







Transport Demand Modeling

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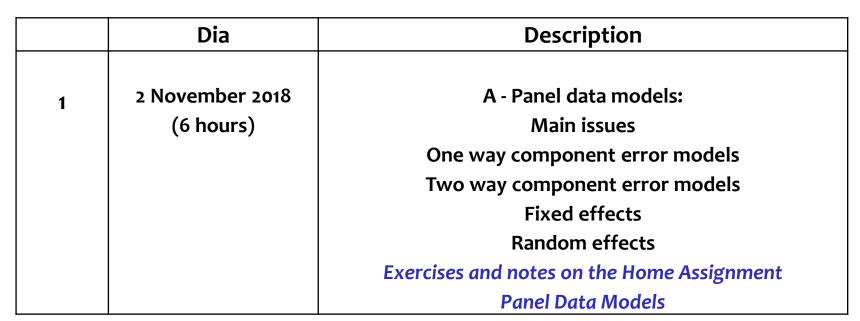
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(adapted from Anabela Ribeiro's)

Session 6
PANEL MODELS

General Framework



Class Structure









General Framework



Correlation does not imply causation!

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Logical fallacies

– Cum hoc ergo propter hoc: "with this, therefore because of this"



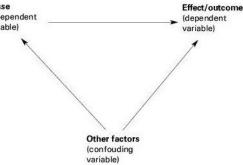
- Post hoc ergo propter hoc: "after this, therefore because of this"



Example: When ice cream sales increase, swimming pool deaths also seem to increase.

Hence, eating ice cream leads to drownings in swimming pools.

· ...)



Correlation is a valuable type of scientific evidence, but after confirmed as real, then every possible causative relationship must be systematically explored.

General Framework



Regression types



Time Series - Regression between a set of variables across time in a certain individual/unit - cross-sectional data in time



Cross section – Regression between a set of variables in a certain moment in time, for a set of individuals/units

Panel Data – Has both a cross-sectional and a time series dimension, where all cross section units are observed during the whole time period

Other names are pooled data, micropanel data, longitudinal data, event history analysis and cohort analysis







Panel Data

- Balanced
- Unbalanced (missing values)

Country	Year	Υ	X1	X2	X3
1	2000	6,0	7,8	5,8	1,3
1	2001	4,6	0,6	7,9	7,8
1	2002	9,4	2,1	5,4	1,1
2	2000	9,1	1,3	6,7	4,1
2	2001	8,3	0,9	6,6	5,0
2	2002	0,6	9,8	0,4	7,2
3	2000	9,1	0,2	2,6	6,4



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Advantages

Longitudinal or cross-sectional time-series data

Panel data are better able to study the dynamics of adjustment. Cross-sectional distributions that look relatively stable hide a multitude of changes

Spells of unemployment, job turnover, residential and income mobility are better studied with panels.

Panel data are also well suited to study the duration of economic states like unemployment and poverty, and if these panels are long enough, they can shed light on the speed of adjustments to economic policy changes.

Micropanel data gathered on individuals, firms and households may be more accurately measured than similar variables measured at the macro level

Biases resulting from aggregation over firms or individuals may be reduced or eliminated

Panel models allow controlling for aggregate effects and individual heterogeneity







Advantages - Example

For example, suppose that a cross-section of public transit agencies reveals that, on average, public transit subsidies are associated with 20% increased ridership.

If a homogeneous population of public transit firms is considered, this might lead to think that a firm's ridership will increase by 20% given transit subsidies

However, an alternative explanation in a sample of heterogeneous public transit firms is that the subsidies have no effect (0% increase) on four fifths of the firms, and raise ridership by 100% on one fifth of the firms. Although these competing hypotheses cannot be tested using a cross-sectional sample (in the absence of a cross-sectional variable that "explains" this difference), it is possible to test between them by identifying the effect of subsidies on a cross section of time series for the different transit systems.

Thus, testing for cross-sectional homogeneity is equivalent to testing the null hypothesis that these additional parameters are equal to zero

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Main issues – specification issues to be accounted for

Explanatory variables - Multicollinearity

Cross-sectional - Heteroscedasticity

Time-series - Correlation in the disturbance terms

Panel Data - Heterogeneity







Main issues

Multicollinearity is a state of very high intercorrelations or inter-associations among the independent variables. It is a type of disturbance in the data, and if present the statistical inferences made about the data **may not** be reliable.

Can be detected through correlation matrix, scatterplot or variance inflation factor

- Variance inflation factor

Step 1 - run an ordinary least square regression that has Xi as a function of all the other explanatory variables $X_i = \alpha_0 + \alpha_2 X_2 + \alpha_3 X_3 + \cdots + \alpha_k X_k + e$

Step 2 - calculate the VIF factor as

$$ext{VIF}_{ ext{i}} = rac{1}{1-R_i^2}$$

Step 3 - Analyze the magnitude of multicollinearity by considering the size of VIF. A rule of thumb is that if VIF > 10 then multicollinearity is high (a cutoff of 5 is also used).

Good planning in the study design is the best remedy for **multicollinearity**.



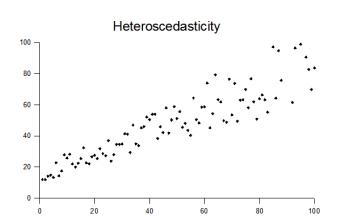


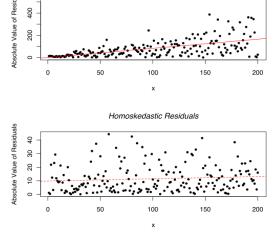


Main issues – (typically Cross-sectional)

Heteroscedasticity, which refers to the variance of the disturbances not being constant across observations.

For example, when analyzing household mobility patterns, there is often greater variation in mobility among high-income families than low-income families, possibly due to the greater flexibility in traveling allowed by higher incomes.





It does not affect consistency of regression but it affects its efficiency.



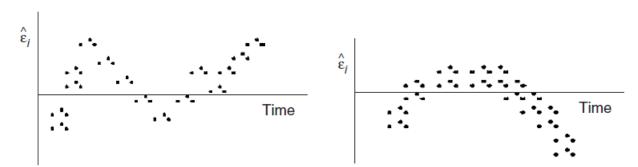




Main issues – (typically Time-series)

Correlation in the disturbance terms - A second issue is **serial correlation** of the disturbance terms, which occurs in time-series studies when the disturbances associated with observations in one time period are dependent on disturbances from prior time periods.

Positive correlation – the estimates of the standard errors are smaller than the true Negative correlation – the estimates of the standard errors are bigger than the true



The regression estimates are unbiased but its errors are biased. It does not affect consistency of regression but it affects its efficiency.







Main issues – (Panel Data)

Heterogeneity - Compared with cross-sectional or time-series data, panel data raise new specification issues that need to be considered during analysis

The most important of these is *heterogeneity* bias

Heterogeneity refers to the differences across cross-sectional units that may not be appropriately reflected in the available data (explanatory variable/s).

Heterogeneity - if not accounted for explicitly, may lead to model parameters that are inconsistent and/or meaningless. With panel data, it is possible to account for cross-sectional *heterogeneity* by introducing additional parameters into the model.

