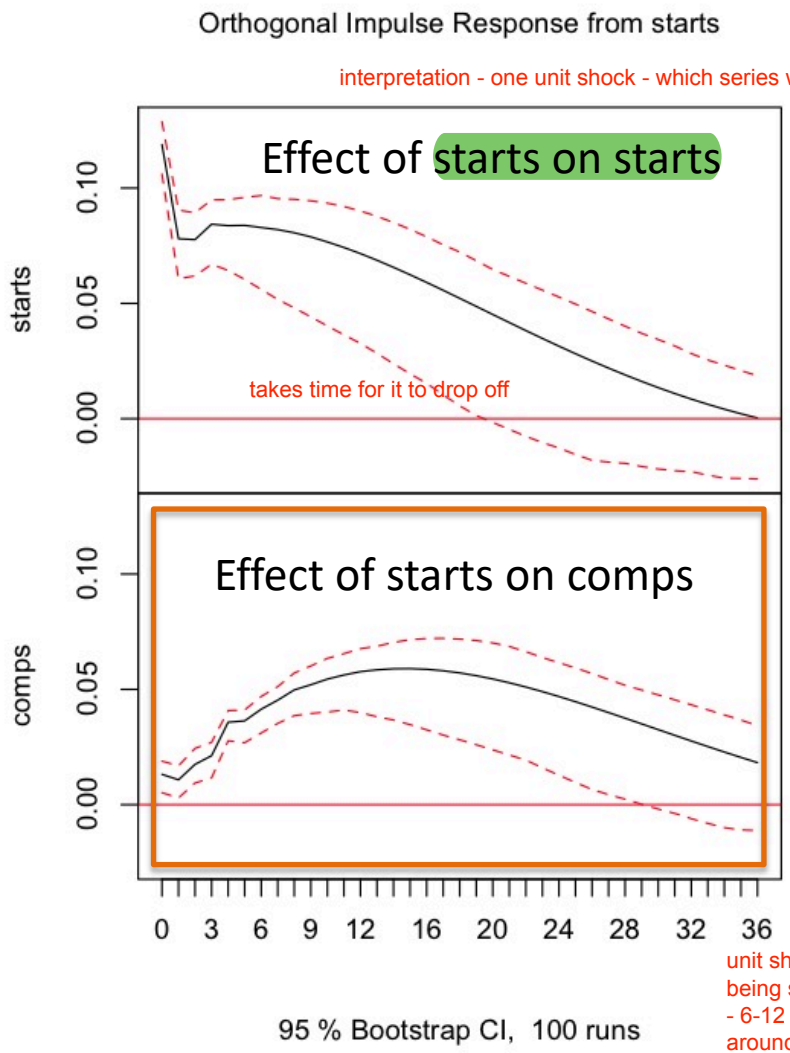
VAR Example 1
Housing Starts and Completions



