

Longitudinal Data Analysis

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Panel Data Analysis: Random Effects Models

In fixed effects models, each dummy variable removes one degree of freedom from the model; thus, fixed effects models work well when you have a substantial number of time periods. To avoid losing the degrees of freedom and to utilize both the information on change over time for a given unit and the information on differences across units, we can estimate random effects models. The model still decomposes the residuals: $Y_{it} = \alpha + X_{it}\beta + u_i + e_{it}$ where u_i represents the effect of unit i and e_{it} is the residual effect for time point t for that unit. But in a random effects model, unit residuals u_i do not have specific values – u_i is a normally distributed random variable (hence the name – random effects).

The nature of the coefficients β also changes as we go from a fixed effects to a random effects model – in a random effects model, we are not only predicting change over time but also explaining the differences among the units. Thus, the data on cross-sectional variation are utilized in estimating independent variables' effects. Because the predictors are used to explain not only change over time but also differences among units, the random unit residual variable u is assumed to be uncorrelated with $X\beta$: $\text{corr}(u_i, X\beta) = 0$. We can now use time-invariant variables in our model.

```
. xtreg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, re cluster(hhid)
Random-effects GLS regression                Number of obs      =       30541
Group variable: hhidpn                      Number of groups   =        6243
R-sq:  within = 0.0229                      Obs per group: min =         1
      between = 0.0309                                avg =         4.9
      overall = 0.0254                                max =         9
Random effects u_i ~ Gaussian                Wald chi2(10)      =       529.71
corr(u_i, X) = 0 (assumed)                  Prob > chi2        =       0.0000
                                           (Std. Err. adjusted for 4635 clusters in hhid)
-----+-----
```

rallparhel~w	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
rworkhours80	-.017518	.0013378	-13.09	0.000	-.02014	-.0148959
rpoorhealth	-.1027325	.0722552	-1.42	0.155	-.2443501	.0388852
rmarried	-.3439424	.0982397	-3.50	0.000	-.5364887	-.1513962
rtotalpar	-.2764635	.0419983	-6.58	0.000	-.3587785	-.1941484
rsiblog	-.3816662	.0643893	-5.93	0.000	-.5078669	-.2554656
hchildlg	-.0431438	.0651145	-0.66	0.508	-.1707658	.0844782
female	.4784234	.0581174	8.23	0.000	.3645154	.5923314
age	-.040811	.0118594	-3.44	0.001	-.0640551	-.017567
minority	-.1316851	.0900886	-1.46	0.144	-.3082556	.0448853
raedyrs	.0647266	.0110043	5.88	0.000	.0431586	.0862946
_cons	4.572378	.7227877	6.33	0.000	3.15574	5.989015
sigma_u	1.6329416					
sigma_e	3.5375847					
rho	.17564702 (fraction of variance due to u_i)					

Note that less variance is attributed to person level in this model than in the fixed effects model, but a significance test for unit-level variance is not included. But we can easily obtain it:

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

rallparhelptw[hhidpn,t] = Xb + u[hhidpn] + e[hhidpn,t]

Estimated results:
-----+-----
rallpar~w |      Var      sd = sqrt(Var)
e |      16.45761      4.056797
u |      12.51451      3.537585
      2.666498      1.632942

Test:  Var(u) = 0
      chi2(1) = 4211.99
      Prob > chi2 = 0.0000
```

Thus, we reject the null hypothesis that person-specific residuals are all zero – there is a significant amount of variance across persons above and beyond that explained by our predictors.

So far we estimated our model using GLS (generalized least squares) estimation method; we could also estimate the same model using maximum likelihood estimation option, although cluster option is not available with this method:

```
. xtreg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, re mle

Fitting constant-only model:
Iteration 0:  log likelihood = -84739.359
Iteration 1:  log likelihood = -84735.952
Iteration 2:  log likelihood = -84735.947

