

Econometric Analysis of Panel Data

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Assignment 4

Parameter Heterogeneity in Linear Models: RPM and HLM

The estimation parts of this assignment will be based on the Baltagi and Griffin gasoline market and the Cornwell and Rupert labor market data sets that are posted on the course website.

We will begin with the gasoline market. The basic linear regression model in use will be

$$y_{it} = \beta_1 + \beta_2 x_{it,1} + \beta_3 x_{it,2} + \beta_4 x_{it,3} + w_{it}$$

where

and i = 1, ..., 18 OECD countries

t = 1, ..., 19 years (1960 to 1978).

y_{it} = *lgaspcar* = log of per capita gasoline use

$x_{it,1}$ = *lincomep* = log of per capita income

$x_{it,2}$ = *lrpmg* = log of gasoline price index

$x_{it,3}$ = *lcarpcap* = log of cars per capita

w_{it} = a disturbance that may have both permanent (time invariant) components and time varying components, and may, under some circumstances, be correlated with \mathbf{x}_{it} .

Denote \mathbf{x}_{it} = $(1, x_{it,1}, x_{it,2}, x_{it,3})$ and

\mathbf{X}_i = the 19×4 matrix containing all the data on \mathbf{x}_{it} for country i .

Part I. Parameter Variation in the Gasoline Market

A. Homogeneous parameters: To begin, we *assume* that all parameters, including the constant term, are homogeneous across countries and through time and that $w_{it} = \varepsilon_{it}$, a classical zero mean, homoscedastic disturbances.

1. Under these assumptions, what are the properties of the pooled OLS estimator?

Under the assumptions, the model is a classical linear regression, so OLS is unbiased, consistent, and efficient by the Gauss Markov Theorem. The asymptotic distribution is normal with mean β and asymptotic covariance matrix $\sigma_\varepsilon^2/(nT) \times \text{plim}[X'X/nT]^{-1}$.

2. Estimate the parameters of the model using OLS and report your results.

```
--> NAMELIST ; X = one,lincomep,lrpmg,lcarspcap $
--> REGRESS ; Lhs = lgaspcar ; Rhs =X $
```

```
-----
Ordinary      least squares regression .....
LHS=LGASPCAR  Mean          =          4.29624
              Standard deviation =          .54891
              Number of observs. =           342
Model size    Parameters      =            4
              Degrees of freedom =           338
Residuals     Sum of squares   =         14.90436
              Standard error of e =          .20999
Fit           R-squared        =          .85494
              Adjusted R-squared =          .85365
Model test    F[ 3, 338] (prob) =        664.0(.0000)
Diagnostic    Log likelihood   =         50.49288
              Restricted(b=0)   =        -279.63574
              Chi-sq [ 3] (prob) =        660.3(.0000)
Info criter.  LogAmemiya Prd. Crt. =        -3.10976
              Akaike Info. Criter. =        -3.10977
              Bayes Info. Criter. =        -3.06491
-----
+-----+-----+-----+-----+-----+
LGASPCAR| Coefficient      Standard      Prob.      Mean
         |               Error        t        t>|T|      of X
+-----+-----+-----+-----+-----+
Constant| 2.39133***        .11693      20.45     .0000
LINCOME| .88996***         .03581      24.86     .0000    -6.13943
LRPMG   | -.89180***         .03031     -29.42     .0000    -.52310
LCARPCAP| -.76337***         .01861     -41.02     .0000   -9.04180
+-----+-----+-----+-----+-----+
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
-----
```

3. As a first cut at assessing whether the assumptions are correct, compute the robust, cluster (country) corrected standard errors for the least squares estimator. Do they appear to be the same, or close to the same, as the uncorrected OLS standard errors? What do you conclude about the disturbances in the equation?

```
--> REGRESS ; Lhs = lgaspcar ; Rhs =X ; Cluster=Country$
+-----+
| Covariance matrix for the model is adjusted for data clustering. |
| Sample of      342 observations contained      18 clusters defined by |
| variable COUNTRY which identifies by a value a cluster ID. |
+-----+

-----
Ordinary      least squares regression .....
LHS=LGASPCAR Mean          =          4.29624
                Standard deviation    =          .54891
                Number of obsvrs.     =          342
Model size    Parameters    =           4
                Degrees of freedom    =          338
Residuals     Sum of squares =         14.90436
                Standard error of e   =          .20999
Fit           R-squared      =          .85494
                Adjusted R-squared    =          .85365
Model test    F[ 3, 338] (prob) =    664.0(.0000)
Diagnostic    Log likelihood =         50.49288
                Restricted(b=0)       =        -279.63574
                Chi-sq [ 3] (prob)   =    660.3(.0000)
Info criter.  LogAmemiya Prd. Crt. =        -3.10976
                Akaike Info. Criter. =        -3.10977
                Bayes Info. Criter.  =        -3.06491
Model was estimated on Feb 09, 2010 at 09:52:38 PM
-----
+-----+
LGASPCAR | Coefficient      Standard      Prob.      Mean
          |              Error        t      t>|T|    of X
          +-----+-----+-----+-----+-----+
Constant | 2.39133***      .44167      5.41   .0000
LINCOMEP | .88996***       .17248      5.16   .0000   -6.13943
LRPMG    | -.89180***      .14578     -6.12   .0000    -.52310
LCARPCAP | -.76337***      .06985    -10.93   .0000   -9.04180
          +-----+-----+-----+-----+
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
-----
```

The standard errors have increased substantially. I suspect that this indicates that there is substantial correlation across observations within a country.

