January 2014

Modeling The Count Data Of Emergency Department Use Among The Chronically Homeless Adults

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MODELING OVERDISPERSED COUNT DATA OF EMERGENCY DEPARTMENT USE AMONG THE CHRONICALLY HOMELESS ADULTS

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Master of Public Health, Yale University

A thesis submitted to the

Faculty of School of Public Health, Yale University

In fulfillment of the requirement for the degree of

Master of Public Health

2014

ACKNOWLEDGEMENTS

I wish to acknowledge Dr. Haiqun Lin and Dr. Robert Rosenheck who supervised and guided this thesis.

I am very grateful for the level of cooperation and assistance provided by virtually every person whom I consulted. Especially I must acknowledge Dr. David Moore and Dr. Forrest Crawford, for their advice and assistance.

Finally, my special thanks are extended to the staff and students at Yale School of Public Health for their company and help along the way.

ABSTRACT

This study explored Emergency department (ED) use among the chronically homeless people based on the data from the federal Collaborative Initiative on Chronic Homelessness (CICH) program. The Behavioral Model for Vulnerable Populations (Gelberg L et al. 2000) was applied to identify and classify factors potentially associated with ED use.

Baseline ED use was modeled on 754 chronically homeless subjects, either later entered the CICH program (n=642) or received local usual care (n=112), in 11 communities. ED use was measured as the number of ED visits during 90 days prior to the interview. At baseline level, medical problems, mental health/substance use problems, substance abuse outpatient service use, alcohol addiction, proportion of time get insured, length of homelessness and overall quality of life are significantly correlated with frequency of ED visit.

Longitudinal ED use was modeled on CICH clients (n=252) receiving comprehensive housing and healthcare services and those receiving local usual care (n=102) in the matched 5 communities. The CICH program was not found to significantly change ED visits. Baseline ED visit is a strong predictor; medical, mental health and substance abuse problems, substance abuse outpatient service use and quality of life are also significantly correlated with the outcome.

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INTRODUCTION

1.1 Problem, Motivations and Literature Review

The Emergency Department (ED) use continues to soar nationally, which is one of the contributors to the rising health care expenditures in the U.S. However it's believed that many of the ED visits can be prevented with timely access to primary care. It has been suggested that at least one-third of all ED visits are avoidable, and over 18 billion dollars are wasted annually for such avoidable ED use [1].

Rather than being equally distributed across the population, approximately 5% of patients are responsible for a quarter of all ED visits [2]. It has been shown that the homeless people have substantially higher rates of ED and hospital use than general population controls [3]. Factors such of severity of sickness, with multiple medical problems, and mental health conditions seem to contribute to frequent ED use among the homeless people [4-6]. It is estimated that over 2 million people in the U.S. experience homelessness in a given year, among which 10% are estimated as chronically homeless [7], defined as "an unaccompanied homeless individual with a disabling condition who has either been continuously homeless for at least 1 year or has had at least 4 episodes of homelessness in the past 3 years". The prevalence of mental health problems, substance abuse problems, and chronic medical problems are substantially high among the general homeless population [8-14].

In this study, we utilized the data from the Federal Collaborative Initiative on Chronic Homeless (CICH) program. The CICH program, developed by members of the Federal Interagency Council, is aimed to eliminate chronic homelessness. 11 communities received funds to provide comprehensive services including permanent supported housing and supportive primary healthcare and mental health services to the chronically homeless people. The subjects were measured every 3 months in terms of housing, income, medical/mental health/substance abuse conditions, medical services use, etc., and their ED visits.

Potential predictors were selected based on Gelberg et al recently published Behavioral Model for Vulnerable Populations [15, 16]. The original Behavioral Model suggests that health-seeking behavior is driven by factors from three aspects: predisposing factors (i.e. personal characteristics, such as demographic and social structure variables), enabling factors (i.e. resources, such as income, insurance and access to health care services) and need factors (i.e. health problems). Gelberg et al extended this framework by adding vulnerable factors especially relevant to the vulnerable populations. In this study the vulnerable factors are length of homelessness, alcohol and drug addictions etc.

In this study we modeled ED visits in both of the baseline data before CICH program get started and the follow-up data where the CICH program is a treatment and local usual care serves as a control. The purpose is not only to compare the CICH program and local usual care in their ability to control ED visits, but also to explore the risk factors proposed by the Behavioral Model for Vulnerable Populations.

1.2 Exploratory Analysis of the CICH Data

The original CICH data utilized in this study include 868 chronically homeless subjects with follow-ups up to 2 years in 11 sites including Chattanooga, TN; Chicago, IL; Columbus, OH; Denver, CO; Ft. Lauderdale, FL; Los Angeles, CA; Martinez, CA; New York, NY; Philadelphia, PA; Portland, OR; and, San Francisco, CA.

The outcome, ED use, was measured as the number of ED visits during 90 days prior to the interview. Most predictors were classified into 4 categories: predisposing factors including gender, age group and race group; enabling factors including site, income and proportion of time insured; need factors including physical and mental health problems, substance abuse disorders; and vulnerable factors including length of homelessness, addition to alcohol and addition to drugs. Different types of outpatient medical service use also were predictors.

The data set was split into two parts for different analysis: a baseline data set and a longitudinal data set. The baseline data from 754 subjects in 11 sites acted as a cross-sectional data to look at factors associated with high rates of ED use. The follow up data analysis was focused on 5 sites that have both the CICH group and local usual care control group (Chattanooga, TN; Los Angeles, CA; Martinez, CA; New York, NY; and, Portland, OR), where we want to identify whether the CICH program actually works to eliminate ED visits, also to confirm what we find in the baseline analysis.

