September 15, 2021 Meeting Document

September 14, 2021

1 Overview

This week I tried a couple more models to estimate the service rate. I tried the all-time min iterative model we discussed as well as a county fixed effects model, I have updated our results table to include them. An overview of the results are below.

Table 1: Summary of Results

Model	Group	Pleas per Day	Days per Trial
Min	County	6.92	4.41
Min	Judge	9.66	6.28
Min	Judge-County	14.97	4.25
All time Min	County	7.12	3.65
All time Min	Judge	16.53	4.52
All time Min	Judge-County	15.05	4.09
Utilization	County	7.56	3.25
Utilization	Judge	13.99	3.12
Utilization	Judge-County	20.90	1.73
Fixed Effects	Judge	9.52	3.86
Fixed Effects	County	10.99	4.34
Fixed Effects	Judge-County	10.1	3.71

2 Iterative Idleness Estimation Taking All Time Mins

Step 0: We estimate the model, $\text{Days}_j = \beta_t \text{Trial}_j + \beta_p \text{Plea}_j + \epsilon_j$.

Steps 1-n: We then use the estimates of $\beta_t^{(1)}$ and $\beta_p^{(1)}$ to estimate the expected number of days it would take each judge to complete their work. Mathematically: $\text{Expected Days}_j^{(1)} = \beta_p^{(1)} \cdot \text{Plea}_j + \beta_t^{(1)} \cdot \text{Trial}_j$. We would then set $\text{Days}_j^{(n)} = \min(\text{Days}_j, \text{Expected Days}_j^{(n-11)}, ..., \text{Expected Days}_j^{(1)})$ We then estimate the model $\text{Days}_j^{(1)} = \beta_t \text{Trial}_j + \beta_p \text{Plea}_j + \epsilon_j$ and repeat until convergence.

2.1 Judge Model

Table 2: Judge Model

Dep. Variable:	y	**R-squared:**	1.000
Model:	OLS	**Adj. R-squared:**	1.000
Method:	Least Squares	**F-statistic:**	1.813e+30
Date:	Tue, 14 Sep 2021	**Prob (F-statistic):**	0.00
Time:	13:26:30	**Log-Likelihood:**	1438.6
No. Observations:	50	**AIC:**	-2871.
Df Residuals:	47	**BIC:**	-2865.
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.243e-14	2.56e-14	-0.485	0.630	-6.4e-14	3.91e-14
Plea	0.0605	6.94e-17	8.72e+14	0.000	0.060	0.060
Trial	4.5182	3e-15	1.51e+15	0.000	4.518	4.518

Omnibus:	8.336	**Durbin-Watson:**	2.156
Prob(Omnibus):	0.015	**Jarque-Bera (JB):**	7.538
Skew:	-0.791	**Prob(JB):**	0.0231
Kurtosis:	4.056	**Cond. No.**	790.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