B. Heterogeneous Constant Terms: Now, consider fixed and random effects formulations of the model. We write the model as

$$y_{it} = \beta_{1i} + \beta_2 x_{it,1} + \beta_3 x_{it,2} + \beta_4 x_{it,3} + \varepsilon_{it}$$

where

$$\beta_{1i} = \beta_1 + u_i \text{ and } E[u_i] = 0.$$

Thus, this is a model with a random constant term. By substituting the second equation into the first, you can see that it is the “effects” model we have discussed in class.

1. **(Fixed Effects)** Using the OECD gasoline data, estimate the parameters of the model under the assumption that $E[u_i|\mathbf{X}_i] = g(\mathbf{X}_i)$ for some nonzero function $g(\cdot)$. Explain the estimator and the motivation for using it. Display your results with the OLS estimates so that you (and your reader) can see the difference between the two. Note that $E[u_i|\mathbf{X}_i] = g(\mathbf{X}_i)$ is consistent with $E[u_i] = 0$. When averaged over \mathbf{X}_i , the overall mean is zero, but the mean is not zero for a specific \mathbf{X}_i . This implies that u_i and \mathbf{X}_i are correlated.

This would be the fixed effects model. The parameters are estimated by using the within estimator – including the country dummy variables in the equation.

OLS Without Group Dummy Variables.....					
Ordinary least squares regression					
LHS=LGASPCAR	Mean	=	4.29624		
	Standard deviation	=	.54891		
	Number of observs.	=	342		
Model size	Parameters	=	4		
	Degrees of freedom	=	338		
Residuals	Sum of squares	=	14.90436		
	Standard error of e	=	.20999		
Fit	R-squared	=	.85494		
	Adjusted R-squared	=	.85365		
Model test	F[3, 338] (prob)	=	664.0(.0000)		
Diagnostic	Log likelihood	=	50.49288		
	Restricted(b=0)	=	-279.63574		
	Chi-sq [3] (prob)	=	660.3(.0000)		
Info criter.	LogAmemiya Prd. Crt.	=	-3.10976		
	Akaike Info. Criter.	=	-3.10977		
	Bayes Info. Criter.	=	-3.06491		
Panel Data Analysis of LGASPCAR [ONE way]					
Unconditional ANOVA (No regressors)					
Source	Variation	Deg. Free.	Mean Square		
Between	85.68228	17.	5.04013		
Residual	17.06068	324.	.05266		
Total	102.74296	341.	.30130		

LGASPCAR	Coefficient	Standard Error	t	Prob. t> T	Mean of X

LINCOMEP	.88996***	.03581	24.86	.0000	-6.13943
LRPMG	-.89180***	.03031	-29.42	.0000	-.52310
LCARPCAP	-.76337***	.01861	-41.02	.0000	-9.04180
Constant	2.39133***	.11693	20.45	.0000	

Least Squares with Group Dummy Variables.....					
Ordinary least squares regression					
LHS=LGASPCAR	Mean	=	4.29624		
	Standard deviation	=	.54891		
	Number of observs.	=	342		
Model size	Parameters	=	21		
	Degrees of freedom	=	321		
Residuals	Sum of squares	=	2.73649		
	Standard error of e	=	.09233		
Fit	R-squared	=	.97337		
	Adjusted R-squared	=	.97171		
Model test	F[20, 321] (prob)	=	586.6(.0000)		
Diagnostic	Log likelihood	=	340.33399		
	Restricted(b=0)	=	-279.63574		
	Chi-sq [20] (prob)	=	1239.9(.0000)		
Info criter.	LogAmemiya Prd. Crt.	=	-4.70517		
	Akaike Info. Criter.	=	-4.70533		
	Bayes Info. Criter.	=	-4.46986		
Estd. Autocorrelation of e(i,t)		=	.775557		
Panel:Groups	Empty 0,	Valid data	18		
	Smallest 19,	Largest	19		
	Average group size in panel		19.00		

LGASPCAR	Coefficient	Standard Error	t	Prob. t> T	Mean of X

LINCOMEP	.66225***	.07339	9.02	.0000	-6.13943
LRPMG	-.32170***	.04410	-7.29	.0000	-.52310
LCARPCAP	-.64048***	.02968	-21.58	.0000	-9.04180

Fixed effects results are somewhat different. But, notice that the estimate price elasticity has fallen by 50%, a large change.

