

Monday 7th Febraury 2005

Analysis of Pigs data

Data: Body weights of 48 pigs at 9 successive follow-up visits.

This is an equally spaced data. It is always a good habit to reshape the data, so we can easily switch form wide to long or long to wide depending on the required analysis. The data is in the wide format; let's reshape it into long format.

```
. set memory 40m
(40960k)
. set matsize 100
```

```
. reshape long week, i(Id) j(time)
(note: j = 1 2 3 4 5 6 7 8 9)
```

Data	wide	->	long
Number of obs.	48	->	432
Number of variables	10	->	3
j variable (9 values)		->	time
xij variables:			
	week1 week2 ... week9	->	week

```
. tsset Id time
      panel variable: Id, 1 to 48
      time variable: time, 1 to 9
```

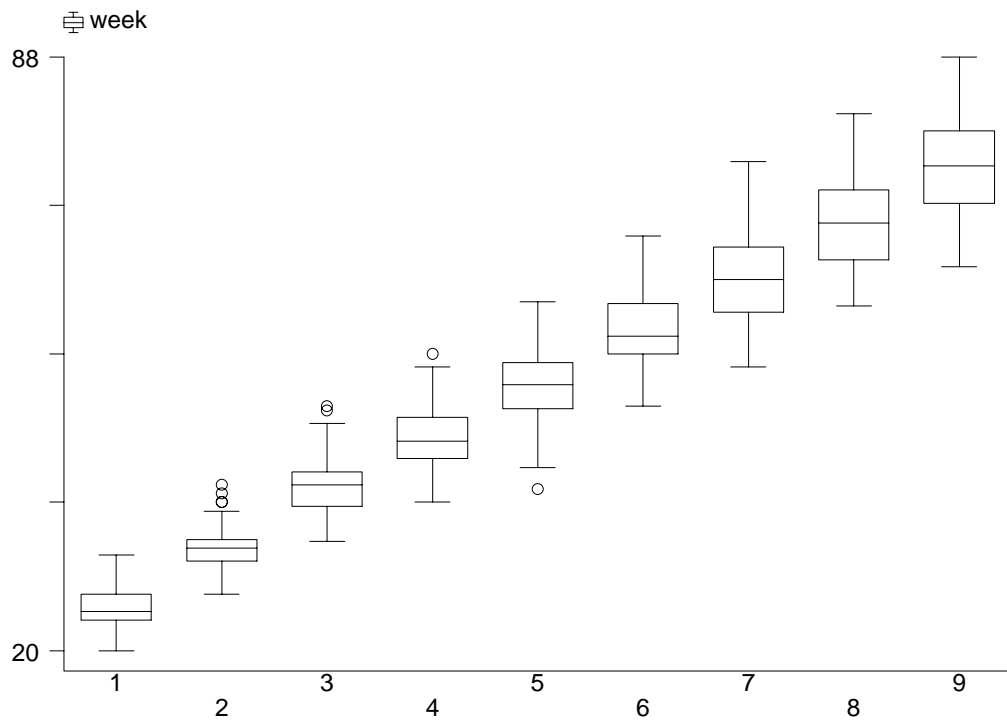
```
. xtides
      Id: 1, 2, ..., 48          n =          48
      time: 1, 2, ..., 9        T =          9
      Delta(time) = 1; (9-1)+1 = 9
      (Id*time uniquely identifies each observation)
```

