Estimation of Dynamic Causal Effects
(SW Chapter 15)

Draft version, changes possible!

Outline

1. Dynamic Causal Effects and the Orange Juice Data
2. Estimation of Dynamic Causal Effects with Exogenous Regressors: The Distributed Lag Model
3. HAC Standard Errors
4. Application to Orange Juice Prices
5. More on Exogeneity

Dynamic Causal Effects and the Orange Juice Data (SW Sections 15.1 and 15.2)

A ***dynamic causal effect*** is the effect on Y of a change in X over time.

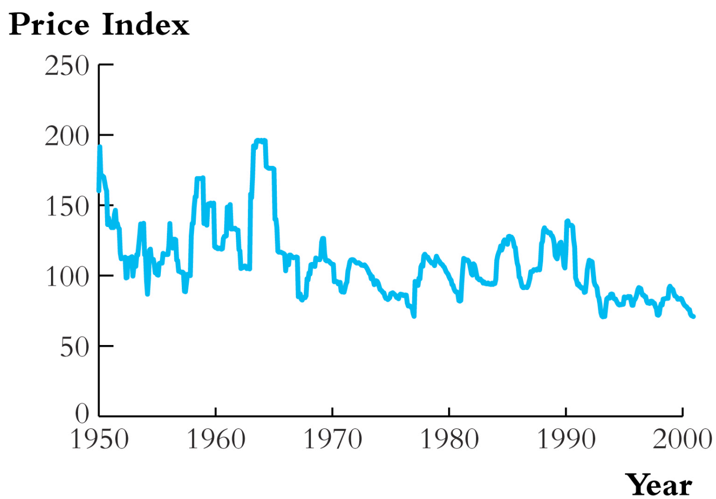
For example:

- The effect of an increase in cigarette taxes on cigarette consumption this year, next year, in 5 years;
- The effect of a change in the Fed Funds rate on inflation, this month, in 6 months, and 1 year;
- The effect of a freeze in Florida on the price of orange juice concentrate in 1 month, 2 months, 3 months…

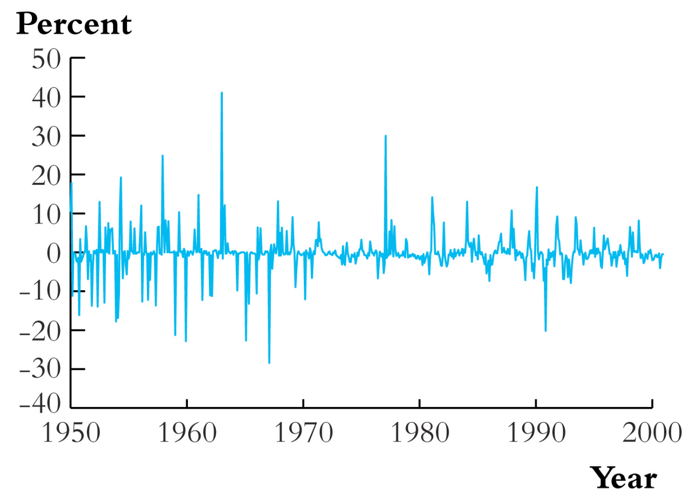
The Orange Juice Data

- Monthly, Jan. 1950 – Dec. 2000 ($T = 612$)
- *Price* = price of frozen OJ (a sub-component of the producer price index; US Bureau of Labor Statistics)
- *%ChgP* = percentage change in price at an annual rate, so $\%ChgP_t = 1200\Delta\ln(Price_t)$
- *FDD* = number of freezing degree-days during the month, recorded in Orlando FL
    - Example: If November has 2 days with lows < 32^o, one at 30^o and at 25^o, then $FDD_{Nov} = 2 + 7 = 9$

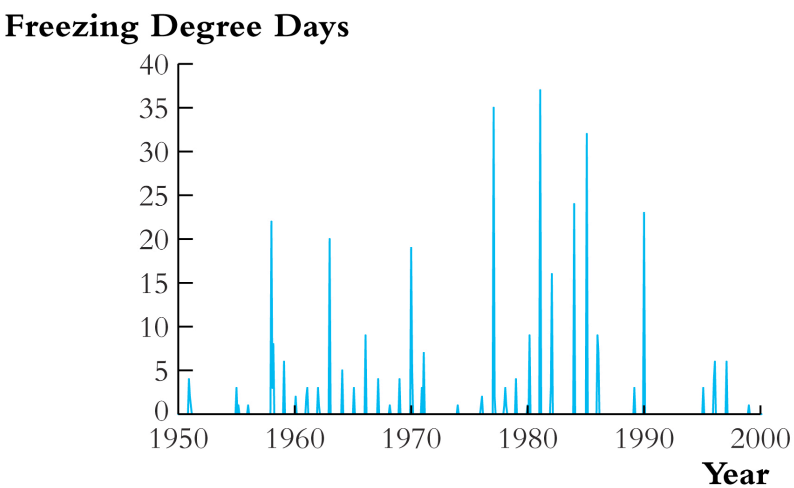
FIGURE 15.1 Orange Juice Prices and Florida Weather, 1950–2000



(a) Price Index for Frozen Concentrated Orange Juice



(b) Percent Change in the Price of Frozen Concentrated Orange Juice



(c) Monthly Freezing Degree Days in Orlando, Florida

Initial OJ regression

$$\widehat{\%ChgP_t} = -.40 + .47FDD_t$$
$$(.22) \quad (.13)$$

- Statistically significant positive relation
- More freezing degree days ⇒ price increase
- Standard errors are heteroskedasticity and autocorrelation-consistent (HAC) SE's – *more on this later*
- But what is the effect of *FDD* over time?

