DOI:
10.1177/1536867X231162031

Document Version
Peer reviewed version

acreg: Arbitrary Correlation Regression

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Abstract. We present `acreg`, a new Stata command that implements the *arbitrary clustering correction of standard errors* proposed in Colella et al. (2019).[1] Arbitrary here refers to the way observational units are correlated with each other: we impose no restrictions so that our approach can be used with a wide range of data. The command accommodates both cross-sectional and panel databases and allows the estimation of OLS and 2SLS coefficients, correcting standard errors in three environments: in a spatial setting using units' coordinates or distance between units; in a network setting starting from the adjacency matrix; and in a multi-way clustering framework taking multiple clustering variables as input. Distance and time cutoffs can be specified by the user and linear decay in time and space are also optional.

Keywords: acreg, inference, arbitrary correlation, geospatial data, network data

1 Introduction

Thanks to increasing computational power, databases have become more and more complex in the past decades. They nowadays embed convoluted correlation structures between observational units that were not common before. For example, fueled by the growing availability of geocoded data and the integration of geographic information systems (GIS) in the toolkit of economists, empirical works using spatial data are proliferating in fields like development economics, urban economics, and economic history. Other examples of *new* correlation structures pertain to network data: individuals are linked, and these links are now measurable through social networks, mobile data, co-working relations or co-authorships.

Statistical inference in these environments is challenging because the underlying data generating process is often unknown and researchers need to make assumptions about the relationship between observations. Available methods to address the correlation between objects build on the sandwich-type variance-covariance estimator proposed by

1. Our statistical package (`acreg`) can be installed directly from the Statistical Software Components (SSC) archive by typing `ssc install acreg`. Complementary material may be found at the dedicated website: https://acregstata.weebly.com.

White (1980). The most common approach is standard clustering (Cameron and Miller 2015) which defines clusters as groups of linked observations that share a common characteristic. With spatial data, a frequently used approach has been developed by Conley (1999) who considers a circle around each unit within which the strength of the dependence between the unit and the surrounding ones is specified. In the case of network data, the practice is less developed; many studies simply do not correct for the potential correlation of unobserved shocks across linked observations.

In our companion paper Colella et al. (2019), we explore pitfalls and provide guidelines for conducting inference in complex settings, allowing for any type of topological and temporal dependence between observational units in large samples. Our *arbitrary clustering* approach builds on the seminal insight by White (1980), using estimated regression errors and knowledge on the clustering structure to re-construct estimates of the unknown elements of the sandwich formula. We perform extensive Monte Carlo simulations for both spatial and network data structures, e.g. U.S. counties and co-authorship in economics. Our simulation results show that arbitrary clustering inference dominates inference based on conventional estimators.

In this current article, we present our new user-written command `acreg` that implements the arbitrary clustering correction of standard errors proposed in Colella et al. (2019). We also provide several examples of how to use it. Our command accommodates OLS and 2SLS estimations and is designed to deal with network clustering and several clustered covariance matrix estimators (Bester et al. 2011), including multi-way clustering (Cameron et al. 2011), spatial clustering (Conley 1999) and HAC (Newey and West 1987).

In network settings, we are not aware of any existing Stata routine designed to correct standard errors starting from the knowledge of the binary links between observations.

In spatial settings, there are three user-written Stata commands available (Conley 1999; Hsiang 2010 and Fetzer 2015): however, they suit only OLS estimation. In addition, they all have pre-set options that are not desirable in all settings. In particular the commands by Conley 1999 and Fetzer 2015 impose a linear decay in the correlation structure between units (*Bartlett*), while Hsiang 2010 and Fetzer 2015 set a time decay (*HAC*) as default.[2] In comparison with those commands, `acreg` is more flexible as it enables the users to freely set the type of correlation structure and decay across observations and time. Moreover, in presence of multiple cross-sectional observational units sharing the same geo-location, our command provides consistent standard errors, replicating the heteroskedasticity-robust standard errors from `ivreg2` (Baum et al. 2003) when the distance correction is set to zero, while the programs by Conley 1999; Hsiang 2010 and Fetzer 2015 do not. Stata 15 introduced a series of commands, named `sp`, to model spatial relations between objects using *spatial autoregressive models* (SAR). These models allow for spatial lags of the dependent variable, which modifies point estimates, or for spatial autocorrelation in the errors. The command closest to ours, `spregress`, allows only for heteroskedasticity-robust and asymptotic maximum-likelihood theory-driven standard errors. Conversely, `acreg` does not modify the point estimates but

2. Conley 1999 allows to correct for only cross-sectional dependence and not time dependence.

improves inference by computing standard errors corrected for spatial correlation.

Concerning multi-way cluster robust standard errors, `ivreg2` and `xtivreg2`, allow the user to specify up to two cluster variables (i.e., two-way clustering). The user-written command by Colin Cameron, `cmreg`, instead accommodates multi-way clustering but suits only OLS estimation and does not allow for the estimation of 2SLS models. *acreg* instead can be used to estimate both OLS and 2SLS coefficients correcting standard errors for an infinite number of cluster dimensions.

The rest of this article is organized as follows. In section 2, we review the arbitrary clustering method developed in Colella et al. (2019). In section 3, we provide a detailed description of the syntax of *acreg*. In section 4, we offer an illustration of our command with several examples in the spatial and the network settings: we show how options of our command can be used to suit many models of correlation structure. Finally, in section 5, we conclude.

2 Estimator for the Variance-Covariance Matrix

Here we present the estimator of the variance-covariance (VCV) proposed in Colella et al. (2019). The proposed estimator builds on the seminal insight from White (1980) and can be seen as an extension of the one-way or multi-way clustering (Cameron et al. 2011) that includes also spatial clustering (Conley 1999).[3]

In our setting, each observation can be correlated to any other and the strength of their correlation is a function of both time and distance. We define a matrix S containing information on cross-observation correlations in errors. With spatial data, S is built from information on the geographic distance between spatial units, e.g., regions, cities, and countries; while in a network context, it reflects the direct links between observations at different degrees. `acreg` computes the matrix S starting from the position of objects in space, using their coordinates, or from the link structure in a network; it also allows the user to define the matrix S to accommodate more complex correlation structures. Entries of the S matrix range from 0 to 1: this measure represents the strength of the correlation between two units and is inversely proportional to their distance. The diagonal of S is a vector of ones, reflecting the self-links.

