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THESIS

PREDICTING HOSPITAL ADMISSIONS WITH POISSON REGRESSION ANALYSIS

by

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June 2009

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13. ABSTRACT (maximum 200 words)

In this thesis, Poisson regression is used to predict and analyze inpatient hospital admissions for two inpatient units (Four East and Four West) at Naval Medical Center San Diego. Data that include age group, gender, beneficiary category, enrollment site and fiscal month are collected for the patient population. This information is used along with additional details about past admissions such as the location and source of admission. These data are next fit to four different models that correspond to Four East (enrolled and un-enrolled beneficiaries) and Four West (enrolled and un-enrolled beneficiaries). Stepwise selection techniques are used to arrive at final models. The final models are used to observe trends in predicted hospital admissions based on trends in current population sizes.

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PREDICTING HOSPITAL ADMISSIONS WITH POISSON REGRESSION ANALYSIS

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requirements for the degree of

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In this thesis, Poisson regression is used to predict and analyze inpatient hospital admissions for two inpatient units (Four East and Four West) at Naval Medical Center San Diego. Data that include age group, gender, beneficiary category, enrollment site and fiscal month are collected for the patient population. This information is used along with additional details about past admissions such as the location and source of admission. These data are next fit to four different models that correspond to Four East (enrolled and un-enrolled beneficiaries) and Four West (enrolled and un-enrolled beneficiaries). Stepwise selection techniques are used to arrive at final models. The final models are used to observe trends in predicted hospital admissions based on trends in current population sizes.

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TABLE OF CONTENTS

LIST OF FIGURES

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LIST OF TABLES

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LIST OF ABBREVIATIONS AND ACRONYMS

ADFM – Active Duty Family Member

AdmitSource – Source of Admission

ADSM – Active Duty Service Member

AGC – Age Group Code or Age Group

AIC – Akaike's Information Criterion

BenCat – Beneficiary Category or Ben Cat Common

CHCS – Composite Health Care System

DMIS – Defense Medical Information System

DoD – Department of Defense

FM – Fiscal month

GAM – Generalized Additive Model

GLM – Generalized Linear Model

HMO – Health Maintenance Organization

MDR – MHS Data Repository

MHS – Military Health System

MTF – Military Treatment Facility

M2 – MHS Management Analysis and Reporting Tool or MHS Mart

NMCSD – Naval Medical Center San Diego

PPO – Preferred Provider Organization

Ret. – Retired

Ret.FM – Retired Family Member

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EXECUTIVE SUMMARY

The cost of healthcare in the United States is rising at an alarming rate. The Military Health System (MHS) is facing the challenge of steep inclines in the cost of providing healthcare as well. Partners within the MHS are continuously exploring opportunities to reduce or contain costs without sacrificing the quality of healthcare that is provided. One way to contain costs is to ensure that hospital resources are allocated to the most appropriate locations. This can be accomplished through regression analysis of patient admission trends. Analysis specific to this study will focus on regression analysis of inpatient admissions in two clinics within Naval Medical Center San Diego.

Regression analysis has been utilized to perform studies on inpatient utilization and hospital admissions in the civilian sector, but there are no known studies that have been conducted within the Military Health System. Regression analysis can be used as a predictive tool to identify trends in hospital admissions that might be tied to a particular patient demographic or combination of demographics. Identification of these trends can be useful when known changes to the patient population are taking place. These trends can also be useful when there is a desire to predict expected future admissions for a population that is relatively constant.

For this thesis, the surgical inpatient units, Four East and Four West were evaluated with Poisson regression analysis. The results of this study show that age, and beneficiary category are very influential in determining the volume of expected admissions to the units being studied. Generally speaking, the results show that as age increases, the expected number of admissions increases as well. There are, however, some interesting results for expected admissions when the factor of age is combined with other factors such as enrollment status or gender.

There is a great deal of potential for studying all types of hospital admissions with regression analysis. This research demonstrates a small portion of the usefulness of regression.

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I. INTRODUCTION

The provision of healthcare in the United States is a topic that remains in the forefront of the minds of many. The cost of healthcare continues to rise at an alarming rate, which has recently become an even greater concern because of the poor economy. Employers and consumers are struggling to manage these costs, which are increasing at a rate higher than inflation [1]. Many hospitals are freezing new hires or reducing staff because there is not enough revenue being generated to sustain operation of their facilities [2]. The challenges of access and decreased utilization have not had the same impact on the Military Health System (MHS) because of the structure of the military healthcare delivery system. However, the rising costs for the provision of healthcare are of concern. This thesis provides a regression analysis of inpatient admissions at Naval Medical Center San Diego relative to the size and demographics of the beneficiary population. Trends that are identified can be used to ensure that hospital resources are allocated to the most appropriate locations. This should result in improvements in resource management and cost containment.

A. OVERVIEW OF MHS

Beneficiaries of the MHS are classified in several different categories. These classifications determine which healthcare coverage options are available to the beneficiary. One very significant difference between civilian and military medical care is that beneficiaries who are eligible to receive their medical care in the military Medical Treatment Facility (MTF) receive this care free of charge. All Active Duty Service Members (ADSM) and their family members are part of this category. TRICARE is the military health insurance plan which provides coverage for care received in civilian facilities. TRICARE offers health plan options that are structured like either a Health Maintenance Organization (HMO) or a Preferred Provider Organization (PPO). All ADSMs are enrolled in the HMO option known as TRICARE Prime. Active Duty Family Members are given a choice between TRICARE Prime and the PPO option known as TRICARE Standard. There is no insurance premium, cost share or co-pay for beneficiaries under TRICARE Prime and there is a small cost-share for the patients who select the TRICARE Standard option because there is greater flexibility for patients to choose among civilian providers.

Although the state of the economy has little impact on the volume of patients flowing through MTFs, and the patient population is relatively predictable, the cost of providing care to the MHS's eligible beneficiaries continues to rise each year. In FY 2007, $21.1 billion was appropriated for defense health [3]. The appropriated amount increased eight percent in FY 2008 and increased another 12.4 percent to $25.8 billion for FY 2009 [4]. The MHS is being challenged to function more like its civilian counterparts by becoming more efficient and striving to improve the quality of healthcare provided. However, there are certain requirements that MTFs must meet that are very different from those of civilian hospitals and clinics.

The United States Military Health System is a partnership of medical educators, medical researchers, and healthcare providers along with their support personnel. The MHS mission is to provide optimal health services in support of our nation's military mission – anytime, anywhere. The primary objectives of this mission are to provide casualty care and humanitarian assistance, to maintain a fit, healthy, and protected force, and to maintain the health and resilience of the individuals, families and communities that account for the 9.2 million Department of Defense (DoD) beneficiaries [5]. There are currently 63 military hospitals and 413 military medical clinics throughout the world [6]. Each facility is tasked with meeting the needs of its local beneficiary population while utilizing portions of its Active Duty staff to meet the larger needs of the U.S. military through deployments. Because there is an ongoing requirement for military medical staff to be able to deploy, medical facilities are staffed by a mixture of military and civilian personnel.