	Baseline (11 sites)		Follow-Up (5 sites)	
ED visits/90dys				
0	425	56.59%	252	71.35%
1	155	20.64%	52	14.75%
>=2	171	22.77%	49	13.90%
Gender/Male	590	78.25%	280	79.06%
Female	164	21.75%	74	20.94%
Age/ <50	495	65.65%	229	64.74%
>50	259	34.35%	125	35.26%
Race/ Minority	472	62.60%	208	58.76%
Caucasian	282	37.40%	146	41.24%
Jail yrs/ 0	213	28.25%	79	22.32%
0~1	268	35.54%	132	37.29%
>1	273	36.21%	143	40.39%
Psych prob / mental health only	183	24.27%	79	22.32%
Substance abuse only	182	24.14%	105	29.66%
Dual prob	389	51.59%	170	48.02%

Table 1. Basic features of the subjects in baseline analysis and in follow-up analysis.

Among the baseline subjects, 56.91% have no ED visit during the past 90days prior to the baseline interview. While among the follow-up subjects, on average 70.8% have no ED visit during the 90 days prior to each follow-up interview.

Most of the subjects are males, have been in jail, and all of the subjects have mental health or substance abuse problems, or both.

Baseline Follow-ups

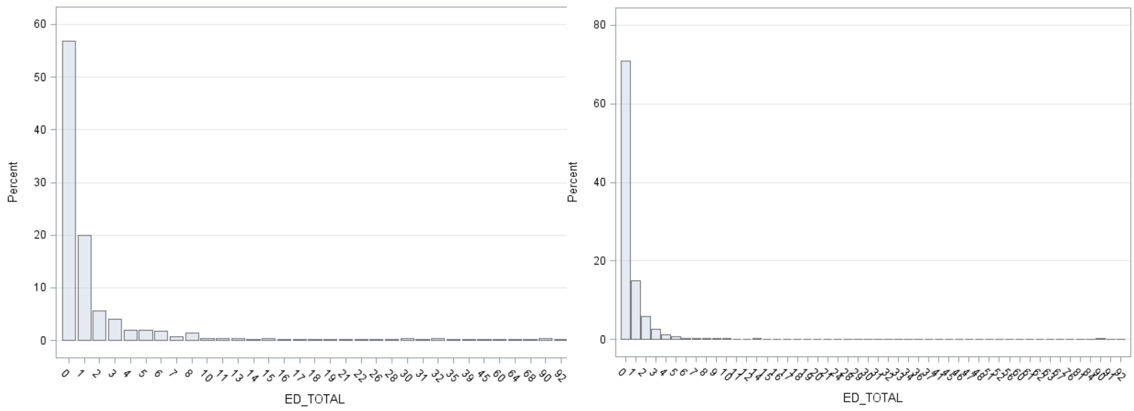


Figure 1. Distribution of ED visits within 90 days, at baseline follow-up levels

From the figure above, ED visits have a very skewed distribution with a big portion of zeros and a long right side tail. The subjects seem to have less ED visits in the follow-up period compared with that at baseline level.

Male Female

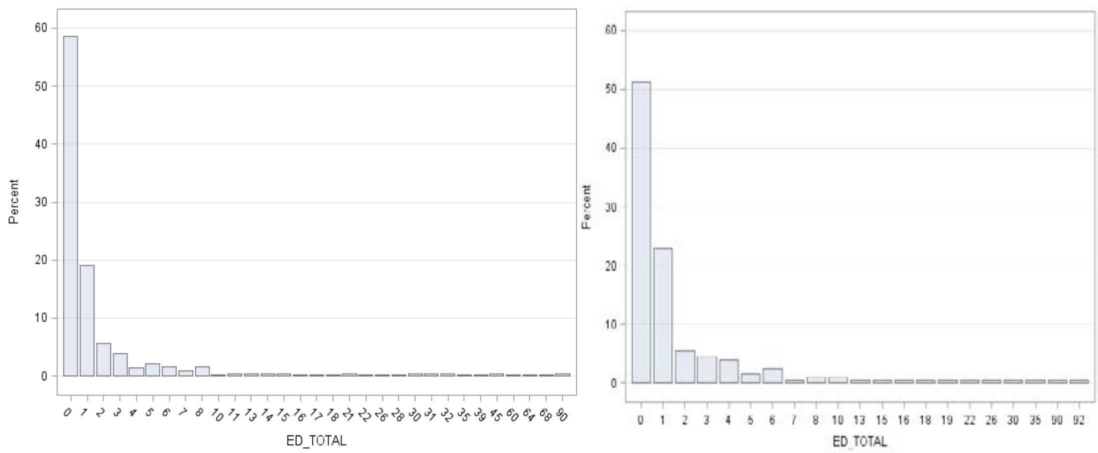


Figure 2. Distribution of ED visits in males and females

Certain males have very frequent ED visits, i.e. the ED visit distribution has a heavier right side tail in males compared with females.

