Effects of Overcrowding on the Probability of Having an AE
Dec 17

Section 1:

Primary Exposure Variables: **"Waiting time to be seen" & "Number of people waiting to be *seen*"**
Primary Outcome Variable: **"Preventable AE" & "Preventable AE related to ED care"**

Individual Level Model

- **Model 1:**

The main crowding associated variable studied in our first model is the "number of people waiting to be seen". This model is a logistic regression model to predict the probability of having a preventable AE related to ED care as a function of several variables (Number of people waiting to be seen and some other patient and system characteristics)

$$\begin{aligned} log\left(\frac{ProbPreventableEDrelatedAE_i}{1-ProbPreventableEDrelatedAE_i}\right) &= \beta_0 + \beta_1 Wtbs\_num_i + \beta_2 Age_i \\ &+ \beta_3 TotalNumberStaff_i + ShiftBlock_i \\ &+ ChronicCondition_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i \end{aligned}$$

{Note that $ShiftBlock_i$, $ChronicCondition_i$, $CTAS_i$, $Site_i$, $Disposition_i$ are the fixed effects considered in Model 1. $Wtbs\_num_i$ also denotes the number of patients waiting to be seen at the time of registration of patient $i. TotalNumberStaff_i$ represents the total number of staff at ED when patient i is registered.}

The results of the above model are presented in the appendix (page 9).

Summary of findings:

- "$Wtbs\_num_i$" has significant impacts on the probability of the occurrence of preventable adverse events.
- *Practical significance:* Coefficient of $Wtbs\_num$ is 0.022, so by increasing the number of people waiting to be seen by 5, the odds ratio of the

probability of the occurrence of preventable adverse event related to ED care increases by 11%.

$$e^{0.022*5} = \frac{\frac{p_2}{1-p_2}}{\frac{p_1}{1-p_1}} = 1.11$$

However, further analysis shows the possibility of having a break point in effect of the number of patients waiting to be seen; that is before and after this threshold the effect of waiting to be seen on the occurrence of preventable adverse events is different. To address this point and estimating the threshold (denoted by T), we consider the following model:

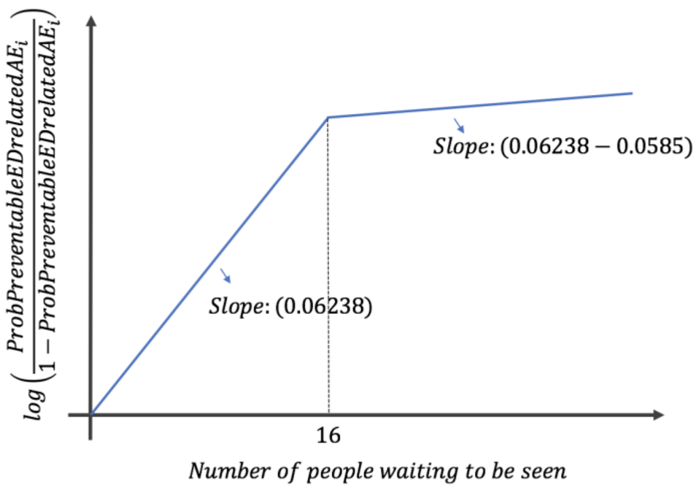
$$\begin{aligned} log\left(\frac{ProbPreventableEDrelatedAE_i}{1-ProbPreventableEDrelatedAE_i}\right) \\ &= \beta_0 + \beta_1 Wtbs\_num_i + \beta_2 (Wtbs\_num_i - T)_+ + \beta_3 Age_i \\ &+ \beta_4 TotalNumberStaff_i + ShiftBlock_i \\ &+ ChronicCondition_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i \end{aligned}$$

In the above model, β_1 is the slope of the left line segment of threshold T, and $\beta_1 + \beta_2$ is the slope of the right line segment. The threshold along with the coefficients of the above model can be estimated through an iterative approach (Muggeo 2003[1]). The results are summarized in the following. The details of the model outcomes from the final iteration of the algorithm can be found in the appendix (page 10).

