Package overview

The **ivreg** package (by John Fox, Christian Kleiber, and Achim Zeileis) provides a comprehensive implementation of instrumental variables regression using two-stage least-squares (2SLS) estimation. The standard regression functionality (parameter estimation, inference, robust covariances, predictions, etc.) is derived from and supersedes the `ivreg()` function in the **AER** package. Additionally, various regression diagnostics are supported, including hat values, deletion diagnostics such as studentized residuals and Cook's distances; graphical diagnostics such as component-plus-residual plots and added-variable plots; and effect plots with partial residuals.

An overview of the package along with vignettes and detailed documentation etc. is available on its web site at https://john-d-fox.github.io/ivreg/. This post is an abbreviated version of the "Getting started" vignette.

The **ivreg** package integrates seamlessly with other packages by providing suitable S3 methods, specifically for generic functions in the base-R **stats** package, and in the **car**, **effects**, **lmtest**, and **sandwich** packages, among others. Moreover, it cooperates well with other object-oriented packages for regression modeling such as **broom** and **modelsummary**.

Illustration: Returns to schooling

For demonstrating the **ivreg** package in practice, we investigate the effect of schooling on earnings in a classical model for wage determination. The data are from the United States, and are provided in the package as `SchoolingReturns`. This data set was originally studied by David Card, and was subsequently employed, as here, to illustrate 2SLS estimation in introductory econometrics textbooks. The relevant variables for this illustration are:

```
data("SchoolingReturns", package = "ivreg")
summary(SchoolingReturns[, 1:8])
##       wage          education        experience      ethnicity
smsa
##  Min.   : 100.0   Min.   : 1.00   Min.   : 0.000   other:2307   no :
864
##  1st Qu.: 394.2   1st Qu.:12.00   1st Qu.: 6.000   afam : 703
yes:2146
##  Median : 537.5   Median :13.00   Median : 8.000
##  Mean   : 577.3   Mean   :13.26   Mean   : 8.856
##  3rd Qu.: 708.8   3rd Qu.:16.00   3rd Qu.:11.000
##  Max.   :2404.0   Max.   :18.00   Max.   :23.000
##  south          age          nearcollege
##  no :1795   Min.   :24.00   no : 957
##  yes:1215   1st Qu.:25.00   yes:2053
##             Median :28.00
##             Mean   :28.12
##             3rd Qu.:31.00
##             Max.   :34.00
```

A standard wage equation uses a semi-logarithmic linear regression for `wage`, estimated by ordinary least squares (OLS), with years of `education` as the primary explanatory variable, adjusting for a quadratic term in labor-market `experience`, as well as for factors coding `ethnicity`, residence in a city (`smsa`), and residence in the U.S. `south`:

```
m_ols <- lm(log(wage) ~ education + poly(experience, 2) + ethnicity +
smsa + south,
  data = SchoolingReturns)
summary(m_ols)
## Call:
## lm(formula = log(wage) ~ education + poly(experience, 2) + ethnicity
+
##     smsa + south, data = SchoolingReturns)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.59297 -0.22315  0.01893  0.24223  1.33190
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           5.259820   0.048871 107.626  < 2e-16 ***
## education             0.074009   0.003505  21.113  < 2e-16 ***
## poly(experience, 2)1  8.931699   0.494804  18.051  < 2e-16 ***
## poly(experience, 2)2 -2.642043   0.374739  -7.050 2.21e-12 ***
## ethnicityafam        -0.189632   0.017627 -10.758  < 2e-16 ***
## smsayes               0.161423   0.015573  10.365  < 2e-16 ***
## southyes             -0.124862   0.015118  -8.259  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3742 on 3003 degrees of freedom
## Multiple R-squared:  0.2905, Adjusted R-squared:  0.2891
## F-statistic: 204.9 on 6 and 3003 DF,  p-value: < 2.2e-16
```

Thus, OLS estimation yields an estimate of 7.4% per year for returns to schooling. This estimate is problematic, however, because it can be argued that `education` is endogenous (and hence also `experience`, which is taken to be `age` minus `education` minus 6). We therefore use geographical proximity to a college when growing up as an exogenous instrument for `education`. Additionally, `age` is the natural exogenous instrument for `experience`, while the remaining explanatory variables can be considered exogenous and are thus used as instruments for themselves. Although it's a useful strategy to select an effective instrument or instruments for each endogenous explanatory variable, in 2SLS regression all of the instrumental variables are used to estimate all of the regression coefficients in the model.

To fit this model with `ivreg()` we can simply extend the formula from `lm()` above, adding a second part after the `|` separator to specify the instrumental variables:

```
library("ivreg")
m_iv <- ivreg(log(wage) ~ education + poly(experience, 2) + ethnicity +
smsa + south |
  nearcollege + poly(age, 2) + ethnicity + smsa + south,
  data = SchoolingReturns)
```

Equivalently, the same model can also be specified slightly more concisely using three parts on the right-hand side indicating the exogenous variables, the endogenous variables, and the additional instrumental variables only (in addition to the exogenous variables).

```
m_iv <- ivreg(log(wage) ~ ethnicity + smsa + south | education +
poly(experience, 2) |
  nearcollege + poly(age, 2), data = SchoolingReturns)
```

