wooldridge-vignette

Justin M Shea

Contents

Introduction

This vignette contains examples from every chapter of *Introductory Econometrics: A Modern Approach* by Jeffrey M. Wooldridge. Each example illustrates how to load data, build econometric models, and compute estimates with **R**.

Economics students new to both econometrics and **R** may find the introduction to both a bit challenging. In particular, the process of loading and preparing data prior to building one's first econometric model can present challenges. The `wooldridge` data package aims to lighten this task. It contains 105 data sets from *Introductory Econometrics: A Modern Approach*, and will load any set by typing its name into the `data()` function.

While the course companion site also provides publicly available data sets for Eviews, Excel, MiniTab, and Stata commercial software, **R** is the open source option. Furthermore, using **R** while building a foundation in econometrics, can become the first step in a student's longer journey toward using the most innovative new methods in statistical computing for handling larger, more modern data sets.

In addition, please visit the **Appendix** for sources on using R for econometrics. For example, an excellent reference is *"Using R for Introductory Econometrics"* by Florian Hess, written to compliment *Introductory Econometrics: A Modern Approach*. The full text can be viewed on the book website.

Now, load the `wooldridge` package and lets get started.

```
library(wooldridge)
```

Chapter 2: The Simple Regression Model

`Example 2.10`: A Log Wage Equation

$$\widehat{log(wage)} = \beta_0 + \beta_1 educ$$

Load the `wage1` data.

```r
data(wage1)
```

Estimate a linear relationship between the *log of wage* and *education*.

```r
log_wage_model <- lm(lwage ~ educ, data = wage1)
```

Print the results. I'm using the `stargazer` package to print the model results in a clean and easy to read format. See the bibliography for more information.

```r
stargazer(log_wage_model, single.row = TRUE, header = FALSE)
```

Table 1:

	Dependent variable:
	lwage
educ	0.083*** (0.008)
Constant	0.584*** (0.097)
Observations	526
R^2	0.186
Adjusted R^2	0.184
Residual Std. Error	0.480 (df = 524)
F Statistic	119.582*** (df = 1; 524)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 3: Multiple Regression Analysis: Estimation

`Example 3.2`: Hourly Wage Equation

$$\widehat{log(wage)} = \beta_0 + \beta_1 educ + \beta_3 exper + \beta_4 tenure$$

Estimate the model regressing *education*, *experience*, and *tenure* against *log(wage)*.

```
hourly_wage_model <- lm(lwage ~ educ + exper + tenure, data = wage1)
```

Print the estimated model coefficients:

```
stargazer(hourly_wage_model,  single.row = TRUE, header = FALSE)
```

Table 2:

	Dependent variable:
	lwage
educ	0.092*** (0.007)
exper	0.004** (0.002)
tenure	0.022*** (0.003)
Constant	0.284*** (0.104)
Observations	526
R^2	0.316
Adjusted R^2	0.312
Residual Std. Error	0.441 (df = 522)
F Statistic	80.391*** (df = 3; 522)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 4: Multiple Regression Analysis: Inference

Example 4.7 Effect of Job Training on Firm Scrap Rates

Load the `jtrain` data set and if you are using R Studio, `View` the data set.

```
data("jtrain")
```

```
View(jtrain)
```

Create a logical index, identifying which observations occur in 1987 and are non-union.

```
index <- jtrain$year == 1987 & jtrain$union == 0
```

Next, subset the jtrain data by the new index. This returns a data.frame of `jtrain` data of non-union firms for the year 1987.

```
jtrain_1987_nonunion <- jtrain[index, ]
```

Now create the linear model regressing `hrsemp`(total hours training/total employees trained), the `lsales`(log of annual sales), and `lemploy`(the log of the number of the employees), against `lscrap`(the log of the scrape rate).

$$lscrap = \alpha + \beta_1 hrsemp + \beta_2 lsales + \beta_3 lemploy$$

```
linear_model <- lm(lscrap ~ hrsemp + lsales + lemploy, data = jtrain_1987_nonunion)
```

Finally, print the complete summary statistic diagnostics of the model.

```
stargazer(linear_model,  single.row = TRUE, header = FALSE)
```

Table 3:

	Dependent variable:
	lscrap
hrsemp	−0.029 (0.023)
lsales	−0.962** (0.453)
lemploy	0.761* (0.407)
Constant	12.458** (5.687)
Observations	29
R^2	0.262
Adjusted R^2	0.174
Residual Std. Error	1.376 (df = 25)
F Statistic	2.965* (df = 3; 25)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 5: Multiple Regression Analysis: OLS Asymptotics

Example 5.3: Economic Model of Crime

$$narr86 = \beta_0 + \beta_1 pcnv + \beta_2 avgsen + \beta_3 tottime + \beta_4 ptime86 + \beta_5 qemp86 + \mu$$

$narr86$: number of times arrested, 1986.