Fitting full model:
Iteration 0:  log likelihood = -84417.691
Iteration 1:  log likelihood = -84386.623
Iteration 2:  log likelihood = -84386.583

Random-effects ML regression
Group variable: hhidpn
Number of obs      =      30541
Number of groups   =       6243

Random effects u_i ~ Gaussian
Obs per group: min =         1
               avg =         4.9
               max =         9

Log likelihood     = -84386.583
LR chi2(10)       =       698.73
Prob > chi2       =       0.0000
```

rallparhel~w	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
rworkhours80	-.0177108	.0011737	-15.09	0.000	-.0200112	-.0154104
rpoorhealth	-.0888093	.0643735	-1.38	0.168	-.214979	.0373604
rmarried	-.3523333	.0784346	-4.49	0.000	-.5060623	-.1986043
rtotalpar	-.3073022	.0323089	-9.51	0.000	-.3706264	-.243978
rsiblog	-.3762714	.0551995	-6.82	0.000	-.4844604	-.2680823
hchildlg	-.0384941	.0582924	-0.66	0.509	-.152745	.0757568
female	.47	.0671802	7.00	0.000	.3383292	.6016708

age		-.0423231	.0107905	-3.92	0.000	-.063472	-.0211741
minority		-.1365561	.0806732	-1.69	0.091	-.2946727	.0215606
raedyrs		.0658393	.0115215	5.71	0.000	.0432574	.0884211
_cons		4.670711	.6493207	7.19	0.000	3.398066	5.943356

/sigma_u		1.882485	.0301588			1.824293	1.942533
/sigma_e		3.524548	.0157879			3.49374	3.555628
rho		.2219534	.0060177			.2103391	.2339254

Likelihood-ratio test of sigma_u=0: chibar2(01) = 2611.48 Prob>=chibar2 = 0.000

The same model can be fit using xtmixed command – we will later use this command for mixed model, and the random effects model is a basic case of such a model:

```
. xtmixed rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs || hhidpn:
Performing EM optimization:
Performing gradient-based optimization:
Iteration 0: log restricted-likelihood = -84415.598
Iteration 1: log restricted-likelihood = -84415.597
Computing standard errors:
Mixed-effects REML regression
Group variable: hhidpn
Number of obs = 30541
Number of groups = 6243
Obs per group: min = 1
                avg = 4.9
                max = 9
Wald chi2(10) = 706.62
Prob > chi2 = 0.0000
Log restricted-likelihood = -84415.597
```

rallparhel~w	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
rworkhours80	-.0177123	.0011738	-15.09	0.000	-.0200128 - .0154117
rpoorhealth	-.0886995	.0643665	-1.38	0.168	-.2148554 .0374565
rmarried	-.3524069	.0784612	-4.49	0.000	-.5061881 -.1986257
rtotalpar	-.307533	.032103	-9.58	0.000	-.3704536 -.2446123
rsiblog	-.3762313	.0552292	-6.81	0.000	-.4844784 -.2679841
hchildlg	-.0384531	.0583245	-0.66	0.510	-.152767 .0758607
female	.469936	.0672173	6.99	0.000	.3381925 .6016796
age	-.0423344	.0107962	-3.92	0.000	-.0634946 -.0211742
minority	-.1365957	.0807244	-1.69	0.091	-.2948126 .0216212
raedyrs	.0658478	.0115284	5.71	0.000	.0432526 .0884431
_cons	4.671444	.6496436	7.19	0.000	3.398166 5.944722

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
hhidpn: Identity			
sd(_cons)	1.884641	.0301846	1.8264 1.944741
sd(Residual)	3.524762	.0157898	3.49395 3.555845

LR test vs. linear regression: chibar2(01) = 2616.90 Prob >= chibar2 = 0.0000

As mentioned above, random effects coefficients have a dual nature: They simultaneously explain change over time and the cross-sectional differences among units. The implicit assumption is that both types of effects are the same. That is, when we say that a one unit increase in X is associated with a b units increase in Y, a one unit increase might mean two things:

1. We observe two different individuals with a one unit difference in X between them.
2. We observe one person, and its X value increases by one unit.

In a random effects model, we are assuming that both of those produce the same effect on Y. That is, for instance, we assume that if one person works one hour more per week than another, and if a given person increases her or his work hours by one hour per week, the effect on hours of help to parents would be the same.

We test this assumption using the Hausman test. The Hausman test checks a more efficient model against a less efficient but consistent model to make sure that the more efficient model also gives consistent results. The null hypothesis is that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator. If they are, then it is safe to use a random effects model. If the two sets of coefficients are significantly different, then the random effects model is problematic. It is best to use hausman test with sigmamore option; it avoids problems with the matrix $[V_b - V_B]$ not being positive definite.