Consider n observations at each t instant of time T from the following linear model:

$$y = X\beta + \epsilon$$

where we observe each unit i several times in different periods t. y is a dependent variable, and X is a matrix of k linearly independent components. X could include a

3. We do not provide any theoretical or empirical validation of our approach here. In Colella et al. (2019) we show results of extensive Monte Carlo simulations based on real-life data on U.S. metropolitan areas, or on co-authors in Economics. We show that our arbitrary clustering estimator of the VCV yields inference at the correct significance level in moderately sized samples, and it always dominates other commonly used approaches to inference. We provide guidance to the applied practitioners on how to cluster and to make reasonable assumptions on the error distribution in absence of prior knowledge about the data generating process.

long list of dummies for each unit, in case we are interested in the within estimates in a Panel dataset. The OLS estimator can be written as follow:

$$b_{OLS} = (X'X)^{-1}X'y$$

and the theoretical VCV of the b_{OLS} is:

$$VCV(b_{OLS}) = (X'X)^{-1}X'\Omega X(X'X)^{-1}$$

where $\Omega \equiv E(\epsilon\epsilon'|X)$ is the unknown VCV of ϵ.

The VCV is estimated by the following sandwich estimator (White 1980):

$$\widehat{VCV}(b_{OLS}) = (X'X)^{-1}X'(S \times (ee'))X(X'X)^{-1}$$

where $e \equiv y - Xb_{OLS}$ represents the vector of residuals and where S is the pattern matrix, and $\times$ is element-by-element matrix multiplication. The key element of this estimator is the middle part $X'(S \times (ee'))X$.

$$X'(S \times (ee'))X = \sum_{i=1}^{n}\sum_{t=1}^{T}\sum_{j=1}^{n}\sum_{s=1}^{T} x_{it}e_{it}e_{js}x'_{js}s_{itjs}$$

where x_{it} is the (column) vector of regressors, and x'_{it} is the row it in matrix X.

This framework can also be used in situations with endogeneity. We refer the reader to our paper (Colella et al. 2019) for an illustration of the 2SLS version of the estimator.

3 The acreg command

`acreg` requires the installation of the latest versions of `ranktest`, `ivreg2` (Baum et al. 2003), and `hdfe` (Correia 2016). To check whether the most up-to-date versions of these packages are installed (and to install them if they are not), please type `acregpackcheck` after having installed `acreg`.

3.1 Syntax

`acreg` *depvar* [*varlist1*] [(*varlist2* = *varlist_iv*)] [*if*] [*in*] [*fweight pweight*]
[, `id`(*idvar*) `time`(*timevar*) `spatial` `network` `latitude`(*latitudevar*) `longitude`(*longitudevar*)
`links_mat`(*varlist_links*) `dist_mat`(*varlist_distances*) `dist`(#) `lag`(#) `weights`(*varlist_weights*)
`cluster`(*varlist_cluster*) `hac` `bartlett` `nbclust`(#) `pfe1`(*fe1var*) `pfe2`(*fe2var*) `correctr2`
`dropsingletons` `storeweights` `storedistances`]

- *depvar* is the dependent variable.
- *varlist1* is the list of exogenous variables.
- *varlist2* is the list of endogenous variables.
- *varlist_iv* is the list of exogenous variables used with varlist1 as instruments for varlist2.

3.2 Options

Panel

- *idvar* is the cross-sectional unit identifier; required in panel setting.
- *timevar* is the time unit variable; required in panel setting.

If *idvar* and *timevar* are not specified, the model is assumed to be cross-sectional.

Spatial Environment

- `spatial` specifies that the environment is a spatial one; not required if arbitrary cluster correction is not performed or in the case it is if varlist_weights, varlist_cluster, or network option is specified.
- *latitudevar* is the variable containing the latitude of each observation in decimal degrees: range[-180.0, 180.0].
- *longitudevar* is the variable containing the longitude of each observation in decimal degrees: range[-180.0, 180.0].
- *varlist_distances* is the list of N variables containing bilateral distances between observations. In the spatial environment, bilateral distance is the spatial distance between observations, e.g., physical or travel distance between two locations. (In the network environment, it is the network distance between observations, i.e., the number of links along the shortest path between two nodes.)
- `dist`(#) specifies the distance cutoff beyond which the correlation between the error terms of two observations is assumed to be zero; required if latitude and longitude are specified or if dist_mat is specified. The distance cutoff is in kilometers if latitude and longitude are specified. It can be in any other meaningful metric if bilateral distances are specified.
- `lag`(#) specifies the time lag cutoff for observations with the same idvar; not required in the cross-sectional environment; default is 0 in panel environment, i.e. when id and time options are specified. In the panel environment when timecutoff is 0 or not specified, standard errors are clustered at id $\times$ time level.

Network Environment

- `network` specifies that the environment is a network one; not required if arbitrary cluster correction is not performed and in the case it is if varlist_weights, varlist_cluster, or spatial option is specified.

- `varlist_links` is the list of N dummy variables specifying the links between observations, i.e., the adjacency matrix. The links between two units can change over time. However, if *distcutoff* is set to be greater than one: only the first observation in time of each individual will be used as input to compute the bilateral distance between two nodes.

- `varlist_distances` is the list of N variables containing bilateral distances between observations. In the network environment, bilateral distance is the network distance between observations, i.e., the number of links along the shortest path between two nodes. (In the spatial environment, it is the spatial distance between observations, i.e. the distance between two locations.)

- `dist`(#) specifies the distance cutoff (geodesic paths) beyond which the correlation between the error terms of two observations is assumed to be zero; required if dist_mat is specified; optional if links_mat is specified; default is 1 in the network environment. When links_mat is specified and distcutoff is greater than 1, acreg computes automatically the bilateral distance between two nodes.

- `lag`(#) specifies the time lag cutoff for observations with the same idvar; not required in the cross-sectional environment, default in panel environment is 0, i.e. when id and time options are specified. In the panel environment when timecutoff is 0 or not specified, standard errors are clustered at id × time level.

Multiway Clustering Environment

- *varlist_cluster* is the list of variables to use for multiway clustered standard errors; not required if arbitrary cluster correction is not performed and in the case it is if spatial option, network option, or varlist_weights is specified.

Arbitrary Clustering Environment

- *varlist_weights* is the list of N × T variables containing the weights that will be used for error correction; not required if the spatial option, network option, or varlist_cluster is specified. The N × T variables need to follow the same order of the observations.

Correlation Structure

- `hac` reports Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors; lagcutoff will be the temporal decay; requires id, time, and lagcutoff.

- `bartlett` imposes a distance linear decay between observations within the cutoff in the correlation structure.

- `nbclust`(#) is the number of clusters used to compute the Kleibergen-Paap statistic in case of arbitrary cluster correction; default is 100.