Heterogeneity in panel data can be tested using several test of hypothesis – Z Test (if the distributions follow a normal distribution).



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Main issues – new specification issues

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Heteroscedasticity

Correlation in the disturbance terms

Heterogeneity



One Way and Two Way component models







Overcoming specification problems in panel data:

One-Way error component models: variable-intercept models across individuals or time

Two-Way error component models: variable-intercept models across individuals and time



Introduction of dummy variables in the model

Modeling specifications:

With fixed effects: effects that are in the sample

With random effect: effect randomly drawn from a population

Panel Data Models: Variable-intercept Error Component Models







Variable-intercept models across individuals or/and time (one/two-way models) are the simplest and most straightforward models for accounting for cross-sectional heterogeneity in panel data, which arise when the null hypothesis of overall homogeneity is rejected

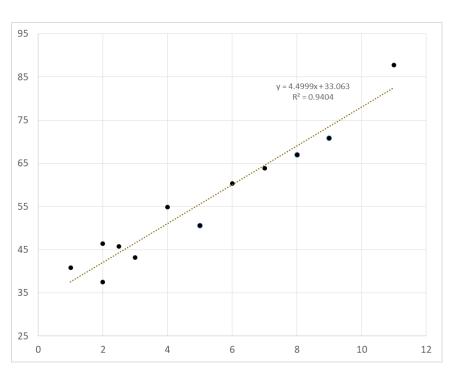
- ➤ The variable-intercept model assumes that the effects of omitted variables may be individually unimportant but are collectively significant, and thus is considered to be a random variable that is independent of included independent variables.
- Because heterogeneity effects are assumed to be constant for given cross-sectional units or for different cross-sectional units during one time period, they are absorbed by the intercept term as a means to account for individual or time heterogeneity

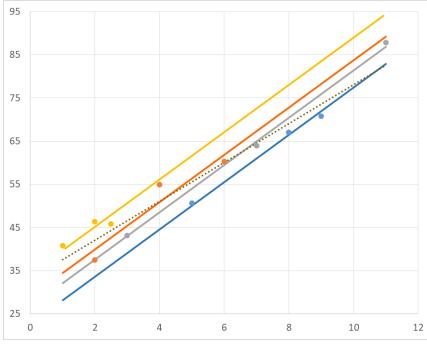
Panel Data Models: Variable-intercept Error Component Models Example 1

















A Panel Data regression is generally written as:

$$Y_{it} = \alpha + X_{it}^{'}\beta + u_{it}, i = 1,...,n; t = 1,...,T$$
 (1)

where *i* refers to the cross-sectional units, *t* refers to the time periods, α is a scalar, β is a Px1 vector, and X_{it} is the *ith* observation on the Pth explanatory variable, and u_{it} is the error term

A One-Way Error component model for the disturbances, which is the most commonly utilized in panel data formulation, is specified as

$$u_{it} = \mu_i + v_{ij} \tag{2}$$

where μ_i is the unobserved cross-sectional specific effect and v_{it} are random disturbances







Fixed Effects (FE)

When the μ_i are assumed to be fixed parameters to be estimated, and the v_{it} are random disturbances that follow the usual regression assumptions, then combining both yields the following model, where inference is conditional on the particular n cross-sectional units that are observed, and is thus called a **Fixed Effects model**

$$Y_{it} = \alpha + X_{it}^{'}\beta + \mu_i + \nu_{it}, i = 1,...,n; t = 1,...,T$$
 (3)

on which ordinary least squares (OLS), which provide best linear unbiased estimators (BLUE), are used to obtain α , β and μ_i

Fixed Effects (FE)

FE explore the relationship between predictor and outcome variables **within** an entity (country, person, company, etc.).

Each entity has its own individual characteristics that may or may not influence the predictor variables (for example, being a male or female)

When using FE we assume that something within the individual may impact or bias the predictor or outcome variables and **we need to control for this**. This is the rationale behind the assumption of the correlation between entity's error term and predictor variables.

FE remove the effect of those time-invariant characteristics so we can assess the net effect of the predictors on the outcome variable.









Another important assumption of the FE model is that those time invariant characteristics are unique to the individual and should not be correlated with other individual characteristics.

Each entity is different therefore the entity's error term and the constant (which captures individual characteristics) should not be correlated with the others.

If the error terms are correlated, then FE is no suitable since inferences may not be correct and you need to model that relationship (**probably using random-effects**), this is the main rationale for the **Hausman test**.

Fixed-effects models are designed to study the causes of changes within a person or entity.









Fixed Effects (FE)

Large Samples: when *n* is large, many indicator variables are included, and a least squares dummy variable (LSDV) estimator is obtained.

Testing for the joint significance of the included fixed effects parameters (the dummy variables) is straightforwardly conducted using the **Chow F** test



$$F_{0} = \frac{(RRSS - URSS)/(n-1)^{H_{0}}}{URSS/(nT - n - P)} \sim F_{n-1,n(T-1)-P}$$
(4)

where RRSS are the restricted residual sums of squares from OLS on the pooled model and URSS are the unrestricted residual sums of squares from the LSDV regression

- If the null is true (no fixed effects) then the correct procedure is to estimate a single regression from all the data.
- If the null is not true (a significant value for F) than we have to account for fixed effects







Random Effects (RE)

The fixed effects specification suffers from an obvious shortcoming in that it requires the estimation of are too many parameters and the associated loss of degrees of freedom

This can be avoided if the μ_i can be assumed random. Unlike the fixed effects model where inferences are conditional on the particular cross-sectional units sampled, an alternative formulation, called the *Random Effects model*.

$$\mu_i \sim IID(0,\sigma_\mu^2), \quad \nu_{it} \sim IID(0,\sigma_\nu^2)$$
 (5)

 \succ The μ_i and ν_{it} are independent, and X_{it} are independent of the μ_i and ν_{it} for all i, t







Random Effects (RE)

The random effects model is an appropriate specification if we are drawing *n* individuals randomly from a large population

This is usually the case for household panel studies. Care is taken in the design of the panel to make it "representative" of the population we are trying to make inferences about

The individual effect is characterised as random and inference pertains to the population from which this sample was randomly drawn.

Furthermore, it can be shown that a random effects specification implies a **homoscedastic** disturbances variance, $VAR(u_{it}) = \sigma_u^2 + \sigma_v^2$ for all *i*, *t*, and serial correlation only for disturbances of the same cross-sectional unit.







Fixed vs. Random Effects

This is not as easy a choice as it might seem. In fact, the fixed versus random effects issue has generated a hot debate in the biometrics and statistics literature which has spilled over into the panel data econometrics literature....

Most commonly accepted:

The most important issue when considering these alternative specifications is the context of the analysis.

The essential difference between these two modeling specifications is:

- whether the inferences are conditional on the effects that are in the sample, i.e. inferences from the estimated model are confined to the effects in the model (the fixed effects model is appropriate);
- whether the inferences are made unconditionally with respect to the population of effects, i.e. inferences are made about a population of effects, from which the effects in the model are a random sample (suited for the random effects model).