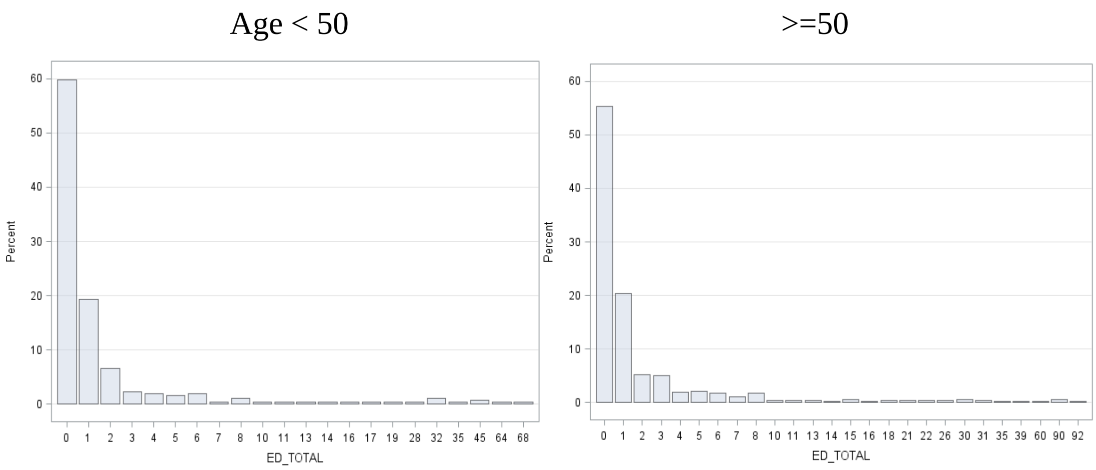


Figure 3. Distribution of ED visits in age<50 and age>=50 groups

Subjects under 50 have higher proportion of 0 ED visits during the last 90 days.

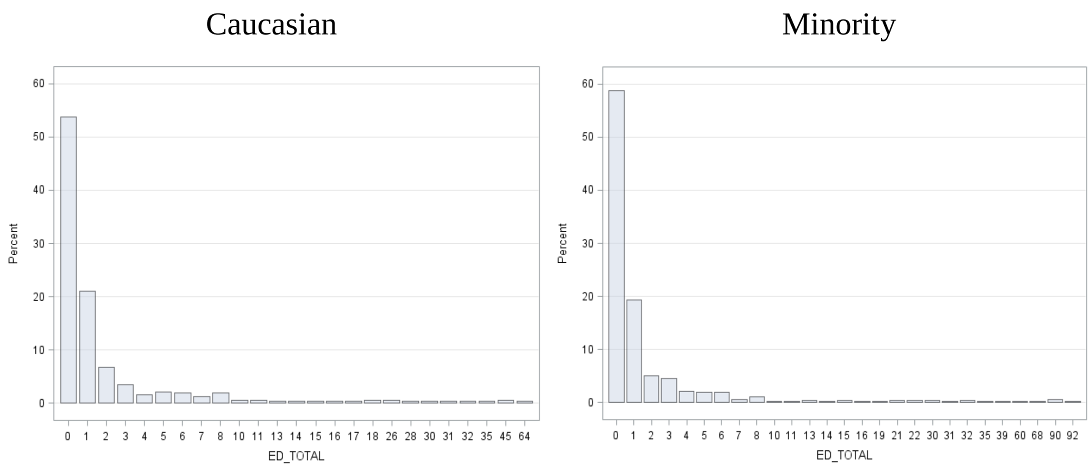
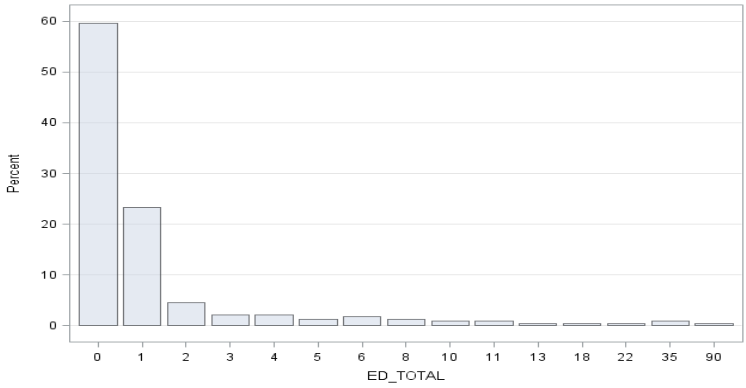
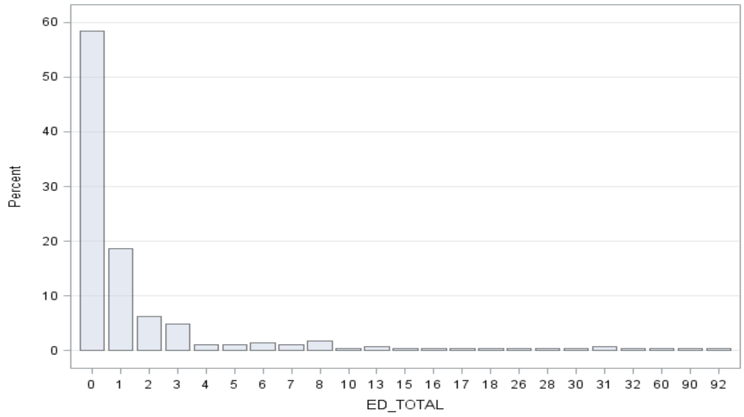


Figure 4. Distribution of ED visits in Caucasians and minorities

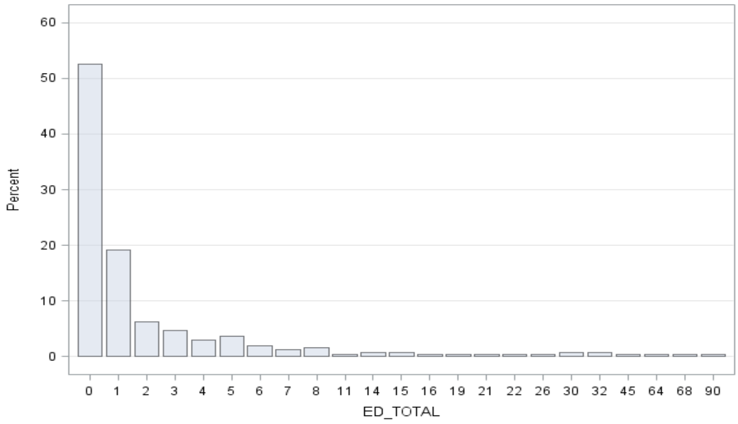
Minorities have a heavier right side tail than Caucasians, since from the figure above minorities tend to have more frequent ED visits.