2. (Random Effects) Estimate the parameters of the model under the more restrictive assumption that $E[u_i|X_i] = 0$.

```
-----
Random Effects Model: v(i,t)      = e(i,t) + u(i)
Estimates:  Var[e]                =      .008525
            Var[u]                =      .035571
            Corr[v(i,t),v(i,s)] =      .806673
Lagrange Multiplier Test vs. Model (3) =1465.55
( 1 degrees of freedom, prob. value =  .000000)
(High values of LM favor FEM/REM over CR model)
Baltagi-Li form of LM Statistic =      1465.55
      Sum of Squares              27.266173
      R-squared                   .734618
-----
```

LGASPCAR	Coefficient	Standard Error	z	Prob. z> Z	Mean of X
LINCOME	.55270***	.05651	9.78	.0000	-6.13943
LRPMG	-.42500***	.03842	-11.06	.0000	-.52310
LCARPCAP	-.60631***	.02446	-24.78	.0000	-9.04180
Constant	1.98508***	.17572	11.30	.0000	

The random effects results resemble the fixed effects results.

3. Use the Wu/Mundlak variable addition test to test for the assumption of the (null) random effects model against the (alternative) fixed effects model. Report your results and your conclusions.

```
Create  ; x1bar = GroupMean(lincomep,str=country)$
Create  ; x2bar = GroupMean(lrpmg,str=country)$
Create  ; x3bar = GroupMean(lcarpcap,str=country)$
REGRESS ; Lhs = lgaspcar
        ; Rhs = x1bar,x2bar,x3bar,X
        ; Str=Country ; Random Effects$
-----
Random Effects Model: v(i,t)      = e(i,t) + u(i)
Estimates:  Var[e]                =      .008605
            Var[u]                =      .030281
            Corr[v(i,t),v(i,s)] =      .778708
Lagrange Multiplier Test vs. Model (3) =1864.35
( 1 degrees of freedom, prob. value =  .000000)
(High values of LM favor FEM/REM over CR model)
Baltagi-Li form of LM Statistic =      1864.35
      Sum of Squares              13.027071
      R-squared                   .873207
-----
```

LGASPCAR	Coefficient	Standard Error	z	Prob. z> Z	Mean of X
X1BAR	.30533*	.15712	1.94	.0520	-6.13943
X2BAR	-.64185***	.12649	-5.07	.0000	-.52310
X3BAR	-.15482*	.07933	-1.95	.0510	-9.04180
LINCOME	.66225***	.07373	8.98	.0000	-6.13943
LRPMG	-.32170***	.04431	-7.26	.0000	-.52310
LCARPCAP	-.64048***	.02982	-21.48	.0000	-9.04180
Constant	2.54163***	.46953	5.41	.0000	

```
-----
--> Matrix ; bm = b(1:3) ; vm=varb(1:3,1:3)
      ; List ; WaldStat = bm'<vm>bm $
-----
Matrix WALDSTAT has 1 rows and 1 columns.
      1
-----+-----+
1| 31.31621
-----+-----+
```

The wald statistic is much larger than the critical value with 3 degrees of freedom. This suggests that the fixed effects specification is the preferred model.

C. General parameter heterogeneity: Let \mathbf{x}_{it} denote $(1, \text{lincomep}, \text{lrpmg}, \text{lcarpcap})_{it}$. We now consider the possibility that there are differences across countries. Write the model

$$(1) \quad y_{it} = \boldsymbol{\beta}_i' \mathbf{x}_{it} + \varepsilon_{it}.$$

Absent any further assumptions about the variation in the parameters across countries, how would you proceed to examine the relationship between per capita gasoline consumption, y_{it} and the other variables, \mathbf{x}_{it} ?

1. Suppose we now assume that all the parameters, not just the constant, are random;

$$(2) \quad \boldsymbol{\beta}_i = \boldsymbol{\beta} + \mathbf{u}_i$$

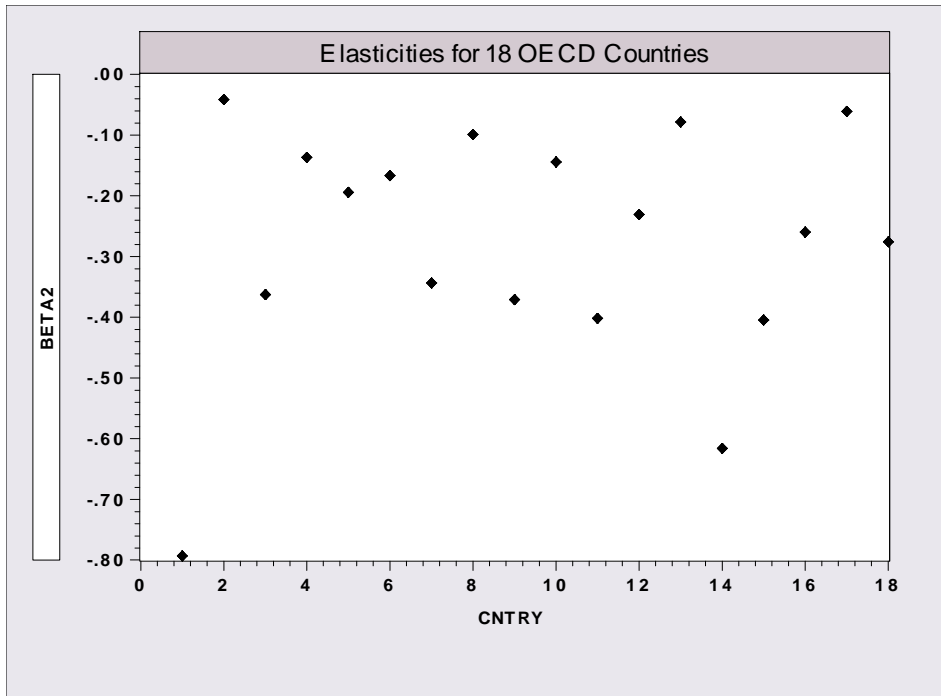
where \mathbf{u}_i has an overall mean of zero, however $E[\mathbf{u}_i | \mathbf{X}_i] = g(\mathbf{X}_i)$, where \mathbf{X}_i is the 19 years of data on \mathbf{x}_{it} for country i ? Note that the assumption of the overall mean of zero states only that $\boldsymbol{\beta}_i$ varies around a mean.