B. BACKGROUND

Of the 9.2 million TRICARE beneficiaries, over five million consist of active duty or active duty family members and the remainder are others such as retirees, retiree family members, active reservists, and their dependents. In order to take care of this many beneficiaries, the Military Health System is staffed with 89,400 military and 44,100 civilian personnel. A civilian network of providers around the world is also heavily utilized to provide care that is not always available within the Military Treatment Facilities. The current beneficiary population results in approximately 664,000 outpatient appointments each week within the MTFs. There are also 4,800 MTF inpatient admissions per week and an additional 13,700 inpatient admissions to the civilian network. Over 2,000 of these weekly admissions are for the birth of a child [6].

Each Military Treatment Facility is unique in its mission and capabilities and is shaped by the size and demographics of its patient population. As military populations shift and change, it is important for the MTFs that provide inpatient services to plan for the appropriate number of inpatient units to offer and the correct mix of inpatient services with which to provide each service area. Over the years, the topics of inpatient bed utilization and planning have received a great deal of attention in the civilian sector. Stochastic modeling is a popular method for exploring methods of inpatient bed allocation. Cochran and Roche [7] use a queuing-based decision support model to estimate hospital inpatient demand while Esogbue and Singh [8] use a stochastic model to determine the optimal inpatient bed distribution. Another common approach has been simulation modeling. Harper and Shahani [9] use statistical distributions coupled with monthly, daily and hourly demand profiles to capture differences in patient Lengths of Stay (LOS). Dumas [10] takes a different approach by building a simulation model to assess currently implemented bed allocation and usage rules. He then uses the analysis to develop several new bed allocation plans.

There has also been attention given to civilian hospitals in the area of statistical analysis. MacStravic [11] uses statistics to determine when it is appropriate to increase the number of hospital beds by expanding his study from the use of average daily census data to include additional detail such as individual analysis of specialized units. Woodruff [12] uses statistical techniques to consider the variability of bed demand on a seasonal, month-to-month and day-to-day basis. To do so she incorporates variables such as population projections by age group, historic rates in discharges by inpatient service, Length of Stay trends by service by age group, and historic hospital market share trends.

Despite the ample research conducted on civilian facilities, almost no attention has been given to conducting studies on any of the aforementioned topics in military facilities. This is likely a reflection of the fact that the MHS is funded by government appropriations so there is less concern about managing inpatient bed utilization and allocation as a method of remaining financially viable. Because the MHS population is so immense, this initial study is conducted on a smaller portion of the system.

C. NAVAL MEDICAL CENTER SAN DIEGO

Naval Medical Center San Diego (NMCSD) is selected for this study because it is one of the three largest MTFs in the Navy. It has a large enough patient population to provide diversity in demographics, but it is of a much more manageable size than the entire population of the Military Health System. Because it is a major research and teaching center, there are many similarities between this facility and civilian facilities of comparable size. Although there are several inpatient units at NNMCS, the scope of this thesis will be limited to the units Four East and Four West, which are the two surgical units in the hospital.

Naval Medical Center San Diego was established as a tent dispensary in 1917. It has since evolved into a high-tech tertiary care facility that provides care to operational forces, their families and to retirees. The number of people eligible to be served by NMCSD is nearly 500,000 and the hospital has a combined military and civilian staff of over 6,000. The hospital has five mobilization teams (including the hospital ship USNS Mercy), which are all staffed by hospital personnel for deployments throughout the year. As part of its commitment to teaching, NMCSD conducts numerous graduate medical education programs and fellowships. Naval Medical Center San Diego is also affiliated with civilian institutions such as the University of California San Diego, Children's Hospital and Health Center and Scripps Clinic and Research Foundation, where Navy trainees perform parts of their residencies or fellowships. NMCSD also operates a network of clinics located at military installations that provide ambulatory care to active duty beneficiaries. There are nine additional clinics located throughout San Diego that are available to family members and retirees [13].

D. THESIS OUTLINE

The next chapter of this thesis explores the source of the data that are being analyzed. It also provides a description of the data fields that are included in the study. The third chapter discusses the formulation of the statistical models that are used and will be followed by a fourth chapter that analyzes results of the model. The final chapter provides conclusions, recommendations, and opportunities for continuing research.

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II. DATA DESCRIPTION

A. DATA SOURCE

1. Composite Health Care System

The clinical data provided for this research originates in the Composite Health Care System (CHCS), which is a worldwide, automated medical information system that supports all MTFs in providing comprehensive care to their beneficiaries. It is the primary automated medical information system for the DoD and provides near real-time access to patient information at DoD hospitals and clinics around the world [14].

2. MHS Data Repository

Data from CHCS and several additional sources are sent to the MHS Data Repository (MDR) for processing. No editing of the information is conducted, but the data are placed into files that are forwarded to various data marts for utilization. The information stored in the MDR is used for most major MHS initiatives such as annual business plans [15].

3. MHS Management Analysis and Reporting Tool

The MHS Management Analysis and Reporting Tool, also known as MHS MART or M2, is an extension of the MHS Data Repository. It is a powerful *ad hoc* query tool for detailed trend analysis such as patient or provider profiling. It is capable of providing summary and detailed views of population, clinical, and financial data from all Military Health System regions worldwide and includes direct and purchased care data [14].

B. REPORTS GENERATED

Three reports are generated to provide quarterly snapshots of population information for the fiscal years 2004-2008. The first report provides data concerning all beneficiaries who are eligible for care within the NMCSD Catchment Area. The Catchment Area is the 40-mile radius around a bedded inpatient facility [16]. The second report provides data about all beneficiaries that are enrolled at the Parent Site NMCSD.

Patients belonging to a parent site are either directly enrolled to a "parent" MTF for care or they are enrolled to a smaller "child" MTF that is an extension of the parent site. The third report provides data about all inpatient visits for each inpatient unit in the hospital.

1. Enrollment Data Fields

In addition to providing a count of the enrolled population, the data can be partitioned into smaller subsets by using different categorical variables. The categorical variables of interest are found in the fields labeled "Fiscal Month," "Enrollment Site," "Ben Cat Common," "Sponsor Service," "Gender" and "Age Group Code." Below is a description of each of these fields.

a. Fiscal Month

The Fiscal Month (FM) is the numeric code used to identify the DoD fiscal month in which the data are extracted. For this study, snapshots of data are taken from the first FM of each quarter. Viewing the data on a quarterly basis provides the opportunity to observe seasonal trends that might be missed if studying data for the entire year. Yearly population totals are computed by averaging the four population totals of the first month of each fiscal quarter. The DoD fiscal year begins in October.

b. Enrollment Site

The Enrollment Site is the Defense Medical Information System (DMIS) identification of the facility where the patient is enrolled for his or her primary care. Branch Health Clinics are generally limited to providing primary care services. Patients enrolled at these clinics will be sent to a larger MTF known as the Enrollment Site Parent for specialty services. All of the Enrollment Sites in the enrollment report fall under the Enrollment Site Parent of NMCSD.

c. Ben Cat Common

This field classifies beneficiaries into one of four broad categories, which are listed in Table 1. For the rest of the discussion the Ben Cat Common will be referred to as the beneficiary category. Also, Dependents of Active Duty Member and Dependents of Retired will be referred to as Active Duty Family Members and Retired Family Members respectively.