Distribution of T_i:	min	5%	25%	50%	75%	95%	max
	9	9	9	9	9	9	9

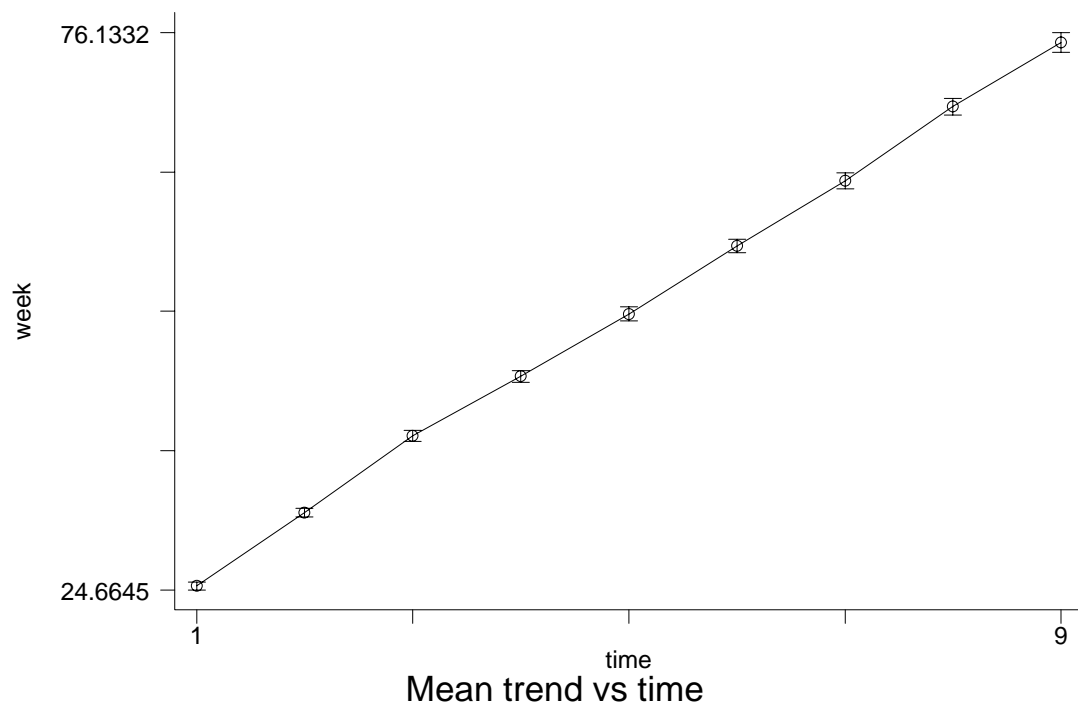
Freq.	Percent	Cum.	Pattern
48	100.00	100.00	111111111
48	100.00		XXXXXXXXXX

Exploratory Data Analysis

```
. sort time  
. graph week, by(time) box  
. ** STATA 8 command : graph box week, by(time) **
```



```
. ** mean trend plot **  
. xtgraph week, ti("Mean trend vs time") bar(se)
```



We can see the mean trend is quite linear across time.

Now we make scatter plots of the data, pair wise scatter plots for data at each two time points. For this we require the data in wide format.

```
. reshape wide week, i(Id) j(time)
```

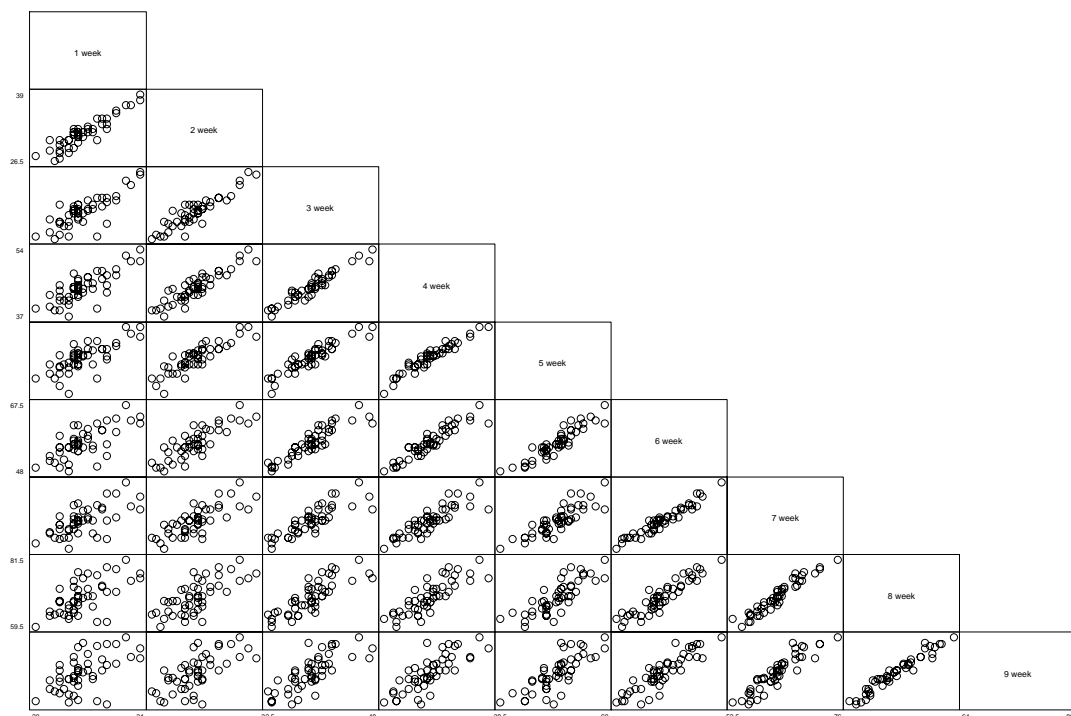
(note: j = 1 2 3 4 5 6 7 8 9)