$pcnv$: proportion of prior arrests leading to convictions.

$avgsen$: average sentence served, length in months.

$tottime$: time in prison since reaching the age of 18, length in months.

$ptime86$: months in prison during 1986.

$qemp86$: quarters employed, 1986.

Load the `crime1` data set.

```
data(crime1)
```

Estimate the model.

```
restricted_model <- lm(narr86 ~ pcnv + ptime86 + qemp86, data = crime1)
```

Create a new variable `restricted_model_u` containing the residuals $\tilde{\mu}$ from the above regression.

```
restricted_model_u <- restricted_model$residuals
```

Next, regress `pcnv`, `ptime86`, `qemp86`, `avgsen`, and `tottime`, against the residuals $\tilde{\mu}$ saved in `restricted_model_u`.

$$\tilde{\mu} = \beta_1 pcnv + \beta_2 avgsen + \beta_3 tottime + \beta_4 ptime86 + \beta_5 qemp86$$

```
LM_u_model <- lm(restricted_model_u ~ pcnv + ptime86 + qemp86 + avgsen + tottime,
    data = crime1)

summary(LM_u_model)$r.square
```

```
## [1] 0.001493846
```

$$LM = 2,725(0.0015)$$

```
LM_test <- nobs(LM_u_model) * 0.0015

LM_test
```

```
## [1] 4.0875
```

```
qchisq(1 - 0.10, 2)
```

```
## [1] 4.60517
```

The p-value is:

$$P(X_2^2 > 4.09) \approx 0.129$$

```
1-pchisq(LM_test, 2)
```

```
## [1] 0.129542
```

Chapter 6: Multiple Regression: Further Issues

`Example 6.1`: Effects of Pollution on Housing Prices, standardized.

$$price = \beta_0 + \beta_1 nox + \beta_2 crime + \beta_3 rooms + \beta_4 dist + \beta_5 stratio + \mu$$

price: median housing price.

nox: Nitrous Oxide concentration; parts per million.

crime: number of reported crimes per capita.

rooms: average number of rooms in houses in the community.

dist: weighted distance of the community to 5 employment centers.

stratio: average student-teacher ratio of schools in the community.

$$\widehat{zprice} = \beta_1 znox + \beta_2 zcrime + \beta_3 zrooms + \beta_4 zdist + \beta_5 zstratio$$

Load the `hrpice2` data.

```
data(hrpice2)
```

```
## Warning in data(hrpice2): data set 'hrpice2' not found
```

Estimate the coefficient with the usual `lm` regression model but this time, standardized coefficients by wrapping each variable with R's `scale` function:

```
housing_standard <- lm(scale(price) ~ 0 + scale(nox) + scale(crime) + scale(rooms) +
    scale(dist) + scale(stratio), data = hprice2)
```

```
stargazer(housing_standard,  single.row = TRUE, header = FALSE)
```

Table 4:

	Dependent variable:
	scale(price)
scale(nox)	−0.340*** (0.044)
scale(crime)	−0.143*** (0.031)
scale(rooms)	0.514*** (0.030)
scale(dist)	−0.235*** (0.043)
scale(stratio)	−0.270*** (0.030)
Observations	506
R^2	0.636
Adjusted R^2	0.632
Residual Std. Error	0.606 (df = 501)
F Statistic	174.822*** (df = 5; 501)
Note:	*p<0.1; **p<0.05; ***p<0.01

`Example 6.2`: Effects of Pollution on Housing Prices, Quadratic Interactive Term

Modify the housing model, adding a quadratic term in *rooms*:

$$log(price) = \beta_0 + \beta_1 log(nox) + \beta_2 log(dist) + \beta_3 rooms + \beta_4 rooms^2 + \beta_5 stratio + \mu$$

```r
housing_interactive <- lm(lprice ~ lnox + log(dist) + rooms+I(rooms^2) + stratio, data = hprice2)
```

Compare the results with the model from `example 6.1`.

```r
stargazer(housing_standard, housing_interactive, single.row = TRUE, header = FALSE)
```

Table 5:

	Dependent variable:	
	scale(price)	lprice
	(1)	(2)
scale(nox)	-0.340^{***} (0.044)	
scale(crime)	-0.143^{***} (0.031)	
scale(rooms)	0.514^{***} (0.030)	
scale(dist)	-0.235^{***} (0.043)	
scale(stratio)	-0.270^{***} (0.030)	
lnox		-0.902^{***} (0.115)
log(dist)		-0.087^{**} (0.043)
rooms		-0.545^{***} (0.165)
I(rooms^2)		0.062^{***} (0.013)
stratio		-0.048^{***} (0.006)
Constant		13.385^{***} (0.566)
Observations	506	506
R^2	0.636	0.603
Adjusted R^2	0.632	0.599
Residual Std. Error	0.606 (df = 501)	0.259 (df = 500)
F Statistic	174.822^{***} (df = 5; 501)	151.770^{***} (df = 5; 500)
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 7: Multiple Regression Analysis with Qualitative Information