Inherit ar forecast property
- done automatically



VAR Example 1 (IRF)
Housing Starts and Completions



Own-Variable Impulse Response

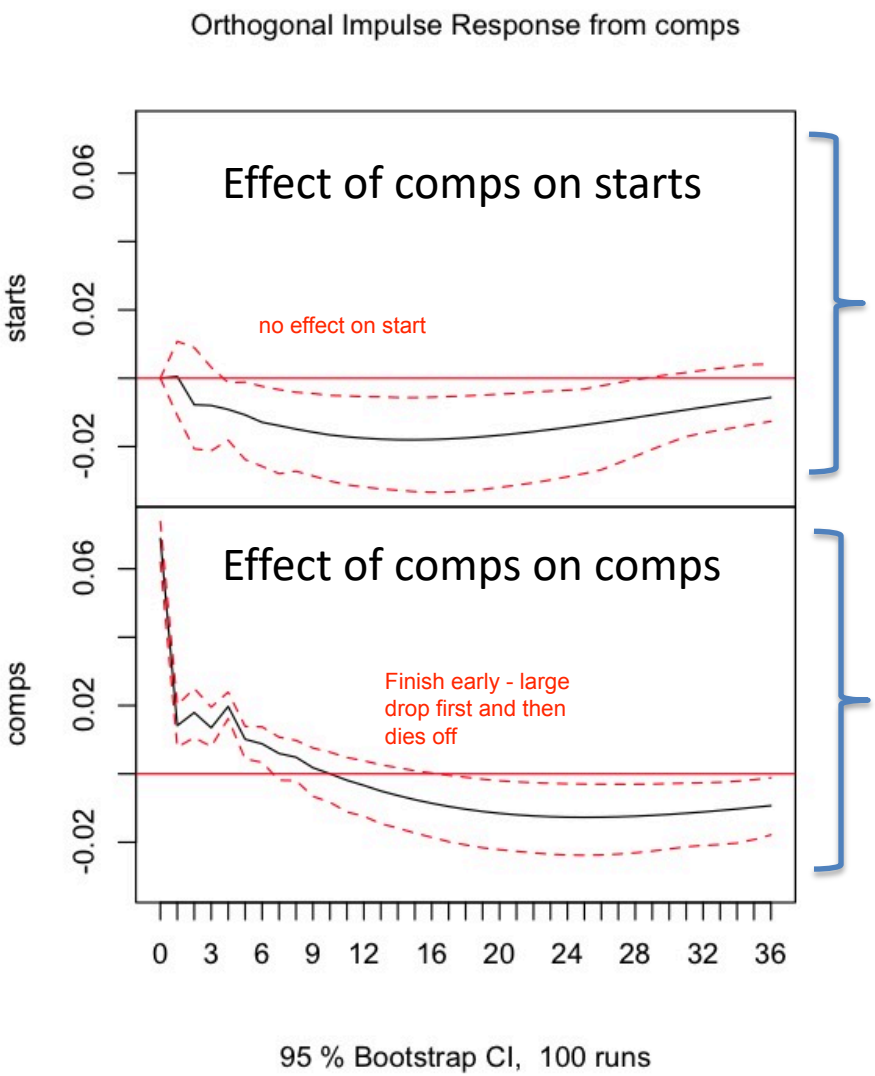
Effect of starts' shock on subsequent starts:
Initially a large effect but then decays slowly.

Cross-Variable Impulse Response

Effect of starts' shock on subsequent comps:
Initially produces no movement, then builds up, peaking around 14 months.

unit shock - suddenly there's an increase in home being start right now, but effect takes some time
- 6-12 month - maximum correlation - more building going on - maximum around this time