Data long -> wide

Number of obs. 432 -> 48
Number of variables 3 -> 10
j variable (9 values) time -> (dropped)
xij variables:

week -> week1 week2 ... week9

```
. graph week1 week2 week3 week4 week5 week6 week7 week8 week9, matrix  
half
```

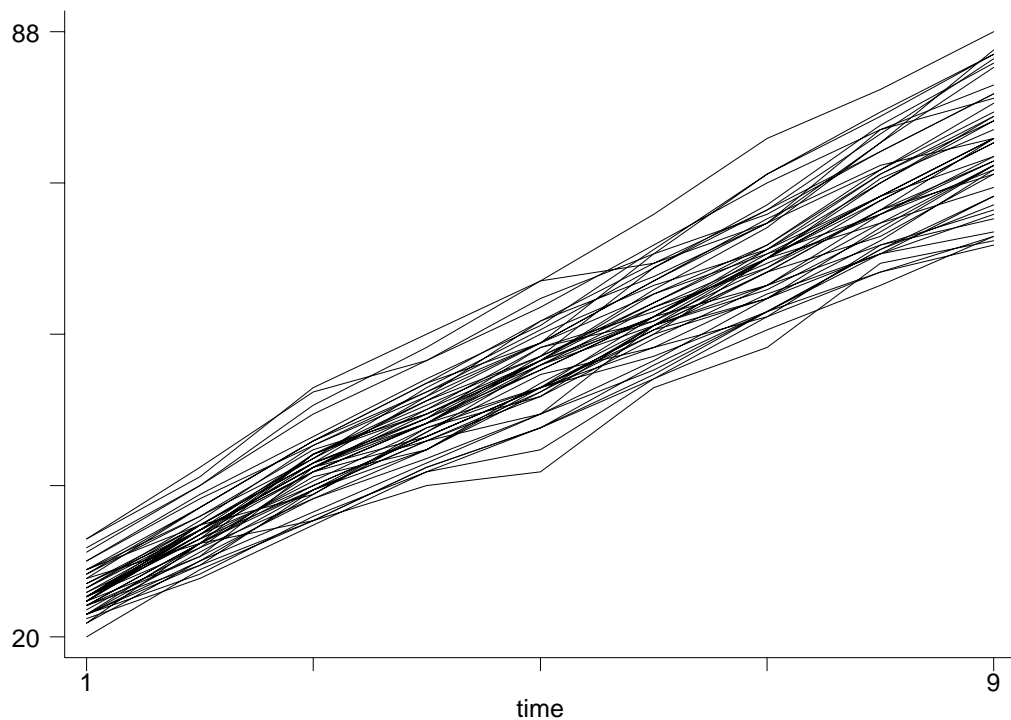


What do you conclude from the above scatter plot matrix?

A relatively constant positive linear trend for all pair wise scatter plots indicates that heavier pigs tend to remain heavier across all time points.

To see if the pigs gained weight over time lets plot the line (spaghetti) plot. For this we need the data in the long form.

```
. sort Id time  
. graph week time, c(L) s(i)  
. ** STATA 8 command : twoway line week time, c(L) s(i) **
```



What do you conclude from the graph?

A linear relationship between outcome and time is showed. Also, not much cross-over of these lines indicates that the relative order of pigs, ordered by their weights, remain unchanged over time, which confirms the conclusion we drew from the scatter matrix plot.