`Example 7.4`: Housing Price Regression, Qualitative Binary variable

This time, use the `hrpice1` data.

```
data(hrpice1)
```

If you recently worked with `hrpice2`, it may be helpful to view the documentation on this data set and read the variable names.

```
?hprice1
```

$$\widehat{log(price)} = \beta_0 + \beta_1 log(lotsize) + \beta_2 log(sqrft) + \beta_3 bdrms + \beta_4 colonial$$

Estimate the coefficients of the above linear model on the `hprice` data set.

```
housing_qualitative <- lm(lprice ~ llotsize + lsqrft + bdrms + colonial, data = hprice1)
```

```
stargazer(housing_qualitative, single.row = TRUE, header = FALSE)
```

Table 6:

	Dependent variable:
	lprice
llotsize	0.168*** (0.038)
lsqrft	0.707*** (0.093)
bdrms	0.027 (0.029)
colonial	0.054 (0.045)
Constant	−1.350** (0.651)
Observations	88
R^2	0.649
Adjusted R^2	0.632
Residual Std. Error	0.184 (df = 83)
F Statistic	38.378*** (df = 4; 83)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 8: Heteroskedasticity

`Example 8.9`: Determinants of Personal Computer Ownership

$$\widehat{PC} = \beta_0 + \beta_1 hsGPA + \beta_2 ACT + \beta_3 parcoll + \beta_4 colonial$$

Load `gpa1` and create a new variable combining the `fathcoll` and `mothcoll`, into `parcoll`. This new column indicates if either parent went to college.

```
data("gpa1")

gpa1$parcoll <- as.integer(gpa1$fathcoll==1 | gpa1$mothcoll)
```

```
GPA_OLS <- lm(PC ~ hsGPA + ACT + parcoll, data = gpa1)
```

Calculate the weights and then pass them to the `weights` argument.

```
weights <- GPA_OLS$fitted.values * (1-GPA_OLS$fitted.values)

GPA_WLS <- lm(PC ~ hsGPA + ACT + parcoll, data = gpa1, weights = 1/weights)
```

Compare the OLS and WLS model in the table below:

```
stargazer(GPA_OLS, GPA_WLS, single.row = TRUE, header = FALSE)
```

Table 7:

	Dependent variable:	
	PC	
	(1)	(2)
hsGPA	0.065 (0.137)	0.033 (0.130)
ACT	0.001 (0.015)	0.004 (0.015)
parcoll	0.221** (0.093)	0.215** (0.086)
Constant	−0.0004 (0.491)	0.026 (0.477)
Observations	141	141
R^2	0.042	0.046
Adjusted R^2	0.021	0.026
Residual Std. Error (df = 137)	0.486	1.016
F Statistic (df = 3; 137)	1.979	2.224*
Note:	*p<0.1; **p<0.05; ***p<0.01	

Chapter 9: More on Specification and Data Issues

Example 9.8: R&D Intensity and Firm Size

$$rdintens = \beta_0 + \beta_1 sales + \beta_2 profmarg + \mu$$

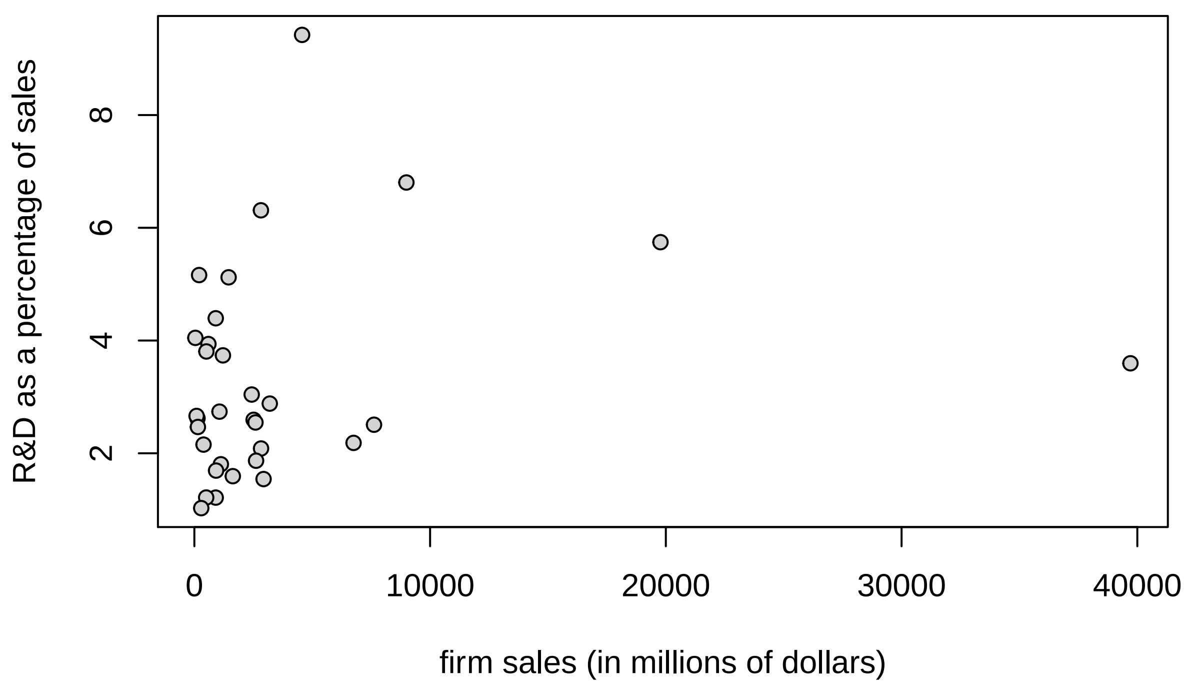
Load the data and estimate the model.

```
data(rdchem)

all_rdchem <- lm(rdintens ~ sales + profmarg, data = rdchem)
```

