

Longitudinal Data Analysis

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Panel Data Analysis: Fixed Effects Models

Panel data are longitudinal data where multiple cases (N cases) are observed over T time periods (two or more), resulting in $N \times T$ observations. The name “panel data” is based on survey panels that typically have many respondents that are observed for only a few time periods. Sometimes people reserve the term “panel data” for those cases where N is relatively large and T is relatively small (say, 5 or less). Also, if N is very large relative to T , people say that the dataset is “cross-sectionally dominated.” In contrast, if you have very long sequences of data over time, but very few cases, people refer to such data as “time series cross section data.” Still, similar techniques can be used to analyze these data, although researchers should pay closer attention to time processes.

There are two kinds of information in such data, regardless of the type: the cross-sectional information reflected in the differences between subjects, and the time-series or within-subject information reflected in the changes within subjects over time. Panel data regression techniques allow us to take advantage of these different types of information.

You should differentiate panel data from the data where multiple independent cross-sections (e.g., different samples at each time point) are combined into a single dataset. There are a few reasons why we might want to combine cross-sections over time. We may be interested in changes over time and such data may be the only ones available. Or we may be simply interested in increasing sample size available for analysis. In any case, using independently pooled cross-sections raises only minor statistical complications. Typically, to reflect the fact that the population distribution may differ over time, we use year dummy variables in the models. This model assumes that the effect of each independent variable remains constant over time. This may or may not be true, and we can test that. If you suspect that effects of some variables change over time, these variables can be interacted with year dummies.

We will focus on data generated by longitudinal study designs – multiple observations on the same unit. Although it may seem that such data are too much hassle, they offer very important advantages, as we can:

1. Assess changes over time
2. Test causal arguments
3. Increase sample size
4. Control for some types of omitted variables even without observing them, by observing changes in the dependent variable over time. This controls for omitted variables that differ among cases but are constant over time. It is also possible to use panel data to control for omitted variables that vary over time but are constant across cases.

There is also a special command to investigate transitions:

```
. xttrans v114
```

type of regime	type of regime				Total
	1	2	3	4	
1	98.28	1.16	0.53	0.03	100.00
2	16.15	83.12	0.55	0.18	100.00
3	20.00	18.10	61.90	0.00	100.00
4	6.42	0.92	0.00	92.66	100.00
Total	90.87	6.62	1.28	1.22	100.00

```
. xttrans v114, freq
```

type of regime	type of regime				Total
	1	2	3	4	
1	7,610 98.28	90 1.16	41 0.53	2 0.03	7,743 100.00
2	88 16.15	453 83.12	3 0.55	1 0.18	545 100.00
3	21 20.00	19 18.10	65 61.90	0 0.00	105 100.00
4	7 6.42	1 0.92	0 0.00	101 92.66	109 100.00
Total	7,726 90.87	563 6.62	109 1.28	104 1.22	8,502 100.00

For our examples, we'll focus on predicting the size of the military:

```
. des v41 v76 v5 v7 v19
```

variable name	storage type	display format	value label	variable label
v41	int	%8.0g		size of military
v76	int	%8.0g		pri + sec enr per capita
v5	int	%8.0g		population density
v7	int	%8.0g		urb 100,000+ per capita
v19	long	%12.0g		revenue per capita

```
. sum v41 v76 v5 v7 v19
```

Variable	Obs	Mean	Std. Dev.	Min	Max
v41	6280	156.2275	388.234	0	4500
v76	6021	1092.985	648.7898	0	3444
v5	8816	1196.446	1501.329	5	13020
v7	7811	97.85418	110.9803	0	671
v19	6334	6089.75	14940.87	7	301233

```
. xtsum v41 v76 v5 v7 v19
```

Variable		Mean	Std. Dev.	Min	Max	Observations
v41	overall	156.2275	388.234	0	4500	N = 6280
	between		197.6826	0	1301.811	n = 136
	within		279.3011	-885.5833	3354.417	T-bar = 46.1765
v76	overall	1092.985	648.7898	0	3444	N = 6021
	between		672.4557	92.55556	3222	n = 146
	within		397.2686	-118.4437	2827.602	T-bar = 41.2397
v5	overall	1196.446	1501.329	5	13020	N = 8816
	between		1772.606	14.51064	12580	n = 158
	within		599.8466	-1616.034	7056.602	T-bar = 55.7975
v7	overall	97.85418	110.9803	0	671	N = 7811
	between		100.4004	0	662.6667	n = 152
	within		71.53064	-204.003	511.7564	T-bar = 51.3882
v19	overall	6089.75	14940.87	7	301233	N = 6334
	between		17454.64	35	157729.2	n = 153
	within		11396.27	-95325.42	149593.6	T-bar = 41.3987