High-Dimensional Fixed Effects

- *fe1var* identifies the first high-dimensional fixed effects variable to be partialled out.

- *fe2var* identifies the second high-dimensional fixed effects variable to be partialled out.
- `correctr2` when pfe1 or pfe2 are specified the r-squared is computed on the "partialled out sample". This option reports the correct r-squared, i.e. the pre-partialling out r-squared. Not allowed with fweights.
- `dropsingletons` drops singleton groups when pfe1 (and pfe2) is (are) specified.

Storing

- `storeweights` stores the computed weights used to correct the VCV for arbitrary cluster correlation as a matrix under the name weightsmat, which may be used as input for the option varlist_weights; optional only if the spatial option, network option, or varlist_cluster is specified.
- `storedistances` stores the computed distances used to correct the VCV for arbitrary cluster correlation as a matrix under the name distancesmat, which may be used as input for the option varlist_distances; optional only if the spatial option or network is specified and varlist_distances is not specified.

3.3 Stored results

`acreg` stores the following in e():

Scalars

- `e(N)` number of observations
- `e(mss)` model sum of squares (centered)
- `e(mssu)` model sum of squares (uncentered)
- `e(rss)` residual sum of squares
- `e(tss)` total sum of squares (centered)
- `e(tssu)` total sum of squares (uncentered)
- `e(r2)` centered R2 (1-rss/tss)
- `e(r2u)` uncentered R2
- `e(widstat)` Kleibergen-Paap Wald rk F statistic

Matrices

- `e(b)` coefficient vector
- `e(V)` corrected variance-covariance matrix of the estimators

Functions

- `e(sample)` marks estimation sample

4 Examples

We illustrate the use of our command in four environments: spatial and network settings, both in cross-sectional and panel contexts. In every environment, we estimate the same equation imposing different assumptions on the error correlation structure: iid, standard clustering, and arbitrary clustering.

4.1 Spatial Environment, Cross-Sectional Setting

For this example, we use the data on the homicides in southern states of the U.S. `homicide_1960_1990.dta` available at the STATA website. Data contain, among others, the county-level homicide rate per year per 100,000 persons (`hrate`), the population in logs (`ln_population`), the logarithm of the average income (`ln_income`), the unemployment rate (`unemployment`), and the average age (`age`). This dataset is an extract of the data originally used by Messner et al. (1999) and concerns 4 different periods (1960, 1970, 1980, 1990). We consider only the cross-sectional database for 1990 and we estimate the effect of *income* on *homicide rate*, controlling for *population*, and *age*. For the sake of illustration, we claim that income is endogenous and we assume that unemployment is a valid instrument for it. Figure 1 shows the spatial dependency of the outcome variable, the endogenous regressor, and the instrument.

We first estimate the model assuming that observations' errors are uncorrelated.[4]

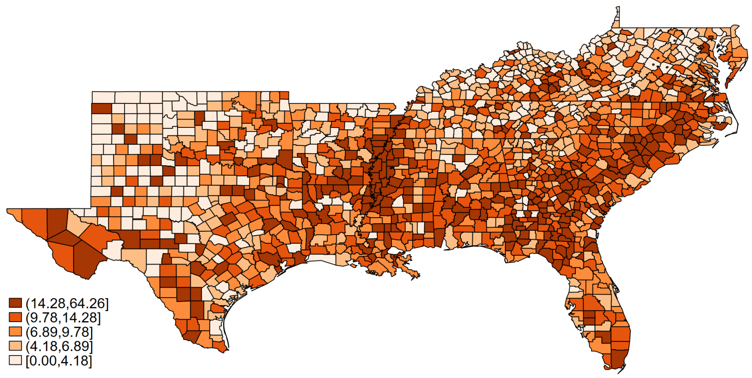
```
. use http://www.stata-press.com/data/r15/homicide1990.dta , clear
(S.Messner et al.(2000), U.S southern county homicide rates in 1990)

. acreg hrate ln_population age (ln_income=unemployment)
HETEROSKEDASTICITY ROBUST STANDARD ERRORS
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic: 990.487
                                                    Number of obs =     1412
Total (centered) SS     =  69908.59003              Centered R2   =   0.1079
Total (uncentered) SS   =  198667.4579              Uncentered R2 =   0.6861
Residual SS             =  62363.84851

------------------------------------------------------------------------------
       hrate | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   ln_income |  -8.822082    1.35491    -6.51   0.000    -11.47766   -6.166507
ln_population|   1.404433   .2769494     5.07   0.000      .861622    1.947244
         age |   -.281615    .050726    -5.55   0.000    -.381036   -.1821939
       _cons |    94.4605   12.42859     7.60   0.000     70.10091    118.8201
------------------------------------------------------------------------------
```

We now estimate the model above clustering standard errors by state.[5]

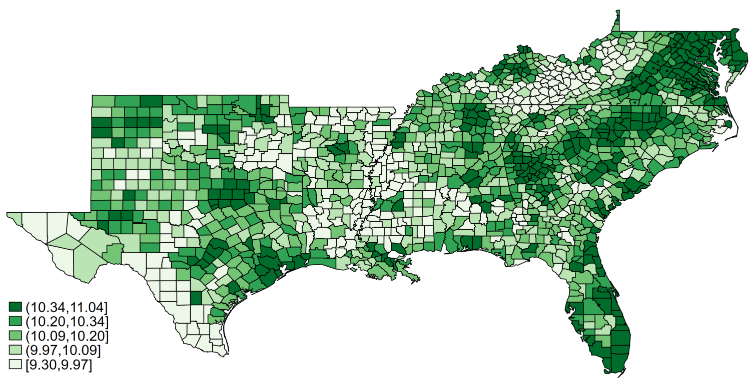
4. This is equivalent to using ivreg2 (Baum et al. 2003) and the following syntax: `ivreg2 hrate ln_population age (ln_income=unemployment), robust`
5. This is equivalent to using ivreg2 (Baum et al. 2003) and the following syntax: `ivreg2 hrate ln_population age (ln_income=unemployment), cluster(sfips)`. We are aware that the number

Figure 1: Homicide rate, log income, and unemployment in 1990 for southern U.S. counties