VAR Example 1 (IRF)
Housing Starts and Completions



Cross-Variable Impulse Response

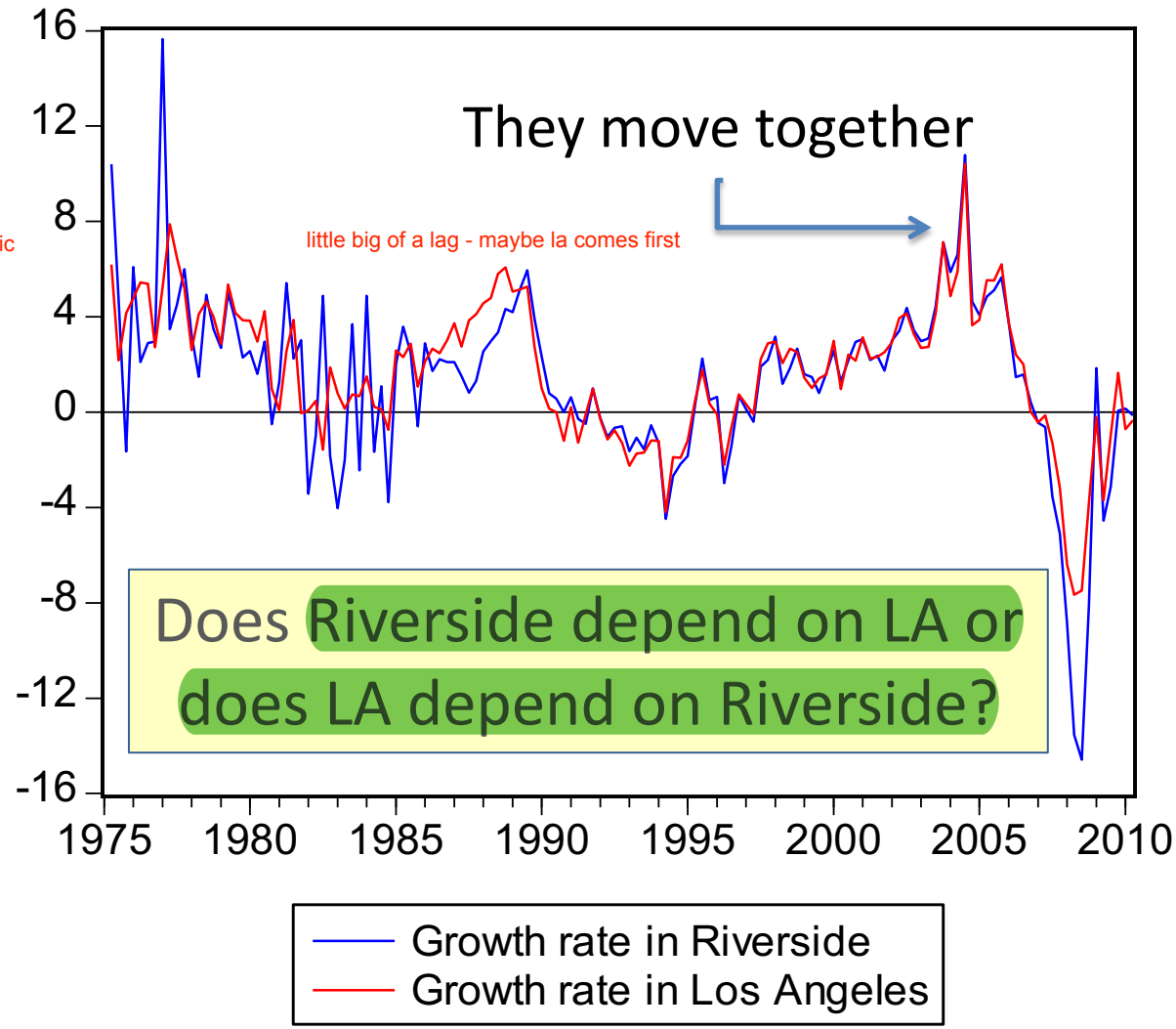
Effect of comps' shock on subsequent starts: Initially produces little movement in starts at all times.

Own-Variable Impulse Response

Effect of comps' shock on subsequent comps: Initially a large effect but then decays slowly.

VAR Example 2
House Price Growth in LA & Riverside

not covar stationary -
work with it
there are shared dynamic



VAR Example 2
House Price Growth in LA & Riverside

- The two economies are linked via commuters

↓

Increase in economic activity in LA

↓

Increase in demand for housing in LA

↓

LA housing prices go up

↓

Demand for houses in Riverside go up

LA Economic Activity → Riverside Economic Activity

Riverside Economic Activity → LA Economic Activity ?

VAR Example 2
House Price Growth in LA & Riverside

- Let Y = Los Angeles and X = Riverside
- Try VAR(1) Model

$$Y_t = c_1 + \alpha_{11} Y_{t-1} + \beta_{11} X_{t-1} + \varepsilon_{1t}$$
$$= 0.25 + 0.79 Y_{t-1} + 0.04 X_{t-1}$$

magnitude difference - .8% compare to .04% - very small

$$X_t = c_2 + \alpha_{21} Y_{t-1} + \beta_{21} X_{t-1} + \varepsilon_{2t}$$
$$= -0.36 + \boxed{0.89} Y_{t-1} + 0.05 X_{t-1}$$

