Preliminaries



Fu Zixuan¹

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Chapter 1
Year 2016-2022

1.1 Regression tables

1.1.1 WG, BG, Random effect, Correlated random effect(Mundlak)

Notation

• Dependent variable:

$$\underbrace{y}_{NT\times 1} = \begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix} \quad \underbrace{y_i}_{T\times 1} = \begin{pmatrix} y_{i1} \\ \vdots \\ y_{iT} \end{pmatrix}$$

• Independent variable:

$$\underbrace{X}_{NT\times K} = \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix} \quad \underbrace{x_i}_{T\times K} = \begin{pmatrix} x_{i1} \\ \vdots \\ x_{iT} \end{pmatrix}$$

• Matrix to calcualte the mean:

$$B_T = d_T (d'_T d_T)^{-1} d'_T$$
 where $d_T = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$

Thus

$$B_T y_1 = \begin{pmatrix} \bar{y}_1 \\ \vdots \\ \bar{y}_1 \end{pmatrix}$$

we set $B = I_N \otimes B_T$

• Matrix to demean the variable:

$$W_T = I_T - B_T$$

Thus,

$$W_T y_i = \begin{pmatrix} y_{i1} - \bar{y}_1 \\ \vdots \\ y_{iT} - \bar{y}_1 \end{pmatrix}$$

we set $W = I_N \otimes W_T$

Estimators

• WG:

$$\hat{\beta}_{WG} = (X'WX)^{-1}X'Wy$$

• BG:

$$\hat{\beta}_{BG} = (X'BX)^{-1}X'By$$

- RE: A linear combination of WG and BG
- CRE (Mundlak): equivalent to WG

In empirical analysis of data consisting of repeated observations on economic units (time series on a cross section) it is often assumed that the coefficients of the quantitative variables (slopes) are the same, whereas the coefficients of the qualitative variables (intercepts or effects) vary over units or periods. This is the constant-slope variable- intercept framework. In such an analysis an explicit account should be taken of the statistical dependence that exists between the quantitative variables and the effects. It is shown that when this is done, the random effect approach and the fixed effect approach yield the same estimate for the slopes, the "within" estimate. Any matrix combination of the "within" and "between" estimates is generally biased. When the "within" estimate is subject to a relatively large error a minimum mean square error can be applied, as is generally done in regression analysis. Such an estimator is developed here from a somewhat different point of departure.

1.1.2 Specification

Model 1 (Pseudoc Poisson)

$$y_{it} = x_{it1}^{\beta_1} x_{it2}^{\beta_2} x_{it3}^{\beta_3} \theta_i \epsilon_{it}$$
$$= f(x_{it}; \beta) \theta_i \epsilon_{it}$$

Tables: Pois

Reference to Koen Jochman's lecture notes on panel data and model with multiplicative effect:

$$y_{it} = f(x_{it}; \beta)\theta_i \epsilon_{it}$$
 where $\mathbb{E}\left[\epsilon_{it} | x_{i1}, \dots, x_{iT}, \theta_i\right] = 1$

Then following the same logic in additive effect, we difference out individual effect to get:

$$\mathbb{E}\left[\frac{y_{it}}{f(x_{it};\beta)} - \frac{y_{i,t-1}}{f(x_{i,t-1};\beta)} \middle| x_{i1}, \dots, x_{iT}\right] = 0$$

Similarly,

$$\mathbb{E}\left[\frac{y_{it}}{f(x_{it};\beta)} - \frac{\sum_{t=1} y_{it}}{\sum_{t=1} f(x_{it};\beta)} \middle| x_{i1}, \dots, x_{iT}\right] = 0$$

One of the unconditional moment equation given rise to is

$$\mathbb{E}\left[x_i t \left(\frac{y_{it}}{f(x_{it};\beta)} - \frac{\sum_{t=1} y_{it}}{\sum_{t=1} f(x_{it};\beta)}\right)\right] = 0$$
(1.1)

The moment condition is often called pseudo-poisson estimator (as if assuming $y_i t | x_{i1}, \ldots, x_{iT}, \theta_i \sim Poisson(f(x_{it}; \beta)\theta_i)$ and then use maximum likelihood.) When regressors are not strictly exogenous, we can construct a **differencing** based estimator based on sequential moment restrictions. The **fixest** package doesn't provide the differencing based estimator.