While it is possible to use ordinary multiple regression techniques on panel data, they are usually not appropriate because of non-independence of observations, heteroskedasticity (both across time and across units) and autocorrelation. For comparison purposes, however, let's use OLS to estimate our model:

```
. reg v41 v76 v5 v7 v19
```

Source	SS	df	MS	Number of obs =	4945
Model	77569027.8	4	19392257	F(4, 4940) =	142.19
Residual	673742407	4940	136385.103	Prob > F =	0.0000
Total	751311435	4944	151964.287	R-squared =	0.1032
				Adj R-squared =	0.1025
				Root MSE =	369.3

v41	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
v76	.0107072	.0107961	0.99	0.321	-.0104579 .0318723
v5	.0038175	.0032207	1.19	0.236	-.0024966 .0101315
v7	.2710273	.0597177	4.54	0.000	.1539542 .3881005
v19	.0073414	.0004123	17.81	0.000	.006533 .0081497
_cons	44.82276	11.10465	4.04	0.000	23.05272 66.5928

```
. reg v41 v76 v5 v7 v19, cluster(v1)
```

Linear regression

Number of clusters (v1) =	124	Number of obs =	4945
		F(4, 123) =	4.08
		Prob > F =	0.0039
		R-squared =	0.1032
		Root MSE =	369.3

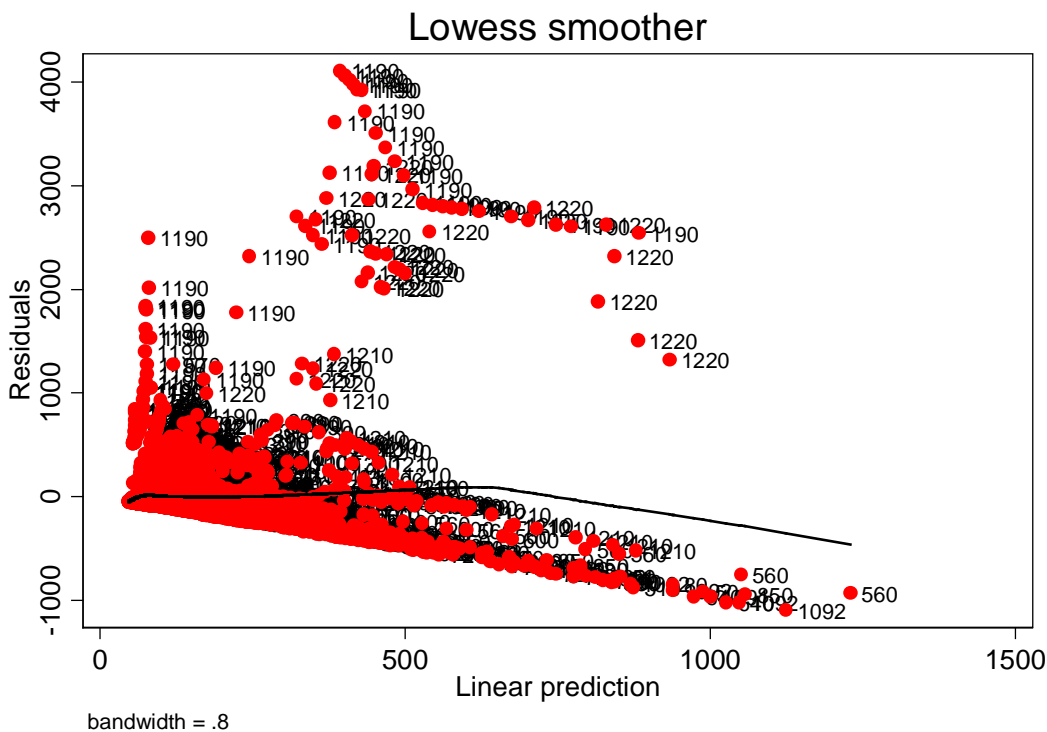
v41	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
v76	.0107072	.0478825	0.22	0.823	-.0840734 .1054878
v5	.0038175	.0243906	0.16	0.876	-.0444623 .0520972
v7	.2710273	.2574062	1.05	0.294	-.2384924 .7805471
v19	.0073414	.0051641	1.42	0.158	-.0028806 .0175634
_cons	44.82276	56.24492	0.80	0.427	-66.51061 156.1561