riverside not as large, but largest value in la

1% growth in LA →0.9% growth in Riverside

la econ activity has strong influence on riverside econ activity

Vector Autoregression Estimates
Sample (adjusted): 1975Q3 2009Q2
Included observations: 136 after adjustments
Standard errors in ( ) & t-statistics in [ ]

la equation

	GLA	GRiv
GLA(−1)	0.788974	0.894338
	(0.08831)	(0.13684)
	[8.93417]	[6.53548]
GRiv(−1)	0.046362	0.053929
	(0.06811)	(0.10555)
	[0.68067]	[0.51094]
C	0.255229	-0.359998
	(0.16840)	(0.26095)
	[1.51564]	[-1.37959]

behind the scene - granger test doing hypo test on coef
- this suggests initial thesis is correct

VAR Example 2
House Price Growth in LA & Riverside

VAR Lag Order Selection Criteria
Endogenous variables: GLA GRiv
Exogenous variables: C
Sample: 1975Q1 2009Q2
Included observations: 129

Preferred Model = VAR(1)

lag 1 seems to be the preferred one

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-569.9297	NA	24.32180	8.867127	8.911465	8.885142
1	-487.7585	160.5205	7.238637*	7.655170*	7.788185*	7.709217*
2	-487.2043	1.065406	7.636332	7.708594	7.930285	7.798671
3	-481.6932	10.42418*	7.460515	7.685165	7.995532	7.811274
4	-477.4558	7.883524	7.434896	7.681485	8.080528	7.843624
5	-476.7097	1.364911	7.822540	7.731933	8.219653	7.930104
6	-472.1276	8.240713	7.756466	7.722908	8.299304	7.957109
7	-470.3528	3.136797	8.034679	7.757408	8.422480	8.027640
8	-469.6694	1.186753	8.466835	7.808827	8.562576	8.115091

*indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schewarz information criterion
HQ: Hannan-Quinn information criterion

VAR Example 2
House Price Growth in LA & Riverside

Granger Causality Test

VAR Granger Causality/Block Exogeneity Wald Tests
Sample: 1975Q1 2009Q2
Included observations: 136