Lifetime years in jail = 0



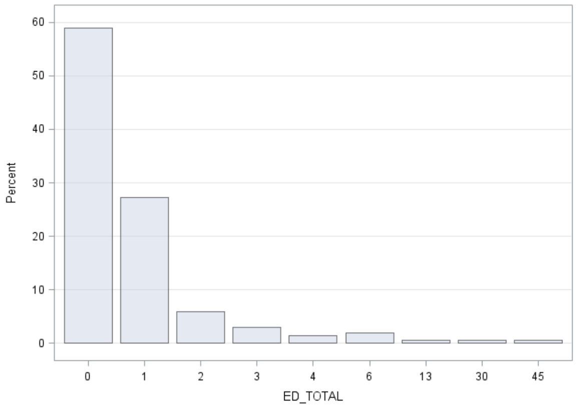
Lifetime years in jail 0~1



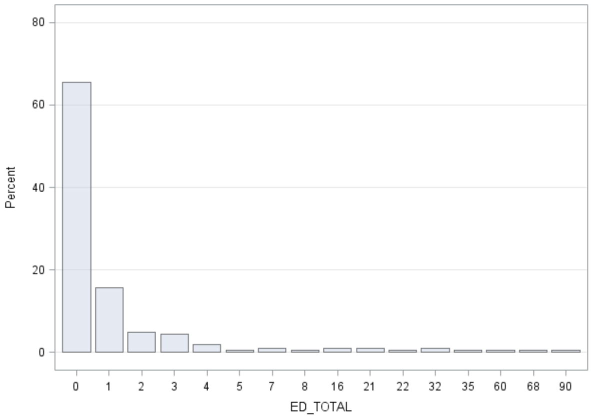
Lifetime years in jail > 1

Figure 5. Distribution of ED visits in different “lifetime years in jail” groups

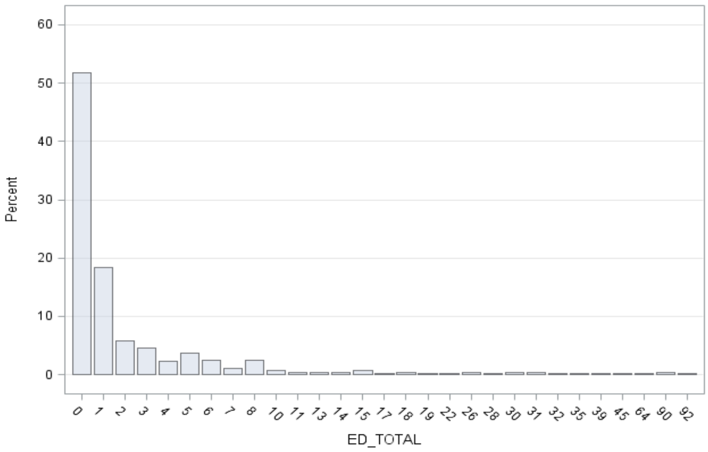
Certainly subjects who have never been in jail have fewer ED visits.



With mental health problem only



With substance abuse problem only



With dual mh/sa problems

Figure 6. Distribution of ED visits in different psych problem groups

Certainly subjects with dual mental health and substance abuse problems have more ED visits.

The skewed ED visits distribution suggests that we should apply a generalized linear model with distributions like Poisson and negative binomial. The big proportion of zeros suggests that we may need to apply a zero-inflated model.

CHAPTER II

MODEL FITTING

2.1 Poisson, Negative Binomial and Generated Poisson Models for Baseline Data

The baseline data recruited in analysis have 754 subjects from 11 sites. After checking bivariate correlation and multicollinearily by variation inflation factor (VIF) among the predicting variables, we fitted several models with those “safe” (VIF < 2.5 and bivariate correlation < 0.4) variables.

The predicting variables include site, gender, race group, age group, lifetime years in jail (0, 0-1, >1), psych groups, days of homelessness, income, proportion of time insured, # of medical problems, # of mental health and substance abuse diagnosis, medical/mental health/substance abuse outpatient visits, quality of life, alcohol and drug addiction severity index (ASI).

2.1.1 Poisson and Negative Binomial Models

Poisson regression is a popular method to model a count outcome. It assumes that the response variable has a Poisson distribution, and that the logarithm of its expected value can be modeled by a linear combination of other variables.

$$\mathrm{E}(\mathrm{Y}|\mathrm{x}) = e^{\theta' x} = \lambda$$

The probability mass function of Poisson distribution if given by

$$\mathrm{p}(\mathrm{y}|\mathrm{x};\theta) = \frac{[E(Y|x)]^{y} \times e^{-E(Y|x)}}{y!} = \frac{e^{y\theta' x} e^{-e^{\theta' x}}}{y!}$$

One drawback of Poisson regression is that the outcome variable should have a variance equal to its expectation, i.e. $\mathrm{E}(\mathrm{Y}|\mathrm{x}) = \mathrm{Var}(\mathrm{Y}|\mathrm{x})$, which is not always the case. Negative binomial regression allows more flexibility since it does not require equal mean and variance.

$$E(Y) = \mu, \quad Var(Y) = \mu + \frac{\mu^2}{k}$$

Again, logarithm of the expected value is modeled by a linear combination of predicting variables. The probability mass function is given by

$$p(y|x) = \frac{\Gamma(y+k)}{\Gamma(k)\Gamma(y+1)} \left(\frac{k}{k+\mu}\right)^k \left(\frac{\mu}{k+\mu}\right)^y$$

The Poisson model (AIC=6489) and negative binomial model (AIC=2486) both have the problem of overdispersion (Deviance=7.6 and 0.86 respectively, Scaled Pearson Chi-Square=16.3 and 1.75 respectively). Overdispersion suggests a zero-inflated model or other models such as mixed Poisson that allow more dispersion of the data.