The above figure is enough to explore the growth data. It is hard to pick out individual response profiles. We can add a second display, obtained from first standardizing each observation. This is achieved by, subtracting the mean, and dividing by the standard deviation of the 48 observations at each time (week). For this we would need the data in wide format.

```
. sort time
. by time: sum week
```

```
-> time = 1
  Variable |      Obs      Mean  Std. Dev.      Min      Max
-----+-----
    week |      48   25.02083   2.468866       20       31
--more--
. reshape wide week, i(Id) j(time)

. gen sweek1 = (week1 - 25.02)/2.47
. gen sweek2 = (week2 - 31.78)/2.79
. gen sweek3 = (week3 - 38.86)/3.54
. gen sweek4 = (week4 - 44.39)/3.73
. gen sweek5 = (week5 - 50.16)/4.53
```

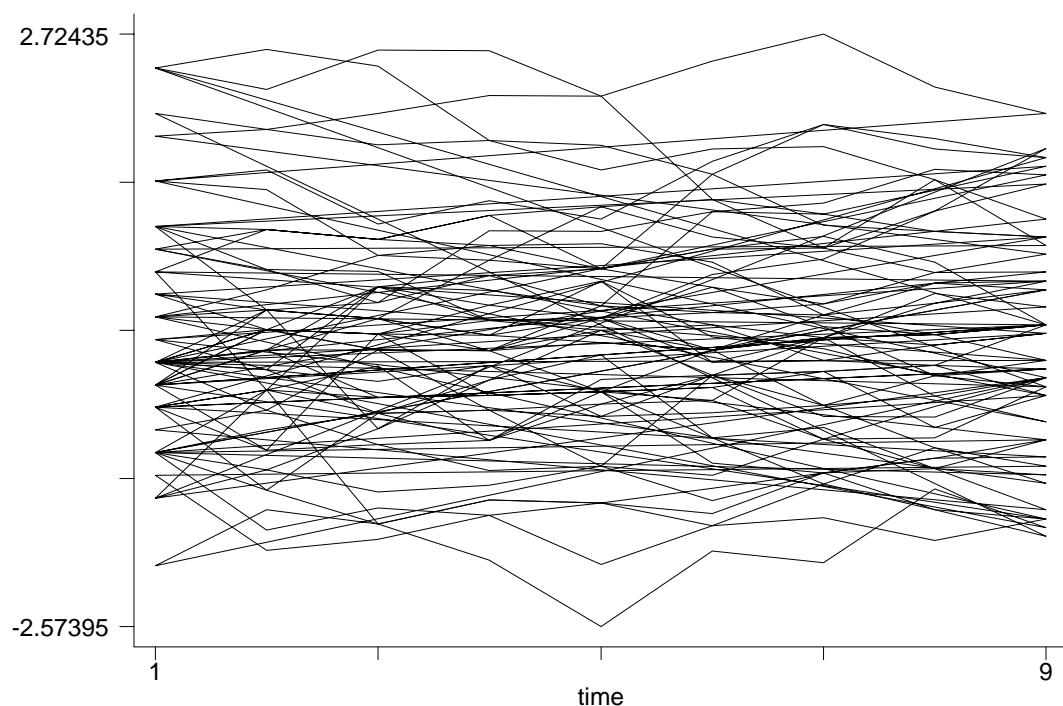
```

. gen sweek6 = (week6 - 56.45)/4.45
. gen sweek7 = (week7 - 62.46)/4.97
. gen sweek8 = (week8 - 69.30)/5.42
. gen sweek9 = (week9 - 75.22)/6.34

. reshape long week sweek, i(Id) j(time)

. sort Id time
. graph sweek time, c(L) s(i)
. ** STATA 8 command : twoway line sweek time, c(L) s(i) **

```



The plot is able to highlight the degree of *tracking*, animals tend to maintain their relative size over time.

Exploring the correlation structure

Auto-correlation function. For this we require the data in long format.

```

. autocor week time Id