We are particularly interested in the price elasticity of the demand for gasoline, the coefficient on *lrpmg*. To explore the cross country variation, compute the linear regression model for each of the 19 countries (separately). Display in a graph or a well labeled table the results of your estimation, to describe the variation in the estimated coefficients on *lrpmg*. Note that the assumption about \mathbf{u}_i is equivalent to the “fixed effects” case, but here we are considering the entire parameter vector, not just the constant term.


```

Matrix ; beta2 = Init(18,1,0)$
Calc ; i1=1 ; i = 0 $
Procedure
Calc ; i2 = i1 + 18 ; i = i + 1 $
Sample ; i1-i2 $
Regress ; quietly ; Lhs = lgaspcar ; Rhs = x $
Matrix ; beta2(i)=b(3) $
Calc ; i1=i1+19 $
EndProc
Execute ; N = 18 $
Matrix ; cntry=[1/2/3/4/5/6/7/8/9/10/11/12/13/14/15/16/17/18]$
Mplot ; Lhs = cntry ; Rhs = beta2
;Title=Elasticities for 18 OECD Countries $

```



2. If we add to A. the assumption $E[\mathbf{u}_i|\mathbf{X}_i] = 0$, the model turns into a “random effects” model, though note, once again, we are considering the entire parameter vector. Under this new assumption, what are the properties of the pooled ordinary least squares estimator? What does \mathbf{b} estimate in this case? For a useful step in the analysis, insert (2) into (1) and analyze the implied model.

Under the random effects assumption, the model turns into a heteroscedastic linear regression. I.e.,

$$y_{it} = \beta_i' x_{it} + \varepsilon_{it}, \quad \beta_i = \beta + u_i,$$

so

$$y_{it} = \beta' x_{it} + \varepsilon_{it} + u_i' x_{it}.$$

This is a linear regression with mean $\beta' x_{it}$ and variance $\sigma_\varepsilon^2 + x_{it}' \Sigma x_{it}$ where Σ is the 4×4 covariance matrix of the random parameters. Since it is a linear regression and the disturbances, though heteroscedastic, are not correlated with x_{it} , it can be fit by OLS, though inefficiently. Note, $u_i' x_{it}$ is not correlated with x_{it} . To see, just note that $E[u_i' x_{it} | x_{it}] = E[u_i'] x_{it} = 0$. (Looks like a trivial proof. But, it's right.) So, pooled OLS has the properties of OLS in the presence of heteroscedasticity. Unbiased (possibly), consistent, asymptotic normal, not efficient.

Part II. Theory and an Example for Simulation Based Estimation:

This theoretical exercise will begin to suggest how simulation based estimation works. Consider a simple regression model

$$y_{it} = \beta_i x_{it} + \varepsilon_{it}$$

There is only one variable and no constant in the model. Assume that $\varepsilon_{it} \sim N[0, \sigma^2]$. We suppose as well that β_i is random; $\beta_i = \beta + w_i$ where $w_i \sim N[0, \theta^2]$. A simpler way to write this is

$$\beta_i = \beta + \theta u_i \text{ where } u_i \sim N[0, 1].$$

Putting θ specifically in the equation simplifies the derivation a bit. The contribution of individual i to the likelihood function is the product of the normal densities,

$$L_i = \prod_{t=1}^T \frac{1}{\sigma} \phi\left(\frac{y_{it} - \beta_i x_{it}}{\sigma}\right)$$

This is not useable for maximum likelihood estimation because $\beta_i = \beta + \theta u_i$ which means that the log likelihood to be maximized involves the unobserved u_i ;

$$L_i = \prod_{t=1}^T \frac{1}{\sigma} \phi\left(\frac{y_{it} - \beta x_{it} - \theta u_i x_{it}}{\sigma}\right)$$