Dynamic Causal Effects

Example: What is the effect of fertilizer on tomato yield?

An ideal randomized controlled experiment

- Fertilize some plots, not others (random assignment)
- Measure yield *over time – over repeated harvests* – to estimate causal effect of fertilizer on:
  - Yield in year 1 of experiment
  - Yield in year 2, etc.
- The result (in a large experiment) is the causal effect of fertilizer on yield *k* years later.

Dynamic causal effects, ctd.

In time series applications, we can't conduct this ideal randomized controlled experiment:

- We only have one US OJ market ….
- We can't randomly assign FDD to different replicates of the US OJ market (what does this even mean?)
- We can't measure the average (across "subjects") outcome at different times – there is only one "subject"!
- So we can't estimate the causal effect at different times using the differences estimator

Dynamic causal effects, ctd.

An alternative thought experiment:

- Randomly give *the same subject* different treatments (FDD_t) *at different times*
- Measure the outcome variable ($\%ChgP_t$)
- The "population" of subjects consists of the same subject (OJ market) but at different dates – sometimes the subject is the treatment group, sometimes the control group!
- If the "subjects" (the subject at different times) are drawn from the same distribution – *that is, if Y_t, X_t are* ***stationary*** – then the dynamic causal effect can be deduced by OLS regression of Y_t on lagged values of X_t.
- This estimator (regression of Y_t on X_t and lags of X_t) is called the ***distributed lag*** estimator.

Dynamic Causal Effects and the Distributed Lag Model

The **distributed lag model** is:

$$Y_t = \beta_0 + \beta_1 X_t + \ldots + \beta_r X_{t-r} + u_t$$

- β_1 = ***impact effect of change in X*** = effect of change in X_t on Y_t, holding past X_t constant
- β_2 = ***1-period dynamic multiplier*** = effect of change in X_{t-1} on Y_t, holding constant X_t, X_{t-2}, X_{t-3},…
- β_3 = ***2-period dynamic multiplier*** (etc.) = effect of change in X_{t-2} on Y_t, holding constant X_t, X_{t-1}, X_{t-3},…
- ***Cumulative dynamic multipliers***
  - The 2-period cumulative dynamic multiplier is $\beta_1 + \beta_2 + \beta_3$ = impact effect + 1-period effect + 2-period effect

Exogeneity in Time Series Regression

Exogeneity (*past and present*)

X is ***exogenous*** if $E(u_t|X_t, X_{t-1}, X_{t-2},\ldots) = 0$.

Strict Exogeneity (*past, present, and future*)

X is ***strictly exogenous*** if $E(u_t|\ldots, X_{t+1}, X_t, X_{t-1}, \ldots) = 0$

- Strict exogeneity implies exogeneity
- For now we suppose that X is exogenous – we'll return (briefly) to the case of strict exogeneity later.
- If X is exogenous, then we can use OLS to estimate the dynamic causal effect on Y of a change in X….

Estimation of Dynamic Causal Effects with Exogenous Regressors (SW Section 15.3)

Distributed Lag Model:

$$Y_t = \beta_0 + \beta_1 X_t + \ldots + \beta_{r+1} \mathrm{X}_{\mathrm{t}-r} + u_t$$

The Distributed Lag Model Assumptions

1. $E(u_t|X_t, X_{t-1}, X_{t-2},\ldots) = 0$ (X is exogenous)
2. (a) Y and X have stationary distributions;
   (b) (Y_t, X_t) and (Y_{t-j}, X_{t-j}) become independent as j gets large
3. Y and X have eight nonzero finite moments
4. There is no perfect multicollinearity.

The distributed lag model, ctd.

- Assumptions 1 and 4 are familiar
- Assumption 3 is familiar, except for 8 (not four) finite moments – this has to do with HAC estimators
- Assumption 2 is different – before it was (X_i, Y_i) are i.i.d. – with time series data this becomes more complicated.

2. (a) Y and X have stationary distributions;
    - If so, the coefficients don't change within the sample (internal validity);
    - and the results can be extrapolated outside the sample (external validity).
    - This is the time series counterpart of the "identically distributed" part of i.i.d.

The distributed lag model, ctd.

2. (b) (Y_t,X_t) and (Y_{t-j}, X_{t-j}) become independent as j gets large
   - Intuitively, this says that we have separate experiments for time periods that are widely separated.
   - In cross-sectional data, we assumed that Y and X were i.i.d., a consequence of simple random sampling – this led to the CLT.
   - A version of the CLT holds for time series variables that become independent as their temporal separation increases – assumption 2(b) is the time series counterpart of the "independently distributed" part of i.i.d.

Under the Distributed Lag Model Assumptions:

- OLS yields **consistent** estimators of β_1, β_2,…,β_r (of the dynamic multipliers)
- In large samples, the sampling distribution of $\hat{\beta}_1$, etc., is normal
- ***BUT*** the formula for the variance of this sampling distribution is not the usual one from cross-sectional (i.i.d.) data, because u_t is not i.i.d. – u_t can be serially correlated!
- This means that the usual OLS standard errors (usual STATA printout) are wrong!
- We need to use, instead, *SE*s that are robust to autocorrelation as well as to heteroskedasticity…

Heteroskedasticity and Autocorrelation-Consistent (HAC) Standard Errors (SW Section 15.4)

- When u_t is serially correlated, the variance of the sampling distribution of the OLS depends on this serial correlation.
- The usual heteroskedasticity-robust standard error formula only works for serially uncorrelated errors.
- We need a new standard error formula: heteroskedasticity- and autocorrelation consistent (HAC) SEs.
- We've encountered this problem before in panel data – we solved it using "clustered" standard errors
  - The "cluster" approach required $n > 1$– so clustered standard errors are only for panel data
  - in TS data, $n = 1$ so we need a different method…

HAC standard errors, ctd.