```
. qui xtreg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog
hchildlg female age minority raedyrs, fe

. est store fixed

. qui xtreg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog
hchildlg female age minority raedyrs, re

. est store random

. hausman fixed random, sigmamore
----- Coefficients -----
      |          (b)          (B)          (b-B)          sqrt(diag(V_b-V_B))
      |          fixed      random      Difference          S.E.
-----+-----
rworkhours80 |  -.0193467   -.017518   -.0018287   .0009452
rpoorhealth  |   .0792176   -.1027325   .1819501   .0499086
rmarried     |  -.6578103   -.3439424   -.3138679   .1128988
rtotalpar   |   -.52481    -.2764635   -.2483466   .0223144
rsiblog     |  -.5767981   -.3816662   -.1951319   .1790009
hchildlg    |   .3859163   -.0431438   .4290601   .1652614
-----+-----

      b = consistent under Ho and Ha; obtained from xtreg
      B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

      chi2(6) = (b-B)' [(V_b-V_B)^(-1)] (b-B)
            =      263.59
      Prob>chi2 =      0.0000
```

In this case, we reject the null hypothesis – fixed effects and random effects coefficients are significantly different. Examining the coefficients, we might suspect that rpoorhealth or hchildlg are responsible.

To better understand the meaning of the Hausman test, let's introduce the between effects model.

```
. xtreg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, be
```

```

Between regression (regression on group means)   Number of obs   =   30541
Group variable: hhidpn                         Number of groups =   6243
R-sq:  within = 0.0008                         Obs per group:  min =    1
          between = 0.0483                       avg =    4.9
          overall = 0.0173                       max =    9
                                                F(10,6232)     =   31.62
sd(u_i + avg(e_i.))= 2.539716                 Prob > F       =   0.0000

```

rallparhel~w	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rworkhours80	-.0097168	.0019226	-5.05	0.000	-.0134858	-.0059478
rpoorhealth	-.3909062	.1052603	-3.71	0.000	-.5972526	-.1845598
rmarried	-.3108795	.0944656	-3.29	0.001	-.4960647	-.1256943
rtotalpar	.3335196	.0595554	5.60	0.000	.2167706	.4502686
rsiblog	-.3402857	.0571287	-5.96	0.000	-.4522776	-.2282937
hchildlg	-.139232	.0610987	-2.28	0.023	-.2590065	-.0194575
female	.683156	.0695158	9.83	0.000	.5468811	.8194309
age	-.0040194	.01099	-0.37	0.715	-.0255636	.0175247
minority	-.0596539	.079881	-0.75	0.455	-.2162482	.0969403
raedys	.0382127	.0116876	3.27	0.001	.0153009	.0611245
_cons	1.80804	.6821661	2.65	0.008	.4707594	3.145321

This type of analysis is equivalent to taking the mean of each variable across time for each case and running a regression on the collapsed dataset of means. As this results in a loss of information, between effects are rarely used. The between effects estimator is mostly important because Stata's random-effects estimator is a weighted average of a fixed effects and a between effects coefficient. Thus, implicitly, the Hausman test assesses whether fixed effects and between effects produce the same coefficients. If they do, it is appropriate to combine them into a random effects model. Comparing these coefficients to the fixed effects coefficients in the Hausman output, we see some major differences for rpoorhealth and hchildlg but also rtotalpar. We could also estimate the two types of effects (over time and across units) separately in a single random effects model using the same kind of person-specific mean variables and mean-differenced variables that we created when examining fixed effects models (this is only done for time-varying variables):