- The estimated value for the break point T is 16. The estimated value for β_1 is 0.06238, which implies by increasing the number of people waiting to be seen by 5, the odds ratio of the probability of the occurrence of preventable adverse event related to ED care increases by 36.6%. This holds until the number of patients waiting to be seen reaches 16. After that point, the marginal increase in the probability of the occurrence of ED related preventable adverse events becomes so small that is shown in the following graph.

$$e^{0.06238*5} = \frac{\frac{p_2}{1-p_2}}{\frac{p_1}{1-p_1}} = 1.366$$

[1] Muggeo, V. M. (2003). Estimating regression models with unknown break-points. Statistics in medicine, 22(19), 3055-3071.



- Older patients have higher rate of preventable AE.
- The probability of the occurrence of preventable AEs is significantly higher for the patients with chronic condition compared to the others.
- The probability of having preventable AE for “the ones who left without being seen” is higher than other groups.
- Site 2 has lower and sites 3 and 4 have higher rates of preventable ED related AE compared to others.

We also used the generalized version of the mentioned iterative approach to analyze the possibility of having more than one threshold, but the best case that can be fitted to the available dataset is having one break point.

The above analysis shows the marginal effects of the number of patients waiting to be seen (WTBS) as a crowding measure on the probability of the occurrence of AEs. In the following, we discuss the tipping point for the number of people waiting to be seen after which the probability of the occurrence of AE becomes significantly different than before. To do so, different types of categorization for the number of people waiting to be seen have been analyzed, and it turned out that the probability of the occurrence of ED related preventable adverse event is significantly higher when the number of people waiting to be seen is larger than 12 compared to the cases that it is less than 12. The model considered for this analysis is as follows.

$$\begin{aligned}
log\left(\frac{ProbPreventableEDrelatedAE_i}{1-ProbPreventableEDrelatedAE_i}\right) \\
&= \beta_0 + \beta_1 CrowdedWtbs_i + \beta_2 Age_i \\
&+ \beta_3 TotalNumberStaff_i + ShiftBlock_i \\
&+ ChronicCondition_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i
\end{aligned}$$

In the above model, a categorical variable, called $CrowdedWtbs,$ is defined to indicate the crowdedness level of the shift with respect to the number of people waiting to be seen at the time of patient $i's$ registration. At the first step, the number of people wtbs is categorized to two groups with the threshold of 3, and as expected for the group with waiting to be seen higher than 3, we got significantly higher risk of having AE compared to the other group. Then 3 groups with thresholds 3 and 6 are considered and again the last group with higher than 6 people wtbs has higher risk of having AE, but there was no statistical difference between the other two groups. We keep repeating this process by adding groups of length 3 until reaching a group for which the probability of having preventable ED related AE is different than before. The results of the last step are included in the appendix (page 11). The threshold obtained above is robust to the considered length for the groups.

- Other results from this model are similar to those discussed above in the "summary of findings section".

- We have done similar analysis to the ones discussed above with considering "preventable AE" as the outcome variable instead of "preventable ED related AE" and got mostly similar results except that now, the probability of having preventable AE for "admitted patients", and "the ones who left without being seen" is higher than other groups, but when we had "preventable ED related AE" as the dependent variable, only "the patients who left without being seen" had higher risk of AE compared to others.