Code	Ben Cat Common
1	Dependents of Active Duty Member
2	Retired
3	Dependent of Retired/Survivor, Other, Unknown
4	Active Duty and Guard

Table 1. Ben Cat Common [from [16]]

d. Sponsor Service

The Sponsor Service provides the branch or service of the Active Duty Member (also known as the sponsor).

e. Gender

Table 2 provides the patient gender categories.

Code	Gender Category
M	Male
F	Female
Z	Unknown

Table 2. Gender Categories [from [16]]

f. Age Group Code

Table 3 provides a description of how patient age groups are partitioned as defined by the DMIS.

Code	Age Group	Code	Age Group
A	0-4	F	35-44
B	5-14	G	45-64
C	15-17	H	65+
D	18-24	X	Unknown
E	25-34		

Table 3. Age Group Codes [from [16]]

2. Inpatient Data Fields

Information is collected about each inpatient admission to the hospital. Each admission record provides entries for the fields labeled "FM," "Treatment DMIS," "Admit Ward," "Person ID" and "Source of Admission." The "Beneficiary Category," "Age Group Code," "Gender," "Enrollment Site" and the "Length of Stay" were also included. Below is a description of the data fields that have not been previously discussed.

a. Treatment DMIS

The Treatment Defense Medical Information System (DMIS) is the code assigned to the MTF responsible for the admission and treatment of the patient during the stay of care. For the purposes of this study, the Treatment DMIS will always be NMCSD.

b. Admission Date

The Admission Date gives the date of admission for each stay of care.

c. Admit Ward

The Admit fields provide a description of the wards to which patients are admitted.

d. Source of Admission

The table below provides a description of the locations from which patients are admitted to the hospital.

Code	Description
0	Emergency Room, Direct to Military Hospital
1	Direct to Military Hospital from other than Emergency Room
4	Initial Admission in Non-US Armed Services Hospital, transferred to MTF (AD only)
5	Initial Admission in Non-US Armed Services Hospital, transferred to MTF (non-AD only)
6	Transfer from Army Hospital
7	Transfer from Navy Hospital
8	Transfer from Air Force Hospital
L	Live birth in this hospital
S	Admission resulting from Ambulatory Procedure, direct to MTF

Table 4. Sources of Admission [from [16]]

e. Enrollment Site

The Enrollment Site is the DMIS identification of the facility where the patient is enrolled for his or her primary care. Because patients can be transferred to MTF from outside of the Catchment Area, not all patients will necessarily fall under the NMCSD for enrollment. For this study, patients will be designated as enrolled to NMCSD or enrolled to other.

f. Length of Stay

The Length of Stay is the number of bed days from admission to discharge date. This field will be used along with the Date of Admission to determine how many beds are occupied in the units of interest each day.

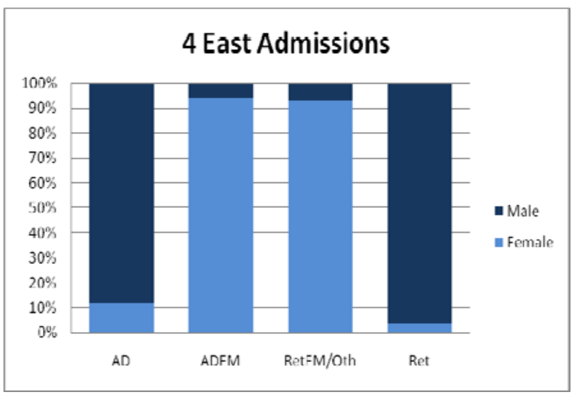
C. DATA FORMATTING

The first step in the analysis is to make sure that all of provided fields are populated. There are five beneficiaries out of 245,792 in the FY 2004 eligible population data who are missing entries for gender. In order to avoid removing data from the study and since there is no way to confirm the gender of these beneficiaries, the M2 value of "Z" for unknown gender is assigned to these entries. All other fields for each fiscal year of the eligible population data set are fully populated. In addition, all of the enrollment and inpatient data is fully populated.

D. DATA EXPLORATION

Due to the large number of inpatient units in the hospital, the scope for the purposes of this thesis is narrowed to the two surgical units of the hospital: Four East and Four West. Four East is where bariatric, general, neurologic, otolaryngology (ENT), ophthalmologic, orthopedic, and plastic surgery patients are cared for. Surgical patients returning from Operations Iraqi Freedom and Enduring Freedom (OIF/OEF) are also treated here. Four West is where care is provided for cardiovascular, thoracic, and vascular surgery patients.

Figure 1 shows a bar graph for each unit, giving the proportion of male and female admissions by beneficiary category. The graphs show that men make up the majority of the patients who are active duty or retired while women make up the majority of the patients who are categorized as active duty family members or retired family members.



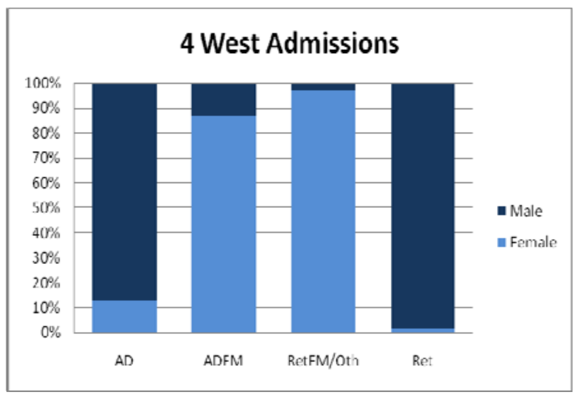


Figure 1. Four East and Four West Admissions by Beneficiary Category

Figure 2 shows a bar graph of the proportion of males and females belonging to the average enrolled population, which are similar to the proportions of admissions to Four East and Four West.

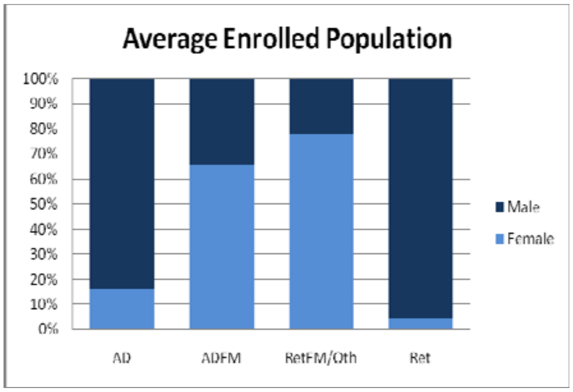


Figure 2. Average Total Enrolled Population by Beneficiary Category

The next step in the analysis is to look at the data over time to see if there are any noticeable trends. Admissions for each year are plotted by fiscal month to look for any variability or seasonality. A complete display of admission plots of Four East and Four West, for each fiscal year is shown in Appendices B and C. Figure 3 shows that Four East admissions during the first quarter of 2004 are extremely low, which can be attributed to a past practice of closing and consolidating certain hospital wards during the holidays. After the holiday period, the number of admissions climbs to a relatively stable number by the middle of the second quarter. Admission numbers remain fairly level throughout 2005 and 2006 but show another decline to very low numbers at the end of the first quarter of 2007 (also shown in Figure 3). This decrease is the result of the ward being shut down for renovations. Admissions again remain level for the rest of 2007 and for all of 2008.