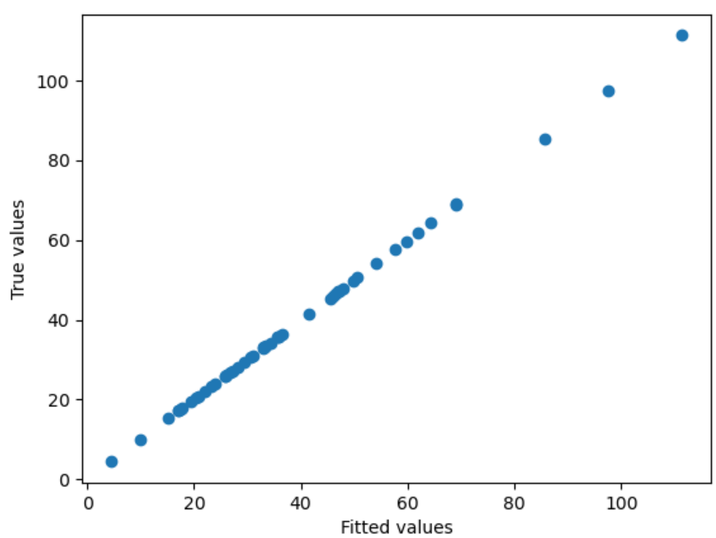


Figure 1: True vs Fitted Values, Judge Model

Table 3: Judge Model

Iteration	Beta P	Beta T
0	0.06	4.52
1	0.06	4.52

2.2 County Model

Table 4: County Model

Dep. Variable:	y	**R-squared:**	0.998
Model:	OLS	**Adj. R-squared:**	0.998
Method:	Least Squares	**F-statistic:**	1.342e+04
Date:	Tue, 14 Sep 2021	**Prob (F-statistic):**	7.67e-61
Time:	13:27:42	**Log-Likelihood:**	-115.16
No. Observations:	46	**AIC:**	236.3
Df Residuals:	43	**BIC:**	241.8
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.7176	0.599	1.199	0.237	-0.490	1.925
Plea	0.1403	0.002	67.351	0.000	0.136	0.144
Trial	3.6474	0.133	27.471	0.000	3.380	3.915

Omnibus:	68.690	**Durbin-Watson:**	2.097
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	840.457
Skew:	-3.638	**Prob(JB):**	3.14e-183
Kurtosis:	22.636	**Cond. No.**	679.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

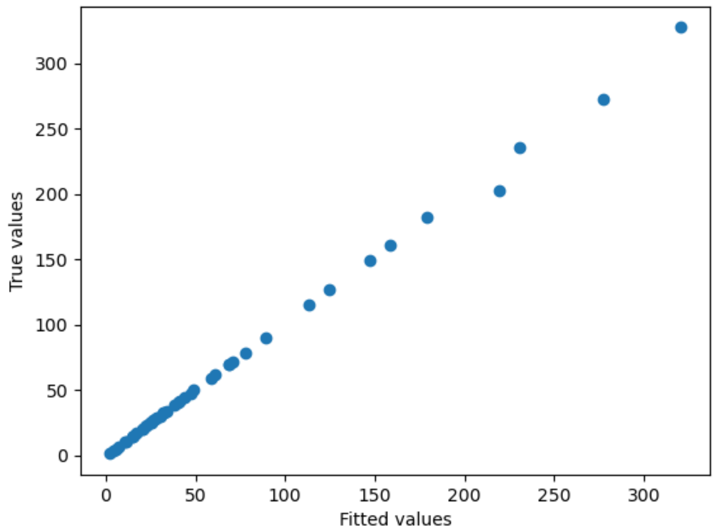


Figure 2: True vs Fitted Values, Judge-County Model

Table 5: Judge Model

Iteration	Beta P	Beta T
0	0.15	3.61
1	0.14	3.67
2	0.14	3.65

2.3 Judge-County Model

Table 6: County Model

Dep. Variable:	y	**R-squared:**	0.977
Model:	OLS	**Adj. R-squared:**	0.977
Method:	Least Squares	**F-statistic:**	5950.
Date:	Tue, 14 Sep 2021	**Prob (F-statistic):**	4.56e-227
Time:	13:28:16	**Log-Likelihood:**	-492.29
No. Observations:	278	**AIC:**	990.6
Df Residuals:	275	**BIC:**	1001.
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.4634	0.110	4.203	0.000	0.246	0.681
Plea	0.0665	0.001	50.392	0.000	0.064	0.069
Trial	4.0877	0.059	68.783	0.000	3.971	4.205

Omnibus:	462.896	**Durbin-Watson:**	2.072
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	159919.551
Skew:	-8.673	**Prob(JB):**	0.00
Kurtosis:	119.212	**Cond. No.**	116.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