Shift Level Model

- **Model 2:**

Another variable that can represent how a shift is crowded is the average time that patients are waiting to be seen. To discuss how this factor affects the occurrence of preventable ED related AEs, we conduct an aggregated level analysis, in which we apply Poisson regression to predict the total number of AEs by shift.

$$
\begin{aligned}
&log\left(NumberPreventableEDrelatedAEsShift_{ijtk}\right)\\
&= \beta_0 + \beta_1 AvgWtbsTimeShift_{ijtk} + \beta_2 AvgNumberStaff_{jtk} + \beta_3 NumberLwbs_{jtk}\\
&+ \beta_4 Numberadmitted_{jtk} + \beta_5 NumberChronicCondition_{jtk} + ShiftBlock_j\\
&+ CTAS_i + Site_k + \varepsilon_{ijtk}
\end{aligned}
$$

{Note that $NumberPreventableEDrelatedAEShift_{ijtk}$ denotes the total number of preventable adverse events related to the index visit for CTAS level i, shift block j, shift date t within site k. Also, $AvgWtbsTimeShift_{ijtk}$ represents the average waiting time to be seen for the patients with CTAS level i within shift block j, shift date t and site k. $AvgNumberStaff_{jtk}$, $NumberLwbs_{jtk}$, $Numberadmitted_{jtk}$ and $NumberChronicCondition_{jtk}$ show the average number of staff, total number of patients who left without being seen, admitted or had a chronic condition within shift block j, shift date t for site k.}

The outcomes of the above model are included in the appendix (page13).

Summary of findings:

- "$AvgWtbsTimeShift$" has significant impacts on the probability of the occurrence of preventable ED related adverse event.
- *Practical significance:* Coefficient of $AvgWtbsTimeShift$ is 0.0083, so by increasing the average waiting time by 30 minutes, number of preventable ED related adverse events within that shift approximately will increase by 28%.

$$\log\left(\frac{NumberPreventableEDrelatedAEsShift_2}{NumberPreventableEDrelatedAEsShift_1}\right) = 0.0083 * 60$$

- The shifts with higher number of admitted patients and the ones with higher number of patients who have chronic condition tend to have larger number of adverse events.
- Similar analysis to the one discussed above for assigning a piece-wise linear model w.r.t. $AvgWtbsTimeShift$ has been done but the algorithm could not match any breakpoint to the available dataset, so a linear model seems to be a good fit here.

Now, similar to Model 1, we discuss the tipping point for average waiting time to be seen over the shift after which the probability of the occurrence of AE becomes significantly different than before. Conducting the same iterative approach and categorizing shifts based on their average waiting time to be seen (intervals with 25 minutes used, though the results are robust to that), it turned out when the average waiting time to be seen reaches to 150 minutes, the number of ED related preventable adverse events is significantly different compared to the cases with the average waiting time to be seen less than this threshold. The results for this model can be found in the appendix (page 14).

$$\begin{aligned}
&log\left(NumberPreventableEDrelatedAEsShift_{ijtk}\right) \\
&= \beta_0 + \beta_1 CrowdedWtbsTime_{ijtk} + \beta_2 AvgNumberStaff_{jtk} + \beta_3 NumberLwbs_{jtk} \\
&+ \beta_4 Numberadmitted_{jtk} + \beta_5 NumberChronicCondition_{jtk} + ShiftBlock_j \\
&+ CTAS_i + Site_k + \varepsilon_{ijtk}
\end{aligned}$$

- The above analysis is repeated considering the outcome variable of “preventable AE” instead of “preventable ED related AE” and we got more or less the similar results.

Section 2:

Primary Exposure Variables: **“Length of stay in ED (LOS)”**
Primary Outcome Variable: **“Preventable AE” & “Preventable AE related to ED care”**

- **Model 3:**

This model is a logistic regression model to predict the probability of having a preventable AE as a function of several available variables (Los of the patient and some other patient and system characteristics)

$$\begin{aligned}
log\left(\frac{ProbPreventableAE_i}{1 - ProbPreventableAE_i}\right) \\
&= \beta_0 + \beta_1 LOS_i + \beta_2 Age_i + ShiftBlock_i \\
&+ ChronicCondition_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i
\end{aligned}$$

{Note that $ShiftBlock_i$, $ChronicCondition_i$, $CTAS_i$, $Site_i$, $Disposition_i$ are the fixed effects considered in Model 1.}