2.1.2 Zero-Inflated Poisson and Zero-Inflated Negative Binomial Models

The zero-inflated models employ two components that correspond to two zero generating processes. The first process is governed by a binary distribution that generates structural zeros by a probability of π. The second process is governed by another distribution (e.g. Poisson) that generates counts, some of which may be zero. Taking zero-inflated Poisson as an example,

$$Pr(Y_i = 0) = \pi + (1-\pi)e^{-\lambda}$$

$$Pr(Y_i = y_i) = (1-\pi)\frac{\exp(-\lambda)\lambda^{y_i}}{y_i\,!}, \; i = 1,2,\ldots,n$$

The covariates are incorporated by a log link for λ, and a logit link for π.

$$\log(\mu_i) = x_i{}^T\beta$$

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = Z_i{}^T\gamma$$

The zero-inflated Poisson (ZIP) model (AIC=4707.3) gives a scaled Pearson chi-square of 3.29. Overdispersion is still a problem, and thus inferences based on these estimates are suspect; the standard errors are likely to be biased downwards.

We may also want to compare the observed relative frequencies of ED visits to the maximum likelihood estimates of their respective probabilities from the ZIP model.

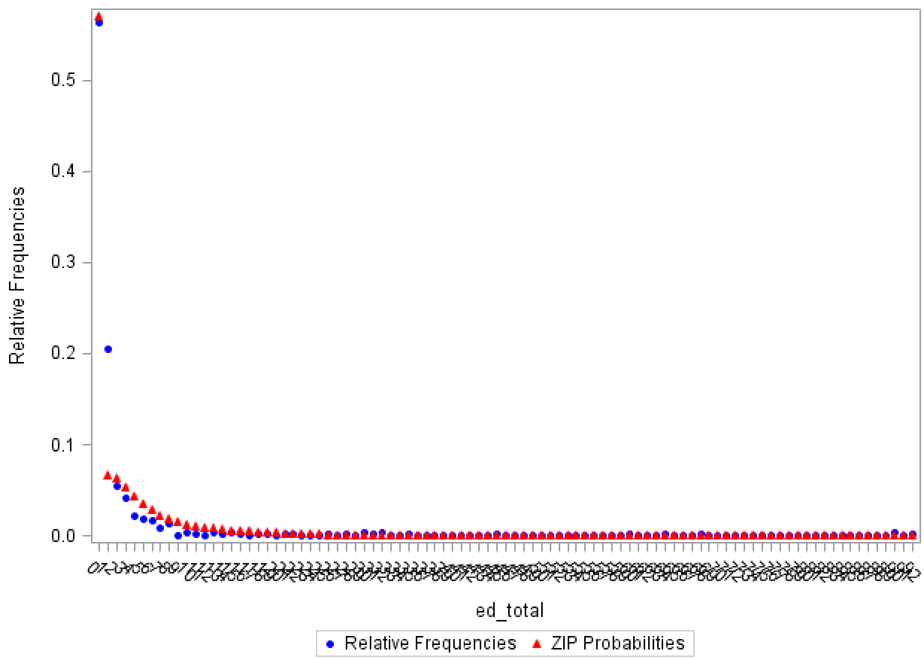


Figure 7. Comparison of ZIP Probabilities to Observed Relative Frequencies

ZIP model accounts for the excess zeros very well and the ZIP distribution reasonably captures the shape of the distribution of the relative frequencies. However since the ZIP model still suffers from dispersion, zero-inflated negative binomial (ZINB) model might fit this data better since it provides a more flexible estimator for the variance of the response variable.

The ZINB model typically handles the problem of excess zeros and overdispersion better than ZIP models. Here a zero-inflated negative binomial model (AIC=2470.5) gives a scaled Pearson Chi-Sqaure of 1.52.

	ZIP	ZINB
Scaled Pearson X^2	3.2882	1.523
Full Log Likelihood	-2322.674	-1203.260
AIC	4707.348	2470.520
BIC	4850.612	2618.405

Table 2. Comparison of ZIP and ZINB Model Fit Criteria

All of the criteria shown above favor ZINB over the ZIP model.

The negative binomial dispersion parameter has an estimated value of 2.933, and the Wald 95% confidence interval (2.397, 3.589) shows that the estimate is significantly different from 0, indicating ZINB is more appropriate than ZIP for this data. We might also want to check the predicted frequencies.