Fixed vs. Random Effects (Lagrange and Hausman Tests)

The FE model has a considerable virtue in that it does not assume that the individual effects μ_i are uncorrelated with the regressors X_{it} as is assumed by the random-effects model.

In fact, the RE model may be biased and inconsistent due to omitted variables (Hausman and Taylor, 1981; Chamberlain, 1978).

With the intent of identifying potential correlation between the individual effects and the regressors, the **Hausman's Test** (Hausman, 1978) examines the null hypothesis of no correlation between the individual effects and X_{it}

A rejection of the null hypothesis of no correlation suggests the possible inconsistency of the RE model and the possible preference for a FE specification (test value significant).







Fixed vs. Random Effects (Lagrange and Hausman Tests)

Breusch and Pagan's **Lagrange multiplier** statistic, is used to test the null hypothesis that there are no group effects in the RE model. Arguably, a rejection of the null hypothesis is as likely to be due to the presence of fixed effects. The statistic is computed from the ordinary least squares residuals from a pooled regression.

Large values of LM favor the FE and RE models over the classical model with no common effects.

A second statistic is **Hausman's Chi Squared** statistic for testing whether the GLS estimator is an appropriate alternative to the LSDV estimator. Computation of the Hausman statistic requires estimates of both the random and fixed effects models.

Large values of H weigh in favor of the FE model.







Fixed Effects

The disturbances presented in (2) are further generalized to include time-specific effects. This generalization is called a **Two-Way Error components model**, whose disturbances are written as

$$u_{it} = \mu_i + \lambda_t + v_{ii}, i = 1,...,n; t = 1,...,T$$
 (10)

where μ_i is the unobserved cross-sectional specific effect, λ_t denotes the unobservable time effects, and v_{it} are random disturbances. Here λ_t is individual invariant and accounts for any time-specific effect that is not included in the regression

When the μ_i and λ_t are assumed to be fixed parameters to be estimated and are random disturbances that follow the usual regression assumptions, combining (1) and (10) yields a model where inferences are conditional on the particular *n* cross-sectional units and are to be made over the specific time period of observation

$$u_{it} = \mu_i + v_{ii}$$

where μ_i is the unobserved cross-sectional specific effect and υ_{it} are random disturbances









Fixed Effects

This model is called a two-way fixed effects error component model and is given as

$$Y_{it} = \alpha + X_{it}^{'}\beta + \mu_i + \lambda_t + \nu_{it}, i = 1,...,n; t = 1,...,T$$
 (11)

where X_{it} are assumed independent of the v_{it} for all i, t.

Inference for this *two-way fixed-effects model* is conditional on the particular *n* individuals and over the T time periods of observation. Similar to the one-way fixed-effects model, the computational difficulties involved with obtaining the OLS estimates for β .







Fixed Effects

Testing for the joint significance of the included cross-sectional and time period fixed effects parameters (the dummy variables) is straightforwardly computed using an *F* test

$$F_0 = \frac{(RRSS - URSS)/(n+T-2)^{H_0}}{URSS/(n-1)(T-1)-P} \sim F_{(n+T-2),(n-1)(T-1)-P}$$
 (12)

where RRSS are the restricted residual sums of squares from OLS on the pooled model and URSS are the unrestricted residual sums of squares from the regression using the within transformation of Wallace and Hussain (1969)









Random Effects

Similar to the one-way error component model case, if both the μ_i and λ_t are random with

$$\mu_i \sim IDD(0, \sigma_\mu^2), \ \lambda_t \sim (0, \sigma_\lambda^2), \ \upsilon_{it} \sim IDD(0, \sigma_\upsilon^2)$$
 (13)

The μ_i , λ_t and ν_{it} are independent, and X_{it} are independent of the μ_i , λ_t and ν_{it} for all i, t.

This formulation is called the *Random-Effects model*

Furthermore, it can be shown that a random effects specification implies a homoscedastic disturbances variance, $VAR(u_{it}) = \sigma_u^2 + \sigma_\lambda^2 + \sigma_\nu^2$ for all *i*, *t*, and serial correlation only for disturbances of the same cross-sectional unit.







Random Effects

Estimation of the two-way random-effects model is typically accomplished using the GLS estimators of Wallace and Hussain (1969) or by using maximum likelihood estimation (Baltagi and Li, 1992)

For this model specification, Breusch and Pagan (1980) derived a **Lagrange-Multiplier** test for the null hypothesis;

$$H_0 = \sigma_{\mu}^2 = \sigma_{\lambda}^2 = 0$$
 this test is based on the normality of the disturbances

If the **Two-Way Error component mode**l specification is **significant**, the quality of its estimates should be always **better** than a **One-way Error Component model** in Fixed Effects or Random Effects model.

Panel Data Models: Example 2







Nlogit with Grunfeld Investment Equation

$$I_{it} = \alpha + \beta_1 F_{it} + \beta_2 C_{it} + v_{it}$$
 (16)

where I_{it} t denotes real gross investment for firm i in year t, F_{it} is the real value of the firm (shares outstanding) and C_{it} is the real value of the capital stock. These panel data consist of 10 large US manufacturing firms over 20 years, 1935–54

Table 1

Variable Abbreviation	Variable Description
invest	Gross investment, defined as additions to plant and equipment plus maintenance and repairs in millions of dollars deflated by the implicit price deflator of producers' durable equipment (base 1947)
value	Market value of the firm, defined as the price of common shares at December 31 (base 1947)
capital	Stock of plant and equipment, defined as the accumulated sum of net additions to plant and equipment deflated by the implicit price deflator for producers' durable equipment (base 1947)
firm	General Motors (GM), US Steel (US), General Electric (GE), Chrysler (CH), Atlantic Rening (AR), IBM, Union Oil (UO), Westinghouse (WH), Goodyear (GY), Diamond Match (DM), American Steel (AS)
year	Year of data
firmcod	Numeric code that identifies each firm