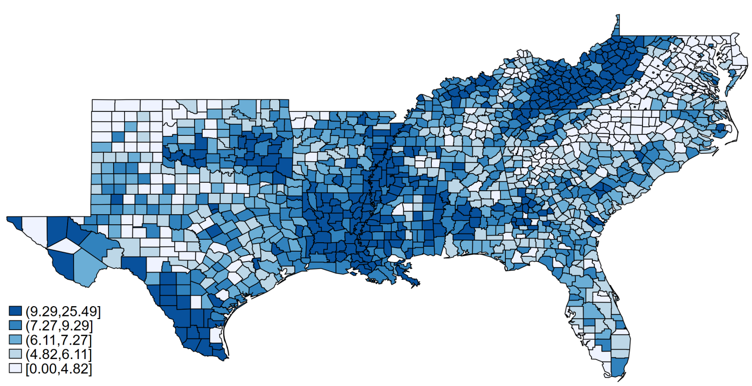
(a) Homicide rate



(b) Income



(c) Unemployment



```
. acreg hrate ln_population age (ln_income=unemployment), cluster(sfips)
MULTIWAY CLUSTERING CORRECTION
Cluster variable(s): sfips
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic: 143.959
                                                       Number of obs =     1412
Total (centered) SS     =  69908.59003                 Centered R2   =   0.1079
Total (uncentered) SS   =  198667.4579                 Uncentered R2 =   0.6861
Residual SS             =  62363.84851
```

hrate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ln_income	-8.822082	1.801762	-4.90	0.000	-12.35347	-5.290693
ln_population	1.404433	.3090553	4.54	0.000	.7986955	2.01017
age	-.281615	.1303804	-2.16	0.031	-.5371558	-.0260741
_cons	94.4605	17.89048	5.28	0.000	59.3958	129.5252

We now estimate the model above using a spatial correction following Conley (1999), with a threshold of 100 kilometers. This means that the error of each county is assumed to be correlated with the counties that are located within a radius of 100 kilometers from it.

```
. acreg hrate ln_population age (ln_income=unemployment), ///
>         spatial latitude(_CX) longitude(_CY) dist(100)
SPATIAL CORRECTION
DistCutoff: 100
LagCutoff:  0
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic: 112.917
                                                       Number of obs =     1412
Total (centered) SS     =  69908.59003                 Centered R2   =   0.1079
Total (uncentered) SS   =  198667.4579                 Uncentered R2 =   0.6861
Residual SS             =  62363.84851
```

hrate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ln_income	-8.822082	2.357644	-3.74	0.000	-13.44298	-4.201183
ln_population	1.404433	.4689154	3.00	0.003	.4853754	2.32349
age	-.281615	.109112	-2.58	0.010	-.4954706	-.0677594
_cons	94.4605	21.86325	4.32	0.000	51.60932	137.3117

of states (clusters) is small and inference would suffer from it, but this is irrelevant to the scope of this exercise.

Additional options

Thresholds. If we want to account for correlation between counties at a greater distance, we can increase the distance cutoff using the `dist()` option. In the following example, we allow for a radius of 200 kilometers.

```
. acreg hrate ln_population age (ln_income=unemployment), ///
> spatial latitude(_CX) longitude(_CY) dist(200)
. estimates store sp1
```

Bartlett. In previous examples the matrix used for the computation of the variance-covariance matrix is binary: for each county pair, it contains 1 if they are located within the distance threshold from each other and 0 otherwise. *acreg* allows for weights in the matrix to linearly decrease as the distance between units increases. To do that we only need to add the option `bartlett` to the syntax.

```
. acreg hrate ln_population age (ln_income=unemployment), ///
> spatial latitude(_CX) longitude(_CY) dist(200) bartlett
. estimates store sp2
```

Partial out high dimensional fixed effects. `acreg` allows for adding high dimensional fixed effects and partial them out, using the `hdfe` command by Correia (2016). Up to two fixed effects variables can be specified through the options `pfe1()` and `pfe2()`. In the example below we estimate the previous model by adding state fixed effects.

```
. acreg hrate ln_population age (ln_income=unemployment), ///
> spatial latitude(_CX) longitude(_CY) dist(100) pfe1(sfips)
. estimates store sp3
```

The following code reports the result of the three estimations in this subsection:

```
. esttab sp1 sp2 sp3, cells(b se) keep(ln_income ln_population age) mtitles(spatial bartlett FE)
```

	(1) spatial b/se	(2) bartlett b/se	(3) FE b/se
ln_income	-8.822082	-8.822082	-13.88229
	2.733507	2.313018	1.835268
ln_populat~n	1.404433	1.404433	1.649735
	.4834539	.4388646	.4000578
age	-.281615	-.281615	-.178832
	.1223503	.1015135	.0960779
N	1412	1412	1412

4.2 Spatial Environment, Panel Setting

For this example we use the same database we used in the previous section: `homicide_1960_1990.dta`. We estimate again the effect of *income* on *homicide rate*, controlling for *population* and *age* and we assume that unemployment is a valid instrument for it. Compared to the previous section, we now use all four waves of the dataset.

Pooled model

We first consider a pooled model in which we do not include any Random or Fixed Effects. We first estimate the model assuming that observations' errors are uncorrelated.[6]

```
. use http://www.stata-press.com/data/r15/homicide_1960_1990.dta, clear
(S.Messner et al.(2000), U.S southern county homicide rate in 1960-1990)

. acreg hrate ln_population age (ln_income=unemployment)
HETEROSKEDASTICITY ROBUST STANDARD ERRORS
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic: 289.132
                                                   Number of obs =     5648
Total (centered) SS     =  286387.1082             Centered R2   =  -0.0447
Total (uncentered) SS   =  781008.6785             Uncentered R2 =   0.6169
Residual SS             =  299188.6495

------------------------------------------------------------------------------
       hrate | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   ln_income |    3.83872   .7815313     4.91   0.000     2.306947    5.370494
ln_population|  -.4411802   .1968992    -2.24   0.025    -.8270955    -.055265
         age |  -.4626917   .0637006    -7.26   0.000    -.5875425   -.3378408
       _cons |  -7.265041   4.126029    -1.76   0.078    -15.35191    .8218268
------------------------------------------------------------------------------
```

We now estimate the same model, but we use the panel feature of `acreg` to account for autocorrelation between observations from the same county over time.[7] We assume no correlation across counties. We specify the option `id()` with the county id, the option `time()` with the year variable and the option `lag()` with a number greater or equal than the maximum lag between observations, which in this case is 30.[8]

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(30)
TEMPORAL CORRECTION
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic: 210.438
                                                   Number of obs =     5648
Total (centered) SS     =  286387.1082             Centered R2   =  -0.0447
```

6. This is equivalent to using ivreg2 (Baum et al. 2003) and the following syntax: `ivreg2 hrate ln_population age (ln_income=unemployment), robust`
7. The estimation of the betas does not change with respect to the previous model, `acreg` is only used for the computation of the standard errors.
8. This is equivalent to using ivreg2 (Baum et al. 2003) and the following syntax: `ivreg2 hrate ln_population age (ln_income=unemployment), cluster(_ID)`. Alternatively, using acreg and the following syntax: `acreg hrate ln_population age (ln_income=unemployment), cluster(_ID)`