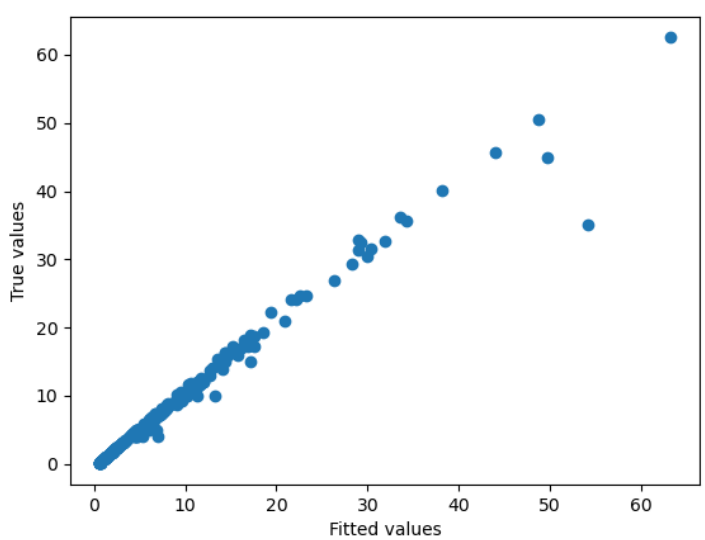


Figure 3: True vs Fitted Values, Judge-County Model

Table 7: Judge-County Model

Iteration	Beta P	Beta T
0	0.10	4.19
1	0.08	4.11
2	0.07	4.09

3 Judge-level Busyness Analysis

The goal of this exercise was to get a better idea of which are the busiest judges. I focused only on GS days. So when I say the number of pleas and number of trials, I mean those that happened on GS days. We have at least three measures of business: the number of pleas, the number of trials, and the number of GS days assigned to a county. I ranked the judges according to a measure that combined the three measures. To create this measure, I ranked all of the judges according to each measure. I then multiplied each county's score in each measure to create an overall measure. So, for example, if Judge 1 had the most pleas, then its ranking according to pleas would be 1. If Judge 1 had the second most trials, then its ranking according to trials would be 2. If it had the sixth most GS days, then its ranking according to GS days would be 6. Judge 1's overall measure would be $1 \cdot 2 \cdot 6 = 12$. This ranking can be seen in table 8. I also created bar charts of the number of pleas, trials, GS days, and the utilization for each county. I calculate the utilization by using the service rate estimates from the county model to calculate the expected number of days it took to process each county's pleas and trials. I then divide the expected number of days by the actual number of assigned days to get the utilization.

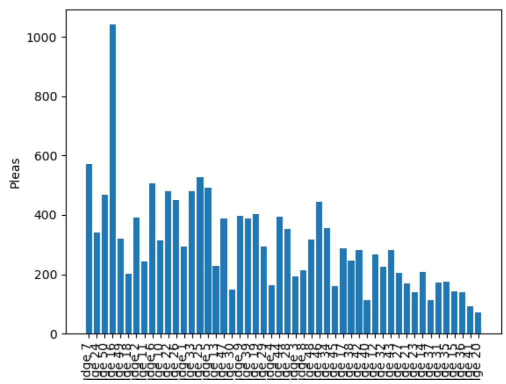
In table 8, the columns PleaShare, TrialShare, and GSShare contain the cumulative share of all pleas, trials, and GS days accounted for by the counties up to that row. So, for example, in the 10th row, if the value of PleaShare is 0.5, that means that the top 10 counties account for 50% of all pleas. Similarly, if in the 15th row the value of Trial share is 0.9, that means that the top 15 counties account for 90% of all trials. GS share refers to the share of all GS days assigned. The counties in table 8 are ranked using the measure described in the beginning of the section.