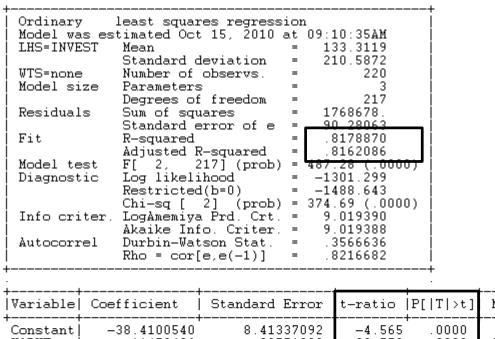
Panel Data Models: Example 2







Ordinary Least Squares Model Estimates Gross Investment











Fixed Effects Panel Data Model Estimates (One-way Error) Gross Investment

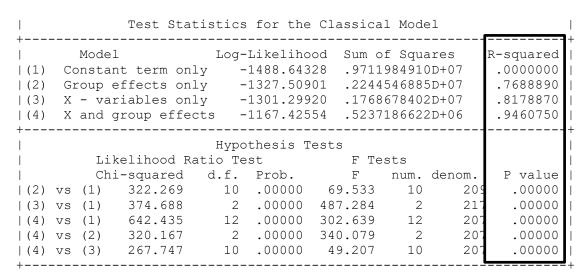
Least Square	s with Group Dummy Vai	riables	+ Estimated Fixed Group	Coefficient	Standard Error	t-ratio
_	least squares regress		1	-70.29907	47.37535	-1.48387
-			2	101.90474		4.28735
	timated Nov 05, 2012 a		9	-235.56939		-10.11632
LHS=INVEST	Mean	= 133.3119	· =	-27.80911	13.41858	-2.07243
	Standard deviation	= 210.5872	5	-114.60252	13.50246	-8.48753
WTS=none	Number of observs.	= 220	1 6	-23.16020	12.07589	-1.91789
Model size	Parameters	= 13	8	-66.54422 -57.54649	12.24204	-5.43572 -4.31451
	Degrees of freedom	= 207		-87.21454	13.33791 12.28873	-7.09712
Residuals	=				11.27363	
Residuals	Sum of squares		1 11	-20.57820		-1.82144
	Standard error of e					
Fit	R-squared	• .9460750	1			
	Adjusted R-squared	.9429489	1			
Model test	F[12, 207] (prob)	4 302.64 (.0	000)			
	Log likelihood					
	Restricted (b=0)					
T C '.	Chi-sq [12] (prob)					
Info criter.	LogAmemiya Prd. Crt.					
	Akaike Info. Criter.	= 7.893264	1			
Estd. Autoco	rrelation of e(i,t)	.549274	1			
			+			
Variable Coef	ficient Standard Erro	· -	· · · · · · · · · · · · · · · · · · ·			
		· 				
VALUE	.11012912 .0112998	9.746	.0000 988.577805			

Significant F value – account for effects





Fixed Effects Panel Data Model Estimates (One-way Error) Gross Investment





Consideration of group effects improve regression

Panel Data Models: Example 2

Estimated Fixed Effects - Full sets of effects, normalized



Fixed Effects Panel Data Model Estimates (Two-way Error)

Gross Investment



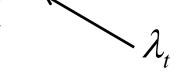
Group		Standard Error	t-ratio
1	-53.14755	42.84415	-1.24049
++ 2	149.17125	16.34968	9.12380
Least Squares with Group and Period Effects 3	-192.46291	15.79790	-12.18282
Λ	35.02275	11.28051	3.10471
Ordinary least squares regression 5	-63.87868	16.09003	-3.97008
Model was estimated Nov 07, 2012 at 01:14:13AM 6	42.16480	12.69795	3.32060
LHS=INVEST	-8.17149	15.43398	52945
	6.90560	11.49035	.60099
Standard deviation = 210.5872 9	-29.34076	13.70930	-2.14021
WTS=none Number of observs. = 220 10	65.11490	15.55637	4.18574
Model size Parameters = 32	48.62208	15.58761	3.11928







-	Ordinary	reast squares regress	TOI	1	1 5	-63.87868	16.09003	-3.97008
	Model was es	timated Nov 07, 2012	at	01:14:13AM	6	42.16480	12.69795	3.32060
i	LHS=INVEST	Mean	=	133 3119	7	-8.17149	15.43398	52945
	LIIO IIVVLOI				, 8	6.90560	11.49035	.60099
- 1		Standard deviation			9	-29.34076	13.70930	-2.14021
	WTS=none	Number of observs.	=	220	10 11	65.11490		4.18574
	Model size	Parameters	=	32	11	48.62208	15.58761	3.11928
i		Degrees of freedom	=	188		Fixed Effects - Ful		
	Residuals			459399.9	Period	Coefficient	Standard Error	t-ratio
- 1	Residuals	Sum of squares			1	41.85916	15.38287	2.72115
		Standard error of e	=	49.43295	2	24.89993		1.65601
-	Fit	R-squared	=	. 9526976	1 3	5.48352		.35454
	1 1 0				' 4	6.23543 -21.24024	14.87055 14.71160	.41931
- 1		Adjusted R-squared] 5	2.03439	14.71160	-1.44377 .13799
	Model test	F[31, 188] (prob)	=	122.14 (.0000)		25.37139		1.73124
-	Diagnostic	Log likelihood	=	-1153.012	l é	23.85983	14.71735	1.62120
i	2	Restricted(b=0)		-1488.643	i 9	4.08671	14.58562	.28019
					10	3.53909	14.57617	.24280
-		Chi-sq [31] (prob)			11	-7.68033	14.59933	52607
	Info criter.	LogAmemiya Prd. Crt.	=	7.937036	12	14.10477	14.64576	.96306
1		Akaike Info. Criter.			13	6.98162	14.67759	. 47567
	D-+-1 7+				14	3.52843	14.82120	. 23807
	Esta. Autoco	rrelation of e(i,t)		.569917	15	-23.34160	14.88759	-1.56786
+					+ 16	-25.52857	14.85283	-1.71877
					17	-12.97548	14.79992	87673
					18	-14.62988	15.04933	97213
					19	-16.65342	15.74591	-1.05763
					20	-39.93475	16.15229	-2.47239
	1	1						





Fixed Effects Panel Data Model Estimates (Two-way Error) Gross Investment





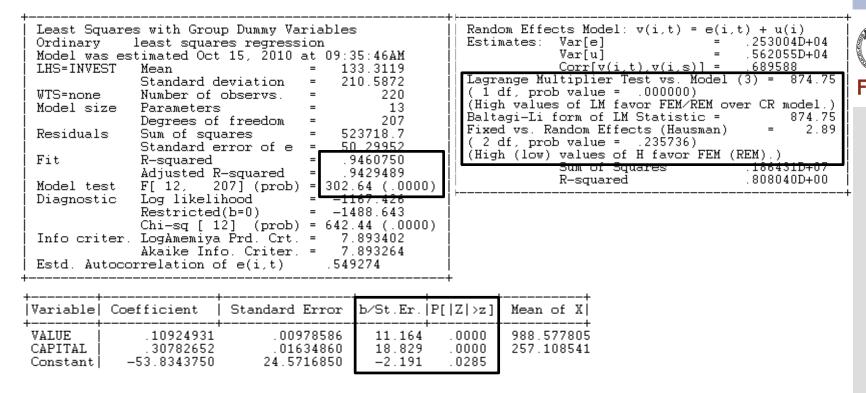
Test Statistics for the Classical Model						
Model (1) Constant term only (2) Group effects only (3) X - variables only (4) X and group effects (5) X ind.&time effects	-1327.59 -1301.29 -1167.49	4328 .9711 0901 .2244 9920 .1768 2554 .5237	of Squar 1984910D 1546885D 3678402D 7186622D 3999310D	+07 +07 +07 +06	R-squared .0000000 .7688890 .8178870 .9460750 .9526976	
Likelihood Rati Chi-squared d (2) vs (1) 322.269 (3) vs (1) 374.688 (4) vs (1) 642.435 (4) vs (2) 320.167 (4) vs (3) 267.747 (5) vs (4) 28.827 (5) vs (3) 296.575		F Te F 0 69.533 0 487.284 0 302.639 0 340.079 0 49.207 1.385	num. d	enom. 209 217 207 207 207 188 188	.00000 .13801	