```

. for var rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg: bysort hhidpn:
egen Xm=mean(X) \ gen Xdiff=X-Xm

-> bysort hhidpn: egen rworkhours80m=mean(rworkhours80)
(36 missing values generated)

-> gen rworkhours80diff=rworkhours80-rworkhours80m
(8015 missing values generated)

-> bysort hhidpn: egen rpoorhealthm=mean(rpoorhealth)

-> gen rpoorhealthdiff=rpoorhealth-rpoorhealthm
(7535 missing values generated)

-> bysort hhidpn: egen rmarriedm=mean(rmarried)

-> gen rmarrieddiff=rmarried-rmarriedm
(7561 missing values generated)

-> bysort hhidpn: egen rtotalparm=mean(rtotalpar)

-> gen rtotalpardiff=rtotalpar-rtotalparm

```

```

(7846 missing values generated)

-> bysort hhidpn: egen rsiblogm=mean(rsiblog)
(6 missing values generated)

-> gen rsiblogdiff=rsiblog-rsiblogm
(81 missing values generated)

-> bysort hhidpn: egen hchildlgm=mean(hchildlg)
(2248 missing values generated)

-> gen hchildlgdiff=hchildlg-hchildlgm
(10457 missing values generated)

. xtreg rallparhelptw rworkhours80m rworkhours80diff rpoorhealthm rpoorhealthdiff
rmarriedm rmarrieddiff rtotalparm rtotalpardiff rsiblogm rsiblogdiff hchildlgm
hchildlgdiff female age minority raedyrs, re cluster(hhid)
Random-effects GLS regression           Number of obs   =       30541
Group variable: hhidpn                 Number of groups =        6243
R-sq:  within = 0.0242                  Obs per group:  min =         1
      between = 0.0409                      avg =         4.9
      overall = 0.0332                      max =         9
Random effects u_i ~ Gaussian           Wald chi2(16)   =       577.31
corr(u_i, X) = 0 (assumed)             Prob > chi2     =       0.0000
                                         (Std. Err. adjusted for 4635 clusters in hhid)
-----+-----
|               |               |               |               |               |               |
rallparhel~w |               |               |               |               |               |
-----+-----
rworkhou~80m | -.0115568 | .0022162 | -5.21 | 0.000 | -.0159006 | -.0072131
rworkhours~f | -.0176429 | .0016761 | -10.53 | 0.000 | -.020928 | -.0143578
rpoorhealthm | -.3904361 | .1203335 | -3.24 | 0.001 | -.6262854 | -.1545869
rpoorhealt~f | .0658695 | .0839301 | 0.78 | 0.433 | -.0986304 | .2303694
  rmarriedm | -.2655983 | .1099098 | -2.42 | 0.016 | -.4810175 | -.050179
rmarrieddiff | -.680859 | .1555738 | -4.38 | 0.000 | -.9857781 | -.3759399
  rtotalparm | .1583439 | .0615846 | 2.57 | 0.010 | .0376404 | .2790474
rtotalpard~f | -.4481539 | .0546544 | -8.20 | 0.000 | -.5552747 | -.3410332
  rsiblogm | -.3632242 | .068526 | -5.30 | 0.000 | -.4975326 | -.2289157
  rsiblogdiff | -.683971 | .1578554 | -4.33 | 0.000 | -.993362 | -.37458
  hchildlgm | -.09689 | .0682514 | -1.42 | 0.156 | -.2306603 | .0368802
hchildlgdiff | .3307412 | .1666087 | 1.99 | 0.047 | .0041942 | .6572882
  female | .6542834 | .0634002 | 10.32 | 0.000 | .5300213 | .7785454
  age | -.0074142 | .0122852 | -0.60 | 0.546 | -.0314927 | .0166644
  minority | -.0700329 | .0907892 | -0.77 | 0.440 | -.2479765 | .1079107
  raedyrs | .0421826 | .0112259 | 3.76 | 0.000 | .0201802 | .064185
  _cons | 2.440797 | .7640383 | 3.19 | 0.001 | .9433094 | 3.938285
-----+-----
sigma_u | 1.627307
sigma_e | 3.5375847
rho | .17464829 (fraction of variance due to u_i)
-----+-----

```

Let's compare pairs of coefficients:

```

. test rworkhours80m=rworkhours80diff

( 1)  rworkhours80m - rworkhours80diff = 0

      chi2( 1) =      4.81
      Prob > chi2 =      0.0284

. test rpoorhealthm=rpoorhealthdiff

```

```

( 1) rpoorhealthm - rpoorhealthdiff = 0

      chi2( 1) =    10.80
      Prob > chi2 =    0.0010

. test rmarriedm=rmarrieddiff

( 1) rmarriedm - rmarrieddiff = 0

      chi2( 1) =     5.93
      Prob > chi2 =    0.0149

. test rtotalparm=rtotalpardiff

( 1) rtotalparm - rtotalpardiff = 0

      chi2( 1) =    54.91
      Prob > chi2 =    0.0000

. test rsiblogm=rsiblogdiff

( 1) rsiblogm - rsiblogdiff = 0

      chi2( 1) =     3.64
      Prob > chi2 =    0.0563

. test hchildlgm=hchildlgdiff

( 1) hchildlgm - hchildlgdiff = 0

      chi2( 1) =     5.80
      Prob > chi2 =    0.0160

```

All differences except for effects of number of siblings are significant if we pick .05 alpha, but because of large sample size and because some of these have different numbers but similar substantive interpretation, I will use .01 alpha level. I will keep coefficients for number of children different for now because the story seems different. So we can constrain the model as follows:

```

. xtreg rallparhelptw rworkhours80 rpoorhealthm rpoorhealthdiff rmarried rtotalparm
rtotalpardiff rsiblog hchildlgm hchildlgdiff female age minority raedys, re
cluster(hhid)
Random-effects GLS regression                Number of obs   =   30541
Group variable: hhidpn                      Number of groups =    6243
R-sq:  within = 0.0242                      Obs per group:  min =     1
        between = 0.0401                      avg =           4.9
        overall = 0.0327                      max =           9
Random effects u_i ~ Gaussian                Wald chi2(13)   =   573.86
corr(u_i, X) = 0 (assumed)                  Prob > chi2     =    0.0000
                                           (Std. Err. adjusted for 4635 clusters in hhid)

```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
rworkhours80	-.0158588	.001346	-11.78	0.000	-.0184969	-.0132208
rpoorhealthm	-.4760427	.115992	-4.10	0.000	-.7033829	-.2487026
rpoorhealt~f	.0787295	.0839293	0.94	0.348	-.0857689	.243228
rmarried	-.4113396	.0988835	-4.16	0.000	-.6051476	-.2175315
rtotalparm	.1822215	.0605674	3.01	0.003	.0635115	.3009316
rtotalpard~f	-.4767525	.0534871	-8.91	0.000	-.5815853	-.3719197