Here, the model we estimated remains unchanged, but the standard errors are adjusted to reflect the fact that, effectively, we have much fewer independent cases than the N=4945. Note that the resulting standard errors are much larger. But an even bigger problem of using OLS is that we are still assuming that error term variances are equal across countries. But even a simple residuals vs predicted values graph shows us that this is not true:

```
. predict resid, res
(4032 missing values generated)

. predict fitted, xb
(3685 missing values generated)

. lowess resid fitted, mlabel(v1) mcolor(red)
```



To avoid the problems of heteroscedasticity across units, we estimate a model that allows for each country to have its own intercept – a fixed effects model:

```
. xtreg v41 v76 v5 v7 v19, fe
Fixed-effects (within) regression      Number of obs   =   4945
Group variable (i): v1                Number of groups =   124

R-sq:  within = 0.1806                Obs per group:  min =    1
      between = 0.0051                    avg   =   39.9
      overall  = 0.0600                    max   =   148

corr(u_i, Xb) = -0.2548                F(4, 4817)      =   265.43
                                          Prob > F         =    0.0000
-----+-----
```

v41	Coef.	Std. Err.	t	P> t	[95% Conf. Inteval]
v76	.0445623	.011977	3.72	0.000	.021082 .0680426

```

      v5 | -.0637468   .007078   -9.01   0.000   -.0776229   -.0498708
      v7 |  .5901123   .0757072    7.79   0.000   .4416916   .7385331
      v19 | .0080274   .0003284   24.44   0.000   .0073836   .0086712
      _cons | 51.30225  11.77021    4.36   0.000   28.22727   74.37723
-----+-----
      sigma_u | 278.56116
      sigma_e | 242.31081
      rho | .56926004   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(123, 4817) =      54.13      Prob > F = 0.0000

```

Although the individual country intercepts are not presented in the output, we can verify that we get the same model:

```

. xi: reg v41 v76 v5 v7 v19 i.v1
i.v1          _Iv1_10-1300      (naturally coded; _Iv1_10 omitted)

-----+-----
Source |           SS          df           MS      Number of obs =      4945
-----+-----+-----+-----
Model | 468483540         127      3688846.77      F(127, 4817) =      62.83
Residual | 282827895        4817      58714.5308      Prob > F      =      0.0000
-----+-----+-----+-----
Total | 751311435        4944     151964.287      R-squared     =      0.6236
                                           Adj R-squared =      0.6136
                                           Root MSE     =      242.31

-----+-----
      v41 |           Coef.      Std. Err.      t      P>|t|      [95% Conf. Interval]
-----+-----+-----+-----+-----+-----
      v76 |  .0445623      .011977       3.72   0.000      .021082      .0680426
      v5  | -.0637468      .007078      -9.01   0.000     -.0776229   -.0498708
      v7  |  .5901123      .0757072     7.79   0.000     .4416916   .7385331
      v19 | .0080274      .0003284    24.44   0.000     .0073836   .0086712
      _Iv1_20 | -63.98205     70.12371     -0.91   0.362     -201.4565   73.49244
      _Iv1_30 | -191.1164     96.24602     -1.99   0.047     -379.8026  -2.430294
      _Iv1_40 | -266.1745     65.57011     -4.06   0.000     -394.7219  -137.6272
      _Iv1_50 | -564.9821     72.4991      -7.79   0.000     -707.1135  -422.8508
      _Iv1_51 | (dropped)
      _Iv1_60 | 245.8339      67.40873      3.65   0.000     113.6821   377.9858
[Output omitted]
      _Iv1_1300 | -269.6325     96.63103     -2.79   0.005     -459.0734  -80.19153
      _cons | 75.37176      57.26024      1.32   0.188     -36.88446   187.628
-----+-----

```

These country-specific intercepts can also be viewed as part of the decomposed residuals: $Y_{it} = \alpha + X_{it}\beta + u_i + e_{it}$ where u_i is the effect of country i and e_{it} is the residual effect for time point t within that country. In a fixed effects model, each of country residuals u_i is assigned a specific value – it’s a fixed intercept for each country. Because country intercepts are essentially separate independent variables in a fixed effects models, these intercepts are allowed to be correlated with the independent variables in the model –e.g., in our output we have

```
corr(u_i, Xb) = -0.2548
```

What this means is that we do not use our independent variables to explain country-specific effects – they are just set aside and we focus on explaining change over time. One big advantage of doing this is that we eliminate all country-specific effects, including those that we could not explicitly model with the variables at hand (omitted variables), so we can focus explicitly on change over time. A disadvantage, however, is that the data on cross-sectional variation are available but not used in estimating independent variables’ effects.