Dependent variable: GLA

Excluded	Chi-sq	df	Prob.
GRiv	0.463310	1	0.4961
All	0.463310	1	0.4961

H_0: Riverside has no effect on LA ($\beta_{11}=0$)
→ Fail to reject H_0

Dependent variable: GRiv

Excluded	Chi-sq	df	Prob.
GLA	42.71250	1	0.0000
All	42.71250	1	0.0000

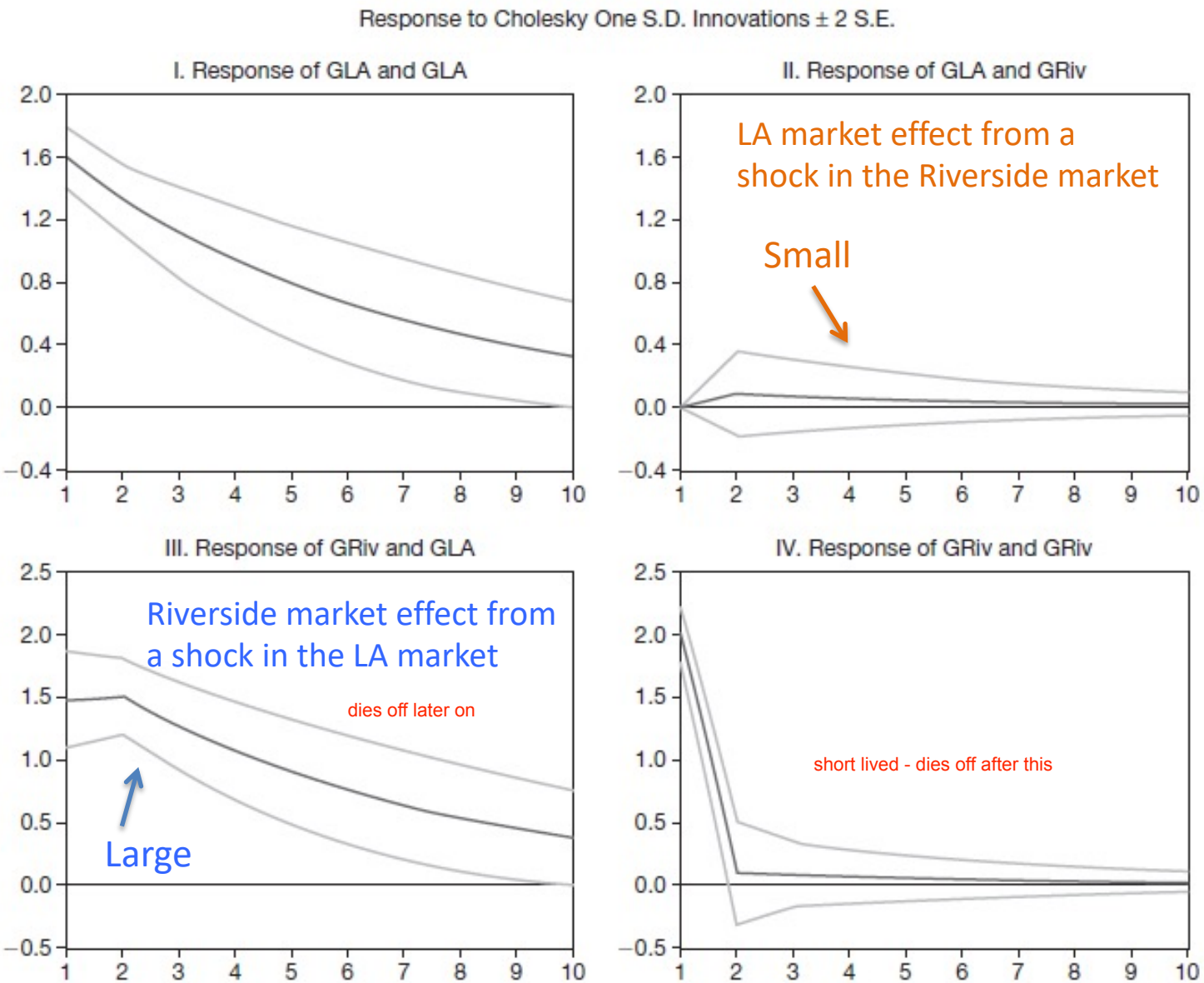
H_0: LA has no effect on Riverside ($\alpha_{21}=0$)
→ Reject H_0

