# CSSS 512: Lab 6

## Panel Data Models with Few Time Periods

2018-5-18

# Agenda

1. Review of Nickell bias, dynamic panel data models, and GMM
2. Fixed effect and random effects models
3. Estimating dynamic panel data models
4. Simulating conditional forecasts
5. Plotting the results

# Nickell bias

Recall that we can remove fixed effects by differencing (different from first differencing):

$$y_{it} = \phi y_{it-1} + \alpha_i + \epsilon_{it}$$

$$y_{it} - \bar{y}_i = \phi(y_{it-1} - \bar{y}_i) + (x_{it} - \bar{x}_{it})\beta + (\epsilon_{it} - \bar{\epsilon}_{it})$$

This is the "within" estimator or fixed effects model.

Alternatively, we can include dummy variables for each group.

# Nickell bias

However, we introduce bias when we difference the model in this way.

$$y_{it} - \bar{y}_i = \phi(y_{it-1} - \bar{y}_i) + (x_{it} - \bar{x}_{it})\beta + (\epsilon_{it} - \bar{\epsilon}_{it})$$

This is because $\bar{y}_i$ is computed using all the past $y$'s. This is correlated with $\bar{\epsilon}_{it}$, which is computed using all the past $\epsilon$'s

Specifically, this creates bias in the LDV (think conditional mean zero assumption). If the other regressors are correlated with the LDV, then their coefficients may also be seriously biased.

# Nickell bias

The degree of bias is order $1/T$, so it is big for small T.

Furthermore,

- The bias increases as $\beta$ decreases
- The bias increases as $\phi$ increases
- Small $N$ is not the problem. Small T is the problem

Increasing $N$ does not mitigate the problem. Purging serial correlation in the errors or getting the specification right (including other regressors) also doesn't solve the problem.

# Instrumental variables

We therefore turn to instrumental variables.

Recall that an instrumental variable must fulfill two conditions: 1) it is correlated with $x$ (relevance); 2) it is uncorrelated with $\epsilon$ (exogeneity). It must influence $y$ only through $x$.

$$y_{it} - \bar{y}_i = \phi(y_{it-1} - \bar{y}_i) + (x_{it} - \bar{x}_{it})\beta + (\epsilon_{it} - \bar{\epsilon}_{it})$$

$$\Delta y_{it} = \phi \Delta y_{it-1} + \Delta x_{it}\beta + \Delta \epsilon_{it}$$

We use lagged levels and lagged differences of $\Delta y_{it}$ as instruments for the LDV. These help to predict $\Delta y_{it}$ but not $\Delta \epsilon_{it}$ if the errors are iid (see lecture slides for why).

Note: This is different than instrumenting $x_{it}$. We are not addressing the endogeneity that may exist there. One should not be conflated with the other.

# Generalized Method of Moments

Estimation is done using GMM. The usual IV approach cannot handle the number of instruments.

To give a brief overview of the intuition behind GMM, consider a linear model:

$$y_t = \boldsymbol{x}_t \boldsymbol{\beta} + e_t$$

Recall that the following condition holds under Gauss-Markov.

$$E[\boldsymbol{x}_t \epsilon_t] = 0$$

Assume there exists some combination instrumental variables $\boldsymbol{z}_t$ that implies the following:

$$E[\boldsymbol{z}_t \epsilon_t] = E[\boldsymbol{z}_t (y_t - \boldsymbol{x}_t \boldsymbol{\beta})] = 0$$

Intuition: GMM attempts to find the $\beta$ that makes this true.

# Generalized method of moments

Population moment:

$$E[\boldsymbol{z}_t(y_t - \boldsymbol{x}_t\beta)] = 0$$

Sample moments:

$$\frac{1}{n}\sum_{t=1}^{n}\boldsymbol{z}_t(y - \boldsymbol{x_t}\beta)$$

$$\begin{matrix} \frac{1}{n}\sum_{t=1}^{n} z_{1t}(y - \boldsymbol{x}_t\beta) \\ \vdots \\ \frac{1}{n}\sum_{t=1}^{n} z_{Kt}(y - \boldsymbol{x}_t\beta) \end{matrix}$$

We therefore have

$$\boldsymbol{S}_{zy} - \boldsymbol{S}_{zx}\beta = 0 \quad \text{where}$$

$$\boldsymbol{S}_{xy} = n^{-1}\sum_{t=1}^{n}\boldsymbol{x}_t y_t \quad \text{and} \quad \boldsymbol{S}_{zx} = n^{-1}\sum_{t=1}^{n}\boldsymbol{z}_t x_t$$

We solve for

$$\hat{\beta} = \boldsymbol{S}_{zx}^{-1}\boldsymbol{S}_{xy}$$

# Generalized method of moments

$$\hat{\beta} = \boldsymbol{S}_{zx}^{-1}\boldsymbol{S}_{xy}$$

Can be solved analytically. But we can also use an iterative search.

**Anderson-Hsiao estimator**: uses the twice and third lagged levels as instruments.

**Arellano-Bond Difference GMM**: uses $\Delta y$ as the outcome and all available lagged levels as instruments in each period.

**Arellano-Bover/Blundell-Bond System GMM**: adds the available lagged differences as instruments.

# Examining the time series

```r
# Clear memory
rm(list=ls())

# Load libraries
library(plm)            # Econometrics package for linear panel models
library(nlme)           # Estimation of mixed effects models
library(lme4)           # Alternative package for mixed effects models
library(tseries)        # For ADF unit root test
library(simcf)          # For panel functions and simulators
library(tile)           # For visualization of model inference
library(RColorBrewer)   # For nice colors
library(MASS)           # For mvrnorm()
source("helperCigs.R")  # For graphics functions

# Load cigarette consumption data (Jonathan Gruber, MIT)
# Variables (see codebook):
# state year    cpi pop packpc  income  tax avgprs  taxs
data <- read.csv("cigarette.csv")                #Load the dataset
data[1:5,]
```

```
##   state year   cpi     pop   packpc   income  tax   avgprs     taxs
## 1    AL 1985 1.076 3973000 116.4863 46014968 32.5 102.1817 33.34834
## 2    AL 1986 1.096 3992000 117.1593 48703940 32.5 107.9892 33.40584
## 3    AL 1987 1.136 4016000 115.8367 51846312 32.5 113.5273 33.46067
## 4    AL 1988 1.183 4024000 115.2584 55698852 32.5 120.0334 33.52509
## 5    AL 1989 1.240 4030000 109.2060 60044480 32.5 133.2560 33.65600
```

```r
library(Ecdat)
help(Cigarette)
```

# Examining the time series

```r
# Quick inflation adjustment to 1995 dollars
inflAdjust <- function(x,cpi,year,target) {
    unique(cpi[year==target])*x/cpi
  #Multiply x with cpi in target year then divide by cpi in observed year
}
#Make adjustments to state personal income
data$income95 <- with(data, inflAdjust(income, cpi, year, 1995))
#Average state, federal, and average local excise taxes
data$tax95 <- with(data, inflAdjust(tax, cpi, year, 1995))
#Average price, including sales taxes
data$avgprs95 <- with(data, inflAdjust(avgprs, cpi, year, 1995))
#Average excise taxes, including sales taxes
data$taxs95 <- with(data, inflAdjust(taxs, cpi, year, 1995))
# Create per capita income (in k)
data$income95pc <- data$income95/data$pop
# Create pretax price, 1995 dollars
data$pretax95 <- data$avgprs95 - data$taxs95

data[1:5,]
```

```
##   state year   cpi     pop   packpc   income  tax   avgprs     taxs
## 1    AL 1985 1.076 3973000 116.4863 46014968 32.5 102.1817 33.34834
## 2    AL 1986 1.096 3992000 117.1593 48703940 32.5 107.9892 33.40584
## 3    AL 1987 1.136 4016000 115.8367 51846312 32.5 113.5273 33.46067
## 4    AL 1988 1.183 4024000 115.2584 55698852 32.5 120.0334 33.52509
## 5    AL 1989 1.240 4030000 109.2060 60044480 32.5 133.2560 33.65600
##   income95    tax95 avgprs95   taxs95 income95pc   pretax95
## 1 65173615 46.03160 144.7257 47.23314   16.40413  97.49257
## 2 67723361 45.19161 150.1601 46.45118   16.96477 103.70893
## 3 69554378 43.60035 152.3025 44.88914   17.31932 107.41336
## 4 71754049 41.86813 154.6331 43.18869   17.83152 111.44437
## 5 73796599 39.94355 163.7759 41.36431   18.31181 122.41162
```

```r
attach(data)
```

# Examining the time series

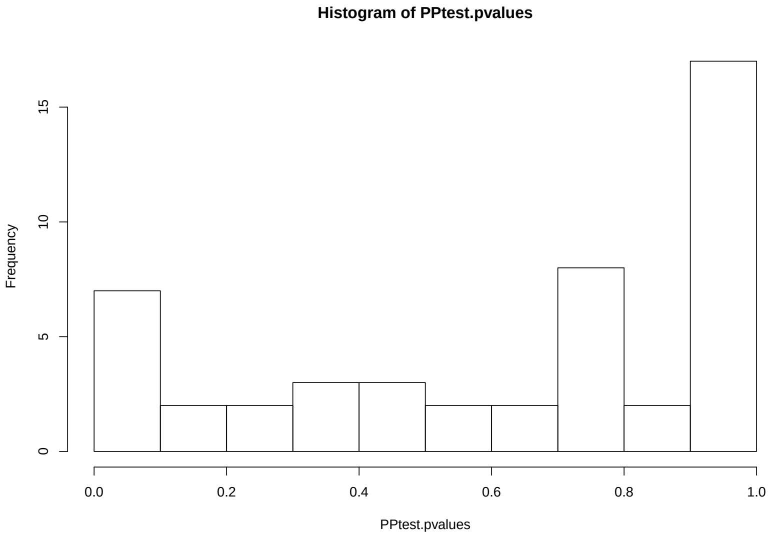
```
setwd("~/desktop/plots")
statelist <- unique(state)
# Look at the consumption time series for each state
for (i in 1:length(statelist)) {#Create a for loop from 1 to the number of states (48)
    currstate <- statelist[i]     #Make note of the state by number in the loop
    filename <- paste("tsPacksPCState",currstate,".pdf",sep="")
    #Create the file name of the plot
    pdf(filename,width=6,height=3.25)#Generate the PDF file
    plot(packpc[state==currstate],type="l",ylab="Packs Per Capita",
         #Generate the plot of packpc for the state by its number
    xlab="Year", main = paste("State",currstate) )
    dev.off()   #Turn off the PDF device
}
# Look at the ACF of consumption for each state
for (i in 1:length(statelist)) {#Create a for loop from 1 to the number of states (48)
    currstate <- statelist[i]   #Make note of the state by its number in the loop
    filename <- paste("acfPacksPCState",currstate,".pdf",sep="")
    #Create the file name of the plot
    pdf(filename,width=6,height=3.25)#Generate the PDF file
    acf(packpc[state==currstate])#Generate the ACF plot of packpc for the state by its number
    dev.off()#Turn off the PDF device
}
# Look at the PACF of consumption for each state
for (i in 1:length(statelist)) {
    currstate <- statelist[i]
    filename <- paste("acfPacksPCState",currstate,".pdf",sep="")
    pdf(filename,width=6,height=3.25)
    pacf(packpc[state==currstate])
    #Generate the PACF plot of packpc for the state by its number
    dev.off()
}
```