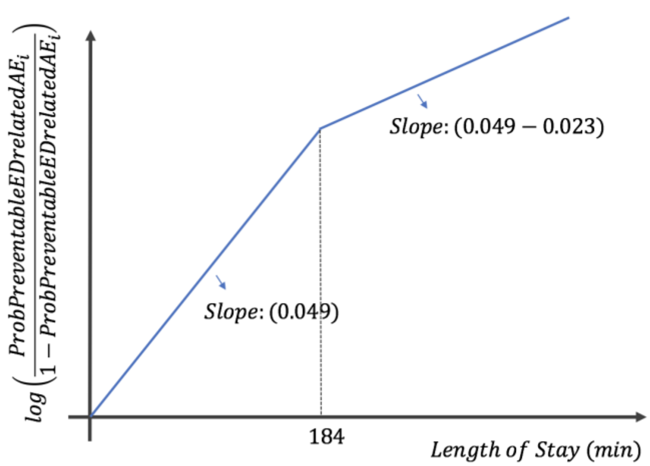
Reverse Causality: Running the above model, we see that “LOS” has significant positive effect on the occurrence of AE. However, on the other hand, patients with AE tend to have larger LOS, which implies the presence of reverse causality. To address that, one possible approach is solving simultaneous equations using 2SLS or 2 Stage Residual Inclusion Model (2SRI). To do so, we run the following model as the first stage and consider the above logit model as the second stage.

First stage:

$$
\begin{aligned}
LOS_i = \beta_0 + \beta_1 PreventableEDrelated_i + \beta_2 Age_i \\
+ \beta_3 Wtbs\_num_i + \beta_4 TotalNumberStaff_i + ShiftBlock_i + CTAS_i \\
+ Site_i + Diagnosis_i + \varepsilon_i
\end{aligned}
$$

Further analysis shows the possibility of having a break point in the effect of LOS on the probability of the occurrence of AE. So, instead of the above second stage, the following model is considered and the next figure represents the obtained results. The detailed outcome of both the first and second stage models are presented on pages 15 and 16 of the appendix.

$$
\begin{aligned}
log\left(\frac{ProbPreventableEDrelatedAE_i}{1 - ProbPreventableEDrelatedAE_i}\right) \\
= \beta_0 + \beta_1 LOS_i + \beta_2 (LOS_i - T)_+ + \beta_3 Age_i + ShiftBlock_i + CTAS_i \\
+ ChronicCondition_i + Site_i + Disposition_i + \varepsilon_i
\end{aligned}
$$



- **Model 4:**

Another approach to study the effect of LOS as a crowding measure on the occurrence of AE is having LOS of the patients with the same CTAS level within the same shift (except the patients' own LOS to avoid reverse causality) as the primary covariate.

$$log\left(\frac{ProbPreventableEDrelatedAE_i}{1 - ProbPreventableEDrelatedAE_i}\right) = \beta_0 + \beta_1 AvgLOS_i + \beta_2 Age_i + ShiftBlock_i + ChronicCondition_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i$$

So, $AvgLOS_i$ denotes the average LOS of other patients presented at the same shift in ED with the same CTAS level as patient i. The results of the above model can be found in the appendix (page 17).

Section 3:

Primary Exposure Variables: **"Number of people waiting to be seen"**
Primary Outcome Variable: **"Probability of leaving ED without being seen (Lwbs)"**

Model 5:

As mentioned in the results of the previous models, one of the important factors that have high association with the probability of the occurrence of AE is the case that a patient leaves ED without being seen. So, it would be interesting to analyze the probability of leaving ED without being seen with respect to some other factors and discuss the relation of crowdedness with the probability of leaving without being seen. Thus, the following model is considered and the outcome of that is presented on page 19 of the appendix. Analyzing the tipping point for the number of people waiting in the waiting area that increases the probability of leaving without being seen can be also interesting.

$$log\left(\frac{Lwbs_i}{1 - Lwbs}\right) = \beta_0 + \beta_1 Wtbs\_num_i + \beta_2 Age_i + ShiftBlock_i + Site_i + \varepsilon_i$$