```

Table 1

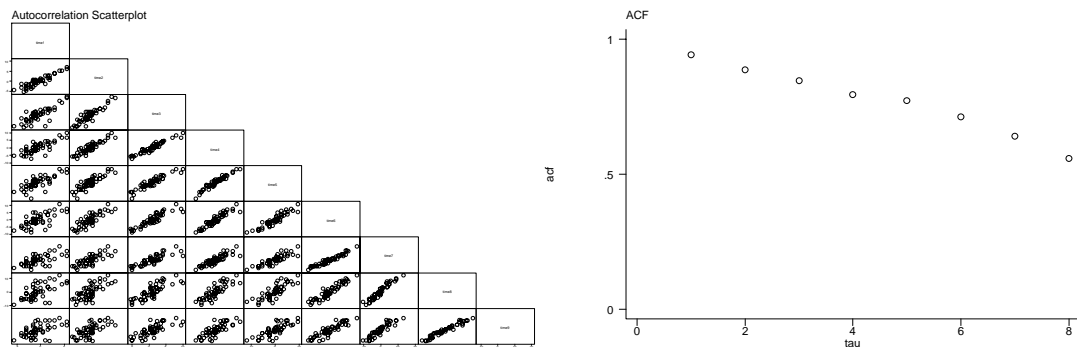
	time1	time2	time3	time4	time5	time6	time7	time8	time9
time1	1.0000								
time2	0.9156	1.0000							
time3	0.8015	0.9118	1.0000						
time4	0.7958	0.9084	0.9582	1.0000					
time5	0.7494	0.8809	0.9280	0.9621	1.0000				
time6	0.7051	0.8353	0.9058	0.9327	0.9219	1.0000			
time7	0.6551	0.7759	0.8435	0.8681	0.8546	0.9633	1.0000		
time8	0.6255	0.7133	0.8167	0.8293	0.8104	0.9280	0.9586	1.0000	
time9	0.5581	0.6638	0.7689	0.7856	0.7856	0.8893	0.9170	0.9695	1.0000

	time1	time2	time3	time4	time5	time6	time7	time8	time9
time1	1.0000								
time2	0.9156	1.0000							
time3	0.8015	0.9118	1.0000						
time4	0.7958	0.9084	0.9582	1.0000					
time5	0.7494	0.8809	0.9280	0.9621	1.0000				
time6	0.7051	0.8353	0.9058	0.9327	0.9219	1.0000			
time7	0.6551	0.7759	0.8435	0.8681	0.8546	0.9633	1.0000		
time8	0.6255	0.7133	0.8167	0.8293	0.8104	0.9280	0.9586	1.0000	
time9	0.5581	0.6638	0.7689	0.7856	0.7856	0.8893	0.9170	0.9695	1.0000

Table 2

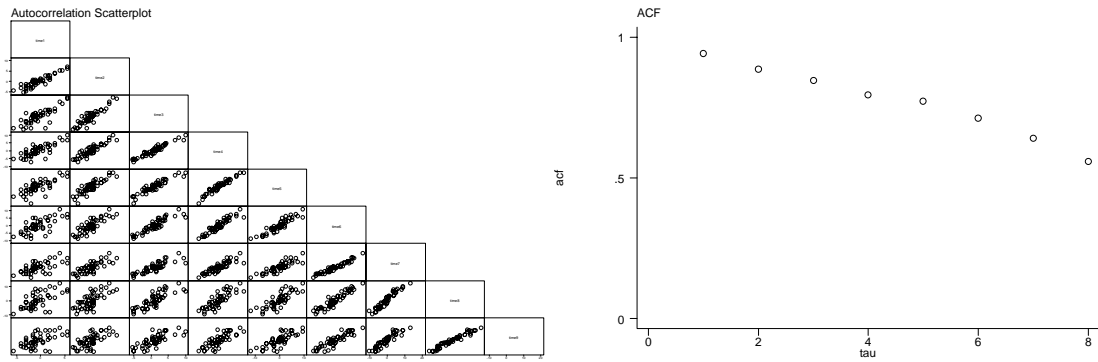
acf

```
1. .9425781
2. .8870165
3. .8462396
4. .7962576
5. .7724156
6. .7121489
7. .6407955
8. .5581002
```



What is the correlation structure taking away the covariate's effect?