```

      rsiblog |   -.380791   .0641246   -5.94   0.000   -.5064729   -.2551091
    hchildlgm |  -.0930924   .0682771   -1.36   0.173   -.226913   .0407282
hchildlgdiff |   .2962874   .1650998    1.79   0.073   -.0273022   .6198771
      female |   .5895598   .0594126    9.92   0.000   .4731133   .7060063
        age |  -.0132152    .01195   -1.11   0.269   -.0366369   .0102064
    minority |  -.0819295   .0900856   -0.91   0.363   -.2584942   .0946351
      raedys |   .043404   .0112664    3.85   0.000   .0213222   .0654857
        _cons |   2.979462   .7336866    4.06   0.000   1.541463   4.417462
-----+-----
      sigma_u |  1.6326049
      sigma_e |  3.5375847
        rho |  .17558732   (fraction of variance due to u_i)
-----+-----

```

```

. test hchildlgm=hchildlgdiff
( 1) hchildlgm - hchildlgdiff = 0
      chi2( 1) =    4.88
      Prob > chi2 =    0.0271

```

Not much of a story left for number of children, so I will further constrain the model:

```

. xtreg rallparhelptw rworkhours80 rpoorhealthm rpoorhealthdiff rmarried rtotalparm
rtotalpardiff rsiblog hchildlg female age minority raedys, re cluster(hhid)

```

```

Random-effects GLS regression                Number of obs   =    30541
Group variable: hhidpn                      Number of groups =    6243
R-sq:  within = 0.0239                      Obs per group: min =     1
      between = 0.0400                          avg =     4.9
      overall = 0.0326                          max =     9
Random effects u_i ~ Gaussian                Wald chi2(12)   =    566.65
corr(u_i, X) = 0 (assumed)                  Prob > chi2     =    0.0000
                                           (Std. Err. adjusted for 4635 clusters in hhid)
-----+-----

```

```

      |               Robust
rallparhel~w |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
rworkhours80 |  -.0159143   .0013455   -11.83   0.000   -.0185514   -.0132772
rpoorhealthm |  -.477944    .115859   -4.13   0.000   -.7050234   -.2508646
rpoorhealth~f |  .0817012    .0839297    0.97   0.330   -.0827979   .2462004
      rmarried | -.4003812   .0985202   -4.06   0.000   -.5934773   -.207285
      rtotalparm | .1815216    .0605404    3.00   0.003   .0628647   .3001786
rtotalpard~f | -.4785309   .0534485   -8.95   0.000   -.5832881   -.3737737
      rsiblog | -.3861979   .0639649   -6.04   0.000   -.5115669   -.260829
      hchildlg | -.0502547   .0641206   -0.78   0.433   -.1759288   .0754194
      female |   .5906606   .0594083    9.94   0.000   .4742225   .7070987
        age |  -.0138068   .0119468   -1.16   0.248   -.0372221   .0096084
    minority |  -.0829326   .0900776   -0.92   0.357   -.2594815   .0936163
      raedys |   .0445902   .0112573    3.96   0.000   .0225263   .0666541
        _cons |   2.95161   .7336181    4.02   0.000   1.513745   4.389475
-----+-----
      sigma_u |  1.6322975
      sigma_e |  3.5375847
        rho |  .17553282   (fraction of variance due to u_i)
-----+-----

```

Thus, there are really two kinds of information in panel data:

1. The cross-sectional information reflected in the differences among units.
2. The time-series or within-unit information reflected in the changes within units.

For that reason, panel data is also called sometimes cross-sectional time-series data.

A between effects model uses only the cross-sectional information and asks: “What is the expected difference in Y between two individuals that differ by 1 in X?”, while a fixed effects model uses only the time-series information and asks, “What is the expected change in a persons’s value of Y if its value of X increases by 1?” A random effects model combines those two questions, but really, it may turn out that the answers to those two questions are the same or they may be different. If they are different, we could either use a fixed effects model, or we can separate the two types of effects within a random effects model, but we should be able to explain why the effects are different. Statistically, a fixed effects model is always a reasonable thing to do with panel data (it always gives consistent results) but it may not be the most efficient model to run. A random effects model will give you lower standard errors as it is a more efficient estimator.

To better understand these choices, see:

Bell, Andrew, Malcolm Fairbrother, and Andrew Bell. 2019. Fixed and random effects models: making an informed choice. *Quality and Quantity*, 53(2):1051–74.

Autocorrelation

Even though we took into account the fact that units have something in common (unit-specific residuals) and that observations are non-independent (by using cluster option), there can still be additional problems, especially with autocorrelation of residuals. We can test for and deal with autocorrelation the same way as in FE models, using xtserial and xtregar commands; the only difference is that we specify re rather than fe in xtregar.