In principle, we would now maximize $\log L = \sum_i \log L_i$ with respect to (β, θ, σ) . The problem is that the unobserved u_i is in the equation and must be integrated out to proceed.. The contribution of individual i to the *unconditional* log likelihood function is

$$\log L_i = \log \int_{-\infty}^{\infty} \left[\prod_{t=1}^T \frac{1}{\sigma} \phi \left(\frac{y_{it} - \beta x_{it} - \theta u_i x_{it}}{\sigma} \right) \right] \phi(u_i) du_i$$

where $\phi(u_i)$ is the standard normal density. The integral of the product above does not exist in closed form, so we will approximate it by simulation. (It could be approximated with quadrature.) Adding up the individual contributions, the *simulated* log likelihood is

$$\log L_S = \sum_{i=1}^n \log \left\{ \frac{1}{R} \sum_{r=1}^R \left[\prod_{t=1}^T \frac{1}{\sigma} \phi \left(\frac{y_{it} - \beta x_{it} - \theta u_{ir} x_{it}}{\sigma} \right) \right] \right\}$$

where u_{ir} is a set of R random draws on the standard normal population for each individual i . (The random draws are reused every time the function or its derivatives are computed. There are a total of nR random draws used in the simulation.) An additional simplification is obtained by using $\gamma = 1/\sigma$. (We make use of the invariance principle for maximum likelihood estimation.) Then,

$$\log L_S = \sum_{i=1}^n \log \left\{ \frac{1}{R} \sum_{r=1}^R \left[\prod_{t=1}^T \gamma \phi(\gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it})) \right] \right\}.$$

The maximum simulated likelihood estimator is the (β, θ, γ) that maximizes this function.

1. Derive the necessary (first order) conditions for maximizing this function. Hint: your derivation is simplified greatly by using the result $d\phi(t)/dt = -t\phi(t)$. You can then just use the chain rule.

$$\frac{\partial \log L_S}{\partial \gamma} = \sum_{i=1}^n \frac{\frac{1}{R} \sum_{r=1}^R \left[\prod_{t=1}^T \gamma \phi(\gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it})) \right] \sum_{t=1}^T \frac{\partial \log \gamma \phi(\gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it}))}{\partial \gamma}}{\left\{ \frac{1}{R} \sum_{r=1}^R \left[\prod_{t=1}^T \gamma \phi(\gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it})) \right] \right\}}$$

(Note I used a trick above, $\partial f / \partial x = f \times \partial \log f / \partial x$. The derivatives with respect to β and θ have the same form save for the derivative in the rightmost sum. These three derivatives are

$$\frac{\partial \log \gamma \phi(\gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it}))}{\partial \begin{pmatrix} \gamma \\ \beta \\ \theta \end{pmatrix}} = \begin{pmatrix} 1/\gamma \\ 0 \\ 0 \end{pmatrix} + \frac{1}{\phi(\cdot)} (-\cdot) \phi(\cdot) \begin{pmatrix} (y_{it} - \beta x_{it} - \theta u_{ir} x_{it}) \\ -\gamma x_{it} \\ -\gamma u_{ir} x_{it} \end{pmatrix}$$

$$\frac{\partial \log \gamma \phi(\gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it}))}{\partial \begin{pmatrix} \gamma \\ \beta \\ \theta \end{pmatrix}} = \begin{pmatrix} 1/\gamma \\ 0 \\ 0 \end{pmatrix} - \gamma(y_{it} - \beta x_{it} - \theta u_{ir} x_{it}) \begin{pmatrix} (y_{it} - \beta x_{it} - \theta u_{ir} x_{it}) \\ -\gamma x_{it} \\ -\gamma u_{ir} x_{it} \end{pmatrix}$$

2. How would you obtain asymptotic standard errors for your estimator?

Notice that the derivatives have to be simulated just like the log likelihood. In principle, you would differentiate this function again and use the negative inverse of the second derivatives. The derivatives are extremely complicated. This looks like a very good candidate for the BHHH estimator. The first derivative vector above, looking at it from the outside, takes the form

$$\frac{\partial \log L_S}{\partial \begin{pmatrix} \gamma \\ \beta \\ \theta \end{pmatrix}} = \sum_{i=1}^n \mathbf{g}_i$$

where \mathbf{g}_i is the vector in the messy expression after the first summation. An estimator that will work asymptotically is just

$$V = \left[\sum_{i=1}^n \mathbf{g}_i \mathbf{g}_i' \right]^{-1}$$

Complicated, but not so bad as the full Hessian.