# Examining the time series

```
# Check for a unit root in each country
PPtest.pvalues <- rep(0,length(statelist))
#Create empty vectors for PP test p-values
adftest.pvalues <- rep(0,length(statelist))
#Create empty vectors for adf test p-values

for (i in 1:length(statelist)) {#Create a for loop from 1 to the number of states
    currstate <- statelist[i]#Make note of the state by its number in the loop

    # Check PP unit root test, omitting errors due to short series
    curPP <- try(PP.test(packpc[state==currstate])$p.value)
    #Find the p-value of the PP test for the state
    if (any(class(curPP)=="try-error")) curPP <- NA
    #Make note if there is an error in the PP test, if so, fill with an NA
    PPtest.pvalues[i] <- curPP
    #Store the p-value of the PP test in the PP test vector

    curadf <- try(adf.test(packpc[state==currstate])$p.value)
    #Do the same with the adf test results
    if (any(class(curadf)=="try-error")) curadf <- NA
    adftest.pvalues[i] <- curadf
  }
```

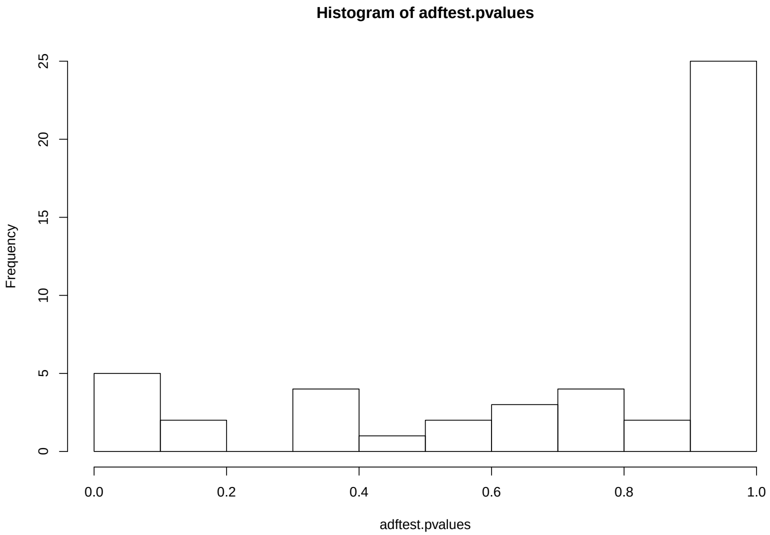
# Examining the time series

```
hist(PPtest.pvalues)          # Plot a histogram of the p-values
```



# Examining the time series

```
hist(adftest.pvalues)          # Plot a histogram of the p-values
```



# Examining the time series

```r
# Alternative model specifications
model1 <- packpc ~ income95pc + avgprs95
model2 <- packpc ~ income95pc + pretax95 + taxs95
model3 <- log(packpc) ~ log(income95pc) + log(avgprs95)

# Simple linear models
lm.res1 <- lm(model1, data)
lm.res2 <- lm(model2, data)
lm.res3 <- lm(model3, data)

summary(lm.res1)
```

```
##
## Call:
## lm(formula = model1, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -50.675 -10.238  -0.840   8.998  63.772
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 199.52434    6.56981  30.370  < 2e-16 ***
## income95pc    1.09830    0.26496   4.145 3.96e-05 ***
## avgprs95     -0.66467    0.03656 -18.182  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18 on 525 degrees of freedom
## Multiple R-squared:  0.3966, Adjusted R-squared:  0.3943
## F-statistic: 172.5 on 2 and 525 DF,  p-value: < 2.2e-16
```

# Examining the time series

```r
summary(lm.res2)
```

```
##
## Call:
## lm(formula = model2, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -49.882  -9.468  -0.588   8.744  66.532
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 191.71631    7.13804  26.858  < 2e-16 ***
## income95pc    1.15300    0.26415   4.365 1.53e-05 ***
## pretax95     -0.54863    0.05616  -9.768  < 2e-16 ***
## taxs95       -0.80264    0.06256 -12.831  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.89 on 524 degrees of freedom
## Multiple R-squared:  0.4049, Adjusted R-squared:  0.4015
## F-statistic: 118.9 on 3 and 524 DF,  p-value: < 2.2e-16
```

# Examining the time series

```r
summary(lm.res3)
```

```
##
## Call:
## lm(formula = model3, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.67369 -0.09012  0.00698  0.09820  0.41951
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      9.68686    0.28810  33.623  < 2e-16 ***
## log(income95pc)  0.24371    0.05367   4.541 6.96e-06 ***
## log(avgprs95)   -1.12181    0.06037 -18.582  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1696 on 525 degrees of freedom
## Multiple R-squared:  0.4036, Adjusted R-squared:  0.4013
## F-statistic: 177.6 on 2 and 525 DF,  p-value: < 2.2e-16
```

# Fixed effects model

```r
# Check for time invariant variables:
pvar(data)
```

```
## no time variation:       state
## no individual variation: year cpi
```

```r
# "within" option tells plm to do fixed effects
# Note that if you want to add year fixed effects then set effect="time" and for both state
# and year fixed effects set effect effect="twoway"
plm.res1 <- plm(packpc ~ income95pc + pretax95 + taxs95,  data = data, model="within", effect="twoway")
```

# Fixed effects model

```r
summary(plm.res1)
```

```
## Twoways effects Within Model
##
## Call:
## plm(formula = packpc ~ income95pc + pretax95 + taxs95, data = data,
##     effect = "twoway", model = "within")
##
## Balanced Panel: n=48, T=11, N=528
##
## Residuals :
##     Min.  1st Qu.   Median  3rd Qu.     Max.
## -16.5000  -1.9400   0.0468   2.1800  18.1000
##
## Coefficients :
##             Estimate Std. Error  t-value  Pr(>|t|)
## income95pc  0.969966   0.410602   2.3623 0.0185709 *
## pretax95   -0.188551   0.051420  -3.6669 0.0002738 ***
## taxs95     -0.481852   0.033595 -14.3429 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    13258
## Residual Sum of Squares: 8257.1
## R-Squared:      0.3772
## Adj. R-Squared: 0.29718
## F-statistic: 94.2779 on 3 and 467 DF, p-value: < 2.22e-16
```

# Fixed effects model

```r
# Some tests for serial correlation of errors (needed because we have a linear regression
# with lags of the dependent variable on the RHS
# the standard LM test (note we could specify order)
pbgtest(plm.res1)
```

```
##
##  Breusch-Godfrey/Wooldridge test for serial correlation in panel
##  models
##
## data:  packpc ~ income95pc + pretax95 + taxs95
## chisq = 129.6, df = 11, p-value < 2.2e-16
## alternative hypothesis: serial correlation in idiosyncratic errors
```

# Fixed effects model

```r
## Robust var-cov matrix alternatives for fixed effects models...
robust <- "None"   # Choose var-cov estimator here
if (robust=="None") vc <- vcov(plm.res1)
if (robust=="Arellano") vc <- vcovHC(plm.res1)
# Arellano (1987) heteroskedastic and serial correlation robust VC
if (robust=="BeckKatz") vc <- vcovBK(plm.res1)# Beck and Katz (1995) panel corrected VC
if (robust=="DriscollKraay") vc <- vcovSCC(plm.res1)# Driscoll and Kraay panel corrected VC

# Extract model results
pe.res1 <- coef(plm.res1) # Point estimates of parameters
vc.res1 <- vc   # Var-cov matrix of point estimates
se.res1 <- sqrt(diag(vc.res1))# std erros of point estimates
tstat.res1 <- abs(pe.res1/se.res1)# t-statistics
df.res1 <- rep(plm.res1$df.residual, length(tstat.res1))  # residual degrees of freedom
pval.res1 <- 2*pt(tstat.res1, df.res1, lower.tail=FALSE)  # p-values
fe.res1 <- fixef(plm.res1)# the (removed) fixed effects by group
resid.res1 <- resid(plm.res1)# Residuals
```

# Random effects model

```
# Estimate a random effects AR(I)MA(p,q) model using lme (Restricted ML)
lme.res1 <- lme(# A formula object including the response,
                # the fixed covariates, and any grouping variables
                fixed = packpc ~ income95pc + pretax95 + taxs95,
                # i.e. response variable and explanatory variables

                # The random effects component
                random = ~ 1 | state,
                # 1 indicates the intercept and state indicates the grouping

                # The TS dynamics: specify the time & group variables,
                # and the order of the ARMA(p,q) process
                correlation = corARMA(form = ~ year | state,
                                      p = 1,  # AR(p) order
                                      q = 0   # MA(q) order
                                      )
                )
```

# Random effects model

```
# Extract model results
pe.res1 <- fixed.effects(lme.res1)        # Point estimates of fixed effects
vc.res1 <- vcov(lme.res1)                 # Var-cov matrix of fixed effects estimates
se.res1 <- sqrt(diag(vc.res1))            # std erros of fixed effects estimates
re.res1 <- random.effects(lme.res1)       # "Estimated" random effects by group
ll.res1 <- logLik(lme.res1)               # Log-likelihood at maximum
resid.res1 <- resid(lme.res1)             # Residuals
aic.res1 <- AIC(lme.res1)                 # Akaike Information Criterion
```

# Random effects model

```r
summary(lme.res1)
```

```
## Linear mixed-effects model fit by REML
##  Data: NULL
##        AIC     BIC    logLik
##   3253.21 3283.04 -1619.605
##
## Random effects:
##  Formula: ~1 | state
##         (Intercept) Residual
## StdDev:  0.01127294 20.92621
##
## Correlation Structure: AR(1)
##  Formula: ~year | state
##  Parameter estimate(s):
##       Phi
## 0.9764735
## Fixed effects: packpc ~ income95pc + pretax95 + taxs95
##                 Value Std.Error  DF    t-value p-value
## (Intercept) 173.08136  8.574965 477  20.184499  0.0000
## income95pc   -1.05746  0.387602 477  -2.728198  0.0066
## pretax95     -0.14537  0.024800 477  -5.861684  0.0000
## taxs95       -0.46630  0.040769 477 -11.437827  0.0000
##  Correlation:
##            (Intr) incm95 prtx95
## income95pc -0.856
## pretax95   -0.099 -0.223
## taxs95     -0.160 -0.097 -0.035
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.79963472 -0.57137010 -0.08122771  0.45749547  3.97887775
##
## Number of Observations: 528
```

# Dynamic panel data models

```r
# Panel based diagnostics available in the plm library
# (This package recently expanded to contain many many panel data tests
#  for serial correlation, fixed effects, and unit roots)

# First, create a plm data frame (special data frame that "knows" the
# unit variable and time variable
pdata <- pdata.frame(data, index=c("state", "year"))
pdata[1:3,]
```

```
##         state year   cpi     pop   packpc   income  tax   avgprs     taxs
## AL-1985    AL 1985 1.076 3973000 116.4863 46014968 32.5 102.1817 33.34834
## AL-1986    AL 1986 1.096 3992000 117.1593 48703940 32.5 107.9892 33.40584
## AL-1987    AL 1987 1.136 4016000 115.8367 51846312 32.5 113.5273 33.46067
##         income95    tax95 avgprs95   taxs95 income95pc  pretax95
## AL-1985 65173615 46.03160 144.7257 47.23314   16.40413  97.49257
## AL-1986 67723361 45.19161 150.1601 46.45118   16.96477 103.70893
## AL-1987 69554378 43.60035 152.3025 44.88914   17.31932 107.41336
```

```r
# Do an panel unit root test on the undifferenced cigarette data;
# there are many options; see ?purtest

# Note:  for some reason this isn't working
#purtest(packpc~1, data=pdata, test="ips")
```