strong influence on riverside

LA does Granger-Cause Riverside

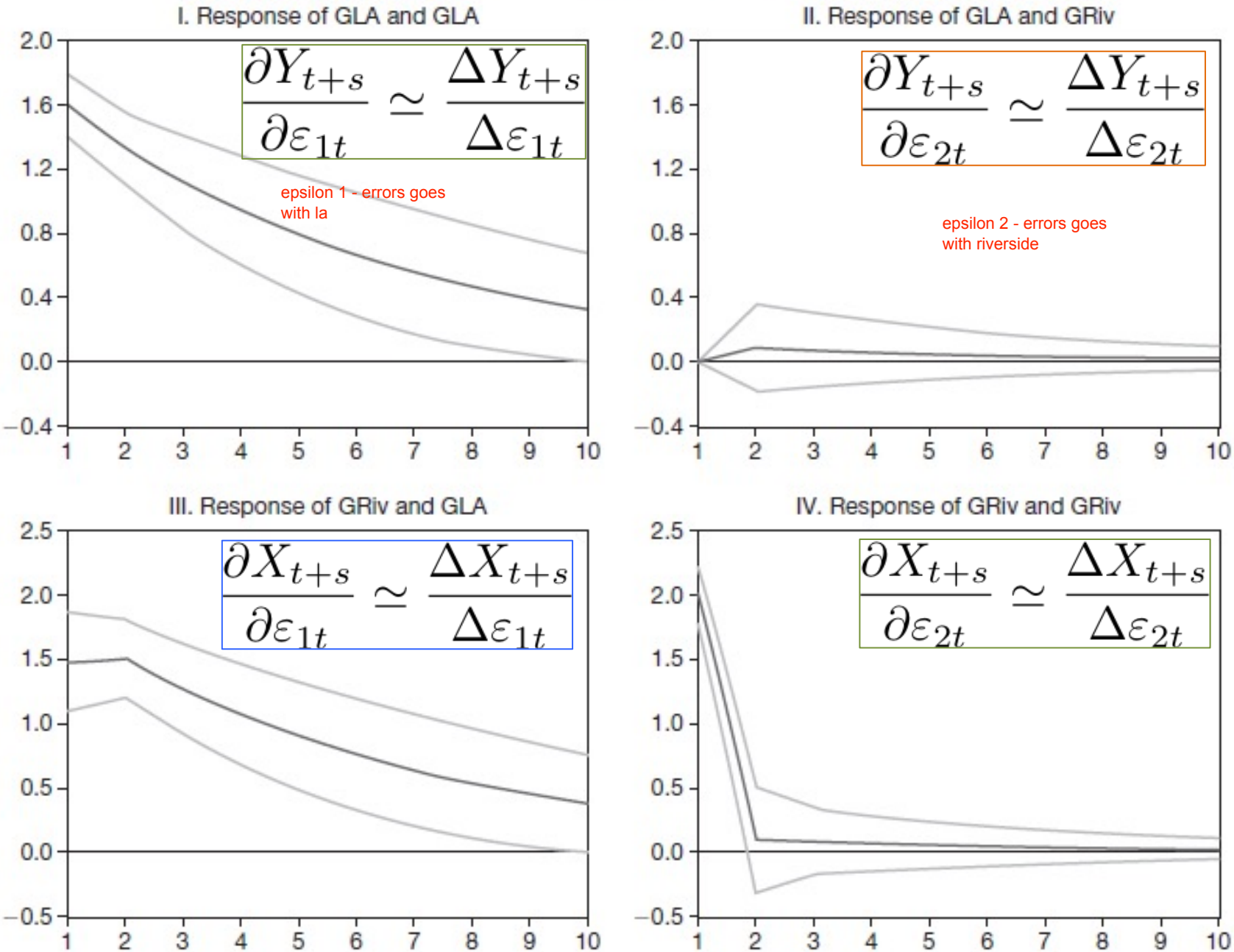
LA Market is useful in predicting the Riverside Market