3. The following small exercise will show this computation at work. This application estimates the parameters of a model that precisely satisfies the assumptions of the model above. Execute these commands and report all of your results

```
? 1,000 observations in total will be n=100, T=10. The x(i,t) is normally distributed
? with mean zero and standard deviation 1. Variable i is the 1,1,1,1...,2,2,2,2... etc.
Sample ; 1 - 1000 $
Create ; xit = Rnn(0,1) ; i = Trn(10,0) $
? We generate b(i) = 0.5 + u(i) where u(i) is normal with mean 0, standard deviation
? .5. Then, y(i,t) = b(i)*x(i,t) + e(i,t) where e(i,t) is normally distributed with zero
? mean and standard deviation 1.
Matrix ; bi = init(100,1,.5) + .5*randm(100)$
Create ; yit = bi(i)*xit + rnn(0,1) $
? This command estimates the random parameters model exactly as shown in
? part 2. above.
Regress ; lhs = yit ; rhs = xit ; rpm ; fcn=xit(n)
; pds=10 ; pts=100 ; halton $
```

```
--> CALC;DELETE I$
--> Sample ; 1 - 1000 $
--> Create ; xit = Rnn(0,1) ; i = Trn(10,0) $
--> Matrix ; bi = init(100,1,.5) + .5*rndm(100)$
--> Create ; yit = bi(i)*xit + rnn(0,1) $
--> Regress ; lhs = yit ; rhs = xit ;rpm ; fcn=xit(n)
; pds=10 ; pts=100 ; halton $
```

OLS Starting values for random parameters model...

```
Ordinary least squares regression .....
LHS=YIT Mean = -.03481
Standard deviation = 1.21392
Number of observs. = 1000
Model size Parameters = 1
Degrees of freedom = 999
Residuals Sum of squares = 1222.62727
Standard error of e = 1.10628
Fit R-squared = .16948
Adjusted R-squared = .16948
Model test F[ 1, 999] (prob) = 203.9(.0000)
Diagnostic Log likelihood = -1519.43957
Restricted(b=0) = -1612.29192
Chi-sq [ 1] (prob) = 185.7(.0000)
Info criter. LogAmemiya Prd. Crt. = .20300
Akaike Info. Criter. = .20300
Bayes Info. Criter. = .20791
```

	YIT	Coefficient	Standard Error	z	Prob. z> Z	Mean of X
	XIT	.48868***	.03414	14.31	.0000	-.00495

Normal exit: 9 iterations. Status=0. F= 1451.252

Random Coefficients LinearRg Model

```
Dependent variable YIT
Log likelihood function -1451.25191
Estimation based on N = 1000, K = 3
Information Criteria: Normalization=1/N
Normalized Unnormalized
AIC 2.90850 2908.50381
Fin.Smpl.AIC 2.90853 2908.52791
Bayes IC 2.92323 2923.22708
Hannan Quinn 2.91410 2914.09968
Sample is 10 pds and 100 individuals
LINEAR regression model
Simulation based on 100 Halton draws
```

	YIT	Coefficient	Standard Error	z	Prob. z> Z	Mean of X
	XIT	.48041***	.03006	15.98	.0000	-.00495
	XIT	.63417***	.02593	24.45	.0000	
Std.Dev.		.96500***	.01908	50.57	.0000	

Estimation begins with OLS (as usual). The OLS (consistent) estimate is 0.48868. The RP estimate of the mean of the distribution is .48041. The standard deviation of the distribution of β_i is 0.63417. The true value is 0.5. The estimate of σ_ε is 0.965. The true value is 1.0.

Part III. Random Parameters Models

This exercise will demonstrate the computation of a fairly elaborate, hierarchical linear model. The computations are based on the Cornwell and Rupert data. Note that the simulations below are based on Halton sequences, not pseudorandom random numbers. As such, the results you obtain below are replicable – in principle, you and I (and your colleagues) should all get the same results. Also, if you fit these equations more than once, you will get the same answers.

1. A simple RPM with one random coefficient. The first model is the regression model discussed in class, now with a random coefficient on education. After fitting the random parameters model, this program computes the posterior estimates of $E[\beta_{i,Ed}|y_i, X_i]$ and plots the distribution with a kernel density estimator and a histogram. Estimate the model and report all results. (Note, you can copy/paste the figure into a Word document.)

```
Sample ; All $
Regress ; Lhs = Lwage ;Rhs = One,Exp,Occ,Ind,South,SMSA,MS,FEM,Union,Ed,Blk
;Pds=7 ;RPM ; Halton ; Pts=100 ;Fcn = Ed(N) ;Parameters ; Maxit = 20 $
Sample ; 1 - 595 $
Create ; Ed_Coeff = 0 $
Create ; Ed_Coeff = beta_i $
Kernel ; Rhs = Ed_Coeff$
Histogram ; Rhs = Ed_Coeff $

--> Sample ; All $
--> Regress ; Lhs = Lwage
; Rhs = One,Exp,Occ,Ind,South,SMSA,MS,FEM,Union,Ed,Blk
;Pds=7 ;RPM ; Halton ; Pts=100 ;Fcn = Ed(N)
;Parameters $
```

OLS Starting values for random parameters model...