```
Total (uncentered) SS   =  781008.6785              Uncentered R2 =   0.6169
Residual SS             =  299188.6495
```

hrate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ln_income	3.83872	.921289	4.17	0.000	2.033027	5.644414
ln_population	-.4411802	.2513095	-1.76	0.079	-.9337379	.0513774
age	-.4626917	.0787756	-5.87	0.000	-.617089	-.3082943
_cons	-7.265041	4.832603	-1.50	0.133	-16.73677	2.206687

We now extend the model above, which takes into account autocorrelation over time, by adding the spatial correction proposed by Conley (1999), with a threshold of 100 kilometers. This means that the error term of each county at a given year is assumed to be correlated with those of all the counties that are located within a radius of 100 kilometers from it observed at the same year while simultaneously correcting for autocorrelation over time for each county. We assume the correlation between near counties but observed at different points in time to be zero.

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(30) ///
>         spatial latitude(_CX) longitude(_CY) dist(100)
SPATIAL CORRECTION
DistCutoff: 100
LagCutoff:  30
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic:  24.838
                                                        Number of obs =     5648
Total (centered) SS     =  286387.1082                  Centered R2   =  -0.0447
Total (uncentered) SS   =  781008.6785                  Uncentered R2 =   0.6169
Residual SS             =  299188.6495
```

hrate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ln_income	3.83872	1.810937	2.12	0.034	.2893488	7.388092
ln_population	-.4411802	.3871668	-1.14	0.254	-1.200013	.3176528
age	-.4626917	.1425257	-3.25	0.001	-.742037	-.1833464
_cons	-7.265041	9.814094	-0.74	0.459	-26.50031	11.97023

FE model

In the following example we replicate the previous model, accounting for both spatial and temporal correlation, but we add to the specification the *county fixed effects* using the option `pfe1`.

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(30) ///
>         spatial latitude(_CX) longitude(_CY) dist(100) pfe1(_ID)
SPATIAL CORRECTION
DistCutoff: 100
LagCutoff:  30
No HAC Correction
```

```
Absorbed FE: _ID
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic:  49.605
                                                   Number of obs =     5648
Total (centered) SS     =  144755.2058             Centered R2   =   0.0175
Total (uncentered) SS   =  144755.2058             Uncentered R2 =   0.0175
Residual SS             =  142223.0274

-------------------------------------------------------------------------------
        hrate | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+----------------------------------------------------------------
    ln_income |   .2588154   1.149746     0.23   0.822    -1.994645    2.512276
ln_population |  -1.630949   1.740873    -0.94   0.349    -5.042997    1.781099
          age |   .1466193   .2006033     0.73   0.465    -.2465559    .5397944
        _cons |  -1.31e-17   .1743959    -0.00   1.000    -.3418097    .3418097
-------------------------------------------------------------------------------

nb: total SS, model and R2s are after partialling out.
To get the corrected ones use the option correctr2
```

We now add to the previous model also time fixed effects using the option `pfe2`.

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(30) ///
>         spatial latitude(_CX) longitude(_CY) dist(100) pfe1(_ID) pfe2(year)
SPATIAL CORRECTION
DistCutoff: 100
LagCutoff:  30
No HAC Correction
Absorbed FE: _ID and year
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic:   3.895
                                                   Number of obs =     5648
Total (centered) SS     =   136166.339             Centered R2   =  -0.0793
Total (uncentered) SS   =   136166.339             Uncentered R2 =  -0.0793
Residual SS             =  146961.8234

-------------------------------------------------------------------------------
        hrate | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+----------------------------------------------------------------
    ln_income |  -13.30126    17.5969    -0.76   0.450    -47.79055    21.18803
ln_population |  -1.602695   2.253785    -0.71   0.477    -6.020033    2.814642
          age |   .0038921   .0937463     0.04   0.967    -.1798472    .1876314
        _cons |  -1.11e-15    .128699    -0.00   1.000    -.2522454    .2522454
-------------------------------------------------------------------------------

nb: total SS, model and R2s are after partialling out.
To get the corrected ones use the option correctr2
```

Additional Options

Thresholds. Now we account for spatial correlation between observations of the same year without accounting for any temporal correlation. We do this by setting the lagcutoff at 0.[9]

9. The result differs from the one obtained in the cross-sectional environment (`acreg hrate ln_population age (ln_income=unemployment), spatial latitude(_CX) longitude(_CY) dist(100)`) because the spatial correlation is assumed to be present only between observa-

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(0) ///
> spatial latitude(_CX) longitude(_CY) dist(100)
. estimates store spp1
```

Now we account for spatial correlation between observations of the same year, and also for temporal correlation between observations from the same county, but only between neighbor decades, i.e. two observations from the same county are assumed to be correlated only if they are observed with less than 10-year difference.[10] We do that by setting the *lagcutoff* equal to 10.

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(10) ///
> spatial latitude(_CX) longitude(_CY) dist(100)
. estimates store spp2
```

HAC. In the previous examples the matrix used for the computation of the variance-covariance matrix is binary. We can use the option `hac` to have a linear decay in time and compute Heteroscedasticity-Autocorrelation-Consistent standard errors, following Newey and West (1987).

```
. acreg hrate ln_population age (ln_income=unemployment), id(_ID) time(year) lagcut(30) ///
> spatial latitude(_CX) longitude(_CY) dist(100) hac
. estimates store spp3
```

The following code reports the result of the three estimations in this subsection.

```
. esttab spp1 spp2 spp3, cells(b se) keep(ln_income ln_population age) mtitles(lag0 lag10 hac)
```

	(1) lag0 b/se	(2) lag10 b/se	(3) hac b/se
ln_income	3.83872	3.83872	3.83872
	1.743993	1.801373	1.785354
ln_populat~n	-.4411802	-.4411802	-.4411802
	.3542752	.377059	.3727145
age	-.4626917	-.4626917	-.4626917
	.1347804	.1403627	.139132
N	5648	5648	5648

4.3 Network Environment, Cross-sectional Setting

For this example, we use a dataset of co-offending in a London-based youth gang. Data were collected by James Densley and Thomas Grund. The data have been used in Grund and Densley (2012) and Grund and Densley (2015). Information on 54 individuals is reported, two individuals are recorded to be linked if they committed at least a crime together. Data contains, among others, the age (`Age`), the birthplace (`Birthplace`),

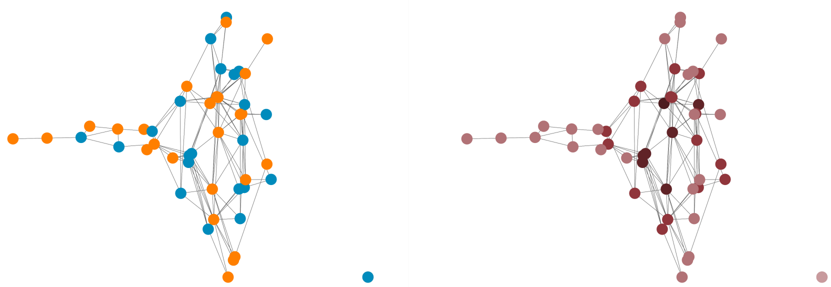
tions from the same year.