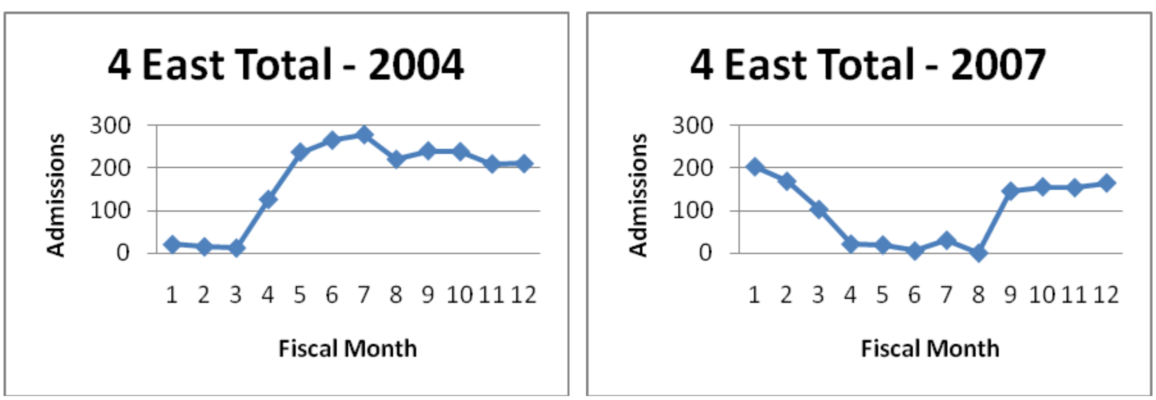


Figure 3. Plots of Total Admissions for Four East Fiscal Years 2004 and 2007

The plots for Four West show that admissions from 2004 through most of 2006 did not have much overall variability. By the third quarter of 2006, there is a noticeable decline in admissions that lasted through the first quarter of 2007, which is also the result of renovations. The remainder of 2007 shows an increase in admissions that is due to the addition of some patients that normally would have been cared for on Four East during that period of time. The admissions for 2008 return to a consistent level throughout the year. Figure 4 provides an illustration of fiscal years 2004 and 2007.

Because the data during the quarters where the wards were closed for the holidays or for renovations is so different from the data when the wards were open, this portion of the data is removed from the study.

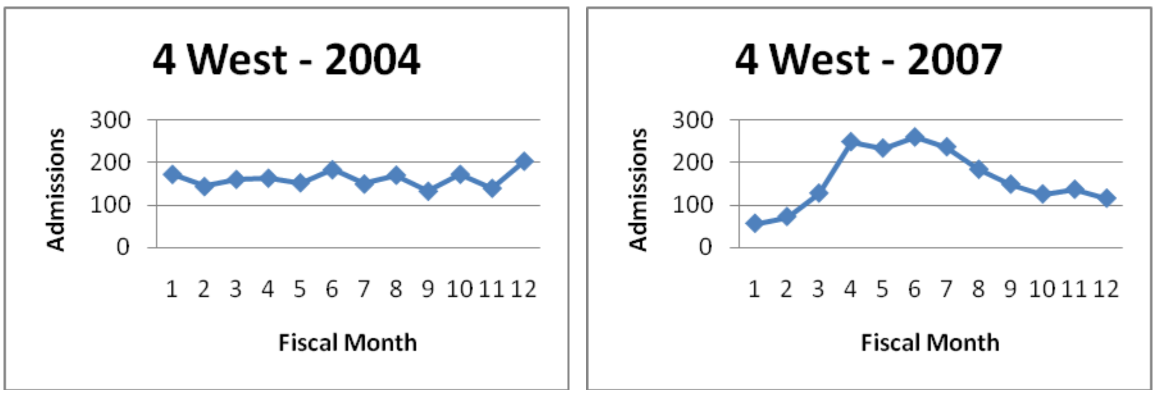


Figure 4. Plots of Total Admissions for Four West Fiscal Years 2004 and 2007

In addition to plots of admissions, the numbers of beds occupied in each unit by day are calculated by using the date of admission and the length of stay and then plotted over time by age group and gender for each quarter. The plots show that there is a great deal of variability within each partition. Figure 5 is a snapshot of Quarter 3 (April-June) 2004, which shows that the overall number of beds occupied for men of the age group 18-24 is higher on Four East than it is on Four West. Both units show a noticeable increase in beds occupied for both men and women of the age groups 45-64 and 65+.

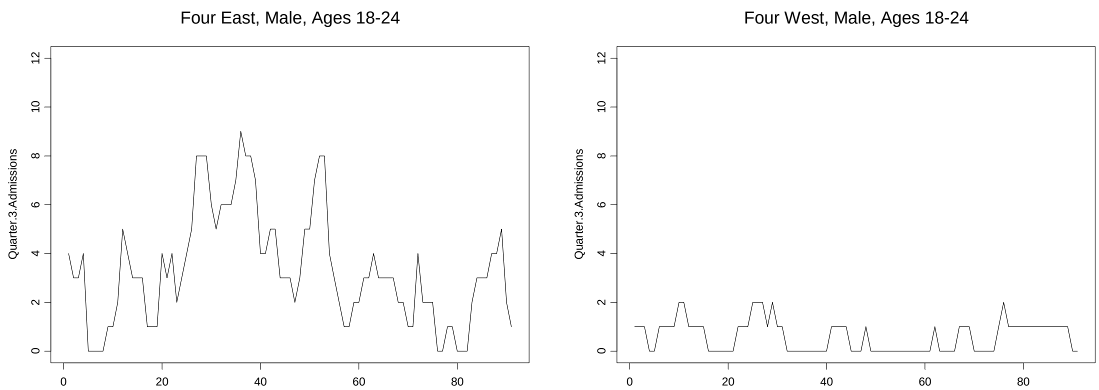


Figure 5. Beds Occupied, Four East/West, Males, Ages 18-24, Quarter 3, FY 2004

Bar plots in Figure 6 show that over half of the admissions on Four East are scheduled/elective in nature. In contrast, over half of the admissions to Four West admissions are unscheduled/urgent in that they result directly from the emergency room or from a scheduled ambulatory appointment.

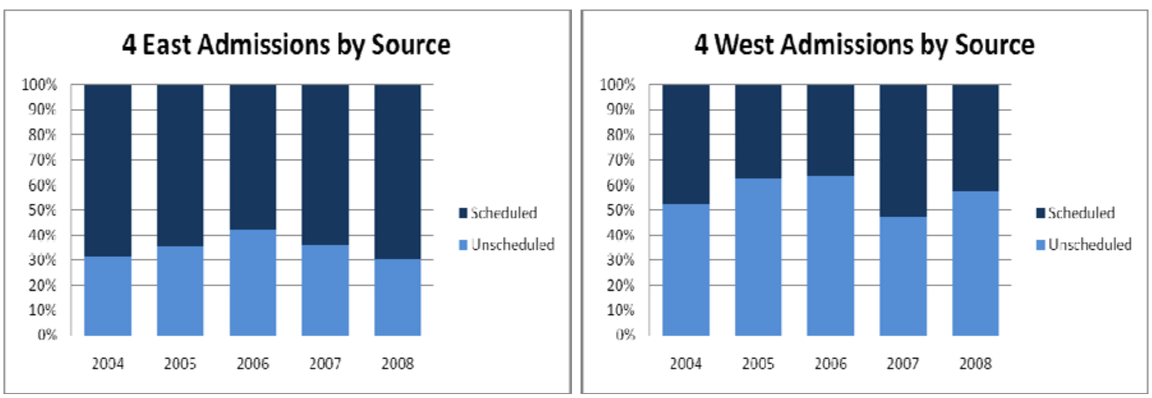


Figure 6. Admissions by Source for Four East and Four West

Although there is considerable variability on a day-to-day basis with the patient mix on each of the units, the overall level of admissions during a year remains relatively stable. The next step is to fit the data to a model to determine if the number of expected scheduled and unscheduled admissions can be predicted based on the population data that is available.