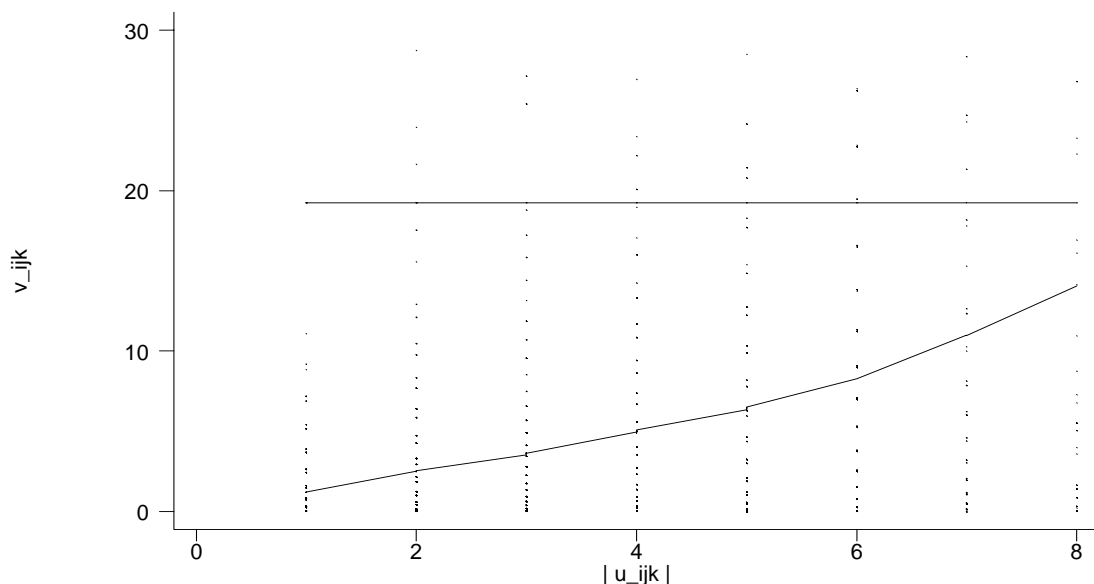
- . regress week time
- . predict weekrs, resid
- . autocor weekrs time Id



Notice from the main diagonal of the scatter plot matrix there is positive correlation between repeated observations on the same animal that are 1 week apart. The degree of correlation decreases as the observations are moved farther from the diagonals. Also the correlation is reasonably consistent along the diagonal in the matrix. This indicates that the correlation depends on the time between observations than their absolute times. The estimated correlation matrix for this data is given in table 1. The correlations show some tendency of decrease with increasing time lag. Assuming stationarity, a single correlation estimate can be obtained for each distinct value of the time separation or lag, $|t_{ij} - t_{ik}|$. This corresponds to pulling observation pairs along the diagonals of the scatter plot matrix. The autocorrelation function takes the value as in table 2.

```
. variogram weekrs
```

Variogram of weekrs (3 percent of v_{ijk} 's excluded)



We can conclude 4 things from this graph:

1. The variogram starts at 0, that means, there is no measurement error.
2. It doesn't reach the total at the end, that means, we need to model a random intercept for the correlation.
3. We observe an ascending line, that means, there is series correlation in the data, the correlation between measurements from the same pig gets smaller when the time interval becomes larger.
4. No need to model random slope, since we don't observe multiple lines.

Before we proceed with the analysis, let's look at some theory.

$y_{ij}, j = 1, 2, \dots, n$ be the sequence of observed measurements on the i th of the m subjects and $t_j, j = 1, 2, \dots, n$ be the corresponding times at which the measurements are taken on each unit. Associated with each y_{ij} are the values, $x_{ijk}, k = 1, 2, \dots, p$ of p explanatory variables. We assume that y_{ij} are realizations of random variables Y_{ij} which follow the regression model

$$Y_{ij} = \beta_1 x_{ij1} + \dots + \beta_p x_{ijp} + \varepsilon_{ij},$$

In the classical linear model we assume the errors to be mutually independent normal random variables. In our context, the longitudinal structure of the data means that we expect the errors to be correlated within subjects.

Let $\mathbf{y}_i = (y_{i1}, y_{i2}, \dots, y_{in})$ be the observed sequence of measurements on the i th subject and $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_m)$ be the complete set of $N = nm$ observations. Let \mathbf{X} be the matrix of explanatory variables.

$$\mathbf{Y} \sim MVN(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{V})$$

The Uniform Correlation Model

In this model we assume that there is positive correlation between any two measurements.

The Exponential Correlation Model

The correlation between a pair of measurements on the same unit decays towards zero as the time separation between measurements increases.

The exponential correlation model is sometimes called the *first order autoregressive model*.

For the data on pigs we fit a couple of models. We require the data in long format.