Consideration of group effects and time effects improve regression



Random Effects Panel Data Model Estimates (One-way Error) Gross Investment

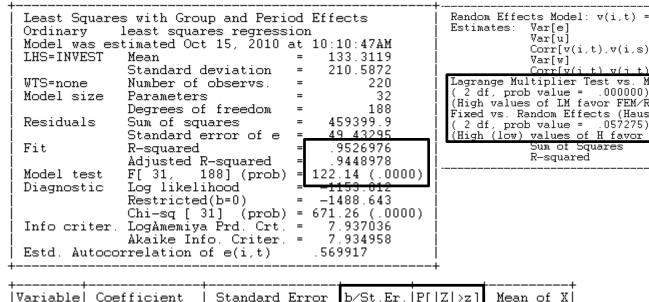






Random Effects Panel Data Model Estimates (Two-way Error) **Gross Investment**





Random Effects Model: $v(i,t) = e(i,t) + u(i) + w(t)$
Estimates: $Var[e]$ = .244362D+04
Var[u] = .447819D+04
Corr[v(i,t),v(i,s)] = .646968
Var[w] = .122879D+04
Corr[v(i,t),v(i,t)] = .334600
Lagrange Multiplier Test vs. Model (3) = 881.07
(2 df. prob value = .000000)
(High values of LM favor FEM/REM over CR model.)
Fixed vs. Random Effects (Hausman) = 5.72
(2 df, prob value = .057275)
(High (low) values of H favor FEM (REM).)
Sum of Squares .186431D+07
R-squared .808040D+00



Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]	Mean of X
VALUE CAPITAL Constant	.11107050 .33700305 -63.1362933	.01021747 .01975302 23.9608695	10.871 17.061 -2.635	.0000 .0000 .0084	988.577805 257.108541



```
Random Effects Model: v(i,t) = e(i,t) + u(i) + w(t)
Estimates:
           Var[e]
            Var[u]
           Corr[v(i,t),v(i,s)] =
            Var[w]
           Corr[v(i,t),v(j,t)] =
Lagrange Multiplier Test vs. Model (3) =
( 2 df, prob value = .000000)
(High values of LM favor FEM/REM over CR model.)
Fixed vs. Random Effects (Hausman)
                                           5.72
(2 df, prob value = .057275)
(High (low) values of H favor FEM (REM).)
           Sum of Squares
                                  .186431D+07
           R-squared
                                    .808040D+00
```





Large values of LM favor the effects model over the classical model with no common effects.

Large values of H weigh in favor of the fixed effects model.

A large value of the LM statistic in the presence of a small H statistic (as in our application) argues in favor of the random effects model.

"LIMDEP, Version 9, Student , Reference Guide"







NLOGIT with Impact of safety belt use on road accident fatalities

The effectiveness of safety belt use in reducing motor vehicle–related fatalities has been the subject of much research interest in the past few years. To investigate the hypothesised relationship between various exogenous factors including seat belt usage rates and traffic fatalities

Derrig et al. (2002) compiled a panel data set of demographic, socioeconomic, political, insurance, and roadway variables for all 50 US states over a 14-year period (1983 through 1996) for a total of 700 observations (state-years)

This data set was subsequently enriched with additional information by R. Noland of Imperial College, U.K., and is used in this analysis



US States Map









Table 1

Variable Abbreviation	Variable Description
STATE	State
YEAR	Year
STATENUM	State ID number
DEATHS	Number of traffic-related deaths
INJURED	Number of traffic-related injuries
PRIMLAW	Primary seat belt law
SECLAW	Secondary seat belt law
TOTVMT	Total VMT
PI92	Per capita income 1992 \$
POP	Total population
HOSPAREA	Hospitals per square mile
ETHANOL	Alcohol consumption total ethanol by volume
ETHPC	Per capita ethanol consumption
SEATBELT	Percent seat belt use
PERC1524	Percent population 15–24
PERC2544	Percent population 25–44
PERC4564	Percent population 45–64
PERC65P	Percent population 65 plus
PERC75P	Percent population 75 plus
INMILES	Total lane miles (excluding local roads)
PRECIP	Annual precipitation in inches
EDUC	Percent bachelors degrees
PERCRINT	Percentage of vehicle miles driven in rural interstate highway miles



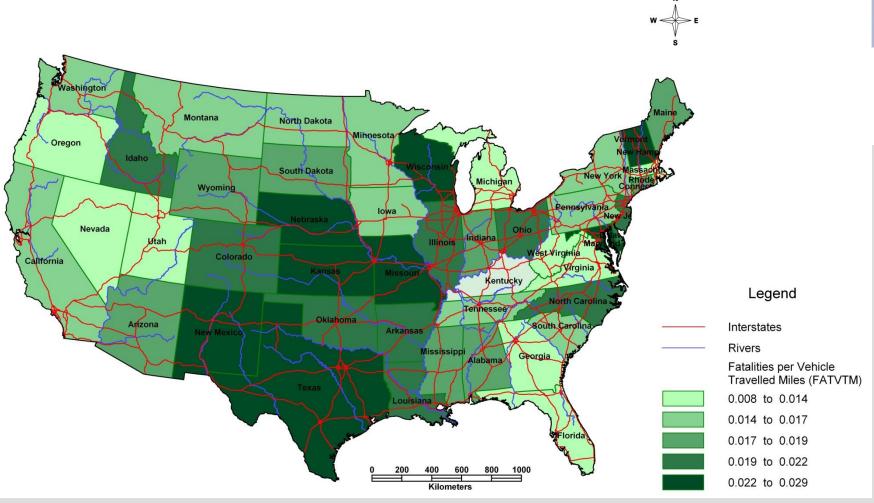




Sample - Fatalities per vehicle travelled mile (FATVTM) - 1995

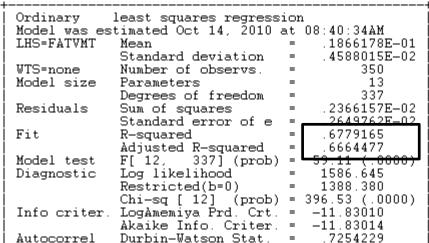








Ordinary Least Squares Model Estimates Fatalities per vehicle travelled mile (FATVTM)



Rho = cor[e,e(-1)]

	1				
Variable	Coefficient	Standard Error	t-ratio	P[T >t]	Mean of X
Constant YEAR PI92 POP HOSPAREA ETHPC SEATBELT PERC1524 PERC2544 PERC4564 PERC75P LNMILES PRECIP	1.99567406 00093815 461127D-06 .919607D-10 36752679 1.97828609 00142761 16843079 22129246 .05561139 34256374 212927D-08 .653803D-04	.449527D-10 .10279119 .46514010 .00144334 .02807833 .01923444 .01714655 .02808903	9.984 -9.385 -4.441 2.046 -3.575 4.253 989 -5.999 -11.505 3.243 -12.196 5.066	.0000 .0000 .0000 .0416 .0004 .0000 .3233 .0000 .0013 .0000 .3553	1993.00000 20460.8038 .513867D+07 .00258178 .00184147 .58400000 .14278826 .31660983 .19345771 .05521571 162439.608 37.1971429