As a preliminary step to estimating a fixed effects model, it is usually helpful to estimate a fully unconditional model:

```
. xtreg v41, fe
Fixed-effects (within) regression           Number of obs   =       6280
Group variable (i): v1                    Number of groups =       136

R-sq:  within = 0.0000                    Obs per group:  min =         1
        between = 0.0019                  avg =       46.2
        overall = 0.0000                  max =       148

corr(u_i, Xb) = -0.0000                    F(0,6144)       =       0.00
                                                Prob > F        =       .

-----+-----
      v41 |          Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      _cons |    156.2275    3.562973    43.85  0.000    149.2429    163.2122
-----+-----
      sigma_u |    197.68264
      sigma_e |    282.35297
      rho    |    .32893849   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(135, 6144) =    42.42      Prob > F = 0.0000
```

Its most important function is to provide information about outcome variability at each of the two levels. `sigma_e` will provide information about level-1 (across time) variability, and `sigma_u` will provide information on level-2 (across country) variability. So running this model allows us to decompose the variance in the dependent variable into variance components -- into within-group and between-group variance (although they are expressed as standard deviations -- to get variances, we'd have to square them). This model does not explain anything, but it allows us to evaluate whether there is variation in group means (here, country means), and how much of it. That's why it is always a good idea to run this basic model when starting the analyses -- it's the null model of our regression analysis. If we find that there is no significant variation across countries, then there is no need for a fixed effects model. That significance test is the F test below the model.

The proportion of variance due to group-level variation in means can be calculated as

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}$$

It can be interpreted as the proportion of variance explained by the unit effects. It can also be interpreted as the average correlation between two randomly chosen time points that are in the same unit; therefore, it is also known as intra-class correlation. Here, we get:

```
. di 197.68264^2 / (197.68264^2 + 282.35297^2)
.32893848
```

which is the rho number in the table. So 33% of the total variance in military size is due to country-specific effects.

Predict command after `xtreg, fe` allows us to get predicted values and residuals. It allows the following options:

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

So to obtain two sets of residuals, level 1 (e) and level 2 (u), we run:

```
. qui xtreg v41 v76 v5 v7 v19, fe

. predict level1, e
(4032 missing values generated)

. predict level2, u
(4032 missing values generated)
```

We can use these residuals to conduct regression diagnostics. Moreover, we can apply all the OLS diagnostic tools to the model with many dummies we estimated earlier (for more details on OLS diagnostics, see SC704 class notes at <http://www.sarkisian.net/sc704>). Alternatively, Stata also has a convenient feature that makes it easier to search for the best model specification; xtdata command allows you to generate a dataset that will produce fixed effects models with regular regress commands. This will also enable you to use OLS diagnostics tools.

```
. use "C:\Documents and Settings\SARKISIN\My Documents\Teaching Grad
Statistics\SC706\sc706\crossnatfull.dta", clear

. xtdata v2 v41 v76 v5 v7 v19, fe clear

. reg v41 v5 v7 v19 v76
```

Source	SS	df	MS			
Model	62338344.4	4	15584586.1	Number of obs =	4945	
Residual	282827895	4940	57252.6103	F(4, 4940) =	272.21	
Total	345166239	4944	69815.1778	Prob > F =	0.0000	
				R-squared =	0.1806	
				Adj R-squared =	0.1799	
				Root MSE =	239.28	

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
v41						
v76	.0445623	.0118269	3.77	0.000	.0213763	.0677483
v5	-.0637468	.0069893	-9.12	0.000	-.077449	-.0500447
v7	.5901123	.0747588	7.89	0.000	.4435519	.7366727
v19	.0080274	.0003243	24.75	0.000	.0073917	.0086632
_cons	51.30225	11.62275	4.41	0.000	28.51649	74.08801

Thus, you can search for model specification using this dataset, and then estimate the final model you select using your original dataset. (You cannot use the model from the modified dataset because significance tests will be incorrect as the degrees of freedom do not take into account the implicit presence of country dummies.)