10. This would allow an observation's error term to be correlated with all other observations within 10-year lags and 10-year leads from the same county.

the number of arrests (`Arrests`), the number of convictions (`Convictions`), and the position in the gang's internal hierarchy (`Ranking`). The symmetric binary links constituting the co-offending network are stored in 54 variables (`_net2_1-_net2_54`). Figure 2 presents the distribution of the variables `Arrest` and `Ranking` within the network. In this example we want to estimate the effect of *ranking* on *arrests*, controlling for *age*, *residence*, and *birthplace FEs*.

Figure 2: Gang Network

(a) Arrest (b) Ranking



Notes: In panel (a), blue dots represent arrested people. In panel (b), darker red dots identify a greater position in the ranking.

The code below is necessary to load the dataset (`webnwuse gang`), load the network (`nwload gang`) and replace the diagonal of the adjacency matrix with ones (*the loop*). This is needed because the original database does not contain self-links.

```
      . webnwuse gang
Loading successful

      (2 networks)
      ____________________

      gang_valued
      gang
      . nwload gang
      . forvalues j = 1(1)54 {
      2. qui replace _net2_`j´ = 1 in `j´
      3. }
```

We first estimate the model assuming that observations' errors are uncorrelated.[11]

```
      . acreg Arrest Ranking Age Residence i.Birthplace
      HETEROSKEDASTICITY ROBUST STANDARD ERRORS
      No HAC Correction
      No Absorbed FEs
      Included instruments: Ranking Age Residence 1b.Birthplace 2.Birthplace 3.Birthplace 4.Birthplace
```

11. This is equivalent to using ivreg2 (Baum et al. 2003) and the following syntax: `ivreg2 Arrest Ranking Age Residence i.Birthplace, robust`

```
                                                     Number of obs =        54
Total (centered) SS     =  2196.537037               Centered R2   =    0.2442
Total (uncentered) SS   =         7497               Uncentered R2 =    0.7786
Residual SS             =  1660.198039
```

Arrests	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Ranking	-2.168476	.8207074	-2.64	0.008	-3.777033	-.5599192
Age	.7665194	.3094139	2.48	0.013	.1600793	1.372959
Residence	-1.534665	1.561649	-0.98	0.326	-4.59544	1.526111
Birthplace						
Caribbean	0	(empty)				
East Africa	-.2523035	2.869505	-0.09	0.930	-5.87643	5.371822
UK	.7012659	2.228246	0.31	0.753	-3.666016	5.068548
West Africa	.8171717	2.012521	0.41	0.685	-3.127297	4.76164
_cons	2.317286	7.506876	0.31	0.758	-12.39592	17.03049

We now estimate the same model using the standard-error correction proposed in our paper (Colella et al. 2019). We assume that the error term of each observation is correlated with that of another if they are linked in the network. To implement this in `acreg`, we provide the variables containing the adjacency matrix as input in the `links_mat` option and set *distcutoff* equal to 1.

```
. acreg Arrest Ranking Age Residence i.Birthplace, network links_mat(_net2_*) dist(1)
NETWORK CORRECTION
DistCutoff: 1
LagCutoff:  0
No HAC Correction
No Absorbed FEs
Included instruments: Ranking Age Residence 1b.Birthplace 2.Birthplace 3.Birthplace 4.Birthplace
                                                     Number of obs =        54
Total (centered) SS     =  2196.537037               Centered R2   =    0.2442
Total (uncentered) SS   =         7497               Uncentered R2 =    0.7786
Residual SS             =  1660.198039
```

Arrests	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Ranking	-2.168476	.7132431	-3.04	0.002	-3.566407	-.7705455
Age	.7665194	.3730319	2.05	0.040	.0353904	1.497648
Residence	-1.534665	1.618858	-0.95	0.343	-4.707568	1.638239
Birthplace						
Caribbean	0	(empty)				
East Africa	-.2523035	2.258789	-0.11	0.911	-4.679449	4.174842
UK	.7012659	2.984775	0.23	0.814	-5.148785	6.551317
West Africa	.8171717	2.260143	0.36	0.718	-3.612627	5.24697
_cons	2.317286	7.825902	0.30	0.767	-13.0212	17.65577

Additional Options

Accounting for degree grater than one. Each node of a network has a certain number of links that connects it to other nodes. This number is called the degree k of a node. `acreg` allows the user to account for correlation between two observations that are not necessarily directly linked but are linked through other observations. Starting from the same 0-1 adjacency matrix used in the previous example, we now want to allow for correlation also between individuals that are linked through another individual (degree 2). To do that we will use the same syntax but we change the *distcutoff* to 2.

```
. acreg Arrest Ranking Age Residence i.Birthplace, network links_mat(_net2_*) dist(2)
. estimates store ne1
```

Bartlett. In previous examples the matrix used for the computation of the variance-covariance matrix is binary: it contains values 1 for each pair of individuals that are first or second degree linked, and zeros otherwise. *acreg* allows for weights in the matrix to linearly decrease as the network distance increases.[12] To do that in our sample, i.e., having ones for first degree linked observations and 0.5 for second degree ones we will use the option `bartlett`.

```
. acreg Arrest Ranking Age Residence i.Birthplace, network links_mat(_net2_*) dist(2) ///
> bartlett
. estimates store ne2
```

Partial out high dimensional fixed effects. `acreg` allows for adding high dimensional fixed effects and partial them out, using the `hdfe` command by Correia (2016): up to two fixed effects variables can be specified through the options `pfe1()` and `pfe2()`. In the example below we estimate the previous model partialing out birthplace FEs instead of adding them as dummies in the main regression.

```
. acreg Arrest Ranking Age Residence, network links_mat(_net2_*) dist(1) pfe1(Birthplace)
. estimates store ne3
```