TO BE CONSTRUCTED BY HAND LATER.

Model 2 (OLS)

$$\log(y_{it}) = \log(x_{it1})\beta_1 + \log(x_{it2})\beta_2 + \log(x_{it3})\beta_3 + \log(\theta_i) + \log(\epsilon_{it})$$

LHS: log(ETP INF);

RHS: log(STAC INPATIENT), log(STAC OUTPATIENT), log(SESSION), CASEMIX

Table: OLS, OLS_lag1 Figure: FixedEffect_OLS

Remark. The Pseudo poisson and Log OLS are equivalent if we assume that ϵ_{it} is independent of x_{it} and θ_i .

Remark. The Mundlak (1978) approach is to include the average of the individual-specific variables \bar{x}_i in the regression. He shows that it is equivalent to within group estimator. (Correlated random effect \sim WG estimator). If the true model is

$$y_{it} = x_{it}\beta + \theta_i + \epsilon_{it}$$

and $E(\theta_i|\bar{x}_i) = \bar{x}_i \gamma + \tilde{\theta}_i$, then

$$y_{it} = (x_{it} - \bar{x}_i)\beta + \bar{x}_i(\gamma + \beta) + \tilde{\theta}_i + \epsilon_{it}(x_{it} - \bar{x}_i)\beta_1 + \bar{x}_i\beta_2 + \tilde{\theta}_i + \epsilon_{it}$$

Only when the θ_i is uncorrelated with x_{it} , the $\beta_1 = \beta_2$.

Pois

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Dependent Variable:	ETP	_INF
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Model:	(1)	(2)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Variables		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\log(\text{SEJHC_MCO})$	0.160^{a}	0.730^{a}
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.028)	(0.025)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\log(\text{SEJHP_MCO})$	0.044^{a}	0.109^{a}
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.011)	(0.020)
$\begin{array}{c cccc} \text{CASEMIX} & 0.007^a & 0.014^a \\ & (0.002) & (0.003) \end{array}$ $\begin{array}{c ccccc} Fixed\text{-}effects & & & & & & & \\ FI & & & & & & & \\ FI & & & & & & & \\ FI & & & & & & & \\ FI & & & & & & & \\ FI & statistics & & & & & \\ Observations & & 3,946 & 3,946 \\ Squared Correlation & 0.995 & 0.983 \end{array}$	$\log(\text{SEANCES_MED})$	0.032^{a}	0.044^{a}
		(0.008)	(0.011)
	CASEMIX	0.007^{a}	0.014^{a}
$\begin{array}{ccc} FI & Yes \\ FI_EJ & Yes \\ \hline \textit{Fit statistics} \\ Observations & 3,946 & 3,946 \\ Squared Correlation & 0.995 & 0.983 \\ \end{array}$		(0.002)	(0.003)
FI_EJ Yes Fit statistics Observations 3,946 3,946 Squared Correlation 0.995 0.983	Fixed-effects		
Fit statistics Observations 3,946 3,946 Squared Correlation 0.995 0.983	FI	Yes	
Observations 3,946 3,946 Squared Correlation 0.995 0.983	$\mathrm{FI}_{-}\mathrm{EJ}$		Yes
Squared Correlation 0.995 0.983	Fit statistics		
_	Observations	3,946	3,946
Pseudo R ² 0.966 0.956	Squared Correlation	0.995	0.983
	Pseudo R ²	0.966	0.956