The math…for a single regressor X_t:

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

The OLS estimator: From SW, App. 4.3,

$$\hat{\beta}_1 - \beta_1 = \frac{\frac{1}{T}\sum_{t=1}^{T}(X_t - \bar{X})u_t}{\frac{1}{T}\sum_{t=1}^{T}(X_t - \bar{X})^2}$$

$$\cong \frac{\frac{1}{T}\sum_{t=1}^{T}v_t}{\sigma_X^2} \text{ (in large samples)}$$

where $v_t = (X_t - \bar{X})u_t$.

HAC standard errors, ctd.

Thus, in large samples,

$$\text{var}(\hat{\beta}_1) = \text{var}\left(\frac{1}{T}\sum_{t=1}^{T} v_t\right)/(\sigma_X^2)^2$$

$$= \frac{1}{T^2}\sum_{t=1}^{T}\sum_{s=1}^{T}\text{cov}(v_t, v_s)/(\sigma_X^2)^2$$

In i.i.d. cross sectional data, $\text{cov}(v_t, v_s) = 0$ for $t \neq s$, so

$$\text{var}(\hat{\beta}_1) = \frac{1}{T^2}\sum_{t=1}^{T}\text{var}(v_t))/(\sigma_X^2)^2 = \frac{\sigma_v^2}{T(\sigma_x^2)^2}$$

This is our usual cross-sectional result (*SW App. 4.3*).

HAC standard errors, ctd.

But in time series data, $\text{cov}(v_t, v_s) \neq 0$ in general.

Consider $T = 2$:

$$\text{var}\left(\frac{1}{T}\sum_{t=1}^{T} v_t\right) = \text{var}[\tfrac{1}{2}(v_1+v_2)]$$

$$= \tfrac{1}{4}[\text{var}(v_1) + \text{var}(v_2) + 2\text{cov}(v_1,v_2)]$$

$$= \tfrac{1}{2}\sigma_v^2 + \tfrac{1}{2}\rho_1\sigma_v^2 \qquad (\rho_1 = \text{corr}(v_1,v_2))$$

$$= \tfrac{1}{2}\sigma_v^2 \times f_2, \text{ where } f_2 = (1+\rho_1)$$

- In i.i.d. data, $\rho_1 = 0$ so $f_2 = 1$, yielding the usual formula
- In time series data, if $\rho_1 \neq 0$ then $\text{var}(\hat{\beta}_1)$ is ***not*** given by the usual formula.

Expression for var($\hat{\beta}_1$), general *T*

$$\text{var}\left(\frac{1}{T}\sum_{t=1}^{T} v_t\right) = \frac{\sigma_v^2}{T}\times f_T$$

so

$$\boxed{\text{var}(\hat{\beta}_1) = \left[\frac{1}{T}\frac{\sigma_v^2}{(\sigma_X^2)^2}\right]\times f_T}$$

where

$$\boxed{f_T = 1 + 2\sum_{j=1}^{T-1}\left(\frac{T-j}{T}\right)\rho_j} \quad (\textit{SW, eq. (15.13)})$$

- Conventional OLS SE's are wrong when u_t is serially correlated (the ",r" STATA printout is wrong).
- The OLS *SE*s are off by the factor f_T
- We need to use a different *SE* formula!!!

HAC Standard Errors

- If we knew the factor f_T, we could just make the adjustment.
  - In panel data, the factor f_T is (implicitly) estimated by using "cluster" – but "cluster" requires n large.
  - In time series data, we need a different formula – we must estimate f_T explicitly

Standard errors that use consistent estimators of f_T are called **H**eteroskedasticity- and **A**utocorrelation-**C**onsistent (**HAC**) standard errors

HAC standard errors, ctd.

$$\text{var}(\hat{\beta}_1) = \left[\frac{1}{T}\frac{\sigma_v^2}{(\sigma_X^2)^2}\right] \times f_T, \text{ where } f_T = 1 + 2\sum_{j=1}^{T-1}\left(\frac{T-j}{T}\right)\rho_j$$

The most commonly used estimator of f_T is:

$$\boxed{\hat{f}_T = 1 + 2\sum_{j=1}^{m-1}\left(\frac{m-j}{m}\right)\tilde{\rho}_j} \quad \text{(Newey-West)}$$

- $\tilde{\rho}_j$ is an estimator of ρ_j
- This is the "Newey-West" HAC *SE* estimator
- m is called the ***truncation parameter***
- How should you choose m?
  - Use the Goldilocks method (not too many, not too few)
  - Or, use the rule of thumb, $m = 0.75T^{1/3}$

Example: OJ and HAC estimators in STATA

```
. gen l0fdd = fdd;                         generate lag #0
. gen l1fdd = L1.fdd;                      generate lag #1
. gen l2fdd = L2.fdd;                      generate lag #2
. gen l3fdd = L3.fdd;                          .
. gen l4fdd = L4.fdd;                          .
. gen l5fdd = L5.fdd;                          .
. gen l6fdd = L6.fdd;

. reg dlpoj fdd if tin(1950m1,2000m12), r;  NOT HAC SEs

Linear regression                                      Number of obs =     612
                                                       F(  1,   610) =   12.12
                                                       Prob > F      =  0.0005
                                                       R-squared     =  0.0937
                                                       Root MSE      =  4.8261

------------------------------------------------------------------------------
             |               Robust
       dlpoj |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         fdd |   .4662182   .1339293     3.48   0.001     .2031998    .7292367
       _cons |  -.4022562   .1893712    -2.12   0.034    -.7741549   -.0303575
------------------------------------------------------------------------------
```