Plotting the data reveals the outlier on the far right of the plot, which will skew the results of our model.

```
plot_title <- "FIGURE 9.1: Scatterplot of R&D intensity against firm sales"
x_axis <- "firm sales (in millions of dollars)"
y_axis <- "R&D as a percentage of sales"

plot(rdintens ~ sales, pch = 21, bg = "lightgrey", data = rdchem, main = plot_title,
    xlab = x_axis, ylab = y_axis)
```

FIGURE 9.1: Scatterplot of R&D intensity against firm sales



So, we can estimate the model without that data point to gain a better understanding of how `sales` and `profmarg` describe `rdintens` for most firms. We can use the `subset` argument of the linear model function to indicate that we only want to estimate the model using data that is less than the highest sales.

```
smallest_rdchem <- lm(rdintens ~ sales + profmarg, data = rdchem,
                      subset = (sales < max(sales)))
```

The table below compares the results of both models side by side. By removing the outlier firm, *sales* become a more significant determination of R&D expenditures.

```r
stargazer(all_rdchem, smallest_rdchem, single.row = TRUE, header = FALSE)
```

Table 8:

	Dependent variable:	
	rdintens	
	(1)	(2)
sales	0.0001 (0.00004)	0.0002** (0.0001)
profmarg	0.045 (0.046)	0.048 (0.044)
Constant	2.625*** (0.586)	2.297*** (0.592)
Observations	32	31
R^2	0.076	0.173
Adjusted R^2	0.012	0.114
Residual Std. Error	1.862 (df = 29)	1.792 (df = 28)
F Statistic	1.195 (df = 2; 29)	2.925* (df = 2; 28)
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 10: Basic Regression Analysis with Time Series Data

`Example 10.2`: Effects of Inflation and Deficits on Interest Rates

$$\widehat{i3} = \beta_0 + \beta_1 inf_t + \beta_2 def_t$$

```r
data("intdef")

tbill_model <- lm(i3 ~ inf + def, data = intdef)
```

```r
stargazer(tbill_model, single.row = TRUE, header = FALSE)
```

Table 9:

	Dependent variable:
	i3
inf	0.606*** (0.082)
def	0.513*** (0.118)
Constant	1.733*** (0.432)
Observations	56
R^2	0.602
Adjusted R^2	0.587
Residual Std. Error	1.843 (df = 53)
F Statistic	40.094*** (df = 2; 53)
Note:	*p<0.1; **p<0.05; ***p<0.01

`Example 10.11`: Seasonal Effects of Antidumping Filings

```r
data("barium")
barium_imports <- lm(lchnimp ~ lchempi + lgas + lrtwex + befile6 + affile6 +
    afdec6, data = barium)
```

Estimate a new model, `barium_seasonal` which accounts for seasonality by adding dummy variables contained in the data. Compute the `anova` between the two models.

```r
barium_seasonal <- lm(lchnimp ~ lchempi + lgas + lrtwex + befile6 + affile6 +
    afdec6 + feb + mar + apr + may + jun + jul + aug + sep + oct + nov + dec,
    data = barium)

barium_anova <- anova(barium_imports, barium_seasonal)
```

```r
stargazer(barium_imports, barium_seasonal, single.row = TRUE, header = FALSE)
```

```r
stargazer(barium_anova, single.row = TRUE, header = FALSE)
```

Table 10:

	Dependent variable:	
	lchnimp	
	(1)	(2)
lchempi	3.117*** (0.479)	3.265*** (0.493)
lgas	0.196 (0.907)	−1.278 (1.389)
lrtwex	0.983** (0.400)	0.663 (0.471)
befile6	0.060 (0.261)	0.140 (0.267)
affile6	−0.032 (0.264)	0.013 (0.279)
afdec6	−0.565* (0.286)	−0.521* (0.302)
feb		−0.418 (0.304)
mar		0.059 (0.265)
apr		−0.451* (0.268)
may		0.033 (0.269)
jun		−0.206 (0.269)
jul		0.004 (0.279)
aug		−0.157 (0.278)
sep		−0.134 (0.268)
oct		0.052 (0.267)
nov		−0.246 (0.263)
dec		0.133 (0.271)
Constant	−17.803 (21.045)	16.779 (32.429)
Observations	131	131
R^2	0.305	0.358
Adjusted R^2	0.271	0.262
Residual Std. Error	0.597 (df = 124)	0.601 (df = 113)
F Statistic	9.064*** (df = 6; 124)	3.712*** (df = 17; 113)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 11:

Statistic	N	Mean	St. Dev.	Min	Max
Res.Df	2	118.500	7.778	113	124
RSS	2	42.545	2.406	40.844	44.247
Df	1	11.000		11	11
Sum of Sq	1	3.403		3.403	3.403
F	1	0.856		0.856	0.856
Pr(>F)	1	0.585		0.585	0.585

Chapter 11: Further Issues in Using OLS with with Time Series Data

Example 11.7: Wages and Productivity

$$\widehat{log(hrwage_t)} = \beta_0 + \beta_1 log(outphr_t) + \beta_2 t + \mu_t$$

```r
data("earns")

wage_time <- lm(lhrwage ~ loutphr + t, data = earns)
```

```r
wage_diff <- lm(diff(lhrwage) ~ diff(loutphr), data = earns)
```

```r
stargazer(wage_time, wage_diff, single.row = TRUE, header = FALSE)
```

Table 12:

	Dependent variable:	
	lhrwage	diff(lhrwage)
	(1)	(2)
loutphr	1.640*** (0.093)	
t	−0.018*** (0.002)	
diff(loutphr)		0.809*** (0.173)
Constant	−5.328*** (0.374)	−0.004 (0.004)
Observations	41	40
R^2	0.971	0.364
Adjusted R^2	0.970	0.348
Residual Std. Error (df = 38)	0.029	0.017
F Statistic	641.224*** (df = 2; 38)	21.771*** (df = 1; 38)
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 12: Serial Correlation and Heteroskedasticiy in Time Series Regressions

Example 12.4: Prais-Winsten Estimation in the Event Study

```
data("barium")
barium_model <- lm(lchnimp ~ lchempi + lgas + lrtwex + befile6 + affile6 + afdec6,
    data = barium)
# Load the `prais` package, use the `prais.winsten` function to estimate.
library(prais)
barium_prais_winsten <- prais.winsten(lchnimp ~ lchempi + lgas + lrtwex + befile6 +
    affile6 + afdec6, data = barium)
```

```
barium_model
```

```
##
## Call:
## lm(formula = lchnimp ~ lchempi + lgas + lrtwex + befile6 + affile6 +
##     afdec6, data = barium)
##
## Coefficients:
## (Intercept)      lchempi         lgas       lrtwex      befile6
##   -17.80300      3.11719      0.19635      0.98302      0.05957
##     affile6       afdec6
##    -0.03241     -0.56524
```

```
barium_prais_winsten
```

```
## [[1]]
##
## Call:
## lm(formula = fo)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.01146 -0.39152  0.06758  0.35063  1.35021
##
## Coefficients:
##            Estimate Std. Error t value Pr(>|t|)
## Intercept -37.07771   22.77830  -1.628   0.1061
## lchempi     2.94095    0.63284   4.647 8.46e-06 ***
## lgas        1.04638    0.97734   1.071   0.2864
## lrtwex      1.13279    0.50666   2.236   0.0272 *
## befile6    -0.01648    0.31938  -0.052   0.9589
## affile6    -0.03316    0.32181  -0.103   0.9181
## afdec6     -0.57681    0.34199  -1.687   0.0942 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5733 on 124 degrees of freedom
## Multiple R-squared:  0.9841, Adjusted R-squared:  0.9832
## F-statistic:  1096 on 7 and 124 DF,  p-value: < 2.2e-16
##
##
## [[2]]
##         Rho Rho.t.statistic Iterations
##   0.2932171        3.483363          8
```

`Example 12.8`: Heteroskedasticity and the Efficient Markets Hypothesis

$$return_t = \beta_0 + \beta_1 return_{t-1} + \mu_t$$

```
data("nyse")

return_AR1 <-lm(return ~ return_1, data = nyse)
```

$$\hat{\mu_t^2} = \beta_0 + \beta_1 return_{t-1} + residual_t$$

```
return_mu <- residuals(return_AR1)

mu2_hat_model <- lm(return_mu^2 ~ return_1, data = return_AR1$model)
```

```
stargazer(return_AR1, mu2_hat_model, single.row = TRUE, header = FALSE)
```

Table 13:

	Dependent variable:	
	return	return_mu^2
	(1)	(2)
return_1	0.059 (0.038)	-1.104^{***} (0.201)
Constant	0.180^{**} (0.081)	4.657^{***} (0.428)
Observations	689	689
R^2	0.003	0.042
Adjusted R^2	0.002	0.041
Residual Std. Error (df = 687)	2.110	11.178
F Statistic (df = 1; 687)	2.399	30.055^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

`Example 12.9`: ARCH in Stock Returns

$$\hat{\mu_t^2} = \beta_0 + \hat{\mu_{t-1}^2} + residual_t$$

We still have `return_mu` in the working environment so we can use it to create $\hat{\mu_t^2}$, (`mu2_hat`) and $\hat{\mu_{t-1}^2}$ (`mu2_hat_1`). Notice the use `R`'s matrix subset operations to perform the lag operation. We drop the first observation of `mu2_hat` and squared the results. Next, we remove the last observation of `mu2_hat_1` using the subtraction operator combined with a call to the `NROW` function on `return_mu`. Now, both contain 688 observations and we can estimate a standard linear model.

```
mu2_hat  <- return_mu[-1]^2

mu2_hat_1 <- return_mu[-NROW(return_mu)]^2

arch_model <- lm(mu2_hat ~ mu2_hat_1)
```

```
stargazer(arch_model, single.row = TRUE, header = FALSE)
```

Table 14:

	Dependent variable:
	mu2_hat
mu2_hat_1	0.337*** (0.036)
Constant	2.947*** (0.440)
Observations	688
R^2	0.114
Adjusted R^2	0.112
Residual Std. Error	10.759 (df = 686)
F Statistic	87.923*** (df = 1; 686)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 13: Pooling Cross Sections across Time: Simple Panel Data Methods

`Example 13.7`: Effect of Drunk Driving Laws on Traffic Fatalities

$$\widehat{\Delta dthrte} = \beta_0 + \Delta open + \Delta admin$$

```r
data("traffic1")

DD_model <- lm(cdthrte ~ copen + cadmn, data = traffic1)
```

```r
stargazer(DD_model, single.row = TRUE, header = FALSE)
```

Table 15:

	Dependent variable:
	cdthrte
copen	−0.420** (0.206)
cadmn	−0.151 (0.117)
Constant	−0.497*** (0.052)
Observations	51
R^2	0.119
Adjusted R^2	0.082
Residual Std. Error	0.344 (df = 48)
F Statistic	3.231** (df = 2; 48)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 14: Advanced Panel Data Methods

`Example 14.1:` Effect of Job Training on Firm Scrap Rates

In this section, we will estimate a linear panel modeg using the `plm` function from the `plm: Linear Models for Panel Data` package. See the bibliography for more information.

```
library(plm)
```

```
## Loading required package: Formula
```

```
data("jtrain")

scrap_panel <- plm(lscrap ~ d88 + d89 + grant + grant_1, data = jtrain, index = c("fcode",
    "year"), model = "within", effect = "individual")
```

```
stargazer(scrap_panel, single.row = TRUE, header = FALSE)
```

Table 16:

	Dependent variable:
	lscrap
d88	−0.080 (0.109)
d89	−0.247* (0.133)
grant	−0.252* (0.151)
grant_1	−0.422** (0.210)
Observations	162
R^2	0.201
Adjusted R^2	−0.237
F Statistic	6.543*** (df = 4; 104)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 15: Instrumental Variables Estimation and Two Stage Least Squares

`Example 15.1`: Estimating the Return to Education for Married Women

$$log(wage) = \beta_0 + \beta_1 educ + \mu$$

```
data("mroz")
wage_educ_model <- lm(lwage ~ educ, data = mroz)
```

$$\widehat{educ} = \beta_0 + \beta_1 fatheduc$$

We run the typical linear model, but notice the use of the `subset` argument. `inlf` is a binary variable in which a value of 1 means they are "In the Labor Force". By sub-setting the `mroz` data.frame by observations in which `inlf==1`, only working women will be in the sample.

```
fatheduc_model <- lm(educ ~ fatheduc, data = mroz, subset = (inlf==1))
```

In this section, we will perform an **Instrumental-Variable Regression**, using the `ivreg` function in the `AER (Applied Econometrics with R)` package. See the bibliography for more information.

```
library("AER")
wage_educ_IV <- ivreg(lwage ~ educ | fatheduc, data = mroz)
```

```
stargazer(wage_educ_model, fatheduc_model, wage_educ_IV, single.row = TRUE,
    header = FALSE)
```

Table 17:

	Dependent variable:		
	lwage	educ	lwage
	OLS	*OLS*	*instrumental variable*
	(1)	(2)	(3)
educ	0.109*** (0.014)		0.059* (0.035)
fatheduc		0.269*** (0.029)	
Constant	−0.185 (0.185)	10.237*** (0.276)	0.441 (0.446)
Observations	428	428	428
R^2	0.118	0.173	0.093
Adjusted R^2	0.116	0.171	0.091
Residual Std. Error (df = 426)	0.680	2.081	0.689
F Statistic (df = 1; 426)	56.929***	88.841***	
Note:			*p<0.1; **p<0.05; ***p<0.01