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III. MODEL FORMULATION

A. THE MODEL

The goal of this study is to model the relationship between number of unscheduled hospital admissions as related to population size and demographics. The Generalized Linear Model (GLM) is used because it has the flexibility of a multiple regression model and because it generalizes multiple regression by allowing the conditional distribution of the dependent variable to belong to any parametric family of distributions contained in the class of exponential families [17]. This class includes the Normal family of distributions, which is used for multiple regression and ANOVA, and the Poisson family of distributions which is often used when the independent variable is a count, as in this study. A GLM with Poisson distributed response variable is often called a Poisson regression model.

In this case, Poisson regression is used to model the relationship between the counts (observed number of admissions) and potentially useful independent variables (population size, age group, gender, etc.). For each combination of enrollments site (Four East and Four West, enrolled and un-enrolled) the observed number of admissions are the frequencies in the 4x2x4x2x6x2 contingency table of admissions by fiscal quarter, gender, beneficiary category, source of admission, age group and enrollment site. The Poisson regression often uses the log link function, which ensures that all of the predicted values of the dependent variable will be nonnegative [17]. In particular, let Y_i, $i = 1, \ldots, n$ be n random variables representing the dependent variable and $x_{i1}, \ldots x_{ik}$, $i = 1, \ldots, n$ be the corresponding values of the k independent variables. For Poisson regression, Y_i $i = 1, \ldots, n$ are modeled as independent Poisson variables. The expected value of Y_i is linked to a linear function of the independent variables, using a log link function:

$$\ln E(Y_i \mid x_{i1}, \ldots, x_{ik}) = \beta_o + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} \qquad \text{for } i = 1, \ldots, n \tag{3.1}$$

where $\beta_o, \ldots, \beta_k$ are the model parameters. We note that for categorical variables such as beneficiary category which has $\ell = 4$ levels, ℓ minus 1 binary dependent variables are used in the right hand side of Equation 3.1. For the categorical variable beneficiary category, for example, the three binary variables are: a binary variable indicating if the individual is an active duty family member, a binary variable indicating if the individual is retired, or a binary variable indicating if the individual is a retired family member. When the value of all three binary variables equal zero, this indicates that the beneficiary category is active duty.

B. VARIABLES

1. Independent Variables

The independent variables were selected based on whether or not they had potential to influence the number of admissions. As a result, variables enrollment site, source of admission, fiscal month, gender, beneficiary category, age group, average total population and the logarithm of the average total population were selected.

The enrollment site is important to consider because a significant number of the inpatient admissions results from patients who are eligible to receive medical care within the military health system but are not enrolled to NMCSD. There is no way to capture the numbers for the entire un-enrolled population, so the numbers for the enrolled population will be substituted.

The source of admission is used to separate those admissions that were urgent/unscheduled from those which could be planned for in advance. This is important because it is possible that scheduled admissions can be adjusted based upon the volume of unplanned admissions that occur.

The fiscal month is used to explore whether or not there is any seasonal influence on the admissions to the locations being observed. The gender, beneficiary category and age group variables have the potential to show that a certain demographic or patient type might have a greater predisposition to needing the types of care that are provided on either Four East of Four West. Records for which the gender is classified as unknown in the enrolled population are excluded from this study because there are no admissions that document an unknown gender for the patient. Observations belonging to the age groups 0-4, 5-14 and 15-17 are also excluded because these age groups are rarely admitted to Four East or Four West.

2. Dependent Variable

The dependent variable is the number of scheduled or unscheduled admissions that can be expected per quarter based on the independent variables previously listed.

C. MODEL FITTING

The data are partitioned by admit ward and enrollment status, which results in fitting four different models: Four East enrolled, Four East un-enrolled, Four West enrolled, and Four West un-enrolled. The same independent variables are used for all four models.

Initial modeling fits four models which are additive in the variables source of admission, fiscal month, gender, beneficiary category, age group and average total population. The only numeric independent variable is average total beneficiary population (which will be referred to as average total population). To explore whether the log expected number of admissions is linear in average total population, we modify the generalized linear model by replacing the linear term for average total population on the right-hand side of Equation (3.1) with a smooth nonparametric function. For example, let x_1 represent average total population, then the model in Equation (3.1) becomes:

$$\ln\, E(Y \mid x_{i1},...,x_{ik}) = \beta_o + s(x_{i1}) + \beta_2 x_{i2} + ... + \beta_k x_{ik} \qquad \text{for } i = 1,\ldots,n \qquad (3.2)$$

where $s(\bullet)$ is a "smooth" function of x_1, continuous with continuous first derivatives. Equation (3.2) along with the modeling assumptions for Poisson regression defines a Generalized Additive Model (GAM) [17]. We estimate the smooth function using a nonparametric estimator called a spline. The details of the algorithms used to fit splines in a generalized additive model and the specifics of their implementation in S-plus can be found in Venables and Ripley [18].

The partial residual plots which plot the estimated function $\hat{s}(x)$ versus x suggest that a log transformation of average total population might be appropriate. Thus the four models are fit with average total population and log of average total population included along with the other categorical variables.

A stepwise selection procedure is then used to see if interaction terms can be added. The stepwise selection is implemented using Venables and Ripley's stepAIC function found in their MASS library of S-Plus function [18]. The criterion for model choice is Akaike's Information Criterion (AIC) which includes a penalty for an excessive number of independent variables. Rather than allow all interactions, two-way interactions between average total population and the categorical variables source of admission, gender, beneficiary category, age group description and fiscal month are allowed. In addition, four-way interaction between source of admission, gender, beneficiary category and age group and all lower interactions among these four categorical variables are allowed.

StepAIC leaves all of the single-order terms in the final models except in Four East (enrolled) where the average total admissions is removed. All models have several two-way interactions included as well. The results for each model are placed into a Generalized Additive Model (GAM) with a smooth function replacing the average total population and/or the logarithm of the average total population. Partial residual plots are created in order to observe visible trends. The best models for each category resulting from stepAIC are expanded upon below.

Figure 7 shows the partial residual plot of the model for Four East (enrolled) which includes the variables source of admission, fiscal month, gender, beneficiary category, age group and smoothed average total population. The model also includes two-way interaction terms between source of admission and age group, beneficiary category and age group, and source of admission and beneficiary category.