# Dynamic panel data models

```r
# Estimate Arellano-Bond GMM for fixed effects with lagged DV
#
# pgmm needs formulas in a specific format:
# 1. in the first part of the RHS, include lags of DV and covariates, as shown
# 2. in the second part, include the panel data instruments (99 here means use
#    up to the 99th lag of the difference as an instrument)
# 3. in an optional (not shown) third part of the RHS, include any other instruments
#
# note that pgmm formulas construct lag() properly for panel data,
# though lag() usually doesn't
pgmmformula.1a <- packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:99)

# We'll run GMM with only unit fixed effects,
# but we could include period fixed effects as well by setting effect to "two-way"
# (often a good practice in short T panels)
pgmm.res1a <- pgmm(pgmmformula.1a,
                   data = pdata,
                   effect = "individual",
                   # should consider two-way for small T
                   transformation = "d")
# should do ld if T=3, d for difference GNN and ld for system GMM
```

# Dynamic panel data models

```r
summary(pgmm.res1a)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.1a, data = pdata, effect = "individual",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -25.4300  -2.5080   0.1463   0.1238   2.7380  25.6000
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.638987   0.055342 11.5462 < 2.2e-16 ***
## income95pc     -0.475568   0.486760 -0.9770    0.3286
## avgprs95       -0.180791   0.027799 -6.5035 7.848e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(44) = 47.99763 (p.value=0.31401)
## Autocorrelation test (1): normal = -3.948861 (p.value=7.8524e-05)
## Autocorrelation test (2): normal = -0.5688819 (p.value=0.56944)
## Wald test for coefficients: chisq(3) = 2496.07 (p.value=< 2.22e-16)
```

# Dynamic panel data models

```
# Good Sargan test, Good AR(2) test
# (Sargan test has a null of the instruments as a group being exogenous)
# (The residuals of the differenced equations should exhibit AR(1) but not AR(2) behavior)


# Let's consider alternative sets of instruments; concern: distant lags are weak instruments
pgmmformula.1b <- packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:5)
pgmm.res1b <- pgmm(pgmmformula.1b,
                   data = pdata,
                   effect = "individual",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3
```

# Dynamic panel data models

```r
# Poor Sargan test, Good AR(2) test
summary(pgmm.res1b)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.1b, data = pdata, effect = "individual",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -25.6900  -2.5360   0.1483   0.1217   2.6740  25.5800
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.650350   0.055545 11.7086 < 2.2e-16 ***
## income95pc     -0.325994   0.497744 -0.6549    0.5125
## avgprs95       -0.181297   0.027242 -6.6550 2.834e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(29) = 42.46279 (p.value=0.050998)
## Autocorrelation test (1): normal = -3.907354 (p.value=9.3312e-05)
## Autocorrelation test (2): normal = -0.5460146 (p.value=0.58506)
## Wald test for coefficients: chisq(3) = 2503.149 (p.value=< 2.22e-16)
```

# Dynamic panel data models

```r
# Keeping just the most recent two instruments makes no substantive difference
pgmmformula.1c <- packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:3)
pgmm.res1c <- pgmm(pgmmformula.1c,
                   data = pdata,
                   effect = "individual",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3
```

# Dynamic panel data models

```r
# Poor Sargan test, Good AR(2) test
summary(pgmm.res1c)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.1c, data = pdata, effect = "individual",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -25.9200  -2.4790   0.1232   0.1159   2.7110  25.6000
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.660475   0.052854 12.4963 < 2.2e-16 ***
## income95pc     -0.258571   0.456052 -0.5670    0.5707
## avgprs95       -0.175368   0.026891 -6.5215  6.96e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(16) = 40.04482 (p.value=0.00076694)
## Autocorrelation test (1): normal = -3.831746 (p.value=0.00012724)
## Autocorrelation test (2): normal = -0.4941905 (p.value=0.62117)
## Wald test for coefficients: chisq(3) = 2405.391 (p.value=< 2.22e-16)
```

# Dynamic panel data models

```r
# Slight difference with one instrument, but not substatively noteworthy?
pgmmformula.1d <- packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2)
pgmm.res1d <- pgmm(pgmmformula.1d,
                   data = pdata,
                   effect = "individual",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3
```

# Dynamic panel data models

```r
# Poor Sargan test, Good AR(2) test
summary(pgmm.res1d)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.1d, data = pdata, effect = "individual",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -26.8300  -2.6300   0.2236   0.1076   2.6800  25.6300
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.700990   0.051462 13.6216 < 2.2e-16 ***
## income95pc      0.112174   0.447504  0.2507    0.8021
## avgprs95       -0.164193   0.027435 -5.9848 2.167e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(8) = 27.75947 (p.value=0.00052221)
## Autocorrelation test (1): normal = -3.658942 (p.value=0.00025326)
## Autocorrelation test (2): normal = -0.3566186 (p.value=0.72138)
## Wald test for coefficients: chisq(3) = 2723.818 (p.value=< 2.22e-16)
```

# Dynamic panel data models

```r
# Try system GMM with all lags
pgmm.res1e <- pgmm(pgmmformula.1a,
                   data = pdata,
                   effect = "individual",   # should consider two-way for small T
                   transformation = "ld")    # should do ld if T=3
```

# Dynamic panel data models

```r
# Good Sargan test, Good AR(2) test
summary(pgmm.res1e)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.1a, data = pdata, effect = "individual",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -35.0200  -2.5250   0.1318   0.2344   2.8280  29.0100
##
## Coefficients
##                   Estimate Std. Error z-value Pr(>|z|)
## lag(packpc, 1)  0.9372190  0.0149757 62.5826   <2e-16 ***
## income95pc      0.2033459  0.1245084  1.6332   0.1024
## avgprs95       -0.0021312  0.0098748 -0.2158   0.8291
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(55) = 47.79775 (p.value=0.74372)
## Autocorrelation test (1): normal = -3.451448 (p.value=0.00055759)
## Autocorrelation test (2): normal = 0.5944316 (p.value=0.55222)
## Wald test for coefficients: chisq(3) = 109661.9 (p.value=< 2.22e-16)
```

# Dynamic panel data models

```r
# Try system GMM with only recent lag
pgmm.res1f <- pgmm(pgmmformula.1d,
                   data = pdata,
                   effect = "individual",   # should consider two-way for small T
                   transformation = "ld")     # should do ld if T=3
```

# Dynamic panel data models

```r
# Poor Sargan test, Good AR(2) test
summary(pgmm.res1f)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.1d, data = pdata, effect = "individual",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -35.0100  -2.7770   0.1193   0.2195   2.8830  28.6200
##
## Coefficients
##                   Estimate  Std. Error z-value Pr(>|z|)
## lag(packpc, 1)  0.91605377  0.01475300 62.0927  < 2e-16 ***
## income95pc      0.29563062  0.14667917  2.0155  0.04385 *
## avgprs95       -0.00075664  0.01219834 -0.0620  0.95054
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(19) = 41.05134 (p.value=0.0023757)
## Autocorrelation test (1): normal = -3.490677 (p.value=0.0004818)
## Autocorrelation test (2): normal = 0.6062896 (p.value=0.54432)
## Wald test for coefficients: chisq(3) = 138138.9 (p.value=< 2.22e-16)
```

# Dynamic panel data models

```r
# Try difference GMM with two way effects
pgmm.res1g <- pgmm(pgmmformula.1a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3
```

# Dynamic panel data models

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res1g)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.1a, data = pdata, effect = "twoways",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -18.940  -1.890  -0.259   0.000   1.824  20.430
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.252415   0.117744  2.1438   0.03205 *
## income95pc      1.062384   0.674055  1.5761   0.11500
## avgprs95       -0.285703   0.060572 -4.7168 2.396e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(44) = 45.92782 (p.value=0.39225)
## Autocorrelation test (1): normal = -3.571843 (p.value=0.00035448)
## Autocorrelation test (2): normal = 0.02846648 (p.value=0.97729)
## Wald test for coefficients: chisq(3) = 35.6544 (p.value=8.8603e-08)
## Wald test for time dummies: chisq(9) = 70.99219 (p.value=9.7258e-12)
```

# Dynamic panel data models

```r
# Try system GMM with two way effects
pgmm.res1h <- pgmm(pgmmformula.1a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "ld")    # should do ld if T=3
```

# Dynamic panel data models

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res1h)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.1a, data = pdata, effect = "twoways",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -31.82000  -2.37500  -0.03745   0.00000   2.18300  27.94000
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.912506   0.035086 26.0074 < 2.2e-16 ***
## income95pc     -0.016144   0.110832 -0.1457  0.884186
## avgprs95       -0.101336   0.032190 -3.1481  0.001644 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(55) = 45.80834 (p.value=0.80677)
## Autocorrelation test (1): normal = -3.133862 (p.value=0.0017252)
## Autocorrelation test (2): normal = 0.7322591 (p.value=0.46401)
## Wald test for coefficients: chisq(3) = 2942.747 (p.value=< 2.22e-16)
## Wald test for time dummies: chisq(9) = 87.03407 (p.value=6.3969e-15)
```

# Dynamic panel data models

```
# Aside: Note that the year fixed effects estimates show a downward trend in smoking,
# but with large CIs

yrs <- coef(pgmm.res1g)[4:12]                       #Extract the year fixed effects from model 1g
yrs.se <- sqrt(diag(vcovHC(pgmm.res1g)))[4:12]  #Extract the standard errors of the year fe
yrsTrace <- scatter(x=1987:1995,                    #X values
                    y=yrs,                          #Y values
                    ylower=yrs-2*yrs.se,            #Upper bound of CI
                    yupper=yrs+2*yrs.se,            #Lower bound of CI
                    fit=list(method="wls", weights=1/yrs.se^2),
                    pch=1, size=.8,
                    plot=1
                    )

tile(yrsTrace,
     width = list(null=5),      # widen plot area for visibility
     output = list(file="yearEffectsModel1g", width=5.5),
     limits = c(1986.5,1995.5,-22,8),
     yaxis=list(major=FALSE),
     xaxistitle = list(labels="Year"),
     yaxistitle = list(labels="Estimated year effects (95% CI)"),
     height=list(plot="golden")
     )
```

# Dynamic panel data models

```r
####
# Now consider last two models with alternative specifications
pgmmformula.2a <- packpc ~ lag(packpc, 1) + income95pc + pretax95 +
  taxs95 | lag(packpc, 2:99)

pgmmformula.3a <- log(packpc) ~ lag(log(packpc), 1) + log(income95pc) +
  log(avgprs95) | lag(log(packpc), 2:99)

pgmmformula.4a <- log(packpc) ~ lag(log(packpc), 1) + log(income95pc) +
  log(pretax95) + log(taxs95) | lag(log(packpc), 2:99)
```

# Model 2: Unique tax effects

```
# Try difference GMM with two way effects
pgmm.res2g <- pgmm(pgmmformula.2a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3


# Try system GMM with two way effects
pgmm.res2h <- pgmm(pgmmformula.2a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "ld")    # should do ld if T=3
```