```
. xtserial rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog
hchildlg female age minority raedyrs
```

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
      F( 1, 4558) = 34.757
      Prob > F = 0.0000
```

Here, the hypothesis of no first order autocorrelation is rejected; therefore, we would want a model explicitly accounting for autoregressive error term. We can use xtregar:

```
. xtregar rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, re lbi
```

```
RE GLS regression with AR(1) disturbances      Number of obs      =      30541
Group variable: hhidpn                        Number of groups   =       6243

R-sq:  within = 0.0231                          Obs per group:  min =          1
      between = 0.0321                                avg =          4.9
      overall = 0.0256                                max =          9
```

```
corr(u_i, Xb)      = 0 (assumed)                  Wald chi2(11)      =      563.33
                                                           Prob > chi2        =      0.0000
```

```
-----+----- theta -----+-----
min      5%      median      95%      max
0.0655  0.0995  0.2270  0.2647  0.2647
```

rallparhel~w	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
rworkhours80	-.0153351	.0012087	-12.69	0.000	-.0177041	-.0129662
rpoorhealth	-.0652898	.0637556	-1.02	0.306	-.1902484	.0596688
rmarried	-.3203856	.0794461	-4.03	0.000	-.476097	-.1646742
rtotalpar	-.2490934	.0334718	-7.44	0.000	-.314697	-.1834898
rsiblog	-.3716501	.0546967	-6.79	0.000	-.4788536	-.2644466
hchildlg	-.0463342	.0577381	-0.80	0.422	-.1594988	.0668305
female	.522334	.0660313	7.91	0.000	.392915	.651753
age	-.0382192	.0106209	-3.60	0.000	-.0590357	-.0174027
minority	-.1338564	.0792718	-1.69	0.091	-.2892263	.0215134
raedyrs	.0611931	.0113042	5.41	0.000	.0390372	.083349
_cons	4.320286	.6392352	6.76	0.000	3.067408	5.573164
rho_ar	.24444212	(estimated autocorrelation coefficient)				
sigma_u	1.4158555					
sigma_e	3.6044943					
rho_fov	.13366962	(fraction of variance due to u_i)				

modified Bhargava et al. Durbin-Watson = 1.5724772
 Baltagi-Wu LBI = 2.0213364

Diagnostics

Same as after xtreg, fe, we can use predict command after xtreg, re to get predicted values and residuals:

xb	xb, fitted values; the default
stdp	standard error of the fitted values
ue	$u_i + e_{it}$, the combined residual
xbu	$xb + u_i$, prediction including effect
u	u_i , the fixed- or random-error component
e	e_{it} , the overall error component

Again, we can use these residuals to conduct regression diagnostics – examine normality, linearity, heteroskedasticity. Note that while in fixed effects models, we were not concerned about heteroskedasticity or non-normality for level 2 residuals, and expected to see some relationships between predictors and level 2 residuals, in random effects models, we have to ensure assumptions of multivariate normality, homoscedasticity, and linearity for both levels of residuals, and we should see no relationship at all between predictors and residuals on both levels.