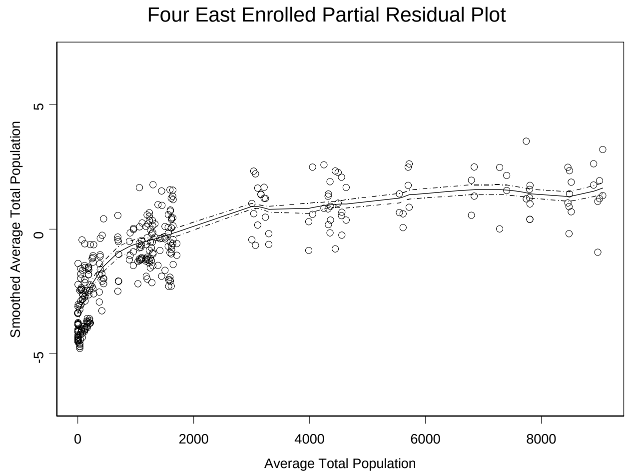

Figure 7. Four East Enrolled Partial Residual Plot $\hat{s}(x)$ versus x

Figure 8 shows the partial residual plot of the model for Four East (un-enrolled) which includes the variables source of admission, fiscal month, gender, beneficiary category, age group and smoothed average total population. The model also includes two-way interaction terms between beneficiary category and age group, gender and beneficiary category, source of admission and beneficiary category, source of admission and age group, gender and age group, and source of admission and average total population.

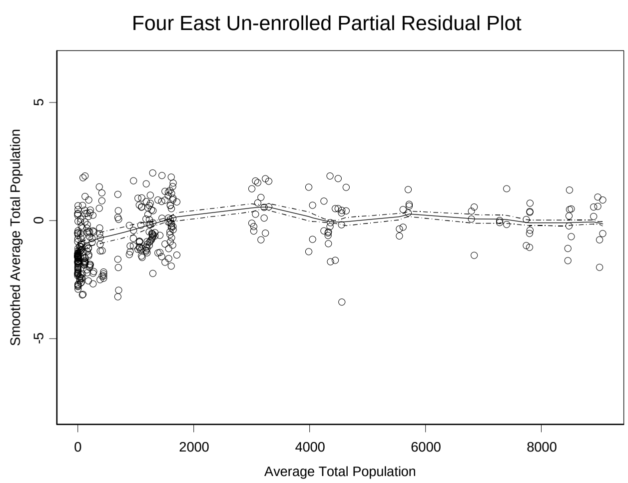

Figure 8. Four East Un-enrolled Partial Residual Plot $\hat{s}(x)$ versus x

The model for Four West (enrolled) includes the variables source of admission, fiscal month, gender, beneficiary category, age group and smoothed average total population. The model also includes two-way interaction terms between source of admission and beneficiary category, gender and beneficiary category, source of admission and age group, source of admission and average total population, and fiscal month and average total population. The partial residual plot is shown in Figure 9.

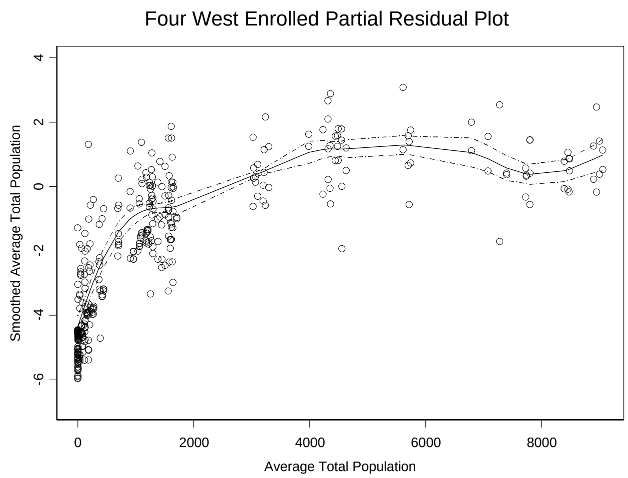

Figure 9. Four West Enrolled Partial Residual Plot $\hat{s}(x)$ versus x

The model for Four West (un-enrolled) includes the variables source of admission, fiscal month, gender, beneficiary category, age group and smoothed average total population. The model also includes two-way interactions between beneficiary category and age group, source of admission and age group, gender and beneficiary category, and gender and age group. The partial residual plot is shown in Figure 10.

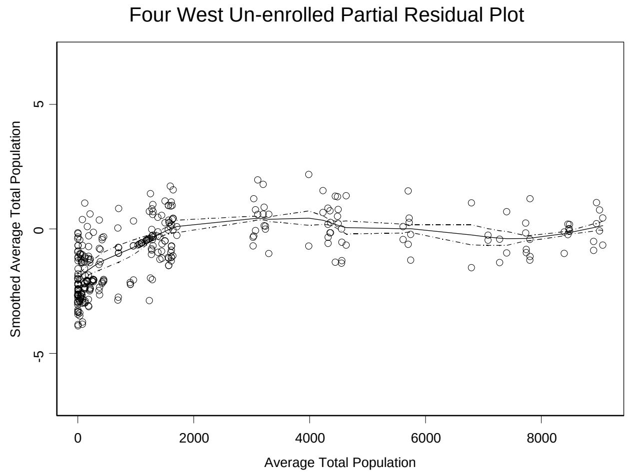

Figure 10. Four West Un-enrolled Partial Residual Plot $\hat{s}(x)$ versus x

The estimated smooth functions represented by the solid lines in each of the four plots confirm that the log transformation of the average total population is appropriate. Since there are a large number of terms left in the non-linear models, the next step is to further reduce them using backwards elimination. The models are again fit in a generalized linear model and an ANOVA test with a level of significance of 0.05 is conducted on each full model against a reduced model that has one term removed at a time. The results show that gender can be removed from the model for Four East (enrolled) and the interaction term between fiscal month and average total population can be removed from Four West (enrolled). The average total population can be removed from the Four West (un-enrolled) model and nothing can be removed from the Four East (un-enrolled) model. A second round of backwards elimination for the Four East (enrolled) and Four West (enrolled and un-enrolled) models show that nothing further can be eliminated. These finalized generalized linear models that will be used for analysis of the effects of potential population changes on admissions at NMCSD are shown in Appendix C.

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IV. DATA ANALYSIS

Quarterly admission predictions are made by estimating the expected number of admissions using the models that were developed for each category with fixed demographics and a varying population size. Unscheduled and scheduled admissions for females and males are plotted by beneficiary category and age group to provide comparisons of trends within similar demographics. Next, predictions are made for the current average population size and the population size is increased and decreased to observe how changes in the actual population could impact volume in the inpatient units. Finally, predictions with 95 percent confidence intervals for the four largest beneficiary categories (two male and two female) are made over the range of average population sizes.

A. COMPARISONS WITHIN BENEFICIARY CATEGORIES

1. Four East Enrolled Beneficiaries

Because the final model for predicting admissions to Four East did not include gender as a factor, males and females of the same admission source and age group have identical predicted values. Figure 11 shows that active duty enrollees ages 18-24 are expected to generate more unscheduled admissions than scheduled admissions. All other age groups are expected to generate more scheduled admissions than unscheduled admissions. An interesting finding about the age group 18-24 is that although this age group does not have the highest proportion of active duty enrollments, it is expected to generate the most admissions. Figure 11 also includes a plot of 45-64 year-olds, who are expected to generate the highest number of scheduled admissions. The age group 45-64 has the second lowest total enrollment for active duty, but is expected to generate the highest number of scheduled admissions.