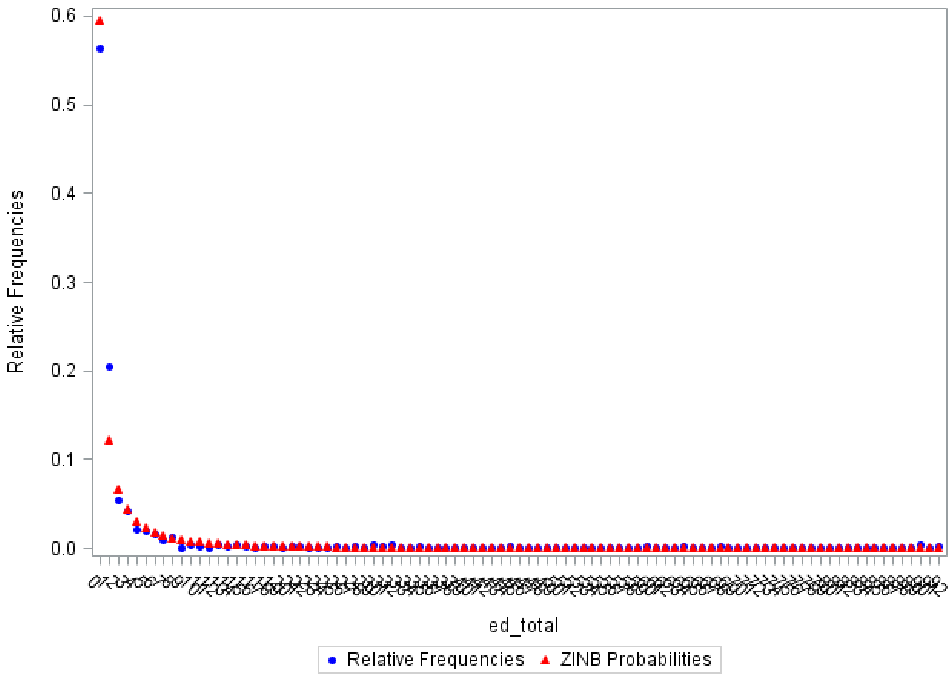


Figure 8. Comparison of ZINB Probabilities to Observed Relative Frequencies

ZINB model also accounts for the excess zeros very well and reasonably captures the shape of the distribution of the relative frequencies.

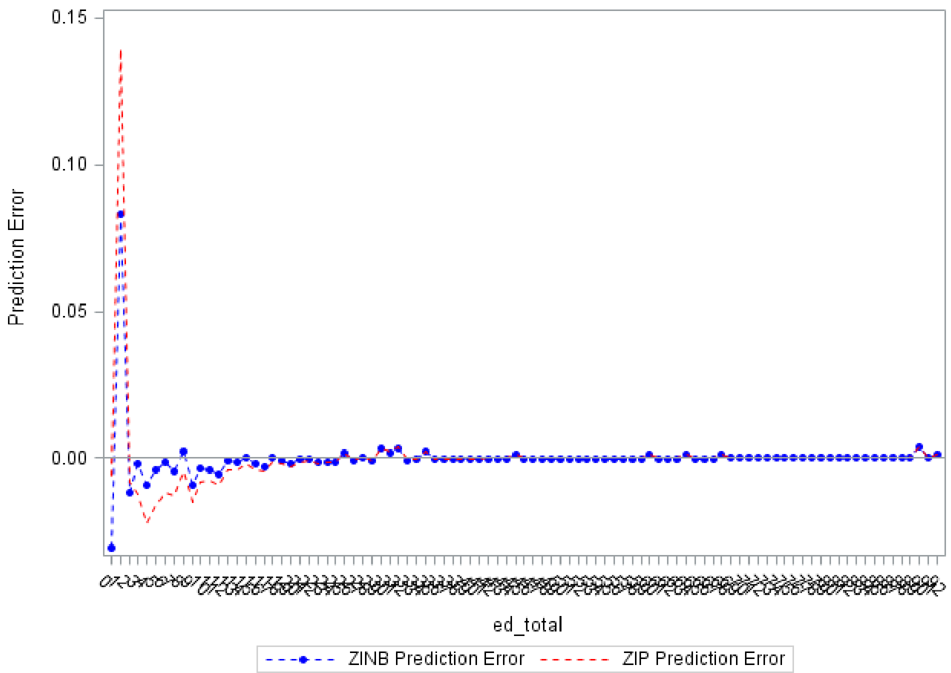


Figure 9. Comparative Fit of ZIP and ZINB Model

The cumulative evidence suggests that the ZINB model provides an adequate fit to the data and it is superior to the ZIP model. However both of them have not captured some rare but very large observations on the right side tail.

Standardized Coefficient Estimate for the Negative Binomial Part			
Variable		Estimate	P value
Intercept		1.0342	0.0177 *
Site	CHA	-0.5248	0.1995
(Ref: SAF)	CHI	0.2795	0.5101
	COL	0.3789	0.3645
	DEN	-0.7177	0.0574
	FTL	-0.6138	0.1666
	LOS	-1.1352	0.0070 *
	MAR	0.4612	0.2069
	NYC	1.0395	0.0269 *

	PHI	-0.1398	0.7334
	POR	0.9404	0.0062 *
Gender	Male (Female)	-0.1498	0.4906
Race	Caucasian (Minority)	-0.1313	0.5124
Lifetime yrs in jail (Ref: >1)	0	-0.3335	0.1342
	0~1	-0.2192	0.2543
Psych problem (Ref: Substance abuse only)	Mental health only	-0.6432	0.0435 *
	Mental health and substance abuse	0.0760	0.7872
Proportion insured		0.3538	0.0008 **
Days homeless		-0.4191	<0.0001 ***
Total income (30 dys)		-0.3458	0.0028 **
# of medical problems		0.2218	0.016 *
# of mental health/substance abuse problems		0.0540	0.6119
Medical outpatient visit		0.1481	0.068
Mental health outpatient visit		0.0261	0.7671
Substance abuse outpatient visit		-0.2359	0.0077 *
Quality of life		0.1966	0.0304 *
Alcohol Addiction Severity Index		0.1794	0.0232 *
Drug Addiction Severity Index		-0.0467	0.5630
Standardized Coefficient Estimate for The Zero Inflation Part			
Intercept		-3.6059	0.0055
# of medical problems		-2.3195	0.0326 *
# of mental health/substance abuse problems		-1.2271	0.0069 *

Table 3. Standardized coefficient estimate in ZINB model

In the ZINB model, variables significantly correlated with the response are: sites, psychological problem group, proportion of time insured, days of homelessness, total income, number of medical problems, substance abuse outpatient visit, quality of life and addiction to alcohol.