Impulse-Response Functions

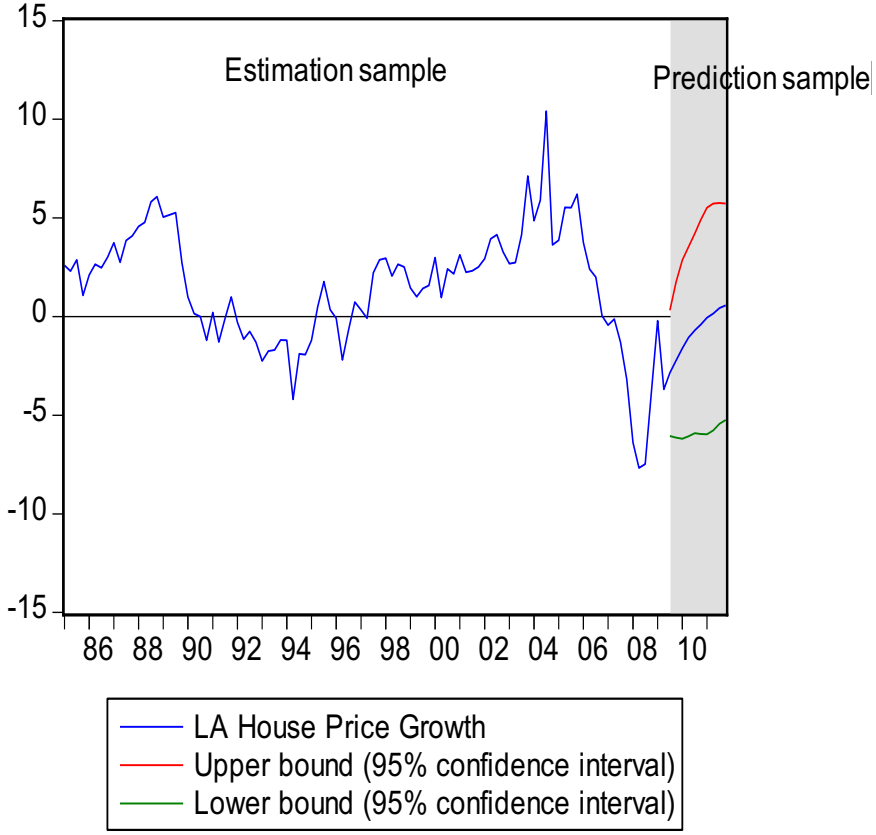


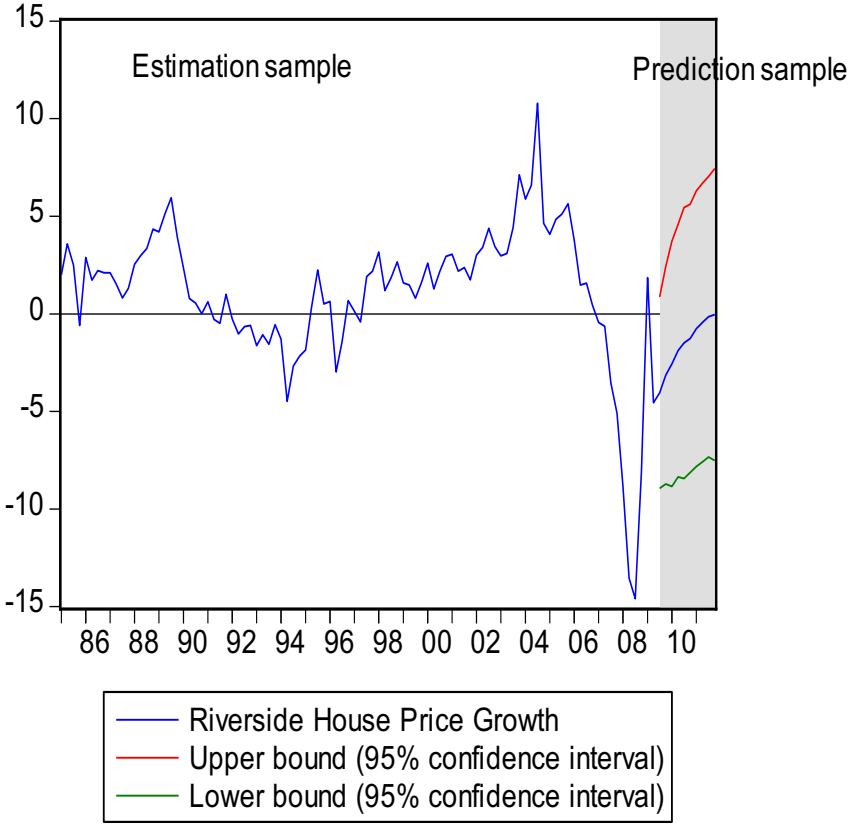
around 0

Response to Cholesky One S.D. Innovations ± 2 S.E.



VAR Example 2
House Price Growth in LA & Riverside





Follow traditional ar forecast

For Next Class

- Readings about today's class:

  Chapter 11^a, 11^b

- Review Exercises / Problems:

  Chapter 11^b: 2, 3, 5, 6, 8

- Readings for next class:

  Chapter 12^a, 12^b