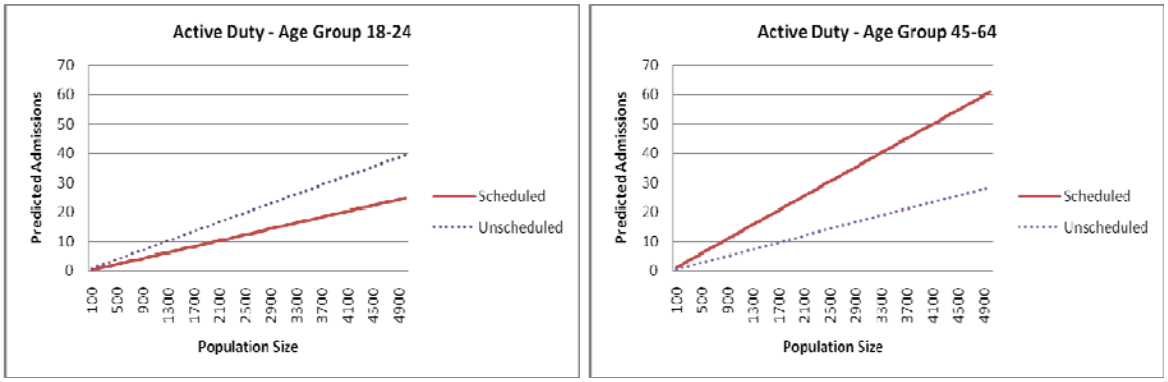

Figure 11. Expected Active Duty Admissions by Age Group

Figure 12 shows that active duty family members ages 18-24 have the lowest expected number of total admissions. As the age groups increase, the number of expected unscheduled admissions shows little change, but there is a significant increase in the expected number of scheduled admissions. The largest difference between expected scheduled and unscheduled admissions is seen in the age groups 45-64 which is also included in Figure 12.

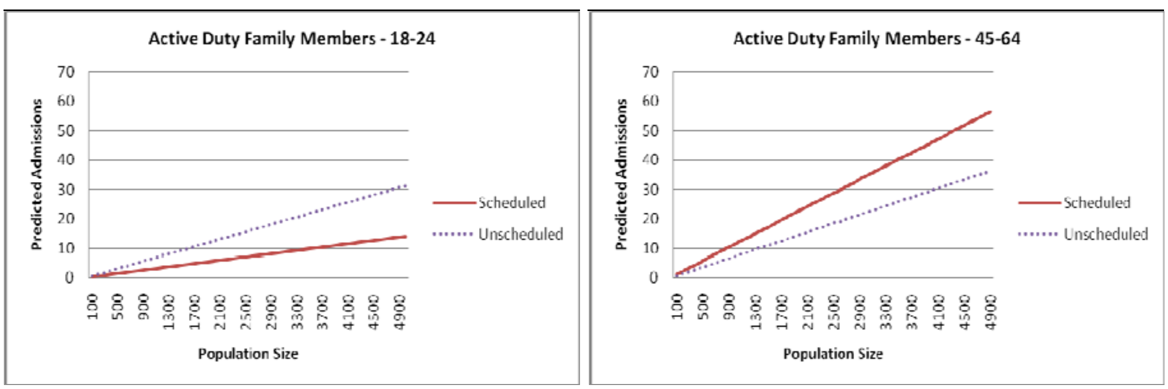

Figure 12. Expected Active Duty Family Member Admissions by Age Group

Figure 13 shows that for both retirees and retired family members, the overall expected number of admissions also increases with age group. The largest age group for female retirees, male retirees and female family members of retirees is 45-64 while the largest age group for male family members of retirees is 18-24. None of these age groups account for the highest expected number of admissions, again suggesting that increasing age has the greatest influence on increased expected admissions.

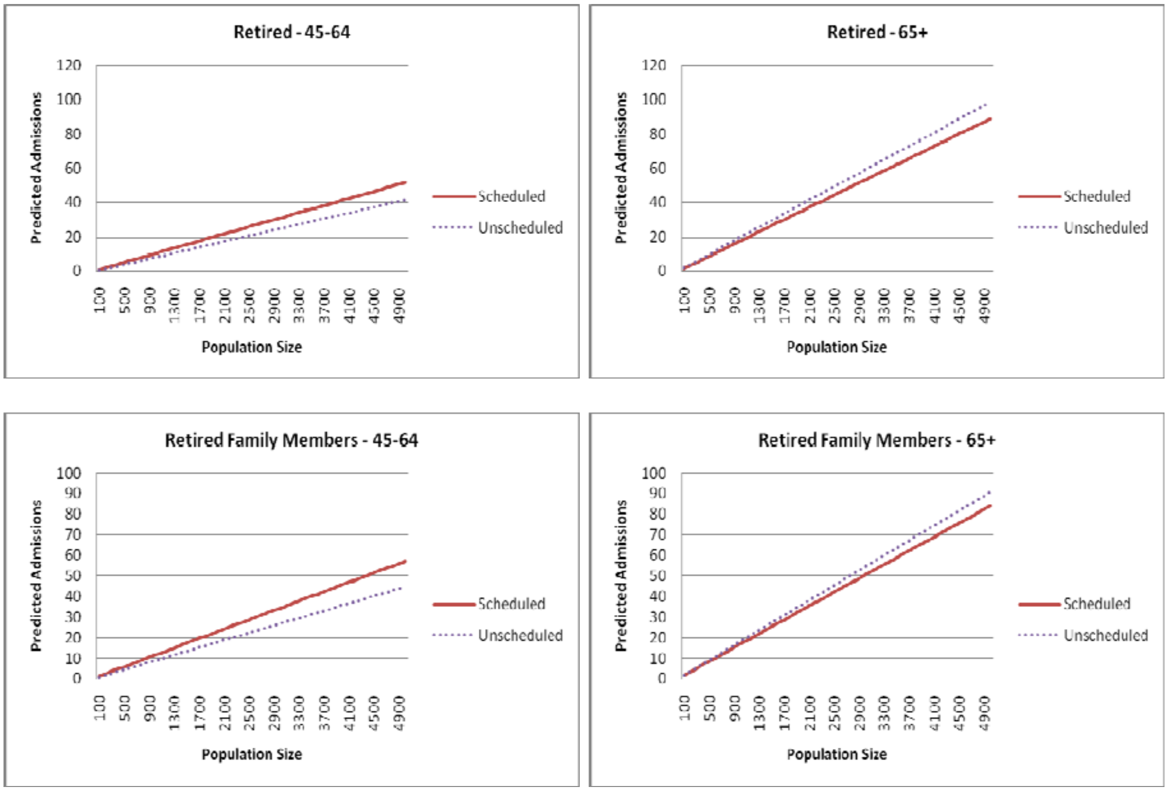

Figure 13. Expected Retired/Retired Family Member Admissions by Age Group

2. Four East Un-enrolled Beneficiaries

Of the four beneficiary categories, un-enrolled 18-24 year-olds are expected to generate the highest number of admissions among all age groups, as shown in Figure 14. The number of expected admissions decreases as the age group increases which contradicts the findings about the influence of age in the enrolled population. This could indicate that there is a much larger population of un-enrolled 18-24 year-olds that present to NMCSD for care than any other age group.