Note that for both fixed effects and between effects, there are straightforward transformations of variables that can be made to obtain the same coefficients without xtreg (i.e., mean-differencing or collapsing dataset to person-mean level). For random effects, such transformation does not exist, but xtdata command in Stata (with re option) does offer an approximation that can be used to conduct faster searches for model specification for a random effects model if you have a lot of predictors and are trying to select the best model. The random effects models estimated in the exploratory dataset generated by xtdata command will not be identical to those estimated in the full dataset--they will be a very close approximation.

```
. xtreg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, re
Random-effects GLS regression                Number of obs      =       30541
Group variable: hhidpn                      Number of groups   =        6243
R-sq:  within = 0.0229                      Obs per group: min =           1
```

```

    between = 0.0309                avg = 4.9
    overall = 0.0254                max = 9
Random effects u_i ~ Gaussian      Wald chi2(10) = 714.51
corr(u_i, X) = 0 (assumed)        Prob > chi2 = 0.0000

```

rallparhel~w	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
rworkhours80	-.017518	.0011596	-15.11	0.000	-.0197907	-.0152452
rpoorhealth	-.1027325	.0636668	-1.61	0.107	-.2275171	.0220522
rmarried	-.3439424	.0757802	-4.54	0.000	-.4924689	-.195416
rtotalpar	-.2764635	.0318816	-8.67	0.000	-.3389502	-.2139767
rsiblog	-.3816662	.0523548	-7.29	0.000	-.4842798	-.2790526
hchildlg	-.0431438	.0552126	-0.78	0.435	-.1513586	.065071
female	.4784234	.0632272	7.57	0.000	.3545003	.6023465
age	-.040811	.0101534	-4.02	0.000	-.0607114	-.0209107
minority	-.1316851	.0759759	-1.73	0.083	-.2805951	.0172248
raedyrs	.0647266	.0108469	5.97	0.000	.0434671	.0859861
_cons	4.572378	.6117239	7.47	0.000	3.373421	5.771334
sigma_u	1.6329416					
sigma_e	3.5375847					
rho	.17564702	(fraction of variance due to u_i)				

Xtdata command requires that we specify the ratio of sigma_u to sigma_e as standard deviations rather than variances; so we calculate it:

```

. di 1.6329416/3.5375847
.46159788

```

```

. xtdata rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, re ratio(.46159788) clear

```

```

----- theta -----
min      5%      median      95%      max
0.0921  0.0921  0.3042  0.4146  0.4146

```

```

. reg rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg
female age minority raedyrs, cluster(hhidpn)
Linear regression

```

```

Number of obs = 30541
F( 10, 6242) = 51.37
Prob > F = 0.0000
R-squared = 0.0228
Root MSE = 3.5801

```

(Std. Err. adjusted for 6243 clusters in hhidpn)

rallparhel~w	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
rworkhours80	-.0158976	.0012812	-12.41	0.000	-.0184092	-.0133861
rpoorhealth	-.0677607	.0706261	-0.96	0.337	-.2062121	.0706907
rmarried	-.3536576	.0956405	-3.70	0.000	-.5411458	-.1661693
rtotalpar	-.3049411	.037739	-8.08	0.000	-.3789226	-.2309597
rsiblog	-.3732796	.0583542	-6.40	0.000	-.4876739	-.2588852
hchildlg	-.0502717	.0575627	-0.87	0.383	-.1631144	.062571
female	.5318233	.0672479	7.91	0.000	.3999942	.6636524
age	-.0000753	.004729	-0.02	0.987	-.0093458	.0091952
minority	-.0763812	.0816494	-0.94	0.350	-.2364422	.0836797
raedyrs	.065813	.01006	6.54	0.000	.0460919	.0855342
_cons	1.529079	.1619631	9.44	0.000	1.211575	1.846582

After converting the data, you may form linear transformations your predictors, but all nonlinear transformations must be done before conversion. You can, however, use some OLS-based diagnostic tools, e.g., examine linearity:

```
. mrunning rallparhelptw rworkhours80 rpoorhealth rmarried rtotalpar rsiblog hchildlg  
female age minority redyrs
```

30541 observations, R-sq = 0.0333