Example: OJ and HAC estimators in STATA, ctd

Rerun this regression, but with Newey-West *SEs*:

```
.  newey dlpoj fdd if tin(1950m1,2000m12), lag(7);

Regression with Newey-West standard errors          Number of obs  =       612
maximum lag: 7                                      F(  1,   610)  =     12.23
                                                    Prob > F       =    0.0005

------------------------------------------------------------------------------
             |             Newey-West
       dlpoj |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         fdd |   .4662182   .1333142     3.50   0.001     .2044077    .7280288
       _cons |  -.4022562   .2159802    -1.86   0.063    -.8264112    .0218987
------------------------------------------------------------------------------
```

Uses autocorrelations up to m = 7 to compute the SEs

rule-of-thumb: $0.75*(612^{1/3}) = 6.4 \approx 7$, rounded up a little.

OK, in this case the difference in SEs is small, but not always so!

Example: OJ and HAC estimators in STATA, ctd.

```
. global lfdd6 "fdd l1fdd l2fdd l3fdd l4fdd l5fdd l6fdd";

.  newey dlpoj $lfdd6 if tin(1950m1,2000m12), lag(7);

Regression with Newey-West standard errors          Number of obs  =       612
maximum lag : 7                                     F(  7,    604)  =      3.56
                                                    Prob > F        =    0.0009

------------------------------------------------------------------------------
             |             Newey-West
       dlpoj |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         fdd |   .4693121   .1359686     3.45   0.001      .2022834    .7363407
       l1fdd |   .1430512   .0837047     1.71   0.088     -.0213364    .3074388
       l2fdd |   .0564234   .0561724     1.00   0.316     -.0538936    .1667404
       l3fdd |   .0722595   .0468776     1.54   0.124     -.0198033    .1643223
       l4fdd |   .0343244   .0295141     1.16   0.245     -.0236383    .0922871
       l5fdd |   .0468222   .0308791     1.52   0.130     -.0138212    .1074657
       l6fdd |   .0481115   .0446404     1.08   0.282     -.0395577    .1357807
       _cons |  -.6505183   .2336986    -2.78   0.006     -1.109479   -.1915578
------------------------------------------------------------------------------
```

- global lfdd6 *defines a string which is all the additional lags*
- *What are the estimated dynamic multipliers (dynamic effects)?*

FAQ: Do I need to use HAC *SE*s when I estimate an AR or an ADL model?

A: NO.

- The problem to which HAC *SE*s are the solution only arises when u_t is serially correlated: if u_t is serially uncorrelated, then OLS *SE*'s are fine
- In AR and ADL models, the errors are serially uncorrelated if you have included enough lags of Y
  - If you include enough lags of Y, then the error term can't be predicted using past Y, or equivalently by past u – so u is serially uncorrelated

Estimation of Dynamic Causal Effects with Strictly Exogenous Regressors (SW Section 15.5)

- X is strictly exogenous if $E(u_t|\ldots,X_{t+1}, X_t, X_{t-1}, \ldots) = 0$
- If X is strictly exogenous, there are more efficient ways to estimate dynamic causal effects than by a distributed lag regression:
    - Generalized Least Squares (GLS) estimation
    - Autoregressive Distributed Lag (ADL) estimation
- But the condition of strict exogeneity is very strong, so this condition is rarely plausible in practice – *not even in the weather/OJ example (why?)*.
- So we won't cover GLS or ADL estimation of dynamic causal effects – for details, see SW Section 15.5.

Orange Juice Prices and Cold Weather
(SW Section 15.6)

What is the dynamic causal effect (*what are the dynamic multipliers*) of a unit increase in FDD on OJ prices?

$$\%ChgP_t = \beta_0 + \beta_1 FDD_t + \ldots + \beta_{r+1} FDD_{t-r} + u_t$$

- *What r to use*?
  How about 18? (Goldilocks method)

- *What m* (*Newey-West truncation parameter*) *to use*?
  $m = .75 \times 612^{1/3} = 6.4 \cong 7$

Digression: Computation of cumulative multipliers and their standard errors

The cumulative multipliers can be computed by estimating the distributed lag model, then adding up the coefficients. However, you should also compute standard errors for the cumulative multipliers and while this can be done directly from the distributed lag model it requires some modifications.

Because cumulative multipliers are linear combinations of regression coefficients, the methods of Section 7.3 can be applied to compute their standard errors.

Computing cumulative multipliers, ctd.

A trick in Section 7.3 is to rewrite the regression so that the coefficients in the rewritten regression are the coefficients of interest – here, the cumulative multipliers.

Example: Rewrite the distributed lag model with 1 lag:

$$\begin{aligned} Y_t &= \beta_0 + \beta_1 X_t + \beta_2 X_{t-1} + u_t \\ &= \beta_0 + \beta_1 X_t - \beta_1 X_{t-1} + \beta_1 X_{t-1} + \beta_2 X_{t-1} + u_t \\ &= \beta_0 + \beta_1 (X_t - X_{t-1}) + (\beta_1 + \beta_2) X_{t-1} + u_t \end{aligned}$$

or

$$Y_t = \beta_0 + \beta_1 \Delta X_t + (\beta_1 + \beta_2) X_{t-1} + u_t$$

Computing cumulative multipliers, ctd.