# Model 2: Unique tax effects

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res2g)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.2a, data = pdata, effect = "twoways",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -18.2600  -1.9650  -0.1188   0.0000   1.7690  20.1100
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.267324   0.119980  2.2281   0.02588 *
## income95pc      0.780413   0.692055  1.1277   0.25946
## pretax95       -0.027143   0.065641 -0.4135   0.67923
## taxs95         -0.407912   0.062596 -6.5166 7.192e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(44) = 46.51024 (p.value=0.36939)
## Autocorrelation test (1): normal = -3.467009 (p.value=0.00052628)
## Autocorrelation test (2): normal = 0.444432 (p.value=0.65673)
## Wald test for coefficients: chisq(4) = 63.13155 (p.value=6.3668e-13)
## Wald test for time dummies: chisq(9) = 100.6487 (p.value=< 2.22e-16)
```

# Model 2: Unique tax effects

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res2h)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.2a, data = pdata, effect = "twoways",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -31.81000  -2.33200  -0.06877   0.00000   2.15400  28.00000
##
## Coefficients
##                 Estimate Std. Error z-value  Pr(>|z|)
## lag(packpc, 1)  0.920875   0.032453 28.3758 < 2.2e-16 ***
## income95pc     -0.032675   0.104547 -0.3125  0.754629
## pretax95       -0.073863   0.034405 -2.1469  0.031803 *
## taxs95         -0.104354   0.036213 -2.8817  0.003956 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(56) = 48 (p.value=0.76774)
## Autocorrelation test (1): normal = -3.108691 (p.value=0.0018792)
## Autocorrelation test (2): normal = 0.7719112 (p.value=0.44017)
## Wald test for coefficients: chisq(4) = 3309.815 (p.value=< 2.22e-16)
## Wald test for time dummies: chisq(9) = 81.95308 (p.value=6.6084e-14)
```

# Model 3: Elasticity specification

```
# Try difference GMM with only unit fixed effects
pgmm.res3a <- pgmm(pgmmformula.3a,
                   data = pdata,
                   effect = "individual",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3


# Try system GMM with all lags
pgmm.res3e <- pgmm(pgmmformula.3a,
                  data = pdata,
                  effect = "individual",   # should consider two-way for small T
                  transformation = "ld")    # should do ld if T=3


# Try difference GMM with two way effects
pgmm.res3g <- pgmm(pgmmformula.3a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3


# Try system GMM with two way effects
pgmm.res3h <- pgmm(pgmmformula.3a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "ld")    # should do ld if T=3
```

# Model 3: Elasticity specification

```r
# Good Sargan test, Good AR(2) test
summary(pgmm.res3a)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.3a, data = pdata, effect = "individual",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.263000 -0.024090  0.002736  0.001092  0.027680  0.216400
##
## Coefficients
##                       Estimate Std. Error z-value  Pr(>|z|)
## lag(log(packpc), 1)  0.674051   0.061660 10.9317 < 2.2e-16 ***
## log(income95pc)     -0.066044   0.111880 -0.5903     0.555
## log(avgprs95)       -0.305656   0.043073 -7.0963 1.281e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(44) = 46.02872 (p.value=0.38824)
## Autocorrelation test (1): normal = -4.050332 (p.value=5.1145e-05)
## Autocorrelation test (2): normal = 0.05678179 (p.value=0.95472)
## Wald test for coefficients: chisq(3) = 2140.806 (p.value=< 2.22e-16)
```

# Model 3: Elasticity specification

```r
# Good Sargan test, Good AR(2) test
summary(pgmm.res3e)
```

```
## Oneway (individual) effect One step model
##
## Call:
## pgmm(formula = pgmmformula.3a, data = pdata, effect = "individual",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.366800 -0.022700  0.002000  0.001797  0.025150  0.278300
##
## Coefficients
##                       Estimate Std. Error  z-value Pr(>|z|)
## lag(log(packpc), 1)  0.9860119  0.0094198 104.6742   <2e-16 ***
## log(income95pc)     -0.0057655  0.0154370  -0.3735   0.7088
## log(avgprs95)        0.0110743  0.0077600   1.4271   0.1535
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(55) = 47.59902 (p.value=0.75038)
## Autocorrelation test (1): normal = -3.352045 (p.value=0.00080217)
## Autocorrelation test (2): normal = 0.982078 (p.value=0.32606)
## Wald test for coefficients: chisq(3) = 4737094 (p.value=< 2.22e-16)
```

# Model 3: Elasticity specification

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res3g)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.3a, data = pdata, effect = "twoways",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.181000 -0.019490 -0.001678  0.000000  0.017810  0.204300
##
## Coefficients
##                     Estimate Std. Error z-value  Pr(>|z|)
## lag(log(packpc), 1)  0.33315    0.14500  2.2976   0.02158 *
## log(income95pc)      0.18131    0.18166  0.9981   0.31825
## log(avgprs95)       -0.62271    0.11127 -5.5965 2.188e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(44) = 43.30027 (p.value=0.5015)
## Autocorrelation test (1): normal = -3.620058 (p.value=0.00029454)
## Autocorrelation test (2): normal = 0.5219654 (p.value=0.60169)
## Wald test for coefficients: chisq(3) = 45.27325 (p.value=8.0946e-10)
## Wald test for time dummies: chisq(9) = 71.0946 (p.value=9.2856e-12)
```

# Model 3: Elasticity specification

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res3h)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.3a, data = pdata, effect = "twoways",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
## -0.3422000 -0.0233100  0.0006081  0.0000000  0.0224300  0.2716000
##
## Coefficients
##                       Estimate Std. Error z-value  Pr(>|z|)
## lag(log(packpc), 1)  0.9454089  0.0286753 32.9694 < 2.2e-16 ***
## log(income95pc)     -0.0072777  0.0214627 -0.3391  0.734544
## log(avgprs95)       -0.1650673  0.0494761 -3.3363  0.000849 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(55) = 44.19932 (p.value=0.85117)
## Autocorrelation test (1): normal = -3.066312 (p.value=0.0021672)
## Autocorrelation test (2): normal = 1.1093 (p.value=0.2673)
## Wald test for coefficients: chisq(3) = 4820.892 (p.value=< 2.22e-16)
## Wald test for time dummies: chisq(9) = 90.44993 (p.value=1.3225e-15)
```

# Model 4: Elasticity specification, components of price

```r
# Try difference GMM with two way effects
pgmm.res4g <- pgmm(pgmmformula.4a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "d")    # should do ld if T=3

# Try system GMM with two way effects
pgmm.res4h <- pgmm(pgmmformula.4a,
                   data = pdata,
                   effect = "twoways",   # should consider two-way for small T
                   transformation = "ld")    # should do ld if T=3
```

# Model 4: Elasticity specification, components of price

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res4g)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.4a, data = pdata, effect = "twoways",
##     transformation = "d")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  432
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.159800 -0.019740 -0.001557  0.000000  0.018140  0.198300
##
## Coefficients
##                      Estimate Std. Error z-value  Pr(>|z|)
## lag(log(packpc), 1)  0.309885   0.135805  2.2818    0.0225 *
## log(income95pc)      0.160518   0.195323  0.8218    0.4112
## log(pretax95)       -0.086999   0.078535 -1.1078    0.2680
## log(taxs95)         -0.287494   0.045624 -6.3013 2.951e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(44) = 44.84174 (p.value=0.43636)
## Autocorrelation test (1): normal = -3.654349 (p.value=0.00025784)
## Autocorrelation test (2): normal = 1.083759 (p.value=0.27847)
## Wald test for coefficients: chisq(4) = 70.23767 (p.value=2.0222e-14)
## Wald test for time dummies: chisq(9) = 70.48873 (p.value=1.2211e-11)
```

# Model 4: Elasticity specification, components of price

```r
# Good Sargan test, Good AR(2) test, Wald supports 2-way
summary(pgmm.res4h)
```

```
## Twoways effects One step model
##
## Call:
## pgmm(formula = pgmmformula.4a, data = pdata, effect = "twoways",
##     transformation = "ld")
##
## Balanced Panel: n=48, T=11, N=528
##
## Number of Observations Used:  912
##
## Residuals
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.356300 -0.022980  0.000891  0.000000  0.022530  0.272700
##
## Coefficients
##                       Estimate Std. Error z-value  Pr(>|z|)
## lag(log(packpc), 1)  0.953854   0.025812 36.9544 < 2.2e-16 ***
## log(income95pc)     -0.013174   0.019295 -0.6828  0.494750
## log(pretax95)       -0.107924   0.040645 -2.6553  0.007925 **
## log(taxs95)         -0.042752   0.014618 -2.9246  0.003450 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sargan Test: chisq(56) = 46.48103 (p.value=0.81385)
## Autocorrelation test (1): normal = -3.05496 (p.value=0.0022509)
## Autocorrelation test (2): normal = 1.104899 (p.value=0.2692)
## Wald test for coefficients: chisq(4) = 5525 (p.value=< 2.22e-16)
## Wald test for time dummies: chisq(9) = 77.97589 (p.value=4.0745e-13)
```

# Simulate conditional forecasts

```
# Forecast for 3 years from 1996 to 1998
periods.out <- 3
sims <- 1000

# How big a change in price to simulate?
# How about "double" the average tax in the most recent year?
summary(pdata$taxs95[pdata$year==1995])
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   34.44   48.75   59.84   61.87   74.78  112.60
```

```
# The average (and median) tax is about 60 cents/pack
sd(pdata$taxs95[pdata$year==1995])
```

```
## [1] 18.47741
```

# Simulate conditional forecasts

```r
# A 60 cent increase would also be about 3 sd's,
# and raise the tax to a bit more than the max observed

# Other possibilities:
# (2) A 10 cent increase
# (3) Raise every state to the max observed for any state in 1995 (112.60 cents)


# Construct the year dummies
yearfe <- makeFEdummies(pdata$year)          # Construct the dummies for each year
yearfe <- yearfe[,3:ncol(yearfe)]            # Why drop first 2 col's?
yearlist <- unique(pdata$year)               # List all the years
yearlist <- yearlist[3:length(yearlist)]     # List the years less the first two
colnames(yearfe) <- paste0("y",yearlist)     # Create names for the year dummies

# Construct formulas -- without year dummies (1a)
formula.1a <- packpc ~ income95pc + avgprs95 -1         #with Income and Price as covariates

# Construct formulas -- without year dummies but with intercept (1e)
formula.1e <- packpc ~ income95pc + avgprs95
```

# Simulate conditional forecasts

```r
# Construct formulas -- with year dummies (1g)
formula <- "packpc ~ income95pc + avgprs95 -1"      #Initial formula with no intercept
datayearfe <- cbind(pdata,yearfe)                   #Combine pdata variables with the year dummies
datayearfe[1:5,]
```

```
##   state year   cpi     pop   packpc   income  tax   avgprs     taxs
## 1    AL 1985 1.076 3973000 116.4863 46014968 32.5 102.1817 33.34834
## 2    AL 1986 1.096 3992000 117.1593 48703940 32.5 107.9892 33.40584
## 3    AL 1987 1.136 4016000 115.8367 51846312 32.5 113.5273 33.46067
## 4    AL 1988 1.183 4024000 115.2584 55698852 32.5 120.0334 33.52509
## 5    AL 1989 1.240 4030000 109.2060 60044480 32.5 133.2560 33.65600
##   income95    tax95 avgprs95   taxs95 income95pc   pretax95 y1987 y1988
## 1 65173615 46.03160 144.7257 47.23314   16.40413  97.49257     0     0
## 2 67723361 45.19161 150.1601 46.45118   16.96477 103.70893     0     0
## 3 69554378 43.60035 152.3025 44.88914   17.31932 107.41336     1     0
## 4 71754049 41.86813 154.6331 43.18869   17.83152 111.44437     0     1
## 5 73796599 39.94355 163.7759 41.36431   18.31181 122.41162     0     0
##   y1989 y1990 y1991 y1992 y1993 y1994 y1995
## 1     0     0     0     0     0     0     0
## 2     0     0     0     0     0     0     0
## 3     0     0     0     0     0     0     0
## 4     0     0     0     0     0     0     0
## 5     1     0     0     0     0     0     0
```

# Simulate conditional forecasts