.6372885



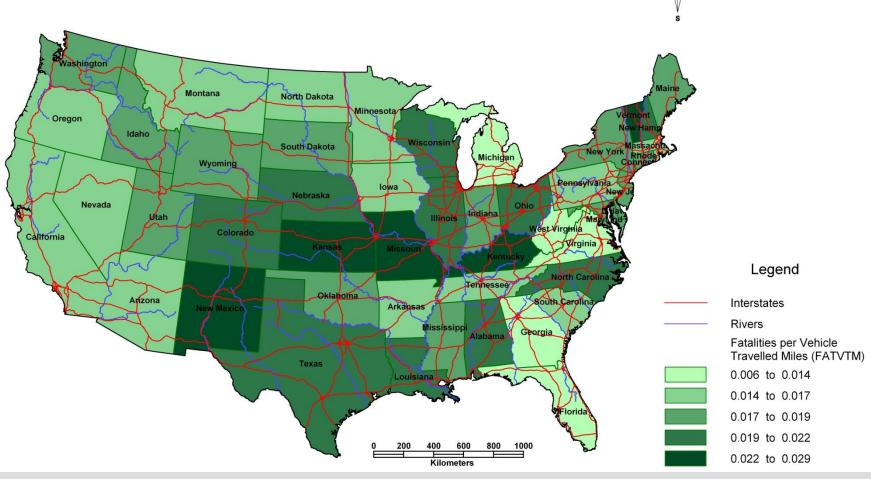














Fixed Effects Panel Data Model Estimates (One-way Error) Fatalities per vehicle travelled mile (FATVTM)

.1866178E-01

.4588015E-02

350

289

5945459E-03

1434312E-02

12

13

14

15

16

17

1.24160

1.23887

9190699

9022677

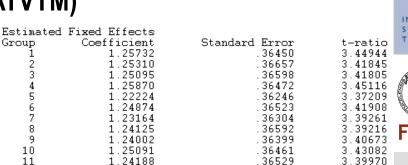
1828.360

1388.380

-12.93707

54.70 (.0000)

61



36539

36327

36417

36357

36317

36477

36604

36598

.36435



3.42080

3.39257

3 40027

+				+	L
Variable	Coefficient	Standard Error	t-ratio	P[T >t]	Mean of X
YEAR PI92 POP HOSPAREA ETHPC SEATBELT PERC1524 PERC2544 PERC75P LNMILES PRECIP	00063812 .567135D-06 .143018D-08 29725499 2.24840288 00498158 .07483185 .03984851 .20873172 643958D-07	3 .547381D-09 .50333761 3.37243604 .00148673 .02716235 .02650378 .12617346	-3.450 1.788 2.613 591 .667 -3.351 2.755 1.504 1.654 -2.193 -1.591	.0006 .0747 .0094 .5552 .5054 .0009 .0062 .1336 .0990 .0290	1993.00000 20460.8038 .513867D+07 .00258178 .00184147 .58400000 .14278826 .31660983 .05521571 162439.608 37.1971429

Least Squares with Group Dummy Variables

Parameters

R-squared

Info criter, LogAmemiya Prd. Crt. =

FF 60.

Estd. Autocorrelation of e(i,t)

Ordinary

WTS=none

LHS=FATVMT

Model size

Residuals

Model test

Diagnostic

Fit

least squares regression

Model was estimated Oct 14, 2010 at 09:01:11AM

Standard deviation

Number of observs.

Degrees of freedom

Standard error of e

Adjusted R-squared

Akaike Info. Criter. =

White/Hetero. corrected covariance matrix used.

289] (prob)

Chi-sq [60] (prob) = 879.96 (.0000)

Sum of squares

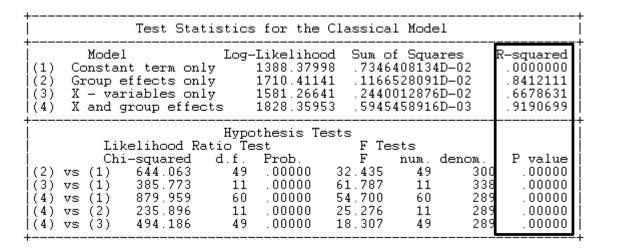
Log likelihood

Restricted(b=0)



Fixed Effects Panel Data Model Estimates (One-way Error) Fatalities per vehicle travelled mile (FATVTM)





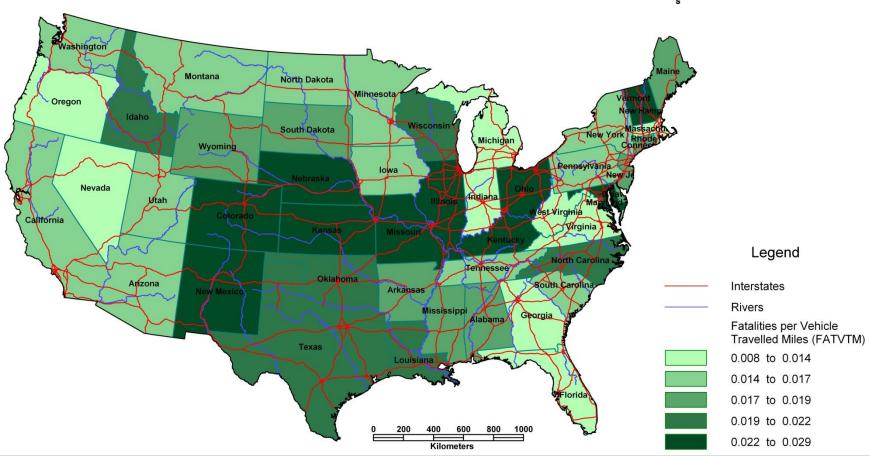
















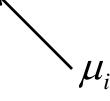




Fixed Effects Panel Data Model Estimates (Two-way Error) Fatalities per vehicle travelled mile (FATVTM)

+			+			
I Least Square	es with Group and Period	Effects		Fixed Effects - Full		
	least squares regression		Group	Coefficient	Standard Error	t-ratio
			1 1	.00857	.00161	5.33434
	stimated Oct 14, 2010 at] 2	.00467	.00734	. 63678
LHS=FATVMT	Mean =	.1866178E-01] 3	.00229	.00260	.87981
1	Standard deviation =	.4588015E-02	1 4	.01006	.00209	4.80648
WTS=none	Number of observs. =	350	į ž	02607	.01455	-1.79161
Model size	Parameters =	67		00014 00922	.00251 .00529	05498 -1.74424
noder size			!	00922 00295	.00473	-1.74424 62258
	Degrees of freedom =	283	!	00293	.00473	70154
Residuals	Sum of squares =	.5273813E-03	1 10	.00222	.00229	.97268
	Standard error of e =_	.1365115E-02	l 11	00353	.00479	73756
Fit	R-squared =	.9282124	1 12	.00596	.00363	1.64151
İ	Adjusted R-squared =	.9114704	j 13	00419	.00478	87677
Model test	F[66, 283] (prob) =		14	00075	.00118	63862
	Log likelihood =	1049.338	15	.00582	.00344	1.69190
Diagnostic			16	.00678	.00427	1.58723
ļ	Restricted(b=0) =	1388.380	17	.00514	.00143	3.59424
	Chi-sq [66] (prob) =	921.92 (.0000)	18	.00665	.00239	2.77882
Info criter.	LogAmemiya Prd. Crt. =	-13.01788	19	00534	.00362	-1.47510
	Akaike Info. Criter. =		20	00606	.00351	-1.72759