So, let $W_{1t} = \Delta X_t$ and $W_{2t} = X_{t-1}$ and estimate the regression,

$$Y_t = \beta_0 + \delta_1 W_{1t} + \delta_2 W_{2t} + u_i$$

Then

$$\delta_1 = \beta_1 = \text{impact effect}$$

$$\delta_2 = \beta_1 + \beta_2 = \text{the first cumulative multiplier}$$

and the (HAC) standard errors on δ_1 and δ_2 are the standard errors for the two cumulative multipliers.

Computing cumulative multipliers, ctd.

In general, the ADL model can be rewritten as,

$$Y_t = \delta_0 + \delta_1\Delta X_t + \delta_2\Delta X_{t-1} + \ldots + \delta_{q-1}\Delta X_{t-q+1} + \delta_q X_{t-q} + u_t$$

where

$$\delta_1 = \beta_1$$

$$\delta_2 = \beta_1 + \beta_2$$

$$\delta_3 = \beta_1 + \beta_2 + \beta_3$$

...

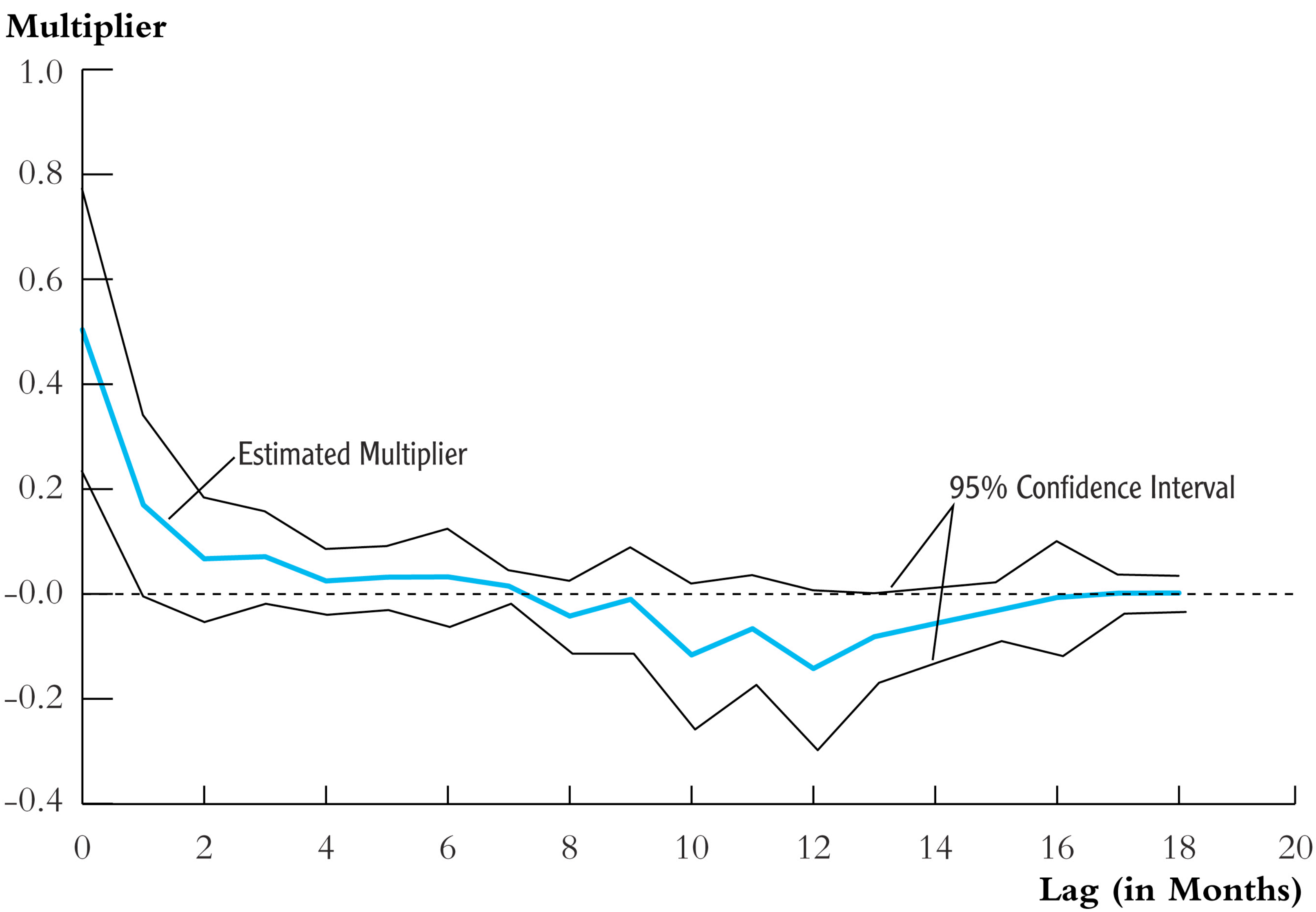
$$\delta_q = \beta_1 + \beta_2 + \ldots + \beta_q$$

Cumulative multipliers and their HAC SEs can be computed directly using this transformed regression