For the zero inflation part, coefficients of both number of medical problems and number of mental health/substance abuse problems are negative and significant. If a subject were to increase his/her number of medical problems by one standard deviation (SD = 3.19), the odds that his/her number of ED visits would be a "certain zero" would decrease by a factor of exp(-2.32) = 0.098. In other words, the more medical problems one has, the less likely his/her number of ED visits is a certain zero.

2.1.3 Generalized Poisson Model

Generalized Poisson (GP) model can also handle a big portion of zeros, at the same time dealing with a relatively long right side tail, since it is heavier in the tails then the negative binomial distribution.

The probability mass function of GP is given by

$$\mathrm{p}(\mathrm{y}) = \frac{\lambda}{y!}\,(\lambda + \varepsilon \mathrm{y})^{y-1} \exp\{-\lambda - \varepsilon \mathrm{y}\} \text{ where } 0 \leq \varepsilon < 1$$

For $\varepsilon = 0$, it resembles the probability mass function of standard Poisson distribution. The mean and variance of Y are given by

$$\mathrm{E(Y)} = \frac{\lambda}{1-\varepsilon} \qquad \mathrm{Var(Y)} = \frac{\lambda}{(1-\varepsilon)^3}$$

Fitting the data with a GP model gives an AIC of 2443.15.

	GP	ZINB
Full Log Likelihood	-1192.58	-1203.260
AIC	2443.15	2470.520
BIC	2577.17	2618.405

Table 4. Comparison of GP and ZINB Model Fit Criteria

The GP model fits better than ZINB in all criteria shown above. Nevertheless the majority of the coefficients in the GP model are similar to those in the ZINB model.

Standardized Coefficient Estimate in the GP model			
Variable		Estimate	P value
Intercept		0.9384	0.0009 **
Site	CHA	-0.3658	0.1428
(Ref: SAF)	CHI	-0.1999	0.4836
	COL	-0.4787	0.0853
	DEN	-0.5728	0.0219 *
	FTL	-0.6709	0.0255 *
	LOS	-1.0812	0.0003 ***
	MAR	-0.0998	0.6594
	NYC	-0.6285	0.0346 *
	PHI	-0.3545	0.1575
	POR	0.2853	0.2018
Gender	Male (Female)	-0.07485	0.5715
Race	Caucasian (Minority)	-0.03324	0.7825
Lifetime yrs in jail	0	0.03050	0.8387
(Ref: >1)	0~1	-0.1785	0.1710
Psych problem	Mental health only	0.2688	0.1943

(Ref: Substance abuse only)	Mental health and substance abuse	0.4355	0.0151 *
Proportion insured		0.1933	0.0038 **
Days homeless		-0.00903	0.8791
Total income (30 dys)		-0.1463	0.0492 *
# of medical problems		0.1985	0.0002 ***
# of mental health/substance abuse problems		0.1087	0.1156
Medical outpatient visit		0.08769	0.0448 *
Mental health outpatient visit		0.03103	0.5516
Substance abuse outpatient visit		-0.05033	0.3966
Quality of life		0.0967	0.0949
Alcohol Addiction Severity Index		0.1876	0.0001 *
Drug Addiction Severity Index		0.0655	0.2514

Table 5. Standardized coefficient estimate in the GP model

In the GP model, variables significantly correlated with the response are: sites, psychological problem group, proportion of time insured, total income, number of medical problems, medical outpatient visit and addiction to alcohol. With dual mental health/substance abuse problems has the strongest effect on ED visits, which could be observed on the standardized coefficient table. Medical outpatient visit is mildly positively associated with ED visit.

For subjects with dual mental health and substance abuse problems, the expected number of ED visits within 90 days would increase by a factor exp(0.4355) = 1.55 compared with subjects with substance abuse problem only, while holding all other variables constant. Similarly, the expected number of ED visits within 90 days would increase by a factor exp(0.1985)=1.22 per standard deviation increase (SD = 3.19) in number of medical problems.

2.2 Mixed Models for Follow-up comparison

The follow-up data used for analysis have 354 subjects in 5 sites. After checking bivariate correlation and multicollinearily by variation inflation factor (VIF) among the predicting variables, we fitted several models with those "safe" (VIF < 2.5 and bivariate correlation < 0.4) variables.

The predicting variables include site, treatment (CICH program or local usual care), follow-up time; log transformed baseline ED visits, gender, race group, age group, lifetime years in jail (0, 0-1, >1), psych problem groups, days of homelessness, income, proportion of time insured, # of medical problems, # of mental health and substance abuse diagnosis, medical/mental health/substance abuse outpatient visits, quality of life, alcohol and drug addiction severity index (ASI).

A ZINB model with random intercepts both in the binary component and in the negative binomial component was applied to the data. For simplicity, the two random effects are assumed to be independent and normally distributed.

Let Y_{ij} (i = 1, 2, …m; j = 1, 2, $\cdots n_i$ and $\sum_{i=1}^{m} n_i$ = n gives the total number of ED visits) be the response variable for the i^{th} individual subject with j^{th} repeated measurement. The random-effects ZINB model is defined as:

$$\log(\lambda_{ij}) = X_{ij}'\beta + u_i$$

$$\text{logit}(\pi_{ij}) = Z_{ij}'\gamma + v_i$$

A GP model with random intercept was also applied. The ZINB mixed model gives an AIC of 4456.2, which is better compared with 4551.62 in the GP mixed model. Nevertheless the majority of the coefficients in the GP model are similar to those in the ZINB model.