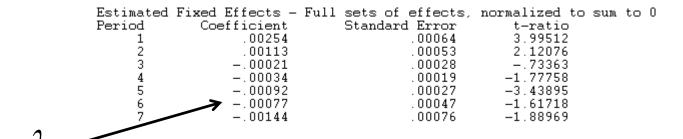
 Variable	Coefficient	Standard Error	t-ratio	P[T >t]	Mean of X
PI92 POP HOSPAREA ETHPC SEATBELT PERC1524 PERC2544 PERC4564 PERC75P LNMILES PRECIP Constant	.226658D-06 .134814D-08 83312526 .83897209 00281535 .06577722 .04788101 .00321838 .15764805 516750D-07 363727D-04	.587353D-09 .86160797 1.59819810 .00142595 .02957799 .04200016 .04736540 .12826417	.807 2.295 967 .525 -1.974 2.224 1.140 .068 1.229 -1.748 -2.263 483	.4204 .0223 .3343 .6000 .0492 .0268 .2551 .9459 .2199 .0814 .0242	20460.8038 .513867D+07 .00258178 .00184147 .5840000 .14278826 .31660983 .19345771 .05521571 162439.608







Fixed Effects Panel Data Model Estimates (Two-way Error) Fatalities per vehicle travelled mile (FATVTM)





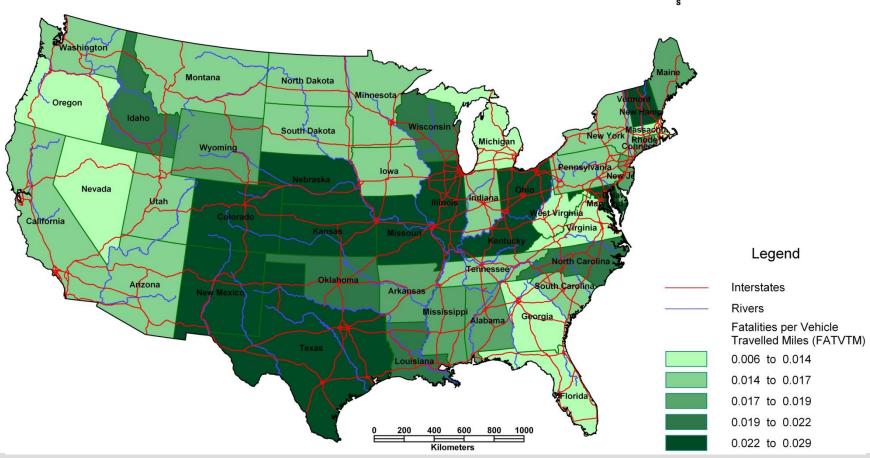
Test Statis	stics for the	Classical Model	
Model (1) Constant term only (2) Group effects only (3) X - variables only (4) X and group effects (5) X ind.&time effects	1710.4114: 1546.0094' 1820.8226	8 .7346408134D- 1 .1166528091D- 9 .2984616903D- 7 .6207110400D-	.02 .0000000 .02 .8412111 .02 .5937311 .03 .9155082
Likelihood Rati Chi-squared of (2) vs (1) 644.063 (3) vs (1) 315.259 (4) vs (1) 864.885 (4) vs (2) 220.823 (4) vs (3) 549.626 (5) vs (4) 57.030 (5) vs (3) 606.656	1.f. Prob. 49 .00000 11 .00000 60 .00000 11 .00000 49 .00000	F Tests	mom. P value 300 .00000 338 .00000 289 .00000 289 .00000 289 .00000 283 .00000



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Fixed Effects Panel Data Model Estimates (Two-way Error) Fatalities per vehicle travelled mile (FATVTM) - 1995







Random Effects Panel Data Model Estimates (One-way Error) Fatalities per vehicle travelled mile (FATVTM)

```
OLS Without Group Dummy Variables
            least squares regression
Ordinary
Model was estimated Oct 14, 2010 at 09:28:52AM
LHS=FATVMT
             Mean
                                       .1866178E-01
             Standard deviation
                                       .4588015E-02
             Number of observs.
WTS=none
                                            350
Model size
             Parameters
                                             13
             Degrees of freedom
                                            337
Residuals
             Sum of squares
                                       .2366157E-02
             Standard error of e
                                        2649761E-02
Fit.
             R-squared
                                        .6779165
             Adjusted R-squared
                                       .6664477
             F[ 12, 337] (prob) =
Model test
                                      59.11 (.0000)
Diagnostic
             Log likelihood
                                       1586.645
             Restricted(b=0)
                                       1388.380
             Chi-sq [ 12] (prob) =
                                     396.53 (.0000)
```

Random Effects Model: v(i,t) = e(i	.t) + u(i)
Estimates: Var[e] =	.205299D-05
Var[u] =	.496825D-05
Corr[v(i,t),v(i,s)] =	.707603
Lagrange Multiplier Test vs. Model	(3) = 291.00
(1 df, prob value = .000000)	
(High values of LM favor FEM/REM of	ver CR model.)
Baltagi-Li form of LM Statistic =	291.00
Fixed vs. Random Effects (Hausman)	= .00
(12 df, prob value = 1.000000)	
(High (low) values of H favor FEM	(REM).)
Sum of Squares	.358714D-02
R-squared	.511715D+00

Info cr					
- 	+	Ctandand Fares	byCt En	Dr 7 \ = 1	W
variable	Coefficient +	Standard Error	D/St.Er.	P[Z >z] 	Mean of X
YEAR PI92 POP HOSPAREA ETHPC SEATBELT PERC1524	00049436 291797D-06 .115470D-09 72287233 1.37233196 00464050	9 .975382D-10 .19328036 .82313631 .00128596 .02335547	-4.298 -1.882 1.184 -3.740 1.667 -3.609	.0000 .0598 .2365 .0002 .0955 .0003	1993.00000 20460.8038 .513867D+07 .00258178 .00184147 .58400000 .14278826
PERC2544 PERC4564 PERC75P	04071682 .03763409 .08847938	.02683827 .02527058 .04345419	-1.517 1.489 -2.036	.1292 .1364 .0417	.31660983 .19345771 .05521571
LNMILES	439628D-08		870	.3844	162439.608