Ordinary least squares regression

LHS=LWAGE Mean = 6.67635

Standard deviation = .46151

Number of obsvrs. = 4165

Model size Parameters = 11

Degrees of freedom = 4154

Residuals Sum of squares = 533.91105

Standard error of e = .35851

Fit R-squared = .39801

Adjusted R-squared = .39656

Model test F[10, 4154] (prob) = 274.6(.0000)

Diagnostic Log likelihood = -1631.91946

Restricted(b=0) = -2688.80603

Chi-sq [10] (prob) = 2113.8(.0000)

Info criter. LogAmemiya Prd. Crt. = -2.04896

Akaike Info. Criter. = -2.04896

Bayes Info. Criter. = -2.03223

Model was estimated on Feb 09, 2010 at 10:51:13 PM

	LWAGE	Coefficient	Standard Error	z	Prob. z> Z	Mean of X
Constant		5.68035***	.04783	118.77	.0000	
EXP		.01024***	.00054	19.11	.0000	19.8538
OCC		-.14664***	.01502	-9.76	.0000	.51116
IND		.05525***	.01208	4.57	.0000	.39544
SOUTH		-.05298***	.01285	-4.12	.0000	.29028
SMSA		.14851***	.01236	12.02	.0000	.65378
MS		.06783***	.02107	3.22	.0013	.81441
FEM		-.36013***	.02569	-14.02	.0000	.11261
UNION		.09158***	.01290	7.10	.0000	.36399
BLK		-.16824***	.02262	-7.44	.0000	.07227
ED		.05669***	.00268	21.16	.0000	12.8454

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Maximum of 100 iterations. Exit iterations with status=1.

```
-----
Random Coefficients LinearRg Model
Dependent variable      LWAGE
Log likelihood function  -264.53571
Estimation based on N = 4165, K = 13
Information Criteria: Normalization=1/N
                    Normalized    Unnormalized
AIC                  .13327      555.07141
Fin.Smpl.AIC         .13329      555.15910
Bayes IC             .15304      637.41954
Hannan Quinn         .14026      584.20182
Model estimated: Feb 09, 2010, 22:54:10
Sample is 7 pds and 595 individuals
LINEAR regression model
Simulation based on 100 Halton draws
-----
```

LWAGE	Coefficient	Standard Error	z	Prob. z> Z	Mean of X

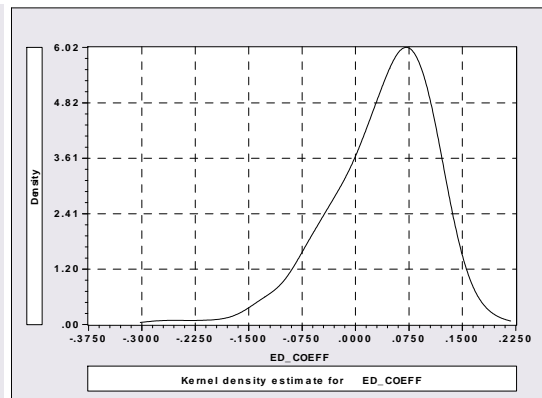
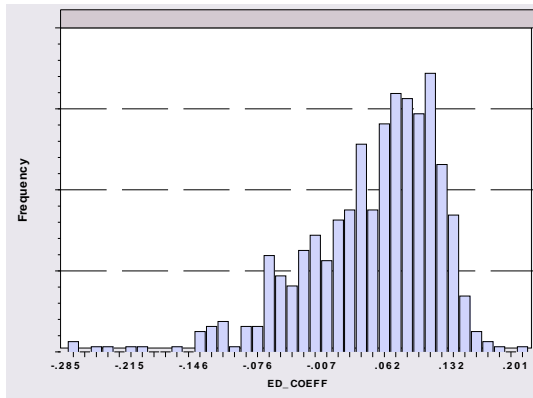
Nonrandom parameters					
Constant	4.57949***	.02054	222.92	.0000	
EXP	.07444***	.00045	166.45	.0000	19.8538
OCC	-.05447***	.00590	-9.23	.0000	.51116
IND	-.04841***	.00483	-10.01	.0000	.39544
SOUTH	.10661***	.00513	20.79	.0000	.29028
SMSA	.07319***	.00478	15.32	.0000	.65378
MS	.00116	.00788	.15	.8832	.81441
FEM	-.09641***	.01056	-9.13	.0000	.11261
UNION	.17620***	.00489	36.02	.0000	.36399
BLK	-.16604***	.01027	-16.17	.0000	.07227
Means for random parameters					
ED	.11889***	.00114	103.87	.0000	12.8454
Scale parameters for dists. of random parameters					
ED	1.34686***	.00162	829.14	.0000	
Variance parameter given is sigma					
Std.Dev.	.15915***	.00075	213.52	.0000	

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Implied standard deviations of random parameters

Matrix S.D_Beta has 1 rows and 1 columns.

```
1
+-----+
1| 1.34686
+-----+
```



2. The second model is a typical hierarchical model. The model is

$$y_{it} = \beta_{1,i} + \beta_{2,i}\text{Exp}_{it} + \beta_{3,i}\text{OCC}_{it} + \dots + \beta_{8,i}\text{Union}_{it} + \varepsilon_{it}$$

$$\beta_{1,i} = \beta_1 + \delta_{1,1}\text{Fem}_i + \delta_{1,2}\text{Ed}_i + \delta_{1,3}\text{Blk}_i + u_{1i},$$

$$\beta_{2,i} = \beta_2 + \delta_{2,1}\text{Fem}_i + \delta_{2,2}\text{Ed}_i + \delta_{2,3}\text{Blk}_i + u_{2i},$$