```
yearfenames <- NULL
for (i in 1:ncol(yearfe)) {
  formula <- paste0(formula,"+ y",yearlist[i]," ")          #Add the year dummies to the initial formula
  yearfenames <- c(yearfenames,paste0("y",yearlist[i]))     #Make a vector of names for the years
}
names(datayearfe) <- c(names(data),yearfenames)
formula.1g <- as.formula(formula)
formula.1g
```

```
## packpc ~ income95pc + avgprs95 - 1 + y1987 + y1988 + y1989 +
##     y1990 + y1991 + y1992 + y1993 + y1994 + y1995
```

```
# Construct formulas -- with year dummies and intercept (1h)
formula <- "packpc ~ income95pc + avgprs95"         #Initial formula without the year dummies
datayearfe <- cbind(pdata,yearfe)                   #Combine pdata variables with the year dummies

yearfenames <- NULL
for (i in 1:ncol(yearfe)) {
  formula <- paste0(formula,"+ y",yearlist[i]," ")  #Add the year dummies to the initial formula
  yearfenames <- c(yearfenames,paste0("y",yearlist[i])) #Make a vector of names for the years
}
names(datayearfe) <- c(names(data),yearfenames)
formula.1h <- as.formula(formula)

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])
```

# Forecast: Model 1a, $+60$

```
# Recall model 1a: packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:99)
# Difference GMM with state fixed effects

# Simulate parameters
simparam.1a <- mvrnorm(sims, coefficients(pgmm.res1a), vcovHC(pgmm.res1a))
#Sample parameters from an mvrnorm
simphis.1a <- simparam.1a[,1]
#Extract the simulated phis
simbetas.1a <- simparam.1a[,2:ncol(simparam.1a)]
#Extract the simulated betas

simphis.1a[1:2]
```

```
## [1] 0.6140859 0.6746660
```

```
simbetas.1a[1:2,]
```

```
##      income95pc   avgprs95
## [1,] -0.1351614 -0.2152776
## [2,] -0.3372169 -0.1391251
```

# Forecast: Model 1a, +60

```r
# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#

# Make matrix of hypothetical x's: covariates
xhyp.1a <- cfMake(formula.1a,datayearfe, periods.out)
#With mean packpc, income, and price for the forecast period

# pgmm uses covariates in differenced form
# so we want most of them to be 0 (no change)
# exceptions:
# (1) changes in covariates of interest
# (2) time dummies aren't differenced
xhyp.1a$x <- xhyp.1a$xpre <- 0*xhyp.1a$x
xhyp.1a <- cfChange(xhyp.1a, "avgprs95", x=60, scen=1)

# We can "ignore" the state fixed effects for now and add them later
# because model is total linear
```

# Forecast: Model 1a, +60

```
# Create baseline scenario
xbase.1a <- xhyp.1a
xbase.1a$x <- xbase.1a$xpre

# We need a lag of the price per pack
lagY.1a <- NULL # Hypothetical previous change in Y for simulation
for (i in 1:length(pgmm.res1a$model))       #For 1 to 48
    lagY.1a <- c(lagY.1a, as.data.frame(pgmm.res1a$model[[i]])["1995",]$packpc)
#Hypothetical change in packpc for each state in 1995
lagY.1a <- mean(lagY.1a, na.rm=TRUE)    #Find the mean of these hypothetical previous changes

# Hypothetical initial level of Y for simulation
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)    #The mean of packpc in 1995
```

# Forecast: Model 1a, +60

```
# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev1a <- ldvsimev(xhyp.1a,               # The matrix of hypothetical x's
                     simbetas.1a,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # NA indicates no constant!
                     phi=simphis.1a,            # estimated AR parameters; length must match lagY
                     lagY=lagY.1a,          # lags of y, most recent last
                     transform="diff",   # "log" to undo log transformation,
                                         # "diff" to under first differencing
                                         # "difflog" to do both
                     initialY=initialY   # for differenced models, the lag of the level of y
                     )
```

# Forecast: Model 1a, +60

```
# Simulate expected values of Y given no change in covariates
sim.base1a <- ldvsimev(xbase.1a,               # The matrix of hypothetical x's
                       simbetas.1a,           # The matrix of simulated betas
                       ci=0.95,            # Desired confidence interval
                       constant=NA,        # NA indicates no constant!
                       phi=simphis.1a,            # estimated AR parameters; length must match lagY
                       lagY=lagY.1a,          # lags of y, most recent last
                       transform="diff",   # "log" to undo log transformation,
                                         # "diff" to under first differencing
                                         # "difflog" to do both
                       initialY=initialY   # for differenced models, the lag of the level of y
                       )
```

# Forecast: Model 1a, +60

```
# Simulate first differences in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.fd1a <- ldvsimfd(xhyp.1a,           # The matrix of hypothetical x's
                     simbetas.1a,       # The matrix of simulated betas
                     ci=0.95,           # Desired confidence interval
                     constant=NA,       # Column containing the constant
                                        # set to NA for no constant
                     phi=simphis.1a,    # estimated AR parameters; length must match lagY
                     lagY=lagY.1a,      # lags of y, most recent last
                     transform="diff",  # Model is differenced
                     #initialY=initialY   # Redundant in this case (fd of linear differenced Y)
                     )
```

# Forecast: Model 1a, +60

```
# Compute revenue effects
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.1a <- lapply(sim.fd1a, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)
#Multiply change in consumption by mean tax revenues in 1995 and divide by 100 (for dollars)
revLost.1a
```

```
## $pe
##             [,1]
## [1,]  -6.702912
## [2,] -10.959510
## [3,] -13.682984
##
## $lower
##             [,1]
## [1,]  -8.822904
## [2,] -13.667745
## [3,] -16.684908
##
## $upper
##             [,1]
## [1,]  -4.547754
## [2,]  -7.836970
## [3,] -10.294249
##
## $se
##           [,1]
## [1,] 1.082076
## [2,] 1.507042
## [3,] 1.660285
```

# Forecast: Model 1a, +60

```r
# Added revenue from higher taxes on remaining consumption, dollars pc
# Sensitive to (implicit) consumption trend assumptions
revGain.1a <- lapply(sim.ev1a, function(x) 60*x/100)
#Multiply expected consumption by 60 cents and divide by 100 (for dollars)
revGain.1a
```

```
## $pe
##           [,1]
## [1,] 51.79673
## [2,] 47.99235
## [3,] 45.56206
##
## $lower
##           [,1]
## [1,] 49.69353
## [2,] 45.25954
## [3,] 42.49394
##
## $upper
##           [,1]
## [1,] 53.96984
## [2,] 51.11894
## [3,] 49.24636
##
## $se
##           [,1]
## [1,] 1.083658
## [2,] 1.530397
## [3,] 1.698681
```

# Forecast: Model 1a, +60

```r
# Net change in revenue, dollars pc
revNet.1a <- list(pe=revLost.1a$pe + revGain.1a$pe,
                  #Lost revenues from reduced consumption plus added revenues from higher taxes
                  lower=revLost.1a$lower + revGain.1a$lower,    #Lower bound
                  upper=revLost.1a$upper + revGain.1a$upper)    #Upper bound
revNet.1a
```

```
## $pe
##          [,1]
## [1,] 45.09382
## [2,] 37.03284
## [3,] 31.87908
##
## $lower
##          [,1]
## [1,] 40.87062
## [2,] 31.59179
## [3,] 25.80903
##
## $upper
##          [,1]
## [1,] 49.42209
## [2,] 43.28197
## [3,] 38.95211
```

# Forecast: Model 1a, +60

```
# Total change in state revenue, in millions of dollars
revNetState.1a <- lapply(revNet.1a, function(x) avgpop1995*x/1000000)
#Multiply state population by net change pc and divide by one million
revNetState.1a
```

```
## $pe
##          [,1]
## [1,] 244.6999
## [2,] 200.9573
## [3,] 172.9906
##
## $lower
##          [,1]
## [1,] 221.7829
## [2,] 171.4317
## [3,] 140.0517
##
## $upper
##          [,1]
## [1,] 268.1871
## [2,] 234.8680
## [3,] 211.3721
```

# Forecast: Model 1e, $+60$

```
# Recall model 1e: packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:99)
# System GMM with state fixed effects

# Simulate parameters
simparam.1e <- mvrnorm(sims, coefficients(pgmm.res1e), vcovHC(pgmm.res1e))
#Sample model parameters
simphis.1e <- simparam.1e[,1]
#Extract the phis
simbetas.1e <- simparam.1e[,2:ncol(simparam.1e)]
#Extract the betas

# System GMM does NOT difference the covariates

# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#

# Make matrix of hypothetical x's: covariates
xhyp.1e <- cfMake(formula.1a, datayearfe, periods.out)
#With mean packpc, income, and price for the forecast period

# system pgmm uses covariates in *level* form
# -> back to our usual use of simcf; note apply to all 3 periods!
xhyp.1e <- cfChange(xhyp.1e, "avgprs95", x=60 + mean(pdata$avgprs95), scen=1:3)
#Add 60 cents to the avg price per pack
```

# Forecast: Model 1e, $+60$

```r
# State fixed effects are not removed from the covariates,
# but from the instruments (so we can ignore them here)

# Create baseline scenario
xbase.1e <- xhyp.1e
xbase.1e$x <- xbase.1e$xpre

# We need a lag of the price per pack, now in levels
# But the code above to extract it from the pgmm object won't work!
lagY.1e <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)     #average packpc in 1995

# Hypothetical initial level of Y for simulation
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)    #average packpc in 1995
```

# Forecast: Model 1e, $+60$

# Forecast: Model 1e, +60

```
# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev1e <- ldvsimev(xhyp.1e,               # The matrix of hypothetical x's
                     simbetas.1e,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # NA indicates no constant!
                     phi=simphis.1e,            # estimated AR parameters; length must match lagY
                     lagY=lagY.1e,          # lags of y, most recent last
                     transform="none",   # NOTE: System GMM is not differenced!
                     initialY=initialY
                     )
```

# Forecast: Model 1e, +60

```
# Simulate expected values of Y given no change in covariates
sim.base1e <- ldvsimev(xbase.1e,               # The matrix of hypothetical x's
                       simbetas.1e,           # The matrix of simulated betas
                       ci=0.95,            # Desired confidence interval
                       constant=NA,        # NA indicates no constant!
                       phi=simphis.1e,            # estimated AR parameters; length must match lagY
                       lagY=lagY.1e,          # lags of y, most recent last
                       transform="none"   # NOTE: System GMM is not differenced!
                       )
```

# Forecast: Model 1e, $+60$

```
# Simulate first differences in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.fd1e <- ldvsimfd(xhyp.1e,           # The matrix of hypothetical x's
                     simbetas.1e,       # The matrix of simulated betas
                     ci=0.95,           # Desired confidence interval
                     constant=NA,       # Column containing the constant
                                        # set to NA for no constant
                     phi=simphis.1e,    # estimated AR parameters; length must match lagY
                     lagY=lagY.1e,      # lags of y, most recent last
                     transform="none"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 1e, $+60$

```
# Simulate relative risks in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.rr1e <- ldvsimrr(xhyp.1e,            # The matrix of hypothetical x's
                     simbetas.1e,        # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # Column containing the constant
                                         # set to NA for no constant
                     phi=simphis.1e,     # estimated AR parameters; length must match lagY
                     lagY=lagY.1e,       # lags of y, most recent last
                     transform="none"    # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 1e, +60