- **General Question:**

Is there any policy or resource changes in any parts of the hospital for any sites during the data collection period? (it can be helpful in addressing the endogeneity issues)

Appendix: (Model 1)

Model 1

	Dependent variable: preventable_EDrelatedAE
Wtbs_num	0.022004**
TotalNumberStaff	0.001891
Age	0.043447**
as.factor(shift_block)1	0.280313
as.factor(shift_block)2	0.367324
as.factor(ctas)2	-0.215505
as.factor(ctas)3	-0.571171
as.factor(ctas)4	-0.561816
as.factor(ctas)5	-0.442954
as.factor(site)1	0.293901
as.factor(site)2	-0.739561*
as.factor(site)3	0.777994**
as.factor(site)4	0.966048***
as.factor(site)5	0.051598
as.factor(site)6	0.080695
as.factor(site)7	0.287995
as.factor(site)8	0.615966
as.factor(pt_disposition)1	0.195616
as.factor(pt_disposition)2	0.834935*
as.factor(pt_disposition)3	-13.314560
as.factor(pt_disposition)4	-14.220870
as.factor(pt_disposition)6	-13.903870
as.factor(pt_disposition)7	-13.987680

as.factor(pt_disposition)8	-14.005560
as.factor(pt_disposition)9	-13.704570
as.factor(pt_disposition)10	-13.542810
as.factor(pt_disposition)11	-13.834510
as.factor(chronic_condition)1	0.462026**
Observations	6,183
Log Likelihood	-608.212200
Akaike Inf. Crit.	1,274.424000
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 1 (Considering the Break Point)

	Dependent variable:
	preventable_EDrelatedAE
Wtbs_num	0.062888**
$(\text{Wtbs\_num}-T)_{+}$	-0.058577*
TotalNumberStaff	-0.005093
Age	0.043786***
as.factor(shift_block)1	0.166263
as.factor(shift_block)2	0.379666
as.factor(site)1	0.325382
as.factor(site)2	-0.728985*
as.factor(site)3	0.938292**
as.factor(site)4	1.007875***
as.factor(site)5	0.105147
as.factor(site)6	0.087547
as.factor(site)7	0.308031
as.factor(site)8	0.584635

as.factor(ctas)2	-0.184277
as.factor(ctas)3	-0.526602
as.factor(ctas)4	-0.529972
as.factor(ctas)5	-0.391162
as.factor(pt_disposition)1	0.172431
as.factor(pt_disposition)2	0.823641*
as.factor(pt_disposition)3	-13.292450
as.factor(pt_disposition)4	-14.188320
as.factor(pt_disposition)6	-13.824080
as.factor(pt_disposition)7	-13.907300
as.factor(pt_disposition)8	-13.819660
as.factor(pt_disposition)9	-13.617750
as.factor(pt_disposition)10	-13.608590
as.factor(pt_disposition)11	-13.737260
as.factor(chronic_condition)1	0.474262**
Observations	6,183
Log Likelihood	-606.396300
Akaike Inf. Crit.	1,274.793000
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 1 (Analyzing the Tipping Point)

	Dependent variable: preventable_EDrelatedAE
as.factor(CrowdedWtbs)1	0.041389
as.factor(CrowdedWtbs)2	-0.372895
as.factor(CrowdedWtbs)3	-0.144033
as.factor(CrowdedWtbs)4	0.635877*