The following code reports the result of the three estimations in this subsection.

```
. esttab ne1 ne2 ne3, cells(b se) keep(Ranking Age Residence) ///
>         mtitles(degree2 bartlett FE)
```

	(1) degree2 b/se	(2) bartlett b/se	(3) FE b/se
Ranking	-2.168476	-2.168476	-2.168476
	.4801238	.7688551	.7132431
Age	.7665194	.7665194	.7665194
	.4001636	.3427023	.3730319
Residence	-1.534665	-1.534665	-1.534665
	2.138931	1.590511	1.618858

12. With distance here we refer to the strength of the link: first degree is distance 1, second degree is distance 2, etc...

```
N                      54          54          54
```

4.4 Network Environment, Panel Setting

For this section we use an ad-hoc database that can be downloaded from our command's website. It is a balanced panel dataset of 1000 observations (NT) referring to 100 (N) individuals at 10 (T) points in time. Individuals are identified through the variable `id`, while time is identified through the variable `time`. Database also contains, among others, the following variables `Y_it`, `X1_it`, `End_it`, and `IV_it`. The symmetric binary links constituting the network are stored in 100 (N) variables (`clus_1-clus_100`). In this example we want to estimate the effect of `End_it` on `Y_it`, controlling for `X_it`. We claim that *End_it* is endogenous and we assume that *IV_it* is a valid instrument for it.

Pooled model

We first consider a pooled model in which we do not include any Random or Fixed Effects. We first estimate the model assuming that observations' errors are uncorrelated.[13]

```
. use https://acregstata.weebly.com/uploads/2/9/1/6/29167217/acregfakedata.dta, clear
. acreg Y_it X1_it (Z_it=IV_it)
HETEROSKEDASTICITY ROBUST STANDARD ERRORS
No HAC Correction
No Absorbed FEs
Included instruments: X1_it
Instrumented: Z_it
Excluded instruments: IV_it
Kleibergen-Paap rk Wald F statistic:  37.874
                                                       Number of obs =     1000
Total (centered) SS     =  2834382.139                 Centered R2   =   0.4913
Total (uncentered) SS   =    4195421.4                 Uncentered R2 =   0.6563
Residual SS             =  1441795.144
------------------------------------------------------------------------------
        Y_it | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        Z_it |    1.02863   .2409828     4.27   0.000     .5563128    1.500948
       X1_it |   1.228864   .3320382     3.70   0.000     .5780809    1.879647
       _cons |   11.61852   3.013075     3.86   0.000     5.713007    17.52404
------------------------------------------------------------------------------
```

We now estimate the same model accounting for correlation between errors from observations of the same individual (`id`). We still assume that there is no correlation between individuals and do not consider the network structure yet. To do this, we use the panel features (options `id()` and `time`) and we set the `lag()` option to be greater than or equal to the maximum distance in time between observations, which in this case is 10.[14]

13. This is equivalent to using ivreg2 (Baum et al. 2003) and the following syntax: `ivreg2 Y_it X1_it (End_it=IV_it), robust`

14. This is equivalent to clustering by individuals using ivreg2 (Baum et al. 2003) and the fol-

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(10)
TEMPORAL CORRECTION
No HAC Correction
No Absorbed FEs
Included instruments: X1_it
Instrumented: Z_it
Excluded instruments: IV_it
Kleibergen-Paap rk Wald F statistic:  30.295
                                                     Number of obs =     1000
Total (centered) SS     =  2834382.139               Centered R2   =   0.4913
Total (uncentered) SS   =    4195421.4               Uncentered R2 =   0.6563
Residual SS             =  1441795.144

------------------------------------------------------------------------------
        Y_it | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        Z_it |    1.02863   .2720916     3.78   0.000     .4953406     1.56192
       X1_it |   1.228864   .3779895     3.25   0.001     .4880181     1.96971
       _cons |   11.61852   3.042037     3.82   0.000     5.656242    17.58081
------------------------------------------------------------------------------
```

We now estimate the model above adding to the temporal correlation the correction for network links as proposed in our paper (Colella et al. 2019). We assume that the error term of each individual is correlated with that of another individual observed in the same year if they are linked in the network while accounting for correlation between errors from observations of the same individual. To implement this in `acreg`, we provide the variables containing the adjacency matrix as input in the `links_mat` option and set *distcutoff* equal to 1.[15] The correlation between linked individuals but observed at different points in time is still assumed to be null.

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(10) ///
>         network links_mat(clus*) dist(1)
NETWORK CORRECTION
DistCutoff: 1
LagCutoff:  10
No HAC Correction
No Absorbed FEs
Included instruments: X1_it
Instrumented: Z_it
Excluded instruments: IV_it
Kleibergen-Paap rk Wald F statistic:  22.720
                                                     Number of obs =     1000
Total (centered) SS     =  2834382.139               Centered R2   =   0.4913
Total (uncentered) SS   =    4195421.4               Uncentered R2 =   0.6563
Residual SS             =  1441795.144

------------------------------------------------------------------------------
        Y_it | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        Z_it |    1.02863   .3842782     2.68   0.007     .2754589    1.781802
       X1_it |   1.228864   .4495232     2.73   0.006     .3478147    2.109913
       _cons |   11.61852   4.743084     2.45   0.014      2.32225     20.9148
------------------------------------------------------------------------------
```

lowing syntax: `ivreg2 Y_it X1_it (End_it=IV_it), cluster(id)`, or acreg: `acreg Y_it X1_it (End_it=IV_it), cluster(id)`

15. The total number of observations in the database is NT (1000), but the total number of individuals is N (100). Since we are using the panel feature, `acreg` will require a link matrix formed by N variables, not NT.

FE model

In the following example we replicate the previous model, accounting for both spatial and temporal correlation, but we add to the specification the *individual fixed effects* using the option `pfe1`.