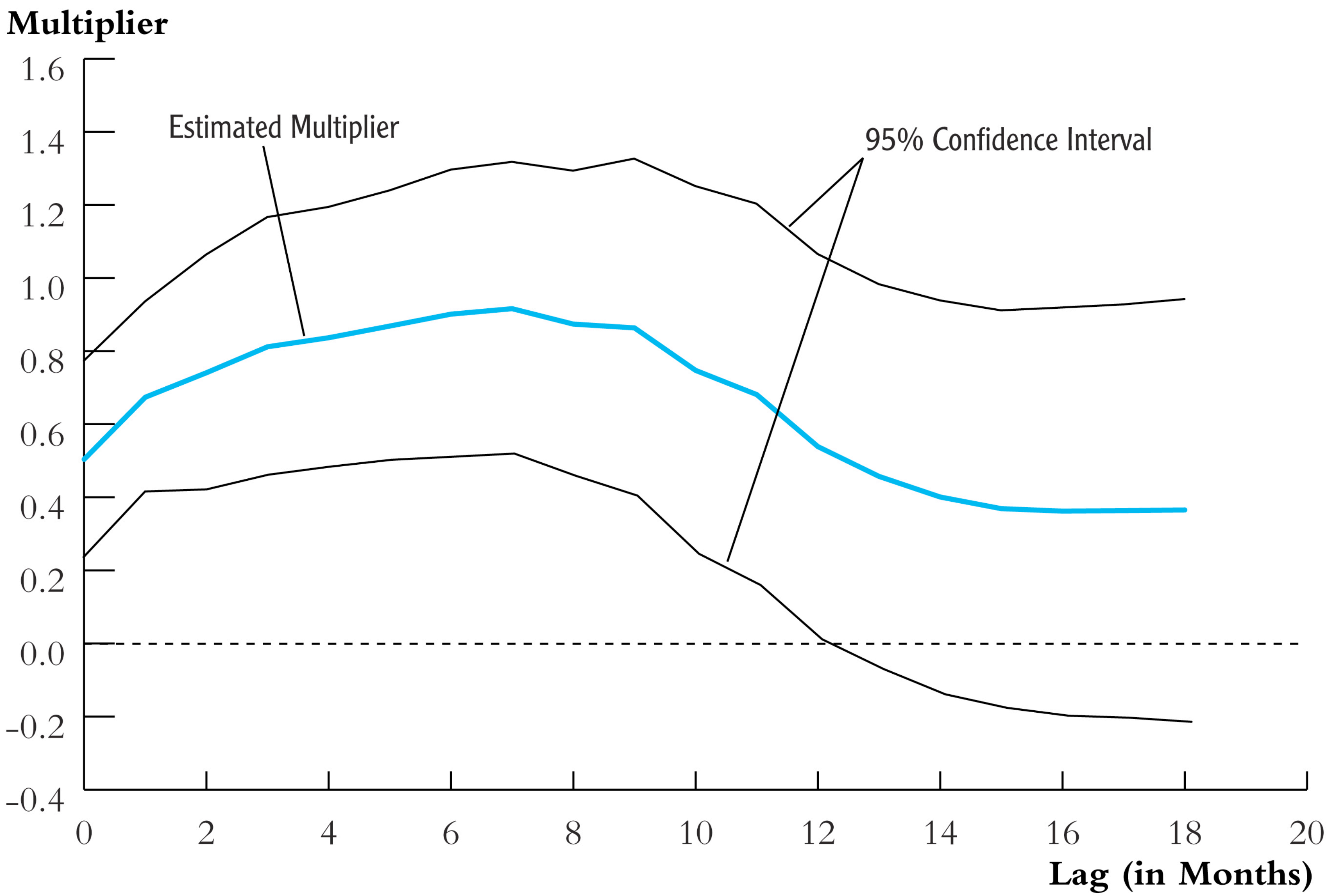
TABLE 15.1 The Dynamic Effect of a Freezing Degree Day (*FDD*) on the Price of Orange Juice: Selected Estimated Dynamic Multipliers and Cumulative Dynamic Multipliers

Lag number	(1) Dynamic Multipliers	(2) Cumulative Multipliers	(3) Cumulative Multipliers	(4) Cumulative Multipliers
0	0.50 (0.14)	0.50 (0.14)	0.50 (0.14)	0.51 (0.15)
1	0.17 (0.09)	0.67 (0.14)	0.67 (0.13)	0.70 (0.15)
2	0.07 (0.06)	0.74 (0.17)	0.74 (0.16)	0.76 (0.18)
3	0.07 (0.04)	0.81 (0.18)	0.81 (0.18)	0.84 (0.19)
4	0.02 (0.03)	0.84 (0.19)	0.84 (0.19)	0.87 (0.20)
5	0.03 (0.03)	0.87 (0.19)	0.87 (0.19)	0.89 (0.20)
6 . . .	0.03 (0.05)	0.90 (0.20)	0.90 (0.21)	0.91 (0.21)
12 . . .	−0.14 (0.08)	0.54 (0.27)	0.54 (0.28)	0.54 (0.28)
18	0.00 (0.02)	0.37 (0.30)	0.37 (0.31)	0.37 (0.30)
Monthly indicators?	No	No	No	Yes $F = 1.01$ ($p = 0.43$)
HAC standard error truncation parameter (m)	7	7	14	7

FIGURE 15.2 The Dynamic Effect of a Freezing Degree Day (*FDD*) on the Price of Orange Juice



(a) Estimated Dynamic Multipliers and 95% Confidence Interval



(b) Estimated Cumulative Dynamic Multipliers and 95% Confidence Interval

Are the OJ dynamic effects stable?