Table 8: CDF table

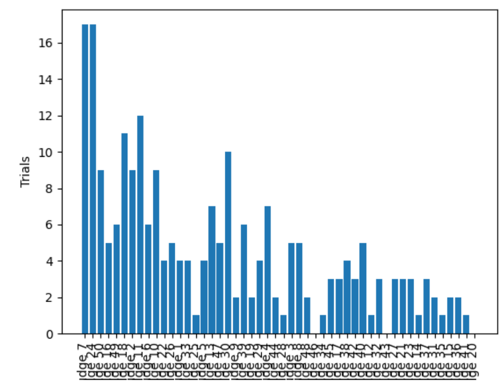
	JudgeID	Plea	Trial	Days	OverallScore	PleaShare	TrialShare	GSDayShare
1	Judge 7	572	17	167.00	4	0.04	0.08	0.04
2	Judge 24	341	17	110.50	133	0.06	0.15	0.07
3	Judge 50	469	9	129.50	144	0.09	0.19	0.10
4	Judge 16	1041	5	90.00	320	0.16	0.21	0.12
5	Judge 49	321	6	137.00	440	0.18	0.24	0.15
6	Judge 18	202	11	123.00	576	0.19	0.29	0.18
7	Judge 2	390	9	121.00	672	0.22	0.33	0.21
8	Judge 11	244	12	107.00	810	0.23	0.38	0.24
9	Judge 6	505	6	89.00	1056	0.27	0.41	0.26
10	Judge 10	315	9	108.50	1232	0.29	0.45	0.28
11	Judge 22	480	4	98.50	1848	0.32	0.47	0.31
12	Judge 26	450	5	103.00	2052	0.35	0.49	0.33
13	Judge 1	293	4	122.00	2300	0.37	0.51	0.36
14	Judge 33	479	4	98.00	2352	0.40	0.52	0.39
15	Judge 25	527	1	87.00	2898	0.43	0.53	0.41
16	Judge 5	492	4	76.00	3360	0.47	0.55	0.42
17	Judge 13	228	7	105.50	3410	0.48	0.58	0.45
18	Judge 47	388	5	100.00	3536	0.51	0.60	0.47
19	Judge 30	147	10	96.50	3870	0.52	0.64	0.50
20	Judge 9	398	2	105.50	4800	0.54	0.65	0.52
21	Judge 39	389	6	76.00	5655	0.57	0.68	0.54
22	Judge 19	404	2	92.00	7524	0.59	0.69	0.56
23	Judge 29	293	4	98.50	8280	0.61	0.71	0.59
24	Judge 4	162	7	85.50	8856	0.62	0.74	0.61
25	Judge 44	395	2	78.00	11934	0.65	0.75	0.63
26	Judge 28	353	1	97.00	13464	0.67	0.75	0.65
27	Judge 3	193	5	72.00	18870	0.68	0.77	0.67
28	Judge 8	215	5	72.00	19008	0.70	0.80	0.68
29	Judge 48	317	2	80.00	20202	0.72	0.80	0.70
30	Judge 46	443	0	48.67	22050	0.75	0.80	0.71
31	Judge 34	355	1	75.00	22950	0.77	0.81	0.73
32	Judge 45	161	3	90.00	23814	0.78	0.82	0.75
33	Judge 17	288	3	73.00	24025	0.80	0.84	0.77
34	Judge 38	247	4	64.00	27550	0.82	0.85	0.79
35	Judge 42	283	3	44.00	31772	0.84	0.87	0.80
36	Judge 40	112	5	40.00	32256	0.84	0.89	0.81
37	Judge 12	268	1	82.00	32900	0.86	0.89	0.83
38	Judge 32	226	3	64.00	34336	0.88	0.91	0.84
39	Judge 43	283	0	72.00	42768	0.89	0.91	0.86
40	Judge 27	204	3	60.00	44800	0.91	0.92	0.87
41	Judge 21	170	3	70.00	46200	0.92	0.93	0.89
42	Judge 23	139	3	64.00	53820	0.93	0.95	0.91
43	Judge 14	208	1	68.00	56304	0.94	0.95	0.92
44	Judge 37	112	3	46.50	60536	0.95	0.96	0.93
45	Judge 31	171	2	58.00	62361	0.96	0.97	0.95
46	Judge 35	176	1	54.00	65436	0.97	0.98	0.96
47	Judge 15	144	2	52.00	66220	0.98	0.99	0.97
48	Judge 36	139	2	49.00	75240	0.99	1.00	0.99
49	Judge 41	91	1	38.00	103243	1.00	1.00	0.99
50	Judge 20	72	0	23.00	125000	1.00	1.00	1.00

3.1 Overall Figures

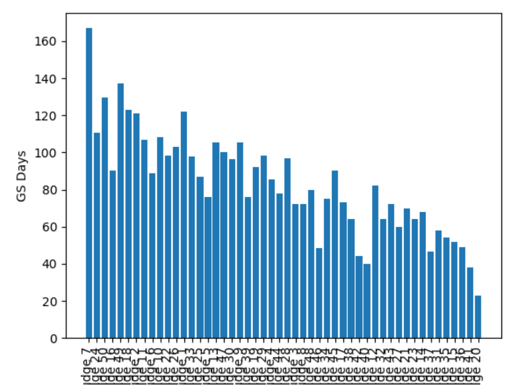
In figure 4, the counties are ordered according to the overall ranking described in the previous section.