1. Ordinary least squares ignoring correlation

```
. regress week time
```

Source	SS	df	MS	Number of obs = 432		
-----+-----				F(1, 430) = 5757.41		
Model	111060.882	1	111060.882	Prob > F = 0.0000		
Residual	8294.72677	430	19.2900622	R-squared = 0.9305		
-----+-----				Adj R-squared = 0.9303		
Total	119355.609	431	276.927167	Root MSE = 4.392		
-----+-----						
week	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
time	6.209896	.0818409	75.88	0.000	6.049038	6.370754
_cons	19.35561	.4605447	42.03	0.000	18.45041	20.26081

2. Independent correlation model

```
. xtgee week time, i(Id) corr(ind)
```

Iteration 1: tolerance = 2.217e-15

GEE population-averaged model		Number of obs	=	432
Group variable:	Id	Number of groups	=	48
Link:	identity	Obs per group: min	=	9
Family:	Gaussian	avg	=	9.0
Correlation:	independent	max	=	9
		Wald chi2(1)	=	5784.19
Scale parameter:	19.20076	Prob > chi2	=	0.0000
Pearson chi2(432):	8294.73	Deviance	=	8294.73
Dispersion (Pearson):	19.20076	Dispersion	=	19.20076

week	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
time	6.209896	.0816513	76.05	0.000	6.049862	6.369929
_cons	19.35561	.4594773	42.13	0.000	18.45505	20.25617
-----+-----						

```
. xtcorr
```

Estimated within-Id correlation matrix R:

	c1	c2	c3	c4	c5	c6	c7	c8	c9
r1	1.0000								
r2	0.0000	1.0000							
r3	0.0000	0.0000	1.0000						
r4	0.0000	0.0000	0.0000	1.0000					

```

r5 0.0000 0.0000 0.0000 0.0000 1.0000
r6 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000
r7 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000
r8 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000
r9 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000

```

```
. xtgls week time, i(Id) corr(ind)
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: homoscedastic

Correlation: no autocorrelation

```

Estimated covariances      =      1      Number of obs      =      432
Estimated autocorrelations =      0      Number of groups   =      48
Estimated coefficients      =      2      No. of time periods=      9
                                   Wald chi2(1)      =    5784.19
Log likelihood              = -1251.251      Prob > chi2        =      0.0000

```

```

-----
      week |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      time |   6.209896   .0816513    76.05  0.000     6.049862    6.369929
      _cons |  19.35561   .4594773    42.13  0.000    18.45505    20.25617
-----

```

3. Uniform correlation model

```
. xtgee week time, i(Id) corr(exc)
```

Iteration 1: tolerance = 5.934e-15

```

GEE population-averaged model      Number of obs      =      432
Group variable:                     Id      Number of groups   =      48
Link:                               identity  Obs per group: min =      9
Family:                             Gaussian      avg =      9.0
Correlation:                        exchangeable      max =      9
                                   Wald chi2(1)      =    25337.48
Scale parameter:                    19.20076      Prob > chi2        =      0.0000

```

```

-----
      week |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      time |   6.209896   .0390124   159.18  0.000     6.133433    6.286359
      _cons |  19.35561   .5974055    32.40  0.000    18.18472    20.52651
-----

```

```
. xtcorr
```

Estimated within-Id correlation matrix R:

	c1	c2	c3	c4	c5	c6	c7	c8	c9
r1	1.0000								
r2	0.7717	1.0000							
r3	0.7717	0.7717	1.0000						
r4	0.7717	0.7717	0.7717	1.0000					
r5	0.7717	0.7717	0.7717	0.7717	1.0000				
r6	0.7717	0.7717	0.7717	0.7717	0.7717	1.0000			
r7	0.7717	0.7717	0.7717	0.7717	0.7717	0.7717	1.0000		
r8	0.7717	0.7717	0.7717	0.7717	0.7717	0.7717	0.7717	1.0000	
r9	0.7717	0.7717	0.7717	0.7717	0.7717	0.7717	0.7717	0.7717	1.0000

```
. xtreg week time, i(Id) pa (equivalent to the previous one)
```

Iteration 1: tolerance = 6.283e-15

GEE population-averaged model

Number of obs	=	432
Group variable: Id	Number of groups	= 48
Link: identity	Obs per group: min	= 9
Family: Gaussian	avg	= 9.0
Correlation: exchangeable	max	= 9
	Wald chi2(1)	= 25337.48
Scale parameter: 19.20076	Prob > chi2	= 0.0000