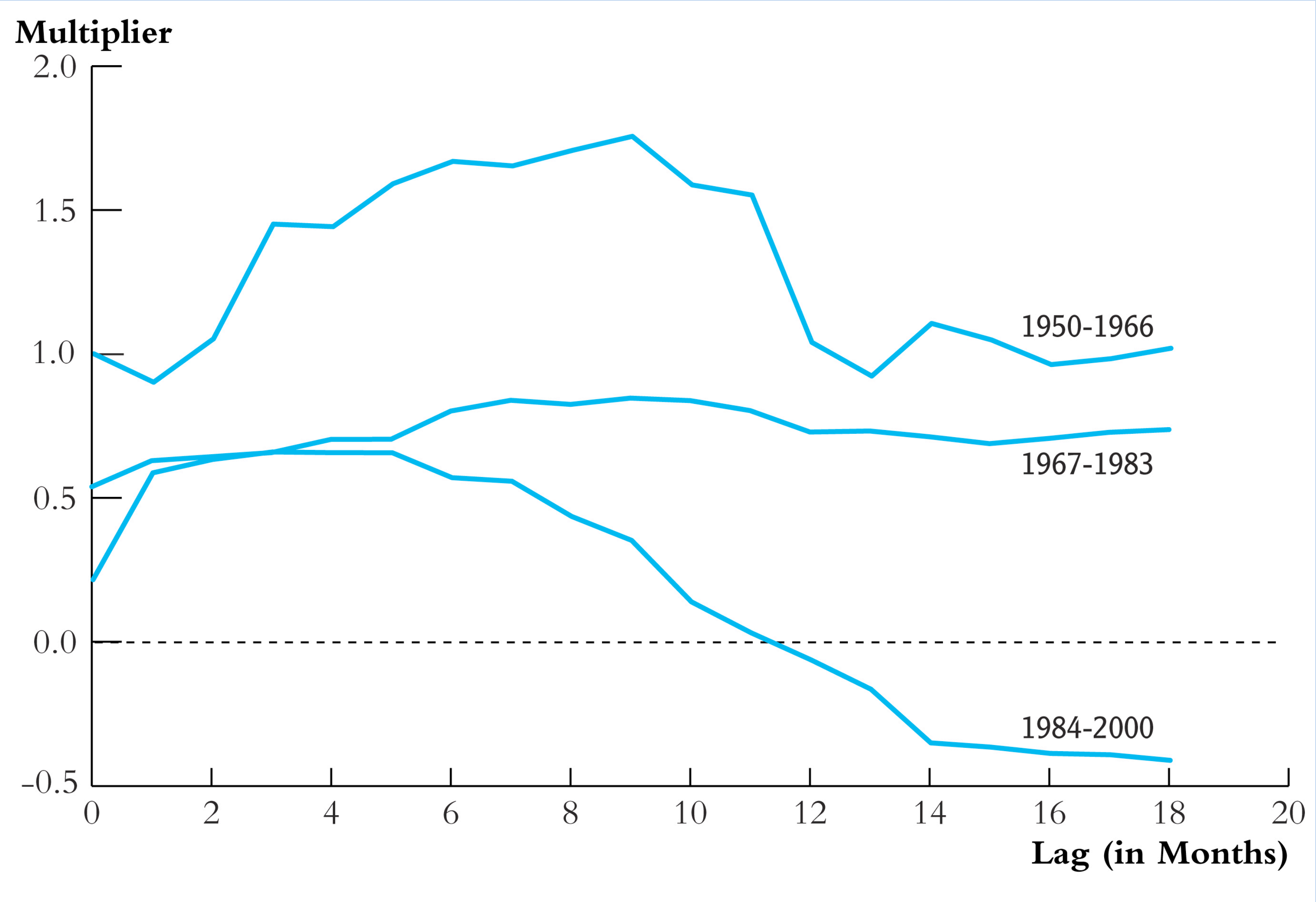
Recall from Section 14.7 that we can test for stability of time series regression coefficients using the QLR statistic. So, we can compute QLR for regression (1) in Table 15.1:

- *Do you need HAC SEs? Why or why not?*
- *How specifically would you compute the Chow statistic?*
- *How would you compute the QLR statistic?*
- *What are the d.f. q of the Chow and QLR statistics?*
- Result: ***QLR* = 21.19**.
  - Is this significant? (see Table 14.6)
  - At what significance level?
- How to interpret the result substantively? Estimate the dynamic multipliers on subsamples and see how they have changed over time…