Signif. Codes: a: 0.01, b: 0.05, c: 0.1

Back

Dependent Variable:	$\log(ET)$	P_INF)
Model:	(1)	(2)
Variables		
$\log(\text{SEJHC_MCO})$	0.184^{a}	0.676^{a}
	(0.026)	(0.031)
$\log(\text{SEJHP_MCO})$	0.032^{a}	0.097^{a}
	(0.011)	(0.022)
$\log(\text{SEANCES_MED})$	0.021^{a}	0.037^{a}
	(0.006)	(0.010)
CASEMIX	0.007^{b}	0.013^{a}
	(0.003)	(0.004)
Fixed-effects		
FI	Yes	
FI_EJ		Yes
Fit statistics		
Observations	3,923	3,923
Squared Correlation	0.993	0.980
Pseudo R ²	1.77	1.39

Signif. Codes: a: 0.01, b: 0.05, c: 0.1

Back

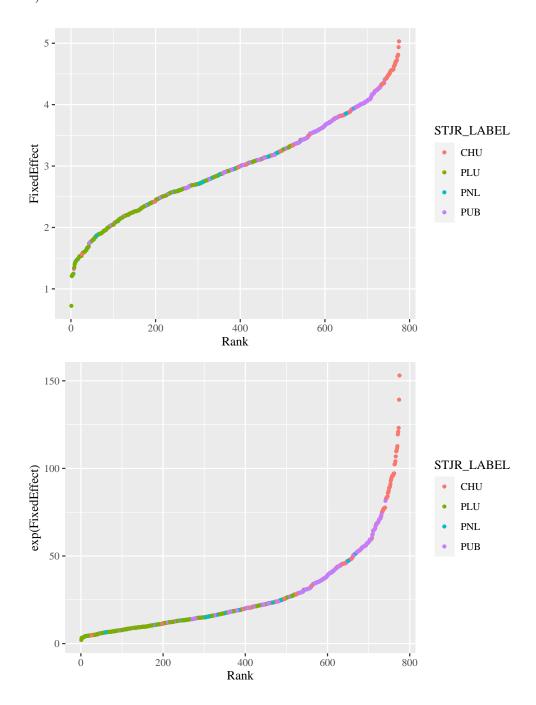
OLS_lag1

Dependent Variable:	log(ET	P_INF)
Model:	(1)	(2)
Variables		
$\log(\text{SEJHC_MCO})$	0.222^{a}	0.692^{a}
	(0.049)	(0.036)
$\log(\text{SEJHP_MCO})$	0.093^{a}	0.111^{a}
	(0.025)	(0.032)
$\log(\text{SEANCES_MED})$	0.040^{c}	0.047^{a}
	(0.023)	(0.015)
CASEMIX	0.013^{a}	0.014^{a}
	(0.003)	(0.005)
Fixed-effects		
FI	Yes	
$\operatorname{FL-EJ}$		Yes
Fit statistics		
Observations	3,151	3,151
Squared Correlation	0.994	0.983
Pseudo R ²	1.84	1.48

Signif. Codes: a: 0.01, b: 0.05, c: 0.1

Back

Fixed Effect_OLS Fixed effects extracted from OLS regression with fixed effect on each ${\rm FI}$ (not ${\rm FI_EJ}$). Back



1.2 Descriptive Statistics

1.2.1 Stays per labor input

	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	51.37	133.48	60.76	70.54	71.12
2	Q2	105.17	181.73	98.77	99.00	124.31
3	Q3	141.30	231.18	155.14	128.60	175.32
4	Mean	106.16	194.39	128.23	103.76	137.71
5	Nobs	2726.00	2004.00	741.00	606.00	6077.00

Table 1.1: SJMD MCO

	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	208.36	181.51	177.67	500.10	198.23
2	Q2	1036.97	272.76	491.50	847.58	493.31
3	Q3	1427.00	430.11	1220.56	1154.48	1180.57
4	Mean	977.18	391.45	734.43	914.89	748.21
5	Nobs	2726.00	2004.00	741.00	606.00	6077.00