```r
# Compute revenue effects
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.1e <- lapply(sim.fd1e, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)
#Multiply change in consumption by mean tax revenues in 1995 and divide by 100 (for dollars)

# Added revenue from higher taxes on remaining consumption, dollars pc
# Sensitive to (implicit) consumption trend assumptions
revGain.1e <- lapply(sim.ev1e, function(x) 60*x/100)
#Multiply expected consumption by 60 cents and divide by 100 (for dollars)

# Net change in revenue, dollars pc
revNet.1e <- list(pe=revLost.1e$pe + revGain.1e$pe,
                  #Lost revenues from reduced consumption plus added revenues from higher taxes
                  lower=revLost.1e$lower + revGain.1e$lower,    #Lower bound
                  upper=revLost.1e$upper + revGain.1e$upper)    #Upper bound

# Total change in state revenue, in millions of dollars
revNetState.1e <- lapply(revNet.1e, function(x) avgpop1995*x/1000000)
#Multiply state population by net change pc and divide by one million
```

# Forecast: Model 1g, +60

```
# Recall model 1g: packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:99)
# Difference GMM with state and year fixed effects

# Simulate parameters
simparam.1g <- mvrnorm(sims, coefficients(pgmm.res1g), vcovHC(pgmm.res1g))      #Sample parameters
simphis.1g <- simparam.1g[,1]                                                    #Extract the phis
simbetas.1g <- simparam.1g[,2:ncol(simparam.1g)]                                 #Extract the betas

# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#
# Issues -- we need to somehow include the state and year FEs:
#           Let's set the state to be an "average" state in 1995,
#           and year to be like the last year (1995)

# Make matrix of hypothetical x's: covariates
xhyp.1g <- cfMake(formula.1g, datayearfe, periods.out)      #Including the year fixed effects

# pgmm uses covariates in differenced form
# so we want most of them to be 0 (no change)
# exceptions:
# (1) changes in covariates of interest
# (2) differenced time dummies require special care
xhyp.1g$x <- xhyp.1g$xpre <- 0*xhyp.1g$x
xhyp.1g <- cfChange(xhyp.1g, "avgprs95", x=60, scen=1)      #Assume tax is raised 60 cents in 1996
```

# Forecast: Model 1g, +60

```r
# We can "ignore" the state fixed effects for now and add them later
# because model is total linear
# Create baseline scenario
xbase.1g <- xhyp.1g
xbase.1g$x <- xbase.1g$xpre
xbase.1g
```

```
## $x
##   packpc income95pc avgprs95 y1987 y1988 y1989 y1990 y1991 y1992 y1993
## 1      0          0        0     0     0     0     0     0     0     0
## 2      0          0        0     0     0     0     0     0     0     0
## 3      0          0        0     0     0     0     0     0     0     0
##   y1994 y1995
## 1     0     0
## 2     0     0
## 3     0     0
##
## $xpre
##   packpc income95pc avgprs95 y1987 y1988 y1989 y1990 y1991 y1992 y1993
## 1      0          0        0     0     0     0     0     0     0     0
## 2      0          0        0     0     0     0     0     0     0     0
## 3      0          0        0     0     0     0     0     0     0     0
##   y1994 y1995
## 1     0     0
## 2     0     0
## 3     0     0
##
## $model
## packpc ~ income95pc + avgprs95 - 1 + y1987 + y1988 + y1989 +
##     y1990 + y1991 + y1992 + y1993 + y1994 + y1995
##
## attr(,"class")
## [1] "list"           "counterfactual"
```

# Forecast: Model 1g, +60

```
xhyp.1g
```

```
## $x
##   packpc income95pc avgprs95 y1987 y1988 y1989 y1990 y1991 y1992 y1993
## 1      0          0       60     0     0     0     0     0     0     0
## 2      0          0        0     0     0     0     0     0     0     0
## 3      0          0        0     0     0     0     0     0     0     0
##   y1994 y1995
## 1     0     0
## 2     0     0
## 3     0     0
##
## $xpre
##   packpc income95pc avgprs95 y1987 y1988 y1989 y1990 y1991 y1992 y1993
## 1      0          0        0     0     0     0     0     0     0     0
## 2      0          0        0     0     0     0     0     0     0     0
## 3      0          0        0     0     0     0     0     0     0     0
##   y1994 y1995
## 1     0     0
## 2     0     0
## 3     0     0
##
## $model
## packpc ~ income95pc + avgprs95 - 1 + y1987 + y1988 + y1989 +
##     y1990 + y1991 + y1992 + y1993 + y1994 + y1995
##
## attr(,"class")
## [1] "list"           "counterfactual"
```

# Forecast: Model 1g, +60

```
# We need a lag of the price per pack
lagY.1g <- NULL # Hypothetical previous change in Y for simulation

pgmm.res1g$model[1]
```

```
## $AL
##          packpc lag(packpc, 1)  income95pc   avgprs95
## 1987 -1.3226623      0.6730347 0.354547306   2.142378  1  0  0  0  0  0  0
## 1988 -0.5782090     -1.3226623 0.512205963   2.330570 -1  1  0  0  0  0  0
## 1989 -6.0524902     -0.5782090 0.480287962   9.142863  0 -1  1  0  0  0  0
## 1990  2.5389175     -6.0524902 0.148464583   3.489286  0  0 -1  1  0  0  0
## 1991 -4.7301254      2.5389175 0.042664143  13.691496  0  0  0 -1  1  0  0
## 1992 -0.1118164     -4.7301254 0.465548804  10.345649  0  0  0  0 -1  1  0
## 1993 -1.9451370     -0.1118164 0.006317597 -17.561808  0  0  0  0  0 -1  1
## 1994 -1.5314713     -1.9451370 0.419305971 -13.036122  0  0  0  0  0  0 -1
## 1995 -2.3408889     -1.5314713 0.288875052  -2.333091  0  0  0  0  0  0  0
##
## 1987  0 0
## 1988  0 0
## 1989  0 0
## 1990  0 0
## 1991  0 0
## 1992  0 0
## 1993  0 0
## 1994  1 0
## 1995 -1 1
```

# Forecast: Model 1g, +60

```r
for (i in 1:length(pgmm.res1g$model))
    lagY.1g <- c(lagY.1g, as.data.frame(pgmm.res1g$model[[i]])["1995",]$packpc)
#Store change in packpc 1995 for each state

lagY.1g <- mean(lagY.1g, na.rm=TRUE)
#Find the mean for all packpc changes in 1995

# Hypothetical initial level of Y for simulation
pdata$packpc[pdata$year==1995]
```

```
##   AL-1995   AR-1995   AZ-1995   CA-1995   CO-1995   CT-1995   DE-1995
## 101.08543 111.04297  71.95417  56.85931  82.58292  79.47219 124.46660
##   FL-1995   GA-1995   IA-1995   ID-1995   IL-1995   IN-1995   KS-1995
##  93.07455  97.47462  92.40160  74.84978  83.26508 134.25835  88.75344
##   KY-1995   LA-1995   MA-1995   MD-1995   ME-1995   MI-1995   MN-1995
## 172.64778 105.17613  76.62064  77.47355 102.46978  81.38825  82.94530
##   MO-1995   MS-1995   MT-1995   NC-1995   ND-1995   NE-1995   NH-1995
## 122.45028 105.58245  87.15957 121.53806  79.80697  87.27071 156.33675
##   NJ-1995   NM-1995   NV-1995   NY-1995   OH-1995   OK-1995   OR-1995
##  80.37137  64.66887  93.52612  70.81732 111.38010 108.68011  92.15575
##   PA-1995   RI-1995   SC-1995   SD-1995   TN-1995   TX-1995   UT-1995
##  95.64309  92.59980 108.08275  97.21923 122.32005  73.07931  49.27220
##   VA-1995   VT-1995   WA-1995   WI-1995   WV-1995   WY-1995
## 105.38687 122.33475  65.53092  92.46635 115.56883 112.23814
```

```r
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)
#Set the initial mean value of pack in 1995 across states
```

# Forecast: Model 1g, +60

```r
# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev1g <- ldvsimev(xhyp.1g,               # The matrix of hypothetical x's
                     simbetas.1g,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # NA indicates no constant!
                     phi=simphis.1g,            # estimated AR parameters; length must match lagY
                     lagY=lagY.1g,          # lags of y, most recent last
                     transform="diff",   # "log" to undo log transformation,
                                         # "diff" to under first differencing
                                         # "difflog" to do both
                     initialY=initialY   # for differenced models, the lag of the level of y
                     )
```

# Forecast: Model 1g, +60

```
# Simulate expected values of Y given no change in covariates
sim.base1g <- ldvsimev(xbase.1g,               # The matrix of hypothetical x's
                       simbetas.1g,           # The matrix of simulated betas
                       ci=0.95,            # Desired confidence interval
                       constant=NA,        # NA indicates no constant!
                       phi=simphis.1g,            # estimated AR parameters; length must match lagY
                       lagY=lagY.1g,          # lags of y, most recent last
                       transform="diff",   # "log" to undo log transformation,
                                         # "diff" to under first differencing
                                         # "difflog" to do both
                       initialY=initialY   # for differenced models, the lag of the level of y
                       )
```

# Forecast: Model 1g, +60

```
# Simulate first differences in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.fd1g <- ldvsimfd(xhyp.1g,           # The matrix of hypothetical x's
                     simbetas.1g,       # The matrix of simulated betas
                     ci=0.95,           # Desired confidence interval
                     constant=NA,       # Column containing the constant
                                        # set to NA for no constant
                     phi=simphis.1g,    # estimated AR parameters; length must match lagY
                     lagY=lagY.1g,      # lags of y, most recent last
                     transform="diff",  # Model is differenced
                     #initialY=initialY   # Redundant in this case (fd of linear differenced Y)
                     )
```

# Forecast: Model 1g, +60

```r
# Compute revenue effects
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.1g <- lapply(sim.fd1g, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)
#Multiply change in consumption by mean tax revenues in 1995 and divide by 100 (for dollars)

# Added revenue from higher taxes on remaining consumption, dollars pc
# Note this is sensitive to assumptions about consumption trends embodied by year effects
revGain.1g <- lapply(sim.ev1g, function(x) 60*x/100)
#Multiply expected consumption by 60 cents and divide by 100 (for dollars)

# Net change in revenue, dollars pc
revNet.1g <- list(pe=revLost.1g$pe + revGain.1g$pe,
                  #Lost revenues from reduced consumption plus added revenues from higher taxes
                  lower=revLost.1g$lower + revGain.1g$lower, #Lower bound
                  upper=revLost.1g$upper + revGain.1g$upper) #Upper bound

# Total change in state revenue, in millions of dollars
revNetState.1g <- lapply(revNet.1g, function(x) avgpop1995*x/1000000)
#Multiply state population by net change pc and divide by one million
```

# Forecast: Model 1h, +60

```
# Recall model 1h: packpc ~ lag(packpc, 1) + income95pc + avgprs95 | lag(packpc, 2:99)
# System GMM with state and year fixed effects