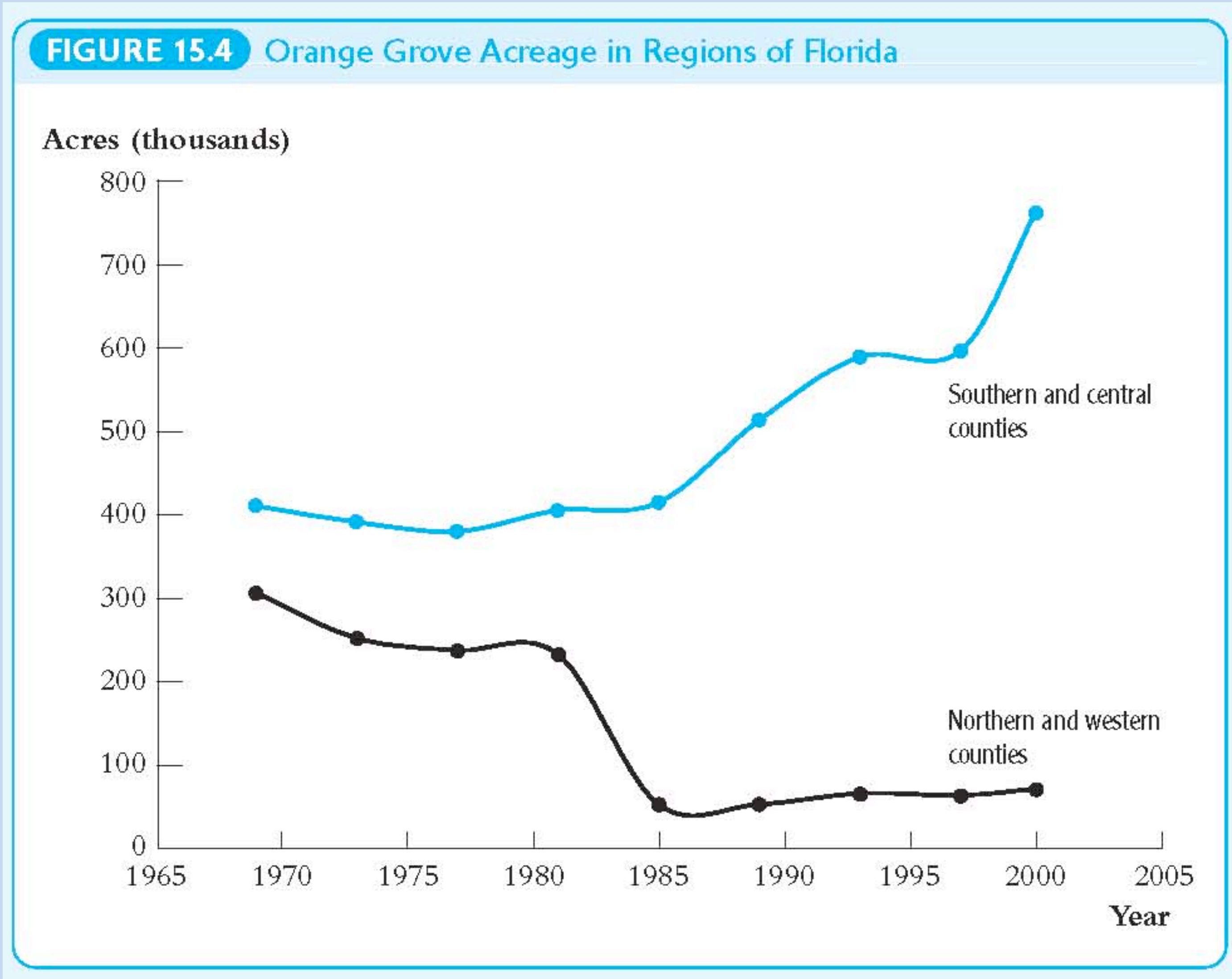
TABLE 14.6 Critical Values of the QLR Statistic with 15% Trimming

Number of Restrictions (q)	10%	5%	1%
1	7.12	8.68	12.16
2	5.00	5.86	7.78
3	4.09	4.71	6.02
4	3.59	4.09	5.12
5	3.26	3.66	4.53
6	3.02	3.37	4.12
7	2.84	3.15	3.82
8	2.69	2.98	3.57
9	2.58	2.84	3.38
10	2.48	2.71	3.23
11	2.40	2.62	3.09
12	2.33	2.54	2.97
13	2.27	2.46	2.87
14	2.21	2.40	2.78
15	2.16	2.34	2.71
16	2.12	2.29	2.64
17	2.08	2.25	2.58
18	2.05	2.20	2.53
19	2.01	2.17	2.48
20	1.99	2.13	2.43

OJ: Do the breaks matter substantively?



The cumulative effect of a *FDD* declines over time? Why?



Fact: After losing many trees to freezes in northern Florida, Florida orange growers planted farther south. *How does this relate to the change in the cumulative impulse responses?*

Is Exogeneity Plausible? Some Examples (SW Section 15.7)

If X is exogenous (and assumptions #2-4 hold), then a distributed lag model provides consistent estimators of dynamic causal effects.

As in multiple regression with cross-sectional data, you must think critically about whether X is exogenous in any application:

- is X exogenous, i.e. $E(u_t|X_t, X_{t-1}, \ldots) = 0$?
- is X strictly exogenous, i.e. $E(u_t|\ldots, X_{t+1}, X_t, X_{t-1}, \ldots) = 0$?

In the following examples, is (a) exogeneity and/or (b) strict exogeneity plausible? *What do you think?*

1. Y = OJ prices, X = FDD in Orlando
2. Y = Australian exports, X = US GDP (effect of US income on demand for Australian exports)
3. Y = EU exports, X = US GDP (effect of US income on demand for EU exports)
4. Y = US rate of inflation, X = percentage change in world oil prices (as set by OPEC) (effect of OPEC oil price increase on inflation)
5. Y = GDP growth, X =Federal Funds rate (the effect of monetary policy on output growth)
6. Y = change in the rate of inflation, X = unemployment rate on inflation (the Phillips curve)

Exogeneity, ctd.

- You must evaluate exogeneity and strict exogeneity on a case by case basis
- Exogeneity is often not plausible in time series data because of simultaneous causality
- Strict exogeneity is rarely plausible in time series data because of feedback.

Estimation of Dynamic Causal Effects: Summary (SW Section 15.8)

- Dynamic causal effects are measurable in theory using a randomized controlled experiment with repeated measurements over time.
- When X is exogenous, you can estimate dynamic causal effects using a distributed lag regression
- If u is serially correlated, conventional OLS *SE*s are incorrect; you must use HAC *SE*s
- To decide whether X is exogenous, think hard about the specifics of the problem!