Table 1.2: SJMD TOT

	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	23.80	138.27	32.23	33.15	35.41
2	Q2	47.15	185.18	62.83	48.93	61.51
3	Q3	62.56	240.04	108.09	57.38	150.86
4	Mean	47.11	214.42	93.66	46.43	108.00
5	Nobs	2736.00	2010.00	730.00	599.00	6075.00

Table 1.3: SJINF MCO

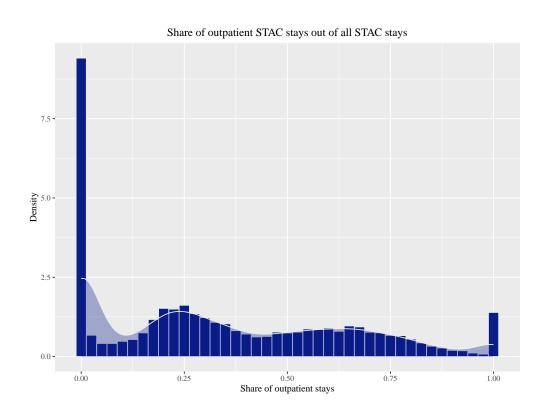
1.2.2 Share of outpatient stays

	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	70.69	210.23	105.91	191.63	167.56
2	Q2	476.89	284.89	304.42	434.84	347.90
3	Q3	639.75	422.14	754.52	571.29	587.61
4	Mean	444.58	361.79	542.56	436.39	428.15
5	Nobs	2736.00	2010.00	730.00	599.00	6075.00

Table 1.4: SJINF TOT

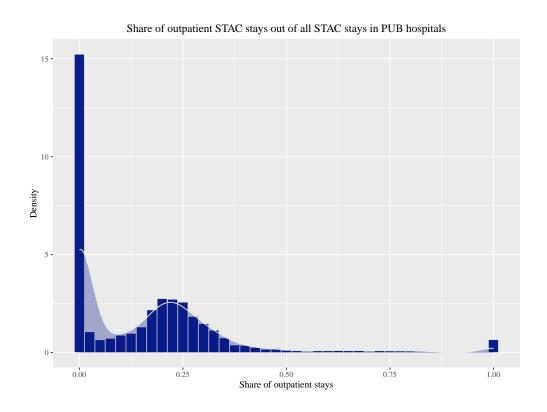
	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	17.37	233.39	27.01	31.97	32.09
2	Q2	50.88	340.07	104.34	62.98	79.42
3	Q3	76.24	487.77	198.55	82.86	257.67
4	Mean	53.11	472.98	152.45	63.58	204.27
5	Nobs	2730.00	1990.00	727.00	600.00	6047.00