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(10) ///
>         network links_mat(clus*) dist(1) pfe1(id)
NETWORK CORRECTION
DistCutoff: 1
LagCutoff:  10
No HAC Correction
Absorbed FE: id
Included instruments: X1_it
Instrumented: Z_it
Excluded instruments: IV_it
Kleibergen-Paap rk Wald F statistic:  38.899
                                                     Number of obs =     1000
Total (centered) SS     =  2331112.842               Centered R2   =   0.4938
Total (uncentered) SS   =  2331112.842               Uncentered R2 =   0.4938
Residual SS             =  1180104.818

------------------------------------------------------------------------------
        Y_it | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        Z_it |   1.368636    .346849     3.95   0.000     .6888244    2.048448
       X1_it |   .7942328   .3663375     2.17   0.030     .0762245    1.512241
       _cons |   9.58e-17   1.266864     0.00   1.000    -2.483007    2.483007
------------------------------------------------------------------------------
nb: total SS, model and R2s are after partialling out.
To get the corrected ones use the option correctr2
```

We now add to the previous model also time fixed effects using the option `pfe2`.

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(10) ///
>         network links_mat(clus*) dist(1) pfe1(id) pfe2(time)
NETWORK CORRECTION
DistCutoff: 1
LagCutoff:  10
No HAC Correction
Absorbed FE: id and time
Included instruments: X1_it
Instrumented: Z_it
Excluded instruments: IV_it
Kleibergen-Paap rk Wald F statistic:  39.988
                                                     Number of obs =     1000
Total (centered) SS     =  2226516.365               Centered R2   =   0.4935
Total (uncentered) SS   =  2226516.365               Uncentered R2 =   0.4935
Residual SS             =  1127664.807

------------------------------------------------------------------------------
        Y_it | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        Z_it |   1.327506   .3119844     4.26   0.000     .7160278    1.938984
       X1_it |   .8232877   .3574087     2.30   0.021     .1227796    1.523796
       _cons |  -7.70e-17   .9797572    -0.00   1.000    -1.920289    1.920289
------------------------------------------------------------------------------
nb: total SS, model and R2s are after partialling out.
To get the corrected ones use the option correctr2
```

Additional Options

Thresholds. Now we still account for network correlation between observations of the same year, but we do not account for any kind of temporal correlation. We do that by setting the lagcutoff at 0.

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(0) ///
> network links_mat(clus*) dist(1)
. estimates store nep1
```

Now we account for network correlation between observations of the same year, and also for temporal correlation between observations from the same individual, but only if they were observed with a lag lower than 3 years. We do that by setting the *lagcutoff* equal to 3.

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(3) ///
> network links_mat(clus*) dist(1)
. estimates store nep2
```

HAC. In the previous examples the matrix used for the computation of the variance-covariance matrix is binary. We can use the option `hac` to have a linear decay in time and compute Heteroscedasticity-Autocorrelation-Consistent standard errors, following Newey and West (1987).

```
. acreg Y_it X1_it (Z_it=IV_it), id(id) time(time) lag(3) ///
> network links_mat(clus*) dist(1) hac
. estimates store nep3
```

The following code reports the result of the three estimations in this subsection.

```
. esttab nep1 nep2 nep3, cells(b se) keep(X1_it Z_it) mtitles(lag0 lag10 hac)
```

	(1) lag0 b/se	(2) lag10 b/se	(3) hac b/se
Z_it	1.02863	1.02863	1.02863
	.3629168	.3783906	.3756538
X1_it	1.228864	1.228864	1.228864
	.4116362	.4578899	.4442984
N	1000	1000	1000

4.5 Multiway clustering

In this section, we illustrate the multiway clustering environment. `acreg` allows for the traditional one-dimension clustering, two-way clustering and multi-way clustering; in the latter scenarios, two observations are considered to be correlated if they share at least one cluster dimension (Cameron and Miller 2015). For this example we use again the data on the homicides in southern states of the U.S. `homicide_1960_1990.dta` available at the STATA website. As in section 4.1 we consider only the cross-sectional database for 1990 and we estimate the effect of *income* on *homicide rate*, controlling for *population*, and *age*. For the sake of illustration, we claim that income is endogenous and we assume that unemployment is a valid instrument for it.

Two-way clustering

In this first example we cluster standard errors following two dimensions: state and age.

```
. use http://www.stata-press.com/data/r15/homicide1990.dta , clear
(S.Messner et al.(2000), U.S southern county homicide rates in 1990)

. acreg hrate ln_population age (ln_income=unemployment), cluster(sfips age)
MULTIWAY CLUSTERING CORRECTION
Cluster variable(s): sfips age
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
Kleibergen-Paap rk Wald F statistic: 141.918
                                                       Number of obs =     1412
Total (centered) SS     =  69908.59003                 Centered R2   =   0.1079
Total (uncentered) SS   =  198667.4579                 Uncentered R2 =   0.6861
Residual SS             =  62363.84851
```

hrate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ln_income	-8.822082	1.818954	-4.85	0.000	-12.38717	-5.256998
ln_population	1.404433	.2960066	4.74	0.000	.8242705	1.984595
age	-.281615	.1315389	-2.14	0.032	-.5394265	-.0238035
_cons	94.4605	17.95901	5.26	0.000	59.26148	129.6595

Multi-way clustering

The example above can be replicated also using the `ivreg2` command, by simply typing `ivreg2 hrate ln_population age (ln_income=unemployment), cluster(sfips age)`. However, `ivreg2` accomodates a maximum of 2 cluster variables, while `acreg` allows for clustering for an infinite number of variables.[16] In the following and last example we cluster standard errors following three dimensions: state, age, and hcount.

```
. acreg hrate ln_population age (ln_income=unemployment), cluster(sfips age hcount)
MULTIWAY CLUSTERING CORRECTION
Cluster variable(s): sfips age hcount
No HAC Correction
No Absorbed FEs
Included instruments: ln_population age
Instrumented: ln_income
Excluded instruments: unemployment
```

16. The `cgmreg` command developed by Collin Cameron allows for multi-way clustering but is not suitable for 2SLS estimation.

```
Kleibergen-Paap rk Wald F statistic: 128.582
                                                     Number of obs =      1412
Total (centered) SS     =  69908.59003               Centered R2   =    0.1079
Total (uncentered) SS   =  198667.4579               Uncentered R2 =    0.6861
Residual SS             =  62363.84851
```

hrate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ln_income	-8.822082	2.240027	-3.94	0.000	-13.21245	-4.431709
ln_population	1.404433	.7062929	1.99	0.047	.0201242	2.788741
age	-.281615	.1261689	-2.23	0.026	-.5289014	-.0343285
_cons	94.4605	21.90178	4.31	0.000	51.53379	137.3872

5 Conclusion

In this article, we presented the `acreg` Stata command: a new user-written routine that allows for standard error correction in OLS and 2SLS estimation of models with complex correlation structure. `acreg` can accommodate in a flexible way dependence of the errors between units in space or in a network and across time. This command includes most of the standard options present in previous commands to estimate regression coefficients. The correlation structure can be inputed by the user in a matrix form or built from information on the geographic distance between spatial units or from the links between observations. We also provide a broad collection of examples with both cross-section and panel data.

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