`Example 15.2:` Estimating the Return to Education for Men

$$\widehat{educ} = \beta_0 + sibs$$

```r
data("wage2")

educ_sibs_model <- lm(educ ~ sibs, data = wage2)
```

$$\widehat{log(wage)} = \beta_0 + educ$$

Again, estimate the model using the `ivreg` function in the `AER (Applied Econometrics with R)` package.

```r
library("AER")

educ_sibs_IV <- ivreg(lwage ~ educ | sibs, data = wage2)
```

```r
stargazer(educ_sibs_model, educ_sibs_IV, wage_educ_IV, single.row = TRUE, header = FALSE)
```

Table 18:

	Dependent variable:		
	educ	lwage	
	OLS	*instrumental variable*	
	(1)	(2)	(3)
sibs	-0.228^{***} (0.030)		
educ		0.122^{***} (0.026)	0.059^{*} (0.035)
Constant	14.139^{***} (0.113)	5.130^{***} (0.355)	0.441 (0.446)
Observations	935	935	428
R^2	0.057	-0.009	0.093
Adjusted R^2	0.056	-0.010	0.091
Residual Std. Error	2.134 (df = 933)	0.423 (df = 933)	0.689 (df = 426)
F Statistic	56.667^{***} (df = 1; 933)		
Note:			*p<0.1; **p<0.05; ***p<0.01

`Example 15.5`: Return to Education for Working Women

$$\widehat{log(wage)} = \beta_0 + \beta_1 educ + \beta_2 exper + \beta_3 exper^2$$

Use the `ivreg` function in the `AER (Applied Econometrics with R)` package to estimate.

```r
data("mroz")
wage_educ_exper_IV <- ivreg(lwage ~ educ + exper + expersq | exper + expersq +
    motheduc + fatheduc, data = mroz)
```

Table 19:

	Dependent variable:
	lwage
educ	0.061* (0.031)
exper	0.044*** (0.013)
expersq	−0.001** (0.0004)
Constant	0.048 (0.400)
Observations	428
R^2	0.136
Adjusted R^2	0.130
Residual Std. Error	0.675 (df = 424)
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 16: Simultaneous Equations Models

`Example 16.4:` INFLATION AND OPENNESS

$$inf = \beta_{10} + \alpha_1 open + \beta_{11} log(pcinc) + \mu_1$$
$$open = \beta_{20} + \alpha_2 inf + \beta_{21} log(pcinc) + \beta_{22} log(land) + \mu_2$$

`Example 16.6:` INFLATION AND OPENNESS

$$\widehat{open} = \beta_0 + \beta_1 log(pcinc) + \beta_2 log(land)$$

```
data("openness")

open_model <-lm(open ~ lpcinc + lland, data = openness)
```

$$\widehat{inf} = \beta_0 + \beta_1 open + \beta_2 log(pcinc)$$

Use the `ivreg` function in the `AER (Applied Econometrics with R)` package to estimate.

```
library(AER)

inflation_IV <- ivreg(inf ~ open + lpcinc | lpcinc + lland, data = openness)
```

```
stargazer(open_model, inflation_IV, single.row = TRUE, header = FALSE)
```

Table 20:

	Dependent variable:	
	open	inf
	OLS	*instrumental variable*
	(1)	(2)
open		-0.337^{**} (0.144)
lpcinc	0.546 (1.493)	0.376 (2.015)
lland	-7.567^{***} (0.814)	
Constant	117.085^{***} (15.848)	26.899^{*} (15.401)
Observations	114	114
R^2	0.449	0.031
Adjusted R^2	0.439	0.013
Residual Std. Error (df = 111)	17.796	23.836
F Statistic	45.165^{***} (df = 2; 111)	
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 17: Limited Dependent Variable Models and Sample Selection Corrections

`Example 17.3:` POISSON REGRESSION FOR NUMBER OF ARRESTS

```
data("crime1")
```

Sometimes, when estimating a model with many variables, defining a `model` object containing the formula makes for much cleaner code.

```
formula <- (narr86 ~ pcnv + avgsen + tottime + ptime86 + qemp86 + inc86 + black +
    hispan + born60)
```

Then, pass the `formula` object into the `lm` function, and define the `data` argument as usual.

```
econ_crime_model <- lm(formula, data = crime1)
```

To estimate the `poisson` regression, use the general linear model function `glm` and define the `family` argument as `poisson`.

```
econ_crim_poisson <- glm(formula, data = crime1, family = poisson)
```

Use the `stargazer` package to easily compare diagnostic tables of both models.

```
stargazer(econ_crime_model, econ_crim_poisson, single.row = TRUE, header = FALSE)
```