.137572D-04

.22911037

644

4.459

.5193

.0000

37.1971429



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.886500D-05

1.02171594

PRECIP

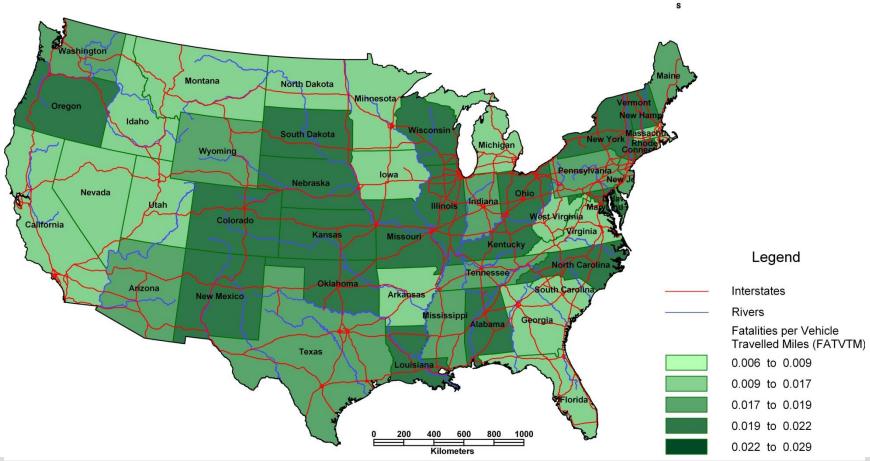
Constant



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Random Effects Panel Data Model Estimates (One-way Error) Fatalities per vehicle travelled mile (FATVTM) - 1995









Alternative Modeling Specifications for Fatalities per VMT (t statistics in parentheses)

	Parameter Estimates					
Independent Variable	Model 1 OLS: No Correction	Model 2 Fixed Effects	Model 3 Two-Way Fixed Effects	Model 4 Random Effects	Model 5 Fixed Effects w/ AR(1)	Model 6 Random Effects w/ AR(1)
Constant	1.69 (9.22)	_	_	0.83 (3.83)	_	0.28 (1.2)
YEAR	-7.90E-04 (-8.62)	-6.71E-04 (-3.75)	_	-4.10E-04 (-3.87)	-4.50E-04 (-2.21)	-1.30E-04 (-1.15)
PI92	-6.50E-07 (-7.12)	3.30E-07 (1.61)	5.5E-08 (0.23)	-1.90E-07 (-1.33)	1.30E-07 (0.62)	-3.70E-07 (-2.57)
POP	1E-10 (2.4)	1.1E-09 (2.21)	9.3E-10 (1.91)	1.30E-10 (1.35)	1.50E-09 (2.81)	1.20E-10 (1.26)
HOSPAREA	-0.18 (-1.88)	-0.35 (-0.61)	-0.55 (-0.95)	-0.64 (-3.22)	-0.19 (-0.35)	-0.54 (-2.79)
ETHPC	1.62 (3.65)	2.6 (1.72)	1.81 (1.19)	1.43 (1.73)	-1.97 (-1.11)	-3.70E-03 (-0.004)
SEATBELT	-2.20E-03 (-1.67)	-4.00E-03 (-3.3)	2.37E-03 (-1.87)	-4.10E-03 (-3.590)	-2.50E-03 (-1.95)	-2.30E-03 (-1.91)
PERC1524	-0.148 (-5.63)	0.084 (3.22)	0.074 (2.85)	0.036 (1.713)	0.13 (4.41)	0.032 (1.33)
PERC2544	-0.184 (-10.61)	0.097 (2.77)	0.081 (2.26)	1.22E-02 (0.51)	0.16 (4.3)	0.031 (1.24)
PERC4564	0.081 (5.48)	0.063 (1.66)	0.022 (0.56)	0.037 (1.6)	0.052 (1.25)	0.011 (0.51)
PERC75P	-0.298 (-11.29)	0.226 (2.29)	0.15 (1.48)	-6.20E-03 (-0.15)	0.31 (2.980)	3.80E-03 (0.090)
INMILES	-2.4E-09 (-1.11)	-3.6E-08 (-1.47)	-3.6E-08 (-1.49)	-2.8E-09 (-0.55)	-3.3E-08 (-1.35)	-4.4E-09 (-0.88)
PRECIP	-3.10E-05 (-0.8)	3.30E-04 (2.210)	2.30E-04 (1.61)	2.10E-04 (2.77)	2.40E-04 (1.48)	1.80E-04 (2.46)
Model Statistic	5					
N	400	400	400	400	350	350
\mathbb{R}^2	0.650	0.916	0.923	0.650	0.926	0.651



Conclusions

The results and the significance of the parameter estimates in particular show ample variation between the different specifications

- ➤ The parameter for percent seat belt use (*seatbelt*) is significant at the 99% level for both the fixed- and random-effects specifications but loses much of this significance when incorporating a two-way fixed-effects model or a correction for serial correlation
 - Indicating that without correction for serial correlation, the standard error of the parameters was downward biased; that is, the models without correction underestimated the standard error
 - Autocorrrelation effects may bias the estimators efficiency, but there is no prove to systematically sustain a bias of the estimates
- > On the other hand, the parameters for the hospitals per square miles (HOSPAREA) variable are significant for both random-effects specifications but are not significant for any of the fixed-effects formulations
 - This fact may indicate that the hospitals density is clearly linked to state characteristics and occupation densities, which are intrinsic to the state panel that was calibrated (μ_i)













Conclusions

This brings up the interesting and at times highly debated issue of model selection As previously discussed, when inferences are confined to the effects in the model, the effects are more appropriately considered to be fixed

When inferences are made about a population of effects from which those in the data are considered to be a random sample, then the effects should be considered random

In these cases, a fixed-effects model is defended on grounds that inferences are confined to the sample. In favor of selecting the fixed-effects rather than the randomeffects formulation based on the LM Test and the Hausman tests.

```
Random Effects Model: v(i,t) = e(i,t) + u(i)
            Var[e]
Estimates:
                                       205299D-05
            Var[u]
                                       496825D-05
            Corr[v(i,t),v(i,s)] =
                                       707603
Lagrange Multiplier Test vs. Model
( 1 df, prob value = .000000)
(High values of LM favor FEM/REM over CR model.)
Baltagi-Li form of LM Statistic =
                                            291.00
Fixed vs. Random Effects (Hausman)
                                               .00
(12 \text{ df, prob value} = 1.000000)
(High (low) values of H favor FEM
                                     REM).)
            Sum of Squares
                                       358714D-02
                                       511715D+00
            R-squared
```

```
Random Effects Model: v(i,t) = e(i,
Estimates:
            Var[e]
                                      253004D+04
            Var[u]
                                      562055D+04
            Corr[v(i,t),v(i,s)] =
                                      689588
Lagrange Multiplier Test vs. Model
                                          874.75
( 1 df, prob value = .000000)
(High values of LM favor FEM/REM over CR model.)
Baltagi-Li form of LM Statistic =
                                           874.75
Fixed vs. Random Effects (Hausman)
                                             2.89
( 2 df, prob value = .235736)
(High (low) values of H favor FEM (
            Sum of Squares
                                      .186431D+07
                                      808040D+00
            R-squared
```

Panel Data Models: Bibliography







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____(1996), A Handbook of the Theory with Applications, Advanced Studies in Theoretical and Applied Econometrics, Vol. 33, Mátyás, László; Sevestre, Patrick (Eds.), Springer.

Hsiao, C. (2003), Analysis of Panel Data, Second Edition, Cambridge University Press, Cambridge.

Frees, E. (2004), Longitudinal and Panel Data, Analysis and Applications in the Social Sciences, Cambridge University Press, Cambridge.