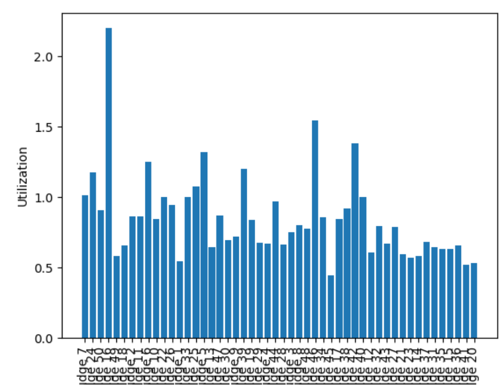
(a) Pleas



(b) Trials



(c) GS Days



(d) Utilization

Figure 4: Number of Pleas, Trials, GS days, and utilization for each county.

3.2 Comparing Busy and Idle Judges

The purpose of this section is to further investigate how 'busy' counties are different from 'idle' counties. To do this, I split the counties into above median and below median in terms of business. Here, business is measured according to the measure described in the beginning of the section.

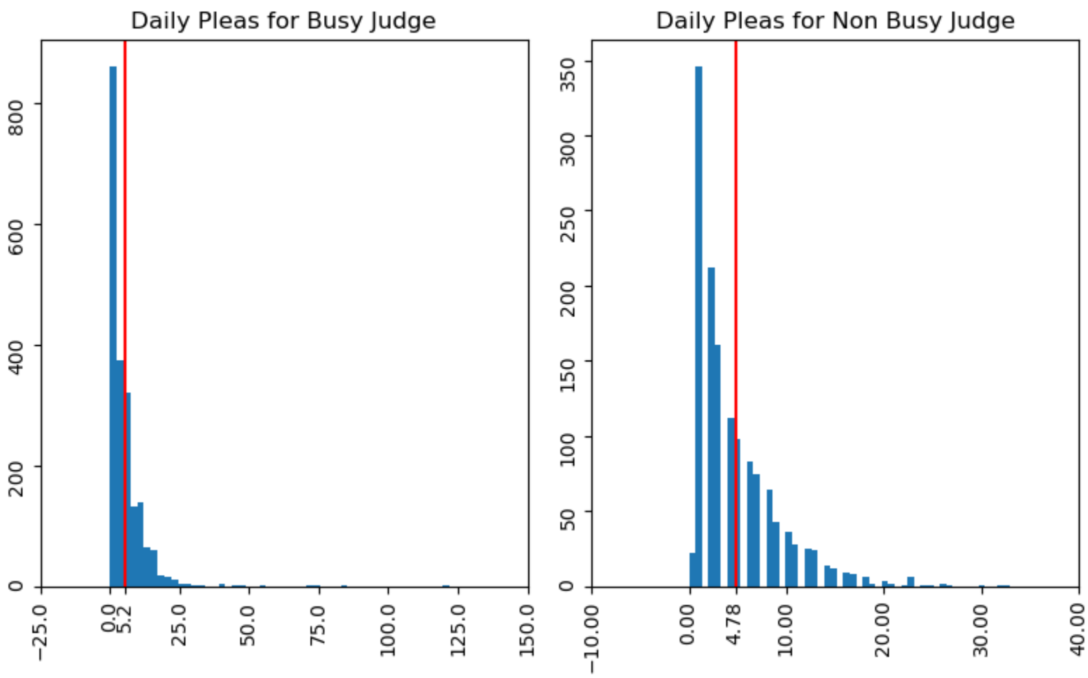


Figure 5: Histogram of pleas processed per day

4 Model with County Fixed Effects

Note, the unit of observation here, i, is the judge-county combination. The regression we are running here is: $\text{Days}_i = \alpha_c + \beta_p \text{Plea}_i + \beta_t \text{Trial}_i + \epsilon_i$