In addition to the one-way fixed effects model that we just estimated, we could also consider estimating a two-way fixed-effects model. It is a good idea in most cases to include time into the model when estimating a fixed-effects model. Unfortunately, Stata does not automatically estimated two-way FE models – we have to introduce year dummies:

```
. xi: xtreg v41 v76 v5 v7 v19 i.v2, fe
i.v2          _Iv2_1815-1973      (naturally coded; _Iv2_1815 omitted)
Fixed-effects (within) regression              Number of obs   =   4945
Group variable (i): v1                        Number of groups =   124
R-sq:  within = 0.2297                          Obs per group:  min =    1
          between = 0.0033                          avg   =   39.9
          overall = 0.0816                          max   =   148
                                                F(151,4670)    =    9.22
corr(u_i, Xb) = -0.3136                          Prob > F       =    0.0000
```

v41	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

v76	.1150898	.0146829	7.84	0.000	.0863044	.1438753
v5	-.0575626	.0076677	-7.51	0.000	-.0725949	-.0425303
v7	.6014044	.0910177	6.61	0.000	.4229667	.779842
v19	.0105129	.0004057	25.91	0.000	.0097176	.0113082
_Iv2_1816	-4.611157	337.4329	-0.01	0.989	-666.139	656.9166
_Iv2_1817	-8.376042	337.433	-0.02	0.980	-669.904	653.152
_Iv2_1818	-13.15861	337.4332	-0.04	0.969	-674.6869	648.3697
_Iv2_1819	-13.14016	337.4332	-0.04	0.969	-674.6686	648.3883
_Iv2_1820	-15.4067	337.4335	-0.05	0.964	-676.9356	646.1222
_Iv2_1821	-19.04943	337.4337	-0.06	0.955	-680.5788	642.48
_Iv2_1822	-22.15934	337.434	-0.07	0.948	-683.6893	639.3707
_Iv2_1823	-25.60122	337.4344	-0.08	0.940	-687.1319	635.9295
_Iv2_1824	-27.20152	337.4348	-0.08	0.936	-688.733	634.33
_Iv2_1825	-30.20079	337.4352	-0.09	0.929	-691.7331	631.3315
_Iv2_1826	-33.83856	337.4357	-0.10	0.920	-695.3717	627.6946
_Iv2_1827	-35.70116	337.4362	-0.11	0.916	-697.2353	625.833
_Iv2_1828	-39.34672	337.4367	-0.12	0.907	-700.882	622.1886
_Iv2_1829	-42.06872	337.4373	-0.12	0.901	-703.6052	619.4678
_Iv2_1830	-44.2462	337.4375	-0.13	0.896	-705.7829	617.2905
_Iv2_1831	-45.12801	337.4377	-0.13	0.894	-706.6651	616.4091
_Iv2_1832	-42.19088	337.4374	-0.13	0.901	-703.7274	619.3457
_Iv2_1833	-68.38697	337.4659	-0.20	0.839	-729.9794	593.2054
_Iv2_1834	-72.5051	337.4749	-0.21	0.830	-734.1152	589.105
_Iv2_1835	-76.84239	337.4851	-0.23	0.820	-738.4724	584.7877
_Iv2_1836	-80.56155	337.496	-0.24	0.811	-742.213	581.0899
_Iv2_1837	-85.53126	337.5081	-0.25	0.800	-747.2065	576.144
_Iv2_1838	-87.45174	337.514	-0.26	0.796	-749.1385	574.235
_Iv2_1839	-89.98519	337.5199	-0.27	0.790	-751.6834	571.7131
_Iv2_1840	-91.83314	337.526	-0.27	0.786	-753.5434	569.8771
_Iv2_1841	-89.39411	337.5341	-0.26	0.791	-751.1204	572.3321
_Iv2_1842	-84.88844	337.5422	-0.25	0.801	-746.6304	576.8536
_Iv2_1843	-81.4473	337.5503	-0.24	0.809	-743.2052	580.3106
_Iv2_1844	-74.86112	337.5515	-0.22	0.824	-736.6214	586.8991
_Iv2_1845	-67.75075	337.5523	-0.20	0.841	-729.5126	594.0111
_Iv2_1846	-61.21163	337.5535	-0.18	0.856	-722.9758	600.5526
_Iv2_1847	-64.73685	337.5865	-0.19	0.848	-726.5657	597.092
_Iv2_1848	-58.4546	337.5786	-0.17	0.863	-720.268	603.3588
_Iv2_1849	-77.81048	294.6038	-0.26	0.792	-655.373	499.7521
_Iv2_1850	-74.84566	294.601	-0.25	0.799	-652.4028	502.7114
_Iv2_1851	-64.33836	294.6082	-0.22	0.827	-641.9095	513.2328
_Iv2_1852	-55.07556	294.6158	-0.19	0.852	-632.6616	522.5104
_Iv2_1853	-44.06957	294.6182	-0.15	0.881	-621.6604	533.5212
_Iv2_1854	-34.29104	294.6213	-0.12	0.907	-611.8878	543.3057
_Iv2_1855	-27.14247	294.6278	-0.09	0.927	-604.7521	550.4672
_Iv2_1856	-14.76211	294.633	-0.05	0.960	-592.3819	562.8577
_Iv2_1857	-3.908854	294.6396	-0.01	0.989	-581.5416	573.7239
_Iv2_1858	5.995196	294.647	0.02	0.984	-571.652	583.6424
_Iv2_1859	15.59062	294.6527	0.05	0.958	-562.0677	593.2489
_Iv2_1860	-119.469	268.0348	-0.45	0.656	-644.9437	406.0057
_Iv2_1861	-115.7792	268.0387	-0.43	0.666	-641.2617	409.7032
_Iv2_1862	-73.90396	262.6063	-0.28	0.778	-588.7362	440.9283
_Iv2_1863	-132.1926	268.1225	-0.49	0.622	-657.8392	393.454
_Iv2_1864	-129.4723	268.1259	-0.48	0.629	-655.1256	396.181
_Iv2_1865	79.99505	248.7892	0.32	0.748	-407.7492	567.7393
_Iv2_1866	78.2552	248.7831	0.31	0.753	-409.4771	565.9875
_Iv2_1867	75.95269	249.5615	0.30	0.761	-413.3057	565.211
_Iv2_1868	47.71354	248.2175	0.19	0.848	-438.91	534.337
_Iv2_1869	52.27472	248.2261	0.21	0.833	-434.3655	538.915
_Iv2_1870	50.76414	248.2284	0.20	0.838	-435.8806	537.4089
_Iv2_1871	63.57293	247.246	0.26	0.797	-421.146	548.2919
_Iv2_1872	58.33883	247.2524	0.24	0.813	-426.3926	543.0703
_Iv2_1873	57.08574	247.2581	0.23	0.817	-427.6568	541.8283
_Iv2_1874	52.42314	247.2684	0.21	0.832	-432.3397	537.186