# Simulate parameters
simparam.1h <- mvrnorm(sims, coefficients(pgmm.res1h), vcovHC(pgmm.res1h))
#Sample parameters
simphis.1h <- simparam.1h[,1]
#Extract the phis
simbetas.1h <- simparam.1h[,2:ncol(simparam.1h)]
#Extract the betas

# System GMM does NOT difference the covariates
# -> with 2-way effects, the model has a constant,
# which pgmm() puts in an odd place
simbetas.1h <- cbind(simbetas.1h[,3], simbetas.1h[,-3])
# Move the constant to the front of the matrix!
```

# Forecast: Model 1g, +60

```r
# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#
# Issues -- we need to somehow include the state and year FEs:
#           Let's set the state to be an "average" state in 1995,
#           and year to be like the last year (1995)

# Make matrix of hypothetical x's: covariates
xhyp.1h <- cfMake(formula.1h, datayearfe, periods.out)
#Create hypothetical matrix with covariates at their mean

# system pgmm uses covariates in *level* form
# -> back to our usual use of simcf; note apply to all 3 periods!
xhyp.1h <- cfChange(xhyp.1h, "avgprs95", x=60 + mean(pdata$avgprs95), scen=1:3)
#Assume tax raises price by 60 cents
```

# Forecast: Model 1g, +60

```r
# The current trend seems to start in 1993; we will average over the
# the last three years of year effects:
xhyp.1h <- cfChange(xhyp.1h, "y1987", x=0, xpre=0, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1988", x=0, xpre=0, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1989", x=0, xpre=0, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1990", x=0, xpre=0, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1991", x=0, xpre=0, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1992", x=0, xpre=0, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1993", x=1/3, xpre=1/3, scen=1:3)
#Start the trend in 1993 averaged over last three years
xhyp.1h <- cfChange(xhyp.1h, "y1994", x=1/3, xpre=1/3, scen=1:3)
xhyp.1h <- cfChange(xhyp.1h, "y1995", x=1/3, xpre=1/3, scen=1:3)


# State fixed effects are not removed from the covariates,
# but from the instruments (so we can ignore them here)

# Create baseline scenario
xbase.1h <- xhyp.1h
xbase.1h$x <- xbase.1h$xpre

# We need a lag of the price per pack, now in levels
# But the code above to extract it from the pgmm object won't work!
lagY.1h <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)
#Find the mean of packpc in 1995 across all states

# Hypothetical initial level of Y for simulation
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)
#Find the mean of packpc in 1995 across all states
```

# Forecast: Model 1g, +60

```
# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev1h <- ldvsimev(xhyp.1h,               # The matrix of hypothetical x's
                     simbetas.1h,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=1,        # NOTE: System GMM has a constant!
                                         # You will need to note the column of the constant in simbetas
                     phi=simphis.1h,            # estimated AR parameters; length must match lagY
                     lagY=lagY.1h,          # lags of y, most recent last
                     transform="none"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 1g, +60

```
# Simulate expected values of Y given no change in covariates
sim.base1h <- ldvsimev(xbase.1h,               # The matrix of hypothetical x's
                       simbetas.1h,           # The matrix of simulated betas
                       ci=0.95,            # Desired confidence interval
                       constant=1,        # NOTE: System GMM has a constant!
                                         # You will need to note the column of the constant in simbetas
                       phi=simphis.1h,           # estimated AR parameters; length must match lagY
                       lagY=lagY.1h,          # lags of y, most recent last
                       transform="none"   # NOTE: System GMM is not differenced!
                       )
```

# Forecast: Model 1g, +60

```r
# Simulate first differences in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.fd1h <- ldvsimfd(xhyp.1h,             # The matrix of hypothetical x's
                     simbetas.1h,         # The matrix of simulated betas
                     ci=0.95,             # Desired confidence interval
                     constant=1,         # Column containing the constant
                                          # set to NA for no constant
                     phi=simphis.1h,      # estimated AR parameters; length must match lagY
                     lagY=lagY.1h,        # lags of y, most recent last
                     transform="none"    # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 1g, +60

```
# Simulate relative risks in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.rr1h <- ldvsimrr(xhyp.1h,           # The matrix of hypothetical x's
                     simbetas.1h,       # The matrix of simulated betas
                     ci=0.95,           # Desired confidence interval
                     constant=1,       # Column containing the constant
                                        # set to NA for no constant
                     phi=simphis.1h,    # estimated AR parameters; length must match lagY
                     lagY=lagY.1h,      # lags of y, most recent last
                     transform="none"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 1g, +60

```
# Compute revenue effects
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.1h <- lapply(sim.fd1h, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)

# Added revenue from higher taxes on remaining consumption, dollars pc
# Note this is sensitive to assumptions about consumption trends embodied by year effects
revGain.1h <- lapply(sim.ev1h, function(x) 60*x/100)

# Net change in revenue, dollars pc
revNet.1h <- list(pe=revLost.1h$pe + revGain.1h$pe,
                  lower=revLost.1h$lower + revGain.1h$lower,
                  upper=revLost.1h$upper + revGain.1h$upper)

# Total change in state revenue, in millions of dollars
revNetState.1h <- lapply(revNet.1h, function(x) avgpop1995*x/1000000)
```

# Forecast: Model 3a, +60

```r
# Recall model 3a: log(packpc) ~ lag(log(packpc), 1) + log(income95pc)
# + log(avgprs95) | lag(log(packpc), 2:99)
# log-log Difference GMM with state fixed effects

# Simulate parameters
simparam.3a <- mvrnorm(sims, coefficients(pgmm.res3a), vcovHC(pgmm.res3a))
simphis.3a <- simparam.3a[,1]
simbetas.3a <- simparam.3a[,2:ncol(simparam.3a)]

# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
# Make matrix of hypothetical x's: covariates
xhyp.3a <- cfMake(formula.1a, datayearfe, periods.out)

# pgmm uses covariates in differenced form
# so we want most of them to be 0 (no change)
# exceptions:
# (1) changes in covariates of interest
# (2) time dummies aren't differenced
xhyp.3a$x <- xhyp.3a$xpre <- 0*xhyp.3a$x

# Need log version of differenced key covariate (doubling tax in avg state)
meanPrice95 <- mean(pdata$avgprs95[pdata$year==1995], na.rm=TRUE)
#Find the mean of avgprs95 across all states
meanTaxs95 <- mean(pdata$taxs95[pdata$year==1995], na.rm=TRUE)
#Find the mean of taxs95 across all states

xhyp.3a <- cfChange(xhyp.3a, "avgprs95",
                    #Change avgprs95 to log difference in mean price
                    x=log(meanPrice95+meanTaxs95) - log(meanPrice95),
                    scen=1)
```

# Forecast: Model 3a, +60

```r
# We can "ignore" the state fixed effects for now and add them later
# because model is total linear

# Create baseline scenario
xbase.3a <- xhyp.3a
xbase.3a$x <- xbase.3a$xpre

# We need a lag of the price per pack
lagY.3a <- NULL # Hypothetical previous change in Y for simulation
for (i in 1:length(pgmm.res3a$model))
    lagY.3a <- c(lagY.3a, as.data.frame(pgmm.res3a$model[[i]])["1995",1])
#Find the change in packpc across all states
lagY.3a <- mean(lagY.3a, na.rm=TRUE)
#Compute the mean

# Hypothetical initial level of Y for simulation
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)


# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev3a <- ldvsimev(xhyp.3a,               # The matrix of hypothetical x's
                     simbetas.3a,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # NA indicates no constant!
                     phi=simphis.3a,            # estimated AR parameters; length must match lagY
                     lagY=lagY.3a,          # lags of y, most recent last
                     transform="difflog",   # "log" to undo log transformation,
                                         # "diff" to under first differencing
                                         # "difflog" to do both
                     initialY=initialY   # for differenced models, the lag of the level of y
                     )
```

# Forecast: Model 3a, +60

```r
# Simulate expected values of Y given no change in covariates
sim.base3a <- ldvsimev(xbase.3a,               # The matrix of hypothetical x's
                       simbetas.3a,           # The matrix of simulated betas
                       ci=0.95,            # Desired confidence interval
                       constant=NA,        # NA indicates no constant!
                       phi=simphis.3a,            # estimated AR parameters; length must match lagY
                       lagY=lagY.3a,          # lags of y, most recent last
                       transform="difflog",   # "log" to undo log transformation,
                                        # "diff" to under first differencing
                                         # "difflog" to do both
                       initialY=initialY   # for differenced models, the lag of the level of y
                       )
```

# Forecast: Model 3e, $+60$

```
# Recall model 3e: log(packpc) ~ lag(log(packpc), 1) + log(income95pc)
# + log(avgprs95) | lag(log(packpc), 2:99)
# log-log System GMM with state fixed effects

# Because system GMM is in levels, it is convenient to
# handle logging through the formula combined with simcf
formula.3e <- log(packpc) ~ log(income95pc) + log(avgprs95) -1

# Simulate parameters
simparam.3e <- mvrnorm(sims, coefficients(pgmm.res3e), vcovHC(pgmm.res3e))
simphis.3e <- simparam.3e[,1]
simbetas.3e <- simparam.3e[,2:ncol(simparam.3e)]

# System GMM does NOT difference the covariates

# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#
# Make matrix of hypothetical x's: covariates
xhyp.3e <- cfMake(formula.3e, datayearfe, periods.out)  #See log transformation in formula.3e

# system pgmm uses covariates in *level* form
# -> back to our usual use of simcf; note apply to all 3 periods!
xhyp.3e <- cfChange(xhyp.3e, "avgprs95", x=60 + mean(pdata$avgprs95), scen=1:3)
```

# Forecast: Model 3e, +60

```
# State fixed effects are not removed from the covariates,
# but from the instruments (so we can ignore them here)

# Create baseline scenario
xbase.3e <- xhyp.3e
xbase.3e$x <- xbase.3e$xpre

# We need a lag of the price per pack, now in logged levels
# But the code above to extract it from the pgmm object won't work!
# Getting this right is crucial
lagY.3e <- log(mean(pdata$packpc[pdata$year==1995], na.rm=TRUE))

# Hypothetical initial level of Y for simulation
# Still in linear levels
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)
```

# Forecast: Model 3e, +60

```r
# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev3e <- ldvsimev(xhyp.3e,               # The matrix of hypothetical x's
                     simbetas.3e,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # NA indicates no constant!
                     phi=simphis.3e,            # estimated AR parameters; length must match lagY
                     lagY=lagY.3e,          # lags of y, most recent last
                     transform="log"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3e, $+60$

```r
# Simulate expected values of Y given no change in covariates
sim.base3e <- ldvsimev(xbase.3e,               # The matrix of hypothetical x's
                     simbetas.3e,           # The matrix of simulated betas
                     ci=0.95,             # Desired confidence interval
                     constant=NA,         # NA indicates no constant!
                     phi=simphis.3e,            # estimated AR parameters; length must match lagY
                     lagY=lagY.3e,          # lags of y, most recent last
                     transform="log",   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3e, $+60$

```
# Simulate first differences in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.fd3e <- ldvsimfd(xhyp.3e,             # The matrix of hypothetical x's
                     simbetas.3e,         # The matrix of simulated betas
                     ci=0.95,             # Desired confidence interval
                     constant=NA,         # Column containing the constant
                                          # set to NA for no constant
                     phi=simphis.3e,      # estimated AR parameters; length must match lagY
                     lagY=lagY.3e,        # lags of y, most recent last
                     transform="log"      # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3e, +60