Table 21:

	Dependent variable:	
	narr86	
	OLS	*Poisson*
	(1)	(2)
pcnv	-0.132^{***} (0.040)	-0.402^{***} (0.085)
avgsen	-0.011 (0.012)	-0.024 (0.020)
tottime	0.012 (0.009)	0.024^{*} (0.015)
ptime86	-0.041^{***} (0.009)	-0.099^{***} (0.021)
qemp86	-0.051^{***} (0.014)	-0.038 (0.029)
inc86	-0.001^{***} (0.0003)	-0.008^{***} (0.001)
black	0.327^{***} (0.045)	0.661^{***} (0.074)
hispan	0.194^{***} (0.040)	0.500^{***} (0.074)
born60	-0.022 (0.033)	-0.051 (0.064)
Constant	0.577^{***} (0.038)	-0.600^{***} (0.067)
Observations	2,725	2,725
R^2	0.072	
Adjusted R^2	0.069	
Log Likelihood		$-2{,}248.761$
Akaike Inf. Crit.		4,517.522
Residual Std. Error	0.829 (df = 2715)	
F Statistic	23.572^{***} (df = 9; 2715)	
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 18: Advanced Time Series Topics

Example 18.8: FORECASTING THE U.S. UNEMPLOYMENT RATE

```
data("phillips")
```

$$\widehat{unemp}_t = \beta_0 + \beta_1 unem_{t-1}$$

Estimate the linear model in the usual way and note the use of the `subset` argument to define data equal to and before the year 1996.

```
unem_AR1 <- lm(unem ~ unem_1, data = phillips, subset = (year <= 1996))
```

$$\widehat{unemp}_t = \beta_0 + \beta_1 unem_{t-1} + \beta_2 inf_{t-1}$$

```
unem_inf_VAR1 <- lm(unem ~ unem_1 + inf_1, data = phillips, subset = (year <= 1996))
```

Table 22:

	Dependent variable:	
	unem	
	(1)	(2)
unem_1	0.732*** (0.097)	0.647*** (0.084)
inf_1		0.184*** (0.041)
Constant	1.572*** (0.577)	1.304** (0.490)
Observations	48	48
R^2	0.554	0.691
Adjusted R^2	0.544	0.677
Residual Std. Error	1.049 (df = 46)	0.883 (df = 45)
F Statistic	57.132*** (df = 1; 46)	50.219*** (df = 2; 45)
Note:		*p<0.1; **p<0.05; ***p<0.01

Bibliography

Yves Croissant, Giovanni Millo (2008). *Panel Data Econometrics in R: The plm Package.* Journal of Statistical Software 27(2). URL www.jstatsoft.org/v27/i02/.

Marek Hlavac (2015). *stargazer: Well-Formatted Regression and Summary Statistics Tables.* R package version 5.2. https://CRAN.R-project.org/package=stargazer

Christian Kleiber and Achim Zeileis (2008). *Applied Econometrics with R.* New York: Springer-Verlag. ISBN 978-0-387-77316-2. URL https://CRAN.R-project.org/package=AER

Franz Mohr (2015). *prais: Prais-Winsten Estimation Procedure for AR(1) Serial Correlation.* R package version 0.1.1. https://CRAN.R-project.org/package=prais

R Core Team (2017). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Hadley Wickham and Winston Chang (2016). *devtools: Tools to Make Developing R Packages Easier.* R package version 1.12.0. https://CRAN.R-project.org/package=devtools

Hadley Wickham. *testthat: Get Started with Testing.* R package version 1.0.2. https://CRAN.R-project.org/package=testthat

Jeffrey M. Wooldridge (2013). *Introductory Econometrics: A Modern Approach.* Mason, Ohio :South-Western Cengage Learning.

Yihui Xie (2017). *knitr: A General-Purpose Package for Dynamic Report Generation in R.* R package version 1.16. https://CRAN.R-project.org/package=knitr

Appendix

Econometrics in R

This 50 pg. document is posted on the Comprehensive R Archive Network site and contains useful econometric recipes as well as general information about R.

Farnsworth, Grant. *Econometrics in R.* 2008, Evanston, IL. url: https://cran.r-project.org/doc/contrib/Farnsworth-EconometricsInR.pdf

Using R for Introductory Econometrics

This excerpt from the books excellent website:

> This book introduces the popular, powerful and free programming language and software package R with a focus on the implementation of standard tools and methods used in econometrics. Unlike other books on similar topics, it does not attempt to provide a self-contained discussion of econometric models and methods. Instead, it builds on the excellent and popular textbook "Introductory Econometrics" by Jeffrey M. Wooldridge.

Hess, Florian. *Using R for Introductory Econometrics.* ISBN: 978-1-523-28513-6, CreateSpace Independent Publishing Platform, 2016, Dusseldorf, Germany. url: https://urfie.net.