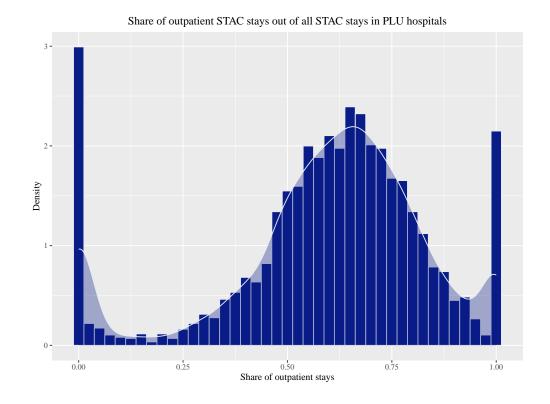
Table 1.5: SJAS MCO

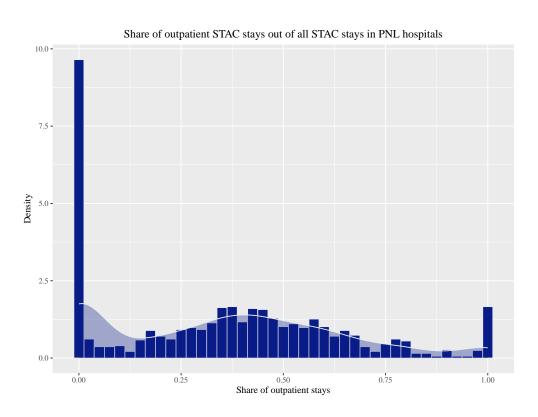


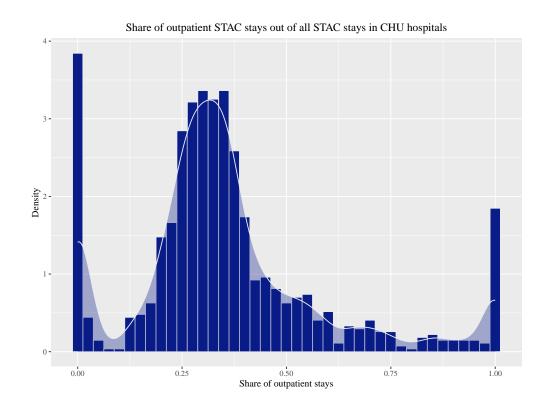
	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	55.09	366.80	96.77	186.98	211.10
2	Q2	508.07	535.53	464.22	582.30	529.11
3	Q3	777.93	848.29	1262.24	826.61	827.01
4	Mean	525.48	828.41	929.30	583.77	679.50
5	Nobs	2730.00	1990.00	727.00	600.00	6047.00

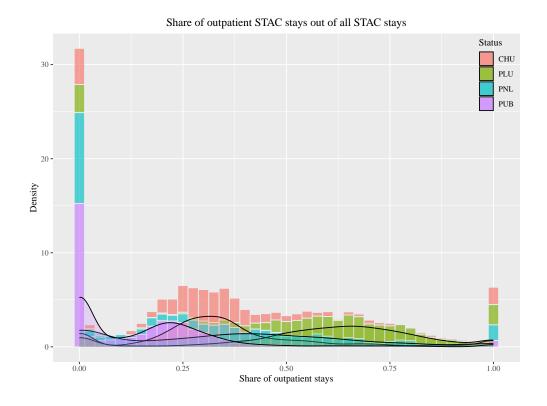
Table 1.6: SJAS TOT





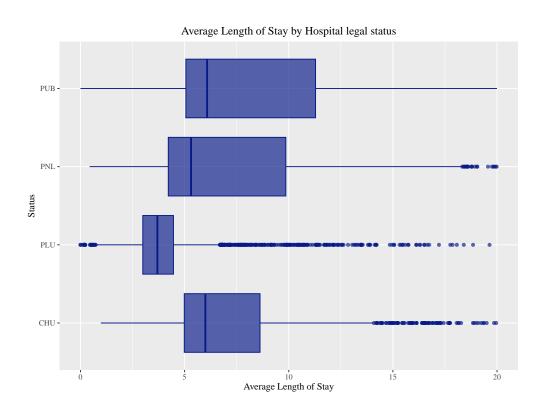






1.2.3 Average length of stay

	STJR_LABEL	PUB	PLU	PNL	CHU	All
1	Q1	5.12	3.13	4.22	5.05	4.05
2	Q2	6.21	3.78	5.46	6.03	5.26
3	Q3	11.83	4.53	10.08	8.60	8.47
4	Mean	8.76	4.18	7.53	7.42	6.99
5	Std_dev	5.25	2.38	5.03	4.00	4.81
6	Nobs	2712.00	1926.00	715.00	584.00	5937.00



1.2.4 Selection of patients

	size	CHU	PLU	PNL	PUB
1	1	11.85	14.89	29.51	34.51
2	2	11.72	4.57	19.02	23.70
3	3	11.73	3.56	10.85	14.75
4	4	11.44	4.59	10.50	13.96

Table 1.7: Average casemix index by hospital legal status and size of hospital