```
# Simulate relative risks in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.rr3e <- ldvsimrr(xhyp.3e,            # The matrix of hypothetical x's
                     simbetas.3e,        # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # Column containing the constant
                                         # set to NA for no constant
                     phi=simphis.3e,     # estimated AR parameters; length must match lagY
                     lagY=lagY.3e,       # lags of y, most recent last
                     transform="log"     # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3e, +60

```
# Compute revenue effects
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.3e <- lapply(sim.fd3e, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)

# Added revenue from higher taxes on remaining consumption, dollars pc
# Sensitive to (implicit) consumption trend assumptions
revGain.3e <- lapply(sim.ev3e, function(x) 60*x/100)

# Net change in revenue, dollars pc
revNet.3e <- list(pe=revLost.3e$pe + revGain.3e$pe,
                  lower=revLost.3e$lower + revGain.3e$lower,
                  upper=revLost.3e$upper + revGain.3e$upper)

# Total change in state revenue, in millions of dollars
revNetState.3e <- lapply(revNet.3e, function(x) avgpop1995*x/1000000)
```

# Forecast: Model 3g, +60

```
# Recall model 3g: log(packpc) ~ lag(log(packpc), 1) + log(income95pc)
#+ log(avgprs95) | lag(log(packpc), 2:99)
# log log Difference GMM with state and year fixed effects

simparam.3g <- mvrnorm(sims, coefficients(pgmm.res3g), vcovHC(pgmm.res3g))
simphis.3g <- simparam.3g[,1]
simbetas.3g <- simparam.3g[,2:ncol(simparam.3g)]

# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#
# Issues -- we need to somehow include the state and year FEs:
#           Let's set the state to be an "average" state in 1995,
#           and year to be like the last year (1995)

# Make matrix of hypothetical x's: covariates
# Still use the 1g formula (no logs) -- we will handle logging manually
#  to get the differences of logs right
xhyp.3g <- cfMake(formula.1g, datayearfe, periods.out)
```

# Forecast: Model 3g, +60

```
# pgmm uses covariates in differenced form
# so we want most of them to be 0 (no change)
# exceptions:
# (1) changes in covariates of interest
# (2) time dummies aren't differenced
xhyp.3g$x <- xhyp.3g$xpre <- 0*xhyp.3g$x

# Need log version of differenced key covariate (doubling tax in avg state)
meanPrice95 <- mean(pdata$avgprs95[pdata$year==1995], na.rm=TRUE)
meanTaxs95 <- mean(pdata$taxs95[pdata$year==1995], na.rm=TRUE)

xhyp.3g <- cfChange(xhyp.3g, "avgprs95",
                    x=log(meanPrice95+meanTaxs95) - log(meanPrice95),
                    scen=1)

xhyp.3g <- cfChange(xhyp.3g, "y1995", x=1, xpre=1, scen=1:3)
```

# Forecast: Model 3g, +60

```
# We can "ignore" the state fixed effects for now and add them later
# because model is total linear

# Create baseline scenario
xbase.3g <- xhyp.3g
xbase.3g$x <- xbase.3g$xpre

# We need a lag of the price per pack
lagY.3g <- NULL # Hypothetical previous change in Y for simulation
for (i in 1:length(pgmm.res3g$model))
    lagY.3g <- c(lagY.3g, as.data.frame(pgmm.res3g$model[[i]])["1995",1])
lagY.3g <- mean(lagY.3g, na.rm=TRUE)


initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)
               # Hypothetical initial level of Y for simulation
```

# Forecast: Model 3g, +60

```
# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev3g <- ldvsimev(xhyp.3g,               # The matrix of hypothetical x's
                     simbetas.3g,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=NA,        # NA indicates no constant!
                     phi=simphis.3g,            # estimated AR parameters; length must match lagY
                     lagY=lagY.3g,          # lags of y, most recent last
                     transform="difflog",   # "log" to undo log transformation,
                                         # "diff" to under first differencing
                                         # "difflog" to do both
                     initialY=initialY   # for differenced models, the lag of the level of y
                     )
```

# Forecast: Model 3g, +60

```
# Simulate expected values of Y given no change in covariates
sim.base3g <- ldvsimev(xbase.3g,               # The matrix of hypothetical x's
                       simbetas.3g,           # The matrix of simulated betas
                       ci=0.95,            # Desired confidence interval
                       constant=NA,        # NA indicates no constant!
                       phi=simphis.3g,            # estimated AR parameters; length must match lagY
                       lagY=lagY.3g,          # lags of y, most recent last
                       transform="difflog",   # "log" to undo log transformation,
                                        # "diff" to under first differencing
                                        # "difflog" to do both
                       initialY=initialY   # for differenced models, the lag of the level of y
                       )
```

# Forecast: Model 3g, +60

```
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.3g <- lapply(sim.fd1g, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)

# Added revenue from higher taxes on remaining consumption, dollars pc
# Note this is sensitive to assumptions about consumption trends embodied by year effects
revGain.3g <- lapply(sim.ev1g, function(x) 60*x/100)

# Net change in revenue, dollars pc
revNet.3g <- list(pe=revLost.3g$pe + revGain.3g$pe,
                  lower=revLost.3g$lower + revGain.3g$lower,
                  upper=revLost.3g$upper + revGain.3g$upper)

# Total change in state revenue, in millions of dollars
revNetState.3g <- lapply(revNet.3g, function(x) avgpop1995*x/1000000)
```

# Forecast: Model 3h, +60

```
# Recall model 3h: log(packpc) ~ lag(log(packpc), 1) + log(income95pc)
# + log(avgprs95) | lag(log(packpc), 2:99)
# log log System GMM with state and year fixed effects

# Because system GMM is in levels, it is convenient to
# handle logging through the formula combined with simcf
formula <- "log(packpc) ~ log(income95pc) + log(avgprs95)"
datayearfe <- cbind(pdata,yearfe)
yearfenames <- NULL                                         #Create an empty vector of the year names
for (i in 1:ncol(yearfe)) {
  formula <- paste0(formula,"+ y",yearlist[i]," ")          #Add year names to formula
  yearfenames <- c(yearfenames,paste0("y",yearlist[i]))
}
names(datayearfe) <- c(names(data),yearfenames)             #Add year names to datayearfe

formula.3h <- as.formula(formula)

# Simulate parameters
simparam.3h <- mvrnorm(sims, coefficients(pgmm.res3h), vcovHC(pgmm.res3h))
simphis.3h <- simparam.3h[,1]
simbetas.3h <- simparam.3h[,2:ncol(simparam.3h)]

# System GMM does NOT difference the covariates
# -> the model has a constant, which pgmm() puts in an odd place
# Move the constant to the front of the matrix!
simbetas.3h <- cbind(simbetas.3h[,3], simbetas.3h[,-3])
```

# Forecast: Model 3h, +60

```
# Make matrix of hypothetical x's:
# Assume an average state raised taxes 60 cents starting 1996
#
# Issues -- we need to somehow include the state and year FEs:
#           Let's set the state to be an "average" state in 1995,
#           and year to be like the last year (1995)

# Make matrix of hypothetical x's: covariates
xhyp.3h <- cfMake(formula.3h, datayearfe, periods.out)


# system pgmm uses covariates in *level* form
# -> back to our usual use of simcf; let simcf handle logging here
xhyp.3h <- cfChange(xhyp.3h, "avgprs95", x=60 + mean(pdata$avgprs95), scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1987", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1988", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1989", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1990", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1991", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1992", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1993", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1994", x=0, xpre=0, scen=1:3)
xhyp.3h <- cfChange(xhyp.3h, "y1995", x=1, xpre=1, scen=1:3)

# State fixed effects are not removed from the covariates,
# but from the instruments (so we can ignore them here)
```

# Forecast: Model 3h, +60

```
# Create baseline scenario
xbase.3h <- xhyp.3h
xbase.3h$x <- xbase.3h$xpre

# We need a lag of the price per pack, now in logged levels
# But the code above to extract it from the pgmm object won't work!
# Getting this right is crucial
lagY.3h <- log(mean(pdata$packpc[pdata$year==1995], na.rm=TRUE))

# Hypothetical initial level of Y for simulation
# Still in linear levels
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)

# Simulate expected values of Y (on original level scale)
# out to periods.out given hypothetical future values of X,
# initial lags of the change in Y, and an initial level of Y
sim.ev3h <- ldvsimev(xhyp.3h,               # The matrix of hypothetical x's
                     simbetas.3h,           # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=1,        # NOTE: System GMM with two-way effects has a constant!
                                         # You will need to note the column of the constant in simbetas
                     phi=simphis.3h,            # estimated AR parameters; length must match lagY
                     lagY=lagY.3h,          # lags of y, most recent last
                     transform="log"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3h, +60

```
# Simulate expected values of Y given no change in covariates
sim.base3h <- ldvsimev(xbase.3h,               # The matrix of hypothetical x's
                       simbetas.3h,           # The matrix of simulated betas
                       ci=0.95,             # Desired confidence interval
                       constant=1,        # NOTE: System GMM with two-way effects has a constant!
                                        # You will need to note the column of the constant in simbetas
                       phi=simphis.3h,            # estimated AR parameters; length must match lagY
                       lagY=lagY.3h,          # lags of y, most recent last
                       transform="log"   # NOTE: System GMM is not differenced!
                       )
```

# Forecast: Model 3h, +60

```
# Simulate first differences in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.fd3h <- ldvsimfd(xhyp.3h,           # The matrix of hypothetical x's
                     simbetas.3h,        # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=1,        # Column containing the constant
                                         # set to NA for no constant
                     phi=simphis.3h,     # estimated AR parameters; length must match lagY
                     lagY=lagY.3h,       # lags of y, most recent last
                     transform="log"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3h, +60

```r
# Simulate relative risks in y
# out to periods.out given hypothetical future values of x, xpre,
# and initial lags of the change in y
sim.rr3h <- ldvsimrr(xhyp.3h,           # The matrix of hypothetical x's
                     simbetas.3h,        # The matrix of simulated betas
                     ci=0.95,            # Desired confidence interval
                     constant=1,        # Column containing the constant
                                         # set to NA for no constant
                     phi=simphis.3h,     # estimated AR parameters; length must match lagY
                     lagY=lagY.3h,       # lags of y, most recent last
                     transform="log"   # NOTE: System GMM is not differenced!
                     )
```

# Forecast: Model 3h, +60

```r
# Compute revenue effects
# Below is a rough attempt; it would be better to directly simulate these quantities
# It would also be better to wrap this in a function, to avoid typos in copy.paste.edit

# Population in 1995 in average state
avgpop1995 <- mean(pdata$pop[pdata$year==1995])

# Lost revenues from reduced consumption, dollars pc
revLost.3h <- lapply(sim.fd3h, function(x) mean(pdata$taxs95[pdata$year==1995])*x/100)

# Added revenue from higher taxes on remaining consumption, dollars pc
# Note this is sensitive to assumptions about consumption trends embodied by year effects
revGain.3h <- lapply(sim.ev3h, function(x) 60*x/100)

# Net change in revenue, dollars pc
revNet.3h <- list(pe=revLost.3h$pe + revGain.3h$pe,
                  lower=revLost.3h$lower + revGain.3h$lower,
                  upper=revLost.3h$upper + revGain.3h$upper)

# Total change in state revenue, in millions of dollars
revNetState.3h <- lapply(revNet.3h, function(x) avgpop1995*x/1000000)


# Make plots of expected values, first differences, and percent changes
# using custom tile code in helperCigs.R

# Hypothetical initial level of Y for simulation
initialY <- mean(pdata$packpc[pdata$year==1995], na.rm=TRUE)
```