Standardized Coefficient Estimate in the ZINB mixed model

Variable		Estimate	P value
Intercept		-0.1457	0.7871
Site (Ref: POR)	CHA	0.1010	0.7740
	LOS	0.0201	0.9599
	MAR	0.6503	0.0586
	NYC	-0.1633	0.7099
Log of baseline ED visits		0.3848	0.0031 **
Treatment (CICH or local usual care)		-0.2884	0.2878
Follow up time		0.02185	0.4302
Gender	Male (Female)	0.01374	0.9566
Race	Caucasian (Minority)	0.4231	0.0786
Lifetime yrs in jail (Ref: >1)	0	-0.4146	0.1674
	0~1	-0.3145	0.2049
Psych problem (Ref: dual MH/SA)	Mental health only	-0.5520	0.0704
	substance abuse only	-0.1947	0.5120
Proportion insured		0.1589	0.1202
Days homeless		0.03589	0.6426
Total income (30 dys)		-0.2948	0.0168 *
# of medical problems		0.0604	0.5114
# of mental health/substance abuse problems		0.2699	0.007 *

Medical outpatient visit	0.03904	0.4687
Mental health outpatient visit	-0.04637	0.4498
Substance abuse outpatient visit	-0.1807	0.0130 *
Quality of life	-0.1522	0.0328 *
Alcohol Addiction Severity Index	0.08368	0.2284
Drug Addiction Severity Index	-0.1038	0.1809
Standardized Coefficient Estimate for The Zero Inflation Part		
Intercept	-1.4609	0.0004 ***
# of medical problems	-1.5421	<0.0001 ***
# of mental health/substance abuse problems	-0.4181	0.3084
Log of baseline ED visits	-0.8503	0.0134

Table 6. Standardized coefficient estimate in the ZINB mixed model

In the follow-up analysis, variables significantly correlated with ED visits in the negative binomial part are: baseline ED visits, income, number of mental health/substance abuse problems, substance abuse outpatient visit and quality of life.

The CICH program has no effect on reducing the number ED visits compared with local usual care. Also after adjusting for other variables, ED visits do not change over time. Baseline ED visits has the strongest influence on follow-up ED visits. Per standard deviation increase in the log of baseline ED visits (SD = 1.87) will increase the follow-up ED visits by a factor of 1.77. Per standard deviation increase in number of substance outpatient visits (SD = 14.59) will decrease the number of ED visits by a factor of exp(0.1848) = 0.83.

For the zero inflation part, both baseline ED visits and number of medical problems are negatively correlated with the chance of having 0 ED visits If a subject were to increase his/her number of medical problems by one standard deviation (SD=3), the odds that his/her number of ED visits would be a “certain zero" would decrease by a factor of exp(-1.65) = 0.19. In other words, the more medical problems one has, the less likely his/her number of ED visits is a certain zero. Also the more ED visits one had at baseline, the smaller chance that he/she would have zero ED visits in the follow-up period.

2.3 Results and Conclusions

Findings from the baseline data suggest that, site, income, proportion of time get insured, length of homelessness, number of medical problems, number of mental health/substance abuse problems, quality of life, severity of alcohol addiction and substance abuse outpatient service use are significantly correlated with ED visit. Findings from the follow-up study suggest that, the CICH program does not help to reduce ED visits. And even after adjusting for the baseline ED visits, mental health/substance abuse problems and substance abuse outpatient service use could significantly affect follow-up ED visit.

More frequent ED users tend to be in bigger cities, have lower income, better insured, more medical/mental health/substance abuse problem, fewer substance abuse outpatient service use, lower quality of life and severer addition to alcohol.

CHAPTER III

DISCUSSION

Using the Gelberg-Anderson Behavioral Model for Vulnerable Populations as a framework, we found that need, enabling and vulnerable factors (income, insurance, medical/mental health/substance abuse problems, addition to alcohol etc.) predominated in the model, with predisposing factors playing a smaller role. Gender, age and race have no significant effect on the frequency of ED visits. Also we found that increased substance abuse outpatient service use helps to reduce ED use among this population with a high prevalence of substance abuse.

Medical, mental health and substance use problems are the driving factors for frequent ED use. At baseline level, medical outpatient visit was found positively correlated with ED visits, which is consistent with the findings of Hansagi et al in 2001 [17]. It also casts doubt on the hypothesis that frequent ED use is a marker of poor access to nonemergency health care. In terms of standardized regression coefficient, having both mental health and substance abuse problems contribute most to frequent ED visits. It’s already been pointed out that the homeless use ED frequently not only for healthcare service, but also for food, shelter and safety [18, 19]. Similarly the chronically homeless people with both medical and mental health problems may not only have a need for ED, but are more demoralized and passive about seeking care.

Although the CICH program greatly improved subjects’ access to health care services and housing status among the chronically homeless adults, ED use was not significantly reduced. This may implicate that changes in frequent ED users should take place in the long run, when broadened access to health care service has improved the overall health status.

The homeless people are known to have more ED visits than the general population. Paradoxically we found that among those chronically homeless people, shorter length of homeless in a short period (90 days) is correlated with more ED visits. It is not surprising since for the chronically homeless population, shorter length of homelessness sometimes indicates more time spent in hospitals and jails. So there is a more complicated relationship between length of homelessness and ED visits in this population.

Based on what we found in this study, actions aimed at reduce ED visits among the chronically homeless people should be firstly targeted at eliminating the need factors, especially dealing with the mental health and substance abuses problems.

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