_Iv2_1875	46.58909	247.2769	0.19	0.851	-438.1904	531.3685
_Iv2_1876	50.30211	247.2793	0.20	0.839	-434.482	535.0863
_Iv2_1877	53.44548	247.281	0.22	0.829	-431.3421	538.233
_Iv2_1878	58.14777	246.8737	0.24	0.814	-425.8411	542.1367
_Iv2_1879	60.72059	246.8735	0.25	0.806	-423.2679	544.7091
_Iv2_1880	60.96324	246.8777	0.25	0.805	-423.0336	544.9601
_Iv2_1881	54.47918	246.8807	0.22	0.825	-429.5235	538.4819
_Iv2_1882	120.5233	243.6352	0.49	0.621	-357.1167	598.1632
_Iv2_1883	116.9519	243.6477	0.48	0.631	-360.7126	594.6163
_Iv2_1884	117.4552	243.6576	0.48	0.630	-360.2288	595.1391
_Iv2_1885	118.2812	243.6641	0.49	0.627	-359.4154	595.9779
_Iv2_1886	134.1985	243.0422	0.55	0.581	-342.2789	610.6759
_Iv2_1887	133.8483	243.0501	0.55	0.582	-342.6446	610.3412
_Iv2_1888	133.5984	243.0589	0.55	0.583	-342.9119	610.1086
_Iv2_1889	135.4529	242.9935	0.56	0.577	-340.929	611.8348
_Iv2_1890	134.2302	243.0041	0.55	0.581	-342.1727	610.633
_Iv2_1891	135.1609	243.0125	0.56	0.578	-341.2583	611.5801
_Iv2_1892	133.7902	243.021	0.55	0.582	-342.6457	610.226
_Iv2_1893	134.3006	243.0302	0.55	0.581	-342.1533	610.7545
_Iv2_1894	132.3594	243.0394	0.54	0.586	-344.1125	608.8313
_Iv2_1895	133.6205	243.0482	0.55	0.583	-342.8688	610.1098
_Iv2_1896	135.5602	243.0535	0.56	0.577	-340.9395	612.0599
_Iv2_1897	139.8735	243.0602	0.58	0.565	-336.6393	616.3862
_Iv2_1898	148.6621	243.0655	0.61	0.541	-327.861	625.1853
_Iv2_1899	144.8076	243.0735	0.60	0.551	-331.7311	621.3464
_Iv2_1900	146.5521	243.0816	0.60	0.547	-330.0026	623.1069
_Iv2_1901	152.3022	243.0262	0.63	0.531	-324.1438	628.7482
_Iv2_1902	151.904	243.0339	0.63	0.532	-324.5572	628.3651
_Iv2_1903	157.344	242.967	0.65	0.517	-318.9861	633.6741
_Iv2_1904	157.613	242.9243	0.65	0.516	-318.6333	633.8593
_Iv2_1905	158.4004	242.9345	0.65	0.514	-317.8658	634.6666
_Iv2_1906	158.2652	242.9479	0.65	0.515	-318.0274	634.5579
_Iv2_1907	169.0869	242.8378	0.70	0.486	-306.9897	645.1636
_Iv2_1908	177.2497	242.8495	0.73	0.466	-298.8501	653.3495
_Iv2_1909	184.7033	242.8653	0.76	0.447	-291.4274	660.8339
_Iv2_1910	189.9074	242.8777	0.78	0.434	-286.2475	666.0623
_Iv2_1911	191.379	242.8929	0.79	0.431	-284.8059	667.5638
_Iv2_1912	191.4271	242.9081	0.79	0.431	-284.7874	667.6417
_Iv2_1913	197.4497	242.9075	0.81	0.416	-278.7635	673.663
_Iv2_1919	243.9048	242.9426	1.00	0.315	-232.3774	720.187
_Iv2_1920	179.8599	242.9599	0.74	0.459	-296.4561	656.176
_Iv2_1921	146.7884	242.9769	0.60	0.546	-329.561	623.1378
_Iv2_1922	133.2224	242.9451	0.55	0.583	-343.0646	609.5095
_Iv2_1923	120.2023	242.9519	0.49	0.621	-356.0982	596.5028
_Iv2_1924	123.8842	242.8121	0.51	0.610	-352.1421	599.9105
_Iv2_1925	116.5109	242.8215	0.48	0.631	-359.5339	592.5557
_Iv2_1926	111.7439	242.85	0.46	0.645	-364.3568	587.8446
_Iv2_1927	113.539	242.8615	0.47	0.640	-362.5842	589.6623
_Iv2_1928	108.6446	242.889	0.45	0.655	-367.5324	584.8216
_Iv2_1929	107.1459	242.9128	0.44	0.659	-369.0779	583.3697
_Iv2_1930	103.1109	242.978	0.42	0.671	-373.2407	579.4625
_Iv2_1931	101.4672	243.006	0.42	0.676	-374.9392	577.8736
_Iv2_1932	106.7174	242.9568	0.44	0.661	-369.5927	583.0274
_Iv2_1933	107.8447	242.9841	0.44	0.657	-368.5189	584.2084
_Iv2_1934	109.5116	243.0077	0.45	0.652	-366.8982	585.9213
_Iv2_1935	116.3512	243.0374	0.48	0.632	-360.1169	592.8193
_Iv2_1936	118.0992	243.0929	0.49	0.627	-358.4776	594.676
_Iv2_1937	120.2123	243.1124	0.49	0.621	-356.4029	596.8275
_Iv2_1938	127.829	243.1484	0.53	0.599	-348.8567	604.5147
_Iv2_1939	136.3224	243.1843	0.56	0.575	-340.4336	613.0783
_Iv2_1946	213.2124	243.4516	0.88	0.381	-264.0677	690.4925
_Iv2_1947	147.499	243.4782	0.61	0.545	-329.8332	624.8311
_Iv2_1948	128.6544	243.5303	0.53	0.597	-348.78	606.0888