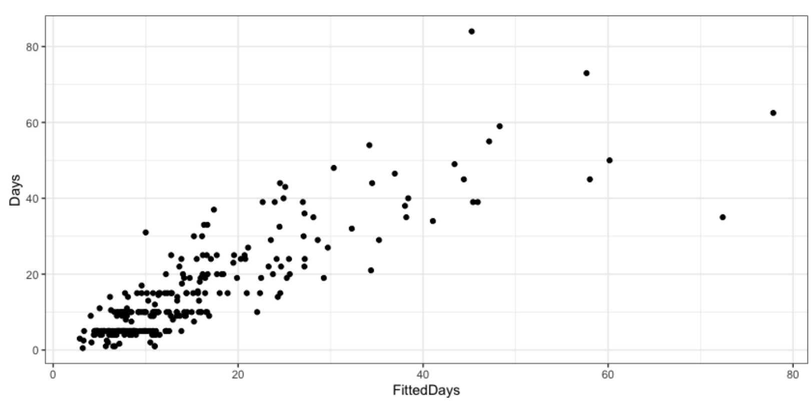


Figure 6: True vs Fitted Values, fixed effects model

Table 9: Model with County Fixed effects, table continues on next page

	Dependent variable:
	Days
Plea	0.091***
	(0.008)
Trial	4.336***
	(0.339)
CountyAbbeville	6.411*
	(3.784)
CountyAiken	3.107
	(2.909)
CountyAllendale	4.425
	(4.360)
CountyAnderson	5.237*
	(2.985)
CountyBamberg	5.443
	(4.364)
CountyBarnwell	2.608
	(3.782)
CountyBeaufort	8.232***
	(2.524)
CountyBerkeley	3.724
	(2.885)
CountyCalhoun	3.852
	(4.361)
CountyCharleston	9.165***
	(2.237)
CountyCherokee	3.112
	(3.408)
CountyChester	14.170***
	(4.365)
CountyChesterfield	4.966
	(3.093)
CountyClarendon	7.305**
	(3.387)
CountyColleton	4.991*
	(2.858)
CountyDarlington	7.293**
	(3.091)
CountyDillon	7.260**
	(3.380)
CountyDorchester	2.073
	(3.876)
CountyEdgefield	7.832*
	(4.371)
CountyFairfield	5.677
	(3.798)
CountyFlorence	9.426***
	(3.229)
CountyGeorgetown	5.565
	(3.415)
CountyGreenville	6.571**
	(2.687)
CountyGreenwood	5.803*
	(3.122)
CountyHampton	4.003
	(3.777)
Observations	[illegible]

Table 10: Model with County Fixed effects, continued

	Dependent variable:
	Days
CountyHorry	5.715**
	(2.482)
CountyJasper	3.514
	(3.779)
CountyKershaw	6.248**
	(2.871)
CountyLancaster	11.090***
	(3.788)
CountyLaurens	7.800**
	(3.106)
CountyLee	4.218
	(3.382)
CountyLexington	4.390**
	(2.219)
CountyMarion	5.295
	(3.790)
CountyMarlboro	10.937***
	(3.792)
CountyMcCormick	6.248
	(4.362)
CountyNewberry	6.035*
	(3.385)
CountyOconee	2.834
	(3.097)
CountyOrangeburg	6.506**
	(2.689)
CountyPickens	6.166**
	(3.101)
CountyRichland	10.717***
	(2.141)
CountySaluda	4.655
	(4.365)
CountySpartanburg	2.984
	(2.897)
CountySumter	6.194**
	(2.883)
CountyUnion	6.537*
	(3.388)
CountyWilliamsburg	5.859**
	(2.675)
CountyYork	7.085***
	(2.651)
Observations	278
R^2	0.881
Adjusted R^2	0.856
Residual Std. Error	7.552 (df = 230)
F Statistic	35.355*** (df = 48; 230)
Note:	*p<0.1; **p<0.05; ***p<0.01

5 Non-linear Approach

I looked into using a log-linear model, however, none of the approaches I found would yield simple to interpret service rates. I think we might be trading off more interpretable fixed effects for more interpretable service rate estimates. For example, we could estimate a Poisson regression with the specification $\text{Days}_i \sim P(\mu_i)$ and $\mu_i = \exp(\beta_p \text{Plea}_i + \beta_t \text{Trial}_i + \alpha_j)$. This would yield nice interpretations for the α_j's. The judge fixed effects would have a mutliplicative effect on the days, and we could interpret this as sort of proportional idleness. However, we would lose the simplicity of the model $\text{Days}_i = \beta_p \text{Trials}_i + \beta_p \text{Pleas}_i + \epsilon_i$. Since we are ultimately most interested in β_p and β_t, I don't think this tradeoff is worth it.