as.factor(CrowdedWtbs)5	0.580533*
Age	0.045227***
TotalNumberStaff	0.002303
as.factor(chronic_condition)1	0.420294**
as.factor(shift_block)1	0.234383
as.factor(shift_block)2	0.331995
as.factor(site)1	0.412051
as.factor(site)2	-0.741149*
as.factor(site)3	0.800182**
as.factor(site)4	1.036787***
as.factor(site)5	0.086958
as.factor(site)6	0.145053
as.factor(site)7	0.331910
as.factor(site)8	0.614314
as.factor(ctas)2	-0.130107
as.factor(ctas)3	-0.402111
as.factor(ctas)4	-0.506169
as.factor(ctas)5	-0.358797
as.factor(pt_disposition)1	0.156821
as.factor(pt_disposition)2	0.814916*
as.factor(pt_disposition)3	-13.407140
as.factor(pt_disposition)4	-14.230580
as.factor(pt_disposition)6	-13.826890
as.factor(pt_disposition)7	-13.879040
as.factor(pt_disposition)8	-13.890900
as.factor(pt_disposition)9	-13.711370
as.factor(pt_disposition)10	-13.533430
as.factor(pt_disposition)11	-13.715870

Observations	6,343
Log Likelihood	-623.435000
Akaike Inf. Crit.	1,312.870000
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 2:

Model 2

	Dependent variable:
	num_preventable_ae_ed_shift
AvgWtbsTimeShift	0.008300***
AvgNumberStaff	0.041334
NumberLwbs	-0.055832
NumberAdmitted	0.093507*
NumberChronicCondition	0.062567**
as.factor(site)1	0.129532
as.factor(site)2	-1.036758**
as.factor(site)3	0.729766*
as.factor(site)4	0.855695**
as.factor(site)5	-0.101674
as.factor(site)6	-0.231636
as.factor(site)7	0.021016
as.factor(site)8	0.140465
as.factor(shift_block)1	0.903030
as.factor(shift_block)2	0.194545
as.factor(ctas)2	1.481144
as.factor(ctas)3	2.189726**
as.factor(ctas)4	2.137855**
as.factor(ctas)5	0.272337

Observations	685
Log Likelihood	-313.905800
Akaike Inf. Crit.	667.811600
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 2 (Analyzing the Tipping Point)

	Dependent variable: num_preventable_ae_ed_shift
as.factor(CrowdedWtbsTime)1	-0.345141
as.factor(CrowdedWtbsTime)2	0.093519
as.factor(CrowdedWtbsTime)3	0.728281
as.factor(CrowdedWtbsTime)4	0.463184
as.factor(CrowdedWtbsTime)5	0.739525
as.factor(CrowdedWtbsTime)6	1.033125*
as.factor(CrowdedWtbsTime)7	1.202156**
AvgNumberStaff	0.037045
NumberLwbs	-0.006387
NumberAdmitted	0.141199***
as.factor(site)1	-0.007722
as.factor(site)2	-0.546454
as.factor(site)3	0.915198**
as.factor(site)4	0.887798**
as.factor(site)5	0.163758
as.factor(site)6	-0.053957
as.factor(site)7	0.125570
as.factor(site)8	0.202987
as.factor(shift_block)1	0.717951

as.factor(shift_block)2	-0.213820
as.factor(ctas)2	1.394206
as.factor(ctas)3	2.102211**
as.factor(ctas)4	2.048618**
as.factor(ctas)5	0.199502
Observations	686
Log Likelihood	-313.920300
Akaike Inf. Crit.	677.840500
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 3:

Model 3 (First Stage)

	Dependent variable: los
PreventableEDrelated	47.718110***
Age	2.147763***
Wtbs_num	3.949844***
TotalNumberStaff	-1.143826**
as.factor(shift_block)1	-31.013930***
as.factor(shift_block)2	11.025710
as.factor(ctas)2	-80.926500***
as.factor(ctas)3	-140.129400***
as.factor(ctas)4	-185.072900***
as.factor(ctas)5	-202.580300***
as.factor(site)1	31.322480***
as.factor(site)2	11.584110*
as.factor(site)3	-34.086890***
as.factor(site)4	6.408838

as.factor(site)5	-8.470699
as.factor(site)6	37.559750***
as.factor(site)7	48.662430***
as.factor(site)8	41.047740***
as.factor(diagnosis)2	122.702700***
as.factor(diagnosis)3	12.841220***
as.factor(diagnosis)4	87.189310***
as.factor(diagnosis)5	-8.824083
as.factor(diagnosis)6	-114.415400***
as.factor(diagnosis)7	-4.365507
Observations	6,064
R2	0.181475
Adjusted R2	0.178222
Residual Std. Error	138.536000
F Statistic	55.787830***
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 3 (Second Stage Considering the Break Point)