```
-----
```

week	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
time	6.209896	.0390124	159.18	0.000	6.133433 6.286359
_cons	19.35561	.5974055	32.40	0.000	18.18472 20.52651

```
-----
```

5. Random effect model with random intercept

```
. xtreg week time, re i(Id)
```

Random-effects GLS regression

Number of obs	=	432
Group variable (i) : Id	Number of groups	= 48
R-sq: within = 0.9851	Obs per group: min	= 9
between = 0.0000	avg	= 9.0
overall = 0.9305	max	= 9
Random effects u_i ~ Gaussian	Wald chi2(1)	= 25271.50
corr(u_i, X) = 0 (assumed)	Prob > chi2	= 0.0000

```
-----
```

week	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
time	6.209896	.0390633	158.97	0.000	6.133333 6.286458
_cons	19.35561	.603139	32.09	0.000	18.17348 20.53774

```
-----
```

```

-----+-----
sigma_u | 3.8912528
sigma_e | 2.0963561
rho | .77505203 (fraction of variance due to u_i)
-----

. xtreg week time, i(Id) mle

Fitting constant-only model:
Iteration 0: log likelihood = -13399.842
Iteration 1: log likelihood = -8045.1554
Iteration 2: log likelihood = -5080.5329
Iteration 3: log likelihood = -3459.5929
Iteration 4: log likelihood = -2593.189
Iteration 5: log likelihood = -2148.9623
Iteration 6: log likelihood = -1938.3661
Iteration 7: log likelihood = -1853.2441
Iteration 8: log likelihood = -1830.3843
Iteration 9: log likelihood = -1827.3012
Iteration 10: log likelihood = -1827.212
Iteration 11: log likelihood = -1827.2118

Fitting full model:
Iteration 0: log likelihood = -1014.9757
Iteration 1: log likelihood = -1014.9268
Iteration 2: log likelihood = -1014.9268

Random-effects ML regression
Group variable (i) : Id

Number of obs      =      432
Number of groups   =      48

Random effects u_i ~ Gaussian
Obs per group: min =      9
               avg  =     9.0
               max  =      9

LR chi2(1)          =    1624.57
Prob > chi2         =     0.0000
Log likelihood = -1014.9268
-----+-----
week |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
time | 6.209896   .0390124   159.18  0.000    6.133433    6.286359
_cons | 19.35561   .5974055   32.40  0.000   18.18472   20.52651
-----+-----
/sigma_u | 3.84935   .4058114    9.49  0.000    3.053974    4.644725
/sigma_e | 2.093625   .0755471   27.71  0.000    1.945555    2.241694
-----+-----
rho | .771714   .0393959                .6876303    .8413114
-----

```

Likelihood ratio test of sigma_u=0: chibar2(01)= 472.65 Prob>=chibar2 = 0.000

6. Exponential correlation model

```
. xtglm week time, igls corr(ar1) i(Id) force
```

Iteration 1: tolerance = 0

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: homoscedastic

Correlation: common AR(1) coefficient for all panels (0.9161)

Estimated covariances	=	1	Number of obs	=	432
Estimated autocorrelations	=	1	Number of groups	=	48
Estimated coefficients	=	2	No. of time periods	=	9
			Wald chi2(1)	=	7867.89
Log likelihood	=	-806.5921	Prob > chi2	=	0.0000

week	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
time	6.272057	.07071	88.70	0.000	6.133467 6.410646
_cons	18.84279	.6001148	31.40	0.000	17.66658 20.01899

```
. xtgee week time, i(Id) corr(ar1) t(time)
```

Iteration 1: tolerance = .02513276

Iteration 2: tolerance = .00009237

Iteration 3: tolerance = 4.366e-07

GEE population-averaged model		Number of obs	=	432
Group and time vars:	Id time	Number of groups	=	48
Link:	identity	Obs per group: min	=	9
Family:	Gaussian	avg	=	9.0
Correlation:	AR(1)	max	=	9
		Wald chi2(1)	=	6254.91
Scale parameter:	19.26754	Prob > chi2	=	0.0000

week	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
time	6.272089	.0793052	79.09	0.000	6.116654 6.427524
_cons	18.84218	.6745715	27.93	0.000	17.52004 20.16431