_Iv2_1949	135.9022	243.4572	0.56	0.577	-341.3888	613.1932
_Iv2_1950	136.2776	243.5207	0.56	0.576	-341.1381	613.6932
_Iv2_1951	163.5896	243.4656	0.67	0.502	-313.7179	640.8972
_Iv2_1952	161.1812	243.5296	0.66	0.508	-316.2518	638.6142
_Iv2_1953	156.4396	243.5878	0.64	0.521	-321.1075	633.9867
_Iv2_1954	143.5888	243.6682	0.59	0.556	-334.116	621.2936
_Iv2_1955	131.2964	243.6301	0.54	0.590	-346.3336	608.9264
_Iv2_1956	115.5452	243.4662	0.47	0.635	-361.7635	592.854
_Iv2_1957	105.6775	243.5525	0.43	0.664	-371.8004	583.1554
_Iv2_1958	96.81203	243.639	0.40	0.691	-380.8353	574.4594
_Iv2_1959	81.72898	243.706	0.34	0.737	-396.0499	559.5078
_Iv2_1960	57.125	243.4462	0.23	0.814	-420.1445	534.3945
_Iv2_1961	44.27294	243.4722	0.18	0.856	-433.0475	521.5934
_Iv2_1962	34.69931	243.4746	0.14	0.887	-442.6258	512.0244
_Iv2_1963	20.52712	243.5572	0.08	0.933	-456.9601	498.0143
_Iv2_1964	5.671429	243.6451	0.02	0.981	-471.988	483.3308
_Iv2_1965	-6.05434	243.7497	-0.02	0.980	-483.9189	471.8102
_Iv2_1966	-15.69307	243.8276	-0.06	0.949	-493.7103	462.3241
_Iv2_1967	-21.36904	243.8979	-0.09	0.930	-499.5241	456.7861
_Iv2_1968	-30.24353	244.0054	-0.12	0.901	-508.6093	448.1222
_Iv2_1969	-48.20492	244.1324	-0.20	0.843	-526.8197	430.4099
_Iv2_1970	-72.38037	244.2656	-0.30	0.767	-551.2562	406.4955
_Iv2_1971	-97.7743	244.4566	-0.40	0.689	-577.0245	381.476
_Iv2_1972	-136.0872	244.659	-0.56	0.578	-615.7343	343.5599
_Iv2_1973	-176.762	244.8916	-0.72	0.470	-656.8652	303.3412
_cons	-133.205	239.7758	-0.56	0.579	-603.2787	336.8687