	Dependent variable: PreventableEDrelated
LOS	0.048963***
$(LOS-T)_+$	-0.022809***
Age	0.046110**
as.factor(chronic_condition)1	0.403682*
as.factor(shift_block)1	0.278315
as.factor(shift_block)2	0.025733
as.factor(site)1	0.439605
as.factor(site)2	-1.424063***
as.factor(site)3	3.870359***
as.factor(site)4	1.827996***

as.factor(site)5	-0.485748
as.factor(site)6	-1.657599***
as.factor(site)7	-0.179287
as.factor(site)8	-0.165818
as.factor(ctas)2	1.447324
as.factor(ctas)3	2.939363**
as.factor(ctas)4	4.646093***
as.factor(ctas)5	5.642864***
as.factor(pt_disposition)1	-0.536212
as.factor(pt_disposition)2	4.166599***
as.factor(pt_disposition)3	-13.619400
as.factor(pt_disposition)4	-13.746660
as.factor(pt_disposition)6	-13.754910
as.factor(pt_disposition)7	-13.058610
as.factor(pt_disposition)8	-12.821150
as.factor(pt_disposition)9	-13.192230
as.factor(pt_disposition)10	-14.534000
as.factor(pt_disposition)11	-11.722580
Observations	6,053
Log Likelihood	-490.041100
Akaike Inf. Crit.	1,040.082000
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 4:

Model 4

	Dependent variable:
	preventable_EDrelated

AvgLOS	0.002201**
Age	0.045993***
as.factor(chronic_condition)1	0.419320**
as.factor(ctas)2	14.128900
as.factor(ctas)3	13.917180
as.factor(ctas)4	13.969220
as.factor(ctas)5	14.048610
as.factor(site)1	0.111267
as.factor(site)2	-0.733318*
as.factor(site)3	0.692892*
as.factor(site)4	0.752076**
as.factor(site)5	0.060592
as.factor(site)6	0.026149
as.factor(site)7	0.107754
as.factor(site)8	0.464008
as.factor(shift_block)1	0.334465*
as.factor(shift_block)2	0.263905
as.factor(pt_disposition)1	0.153660
as.factor(pt_disposition)2	0.891043**
as.factor(pt_disposition)3	-13.281390
as.factor(pt_disposition)4	-13.797240
as.factor(pt_disposition)6	-13.922430
as.factor(pt_disposition)7	-14.122090
as.factor(pt_disposition)8	-14.327690
as.factor(pt_disposition)9	-13.668610
as.factor(pt_disposition)10	-13.601080
as.factor(pt_disposition)11	-13.585540
Observations	6,170
Log Likelihood	-605.456700

Akaike Inf. Crit.	1,266.913000
Note:	*p<0.1; **p<0.05; ***p<0.01

Model 5:

Model 5

	Dependent variable: lwbs
Wtbs_num	0.078867***
Age	-0.082838***
as.factor(shift_block)1	0.575982**
as.factor(shift_block)2	1.359302***
as.factor(ctas)2	9.678704
as.factor(ctas)3	12.271470
as.factor(ctas)4	13.218150
as.factor(ctas)5	13.856090
as.factor(site)1	2.436881***
as.factor(site)2	0.553967
as.factor(site)3	0.921995
as.factor(site)4	1.703859***
as.factor(site)5	0.730476
as.factor(site)6	0.917433**
as.factor(site)7	2.189838***
as.factor(site)8	1.632939***
Observations	6,194
Log Likelihood	-519.883100
Akaike Inf. Crit.	1,073.766000
Note:	*p<0.1; **p<0.05; ***p<0.01