This is a common sort of model in which the regression of interest is based on the time varying attributes and the variation in the parameters is explained by the randomness, $u_{k,i}$ and by the demographics that do not vary across time, here Gender, Education and Race. Fit the model and report all results, identifying what parameter is what in your report.

```
Sample ; All $
Regress ; Lhs = Lwage
;Rhs = One,Exp,Occ,Ind,South,SMSA,MS,Union
;Pds=7
;RPM=Fem,Ed,Blk
;Halton ; Pts=100
;Fcn = one(n),exp(n)
;Parameters $
-----
OLS Starting values for random parameters model...
Ordinary least squares regression .....
LHS=LWAGE Mean = 6.67635
Standard deviation = .46151
Number of observs. = 4165
Model size Parameters = 8
Degrees of freedom = 4157
Residuals Sum of squares = 633.19640
Standard error of e = .39028
Fit R-squared = .28606
Adjusted R-squared = .28486
Model test F[ 7, 4157] (prob) = 237.9(.0000)
Diagnostic Log likelihood = -1987.09274
Restricted(b=0) = -2688.80603
Chi-sq [ 7] (prob) = 1403.4(.0000)
Info criter. LogAmemiya Prd. Crt. = -1.87985
Akaike Info. Criter. = -1.87985
Bayes Info. Criter. = -1.86768
Model was estimated on Feb 09, 2010 at 10:57:31 PM
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+-----+-----+-----+-----+-----+
| LWAGE | Coefficient | Standard | z | Prob. | Mean |
| | | Error | | z>|Z| | of X |
+-----+-----+-----+-----+-----+
| OCC | -.32393*** | .01373 | -23.59 | .0000 | .51116 |
| IND | .04033*** | .01301 | 3.10 | .0019 | .39544 |
| SOUTH | -.11104*** | .01373 | -8.09 | .0000 | .29028 |
| SMSA | .15575*** | .01327 | 11.73 | .0000 | .65378 |
| MS | .33545*** | .01611 | 20.83 | .0000 | .81441 |
| UNION | .06787*** | .01398 | 4.86 | .0000 | .36399 |
| Constant | 6.31844*** | .02106 | 300.02 | .0000 | |
| EXP | .00705*** | .00057 | 12.44 | .0000 | 19.8538 |
+-----+-----+-----+-----+-----+
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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```

Warning 141: Iterations:current or start estimate of sigma is nonpositiv
Maximum of 20 iterations. Exit iterations with status=1.

```
-----
Random Coefficients LinearRg Model
Dependent variable LWAGE
Log likelihood function 468.34115
Restricted log likelihood .00000
Chi squared [ 8 d.f.] 936.68230
Significance level .00000
Estimation based on N = 4165, K = 17
Information Criteria: Normalization=1/N
Normalized Unnormalized
AIC -2.21673 -902.68230
```



```

Fin.Smpl.AIC      -.21670      -902.53472
Bayes IC          -.19088      -794.99628
Hannan Quinn      -.20758      -864.58870
Model estimated: Feb 09, 2010, 22:59:14
Sample is 7 pds and 595 individuals
LINEAR regression model
Simulation based on 100 Halton draws

```

LWAGE	Coefficient	Standard Error	z	Prob. z> Z	Mean of X
Nonrandom parameters					
OCC	-.02885***	.00575	-5.02	.0000	.51116
IND	.05175***	.00455	11.38	.0000	.39544
SOUTH	-.03755***	.00494	-7.60	.0000	.29028
SMSA	.00458	.00477	.96	.3364	.65378
MS	-.06154***	.00814	-7.56	.0000	.81441
UNION	.05017***	.00477	10.52	.0000	.36399
Means for random parameters					
Constant	5.10687***	.02754	185.43	.0000	
EXP	.02578***	.00085	30.33	.0000	19.8538
Scale parameters for dists. of random parameters					
Constant	.19776***	.00509	38.88	.0000	
EXP	.00070***	.8794D-04	7.98	.0000	
Heterogeneity in the means of random parameters					
cONE_FEM	-.13431***	.01417	-9.48	.0000	
cONE_ED	-.01659***	.00180	-9.19	.0000	
cONE_BLK	.36096***	.01871	19.29	.0000	
cEXP_FEM	-.00572***	.00056	-10.19	.0000	
cEXP_ED	.00460***	.6620D-04	69.50	.0000	
cEXP_BLK	-.01732***	.00073	-23.58	.0000	
Variance parameter given is sigma					
Std.Dev.	.15238***	.00075	204.11	.0000	

```

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

```

3. Construct a different random parameters specification, modify the command above accordingly and fit your model. Report your results and interpret the estimates you obtain.