sigma_u	295.44271	
sigma_e	238.60108	
rho	.60524399	(fraction of variance due to u_i)

F test that all u_i=0: F(123, 4670) = 55.28 Prob > F = 0.0000

It looks like on average, there is an increase in military size over time, so we could consider modeling it as a linear trend:

```
. xi: xtreg v41 v76 v5 v7 v19 v2, fe
Fixed-effects (within) regression      Number of obs   =   4945
Group variable (i): v1                 Number of groups =   124
R-sq:  within = 0.1837                  Obs per group:  min =    1
      between = 0.0375                      avg   =   39.9
      overall  = 0.0347                      max   =   148
                                          F(5,4816)      =   216.83
                                          Prob > F        =    0.0000
```

v41	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
v76	.0219487	.0130567	1.68	0.093	-.0036484	.0475457
v5	-.0754687	.0075709	-9.97	0.000	-.0903111	-.0606263
v7	.3923511	.0884183	4.44	0.000	.2190108	.5656913
v19	.0075463	.0003463	21.79	0.000	.0068674	.0082252
v2	1.185237	.2751054	4.31	0.000	.6459043	1.724569
_cons	-2168.702	515.4194	-4.21	0.000	-3179.159	-1158.245

sigma_u	293.26756	
sigma_e	241.87032	
rho	.59516697	(fraction of variance due to u_i)

F test that all u_i=0: F(123, 4816) = 53.09 Prob > F = 0.0000

To test whether it is appropriate to assume a linear trend, we test this model against the previous one in terms of its fit:

```
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	4945	-34593.44	-34091.44	6	68194.88	68233.92

Note: N=Obs used in calculating BIC; see [R] BIC note

```
. xi: qui xtreg v41 v76 v5 v7 v19 i.v2, fe
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	4945	-34593.44	-33948.03	152	68200.06	69188.99

Note: N=Obs used in calculating BIC; see [R] BIC note

BIC difference: $69188.99 - 68233.92 = 955.07$

The model with smaller BIC has better fit, and the strength of evidence in its favor is evaluated as follows:

BC Difference	Evidence
0-2	Weak
2-6	Positive
6-10	Strong
>10	Very strong

So in this case, the model with linear trend is clearly a better choice. We can also examine the trend graphically in the FE exploratory dataset we created. We could also follow with some linearity diagnostics, e.g. using `mrunning`, `boxtid`, etc.

```
.lowess v41 v2, mcolor(yellow)
```