Both models yield the following results:

```
summary(m_iv)
## Call:
## ivreg(formula = log(wage) ~ education + poly(experience, 2) +
##     ethnicity + smsa + south | nearcollege + poly(age, 2) +
ethnicity +
##     smsa + south, data = SchoolingReturns)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.82400 -0.25248  0.02286  0.26349  1.31561
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             4.48522    0.67538   6.641 3.68e-11 ***
## education               0.13295    0.05138   2.588 0.009712 **
## poly(experience, 2)1    9.14172    0.56350  16.223  < 2e-16 ***
## poly(experience, 2)2   -0.93810    1.58024  -0.594 0.552797
## ethnicityafam          -0.10314    0.07737  -1.333 0.182624
## smsayes                 0.10798    0.04974   2.171 0.030010 *
## southyes               -0.09818    0.02876  -3.413 0.000651 ***
##
## Diagnostic tests:
##                                          df1  df2 statistic  p-value
## Weak instruments (education)               3 3003     8.008 2.58e-05
***
## Weak instruments (poly(experience, 2)1)    3 3003  1612.707  < 2e-16
***
## Weak instruments (poly(experience, 2)2)    3 3003   174.166  < 2e-16
***
## Wu-Hausman                                 2 3001     0.841    0.432
## Sargan                                     0   NA        NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4032 on 3003 degrees of freedom
## Multiple R-Squared: 0.1764,  Adjusted R-squared: 0.1747
## Wald test: 148.1 on 6 and 3003 DF,  p-value: < 2.2e-16
```

Thus, using two-stage least squares to estimate the regression yields a much larger coefficient for the returns to schooling, namely 13.3% per year. Notice as well that the standard errors of the coefficients are larger for 2SLS estimation than for OLS, and that, partly as a consequence, evidence for the effects of `ethnicity` and the quadratic component of `experience` is now weak. These differences are brought out more clearly when showing coefficients and standard errors side by side, e.g., using the `compareCoefs()` function from the **car** package or the `msummary()` function from the **modelsummary** package:

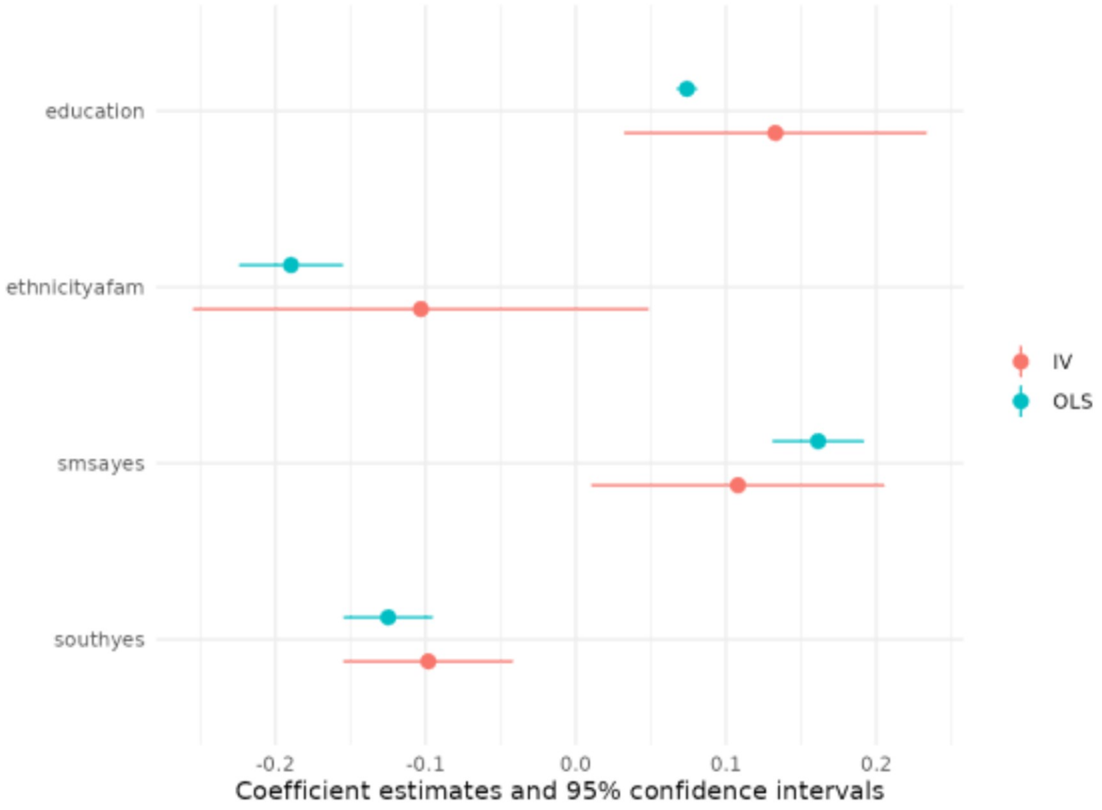
```
library("modelsummary")
```

```
m_list <- list(OLS = m_ols, IV = m_iv)
msummary(m_list)
```

	OLS	**IV**
(Intercept)	5.260	4.485
	(0.049)	(0.675)
education	0.074	0.133
	(0.004)	(0.051)
poly(experience, 2)1	8.932	9.142
	(0.495)	(0.564)
poly(experience, 2)2	-2.642	-0.938
	(0.375)	(1.580)
ethnicityafam	-0.190	-0.103
	(0.018)	(0.077)
smsayes	0.161	0.108
	(0.016)	(0.050)
southyes	-0.125	-0.098
	(0.015)	(0.029)
Num.Obs.	3010	3010
R2	0.291	0.176
R2 Adj.	0.289	0.175
AIC	2633.4	
BIC	2681.5	
Log.Lik.	-1308.702	
F	204.932	

The change in coefficients and associated standard errors can also be brought out graphically using the `modelplot()` function from **modelsummary** which shows the coefficient estimates along with their 95% confidence intervals. Below we omit the intercept and experience terms as these are on a different scale than the other coefficients.

```
modelplot(m_list, coef_omit = "Intercept|experience")
```


education
ethnicityafam
smsayes
southyes
IV
OLS
-0.2
-0.1
0.0
0.1
0.2
Coefficient estimates and 95% confidence intervals