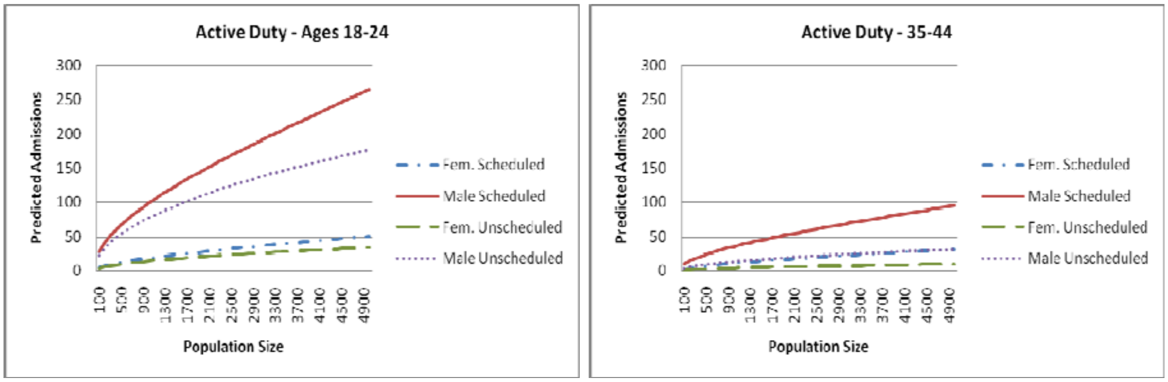

Figure 14. Expected Active Duty Admissions by Age Group

Figure 15 shows that the highest expected number of scheduled and unscheduled admissions for active duty family members is generated from females ages 25-34. The number of expected unscheduled admission decreases as age increases. The expected number of admissions for males holds relatively steady across all ages.

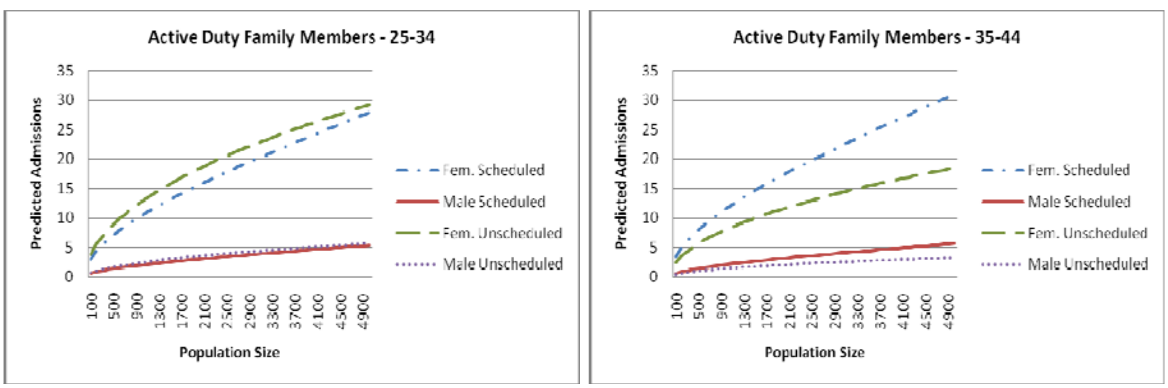

Figure 15. Expected Active Duty Family Member Admissions by Age Group

The ordering of expected admissions for retirees remains the same across all age groups. Retired males with scheduled admissions have the highest predicted values followed by retired males with unscheduled admissions, retired females with scheduled admissions and retired females with unscheduled admissions. This ordering is logical because the retired male population is several times larger than the retired female population. Figure 16 shows that the expected number of admissions of retirees and retired family members also increases with age.

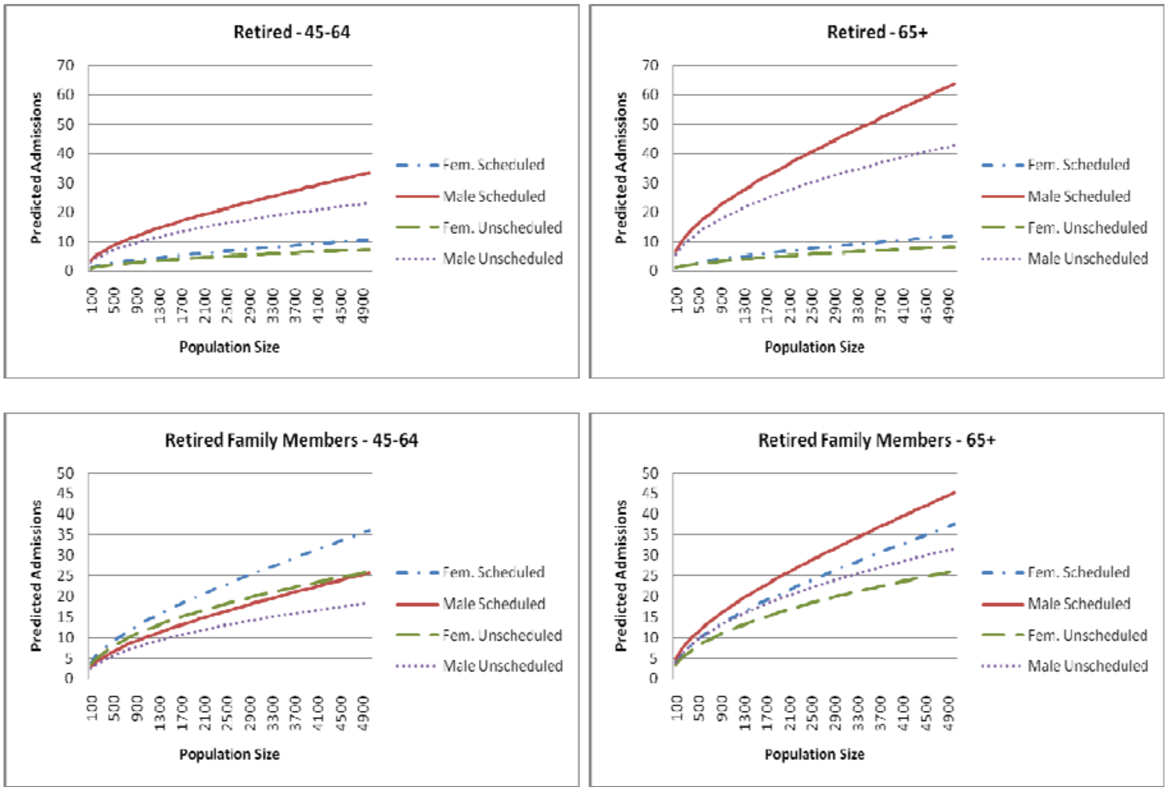

Figure 16. Expected Retired/Retired Family Member Admissions by Age Group

3. Four West Enrolled Beneficiaries

Active duty males and females generate very few expected admissions from age 18-34 and there is almost no difference between scheduled and unscheduled admissions. Active duty family members show an almost identical trend. Figure 17 shows that as age increases the expected admissions begin to differentiate by gender and admissions source for both active duty and active duty family members. Unscheduled admissions are expected to be higher than scheduled admissions with females having higher expected admissions than males. This is interesting because the population of active duty males is several times greater than the active duty female population for both age groups.

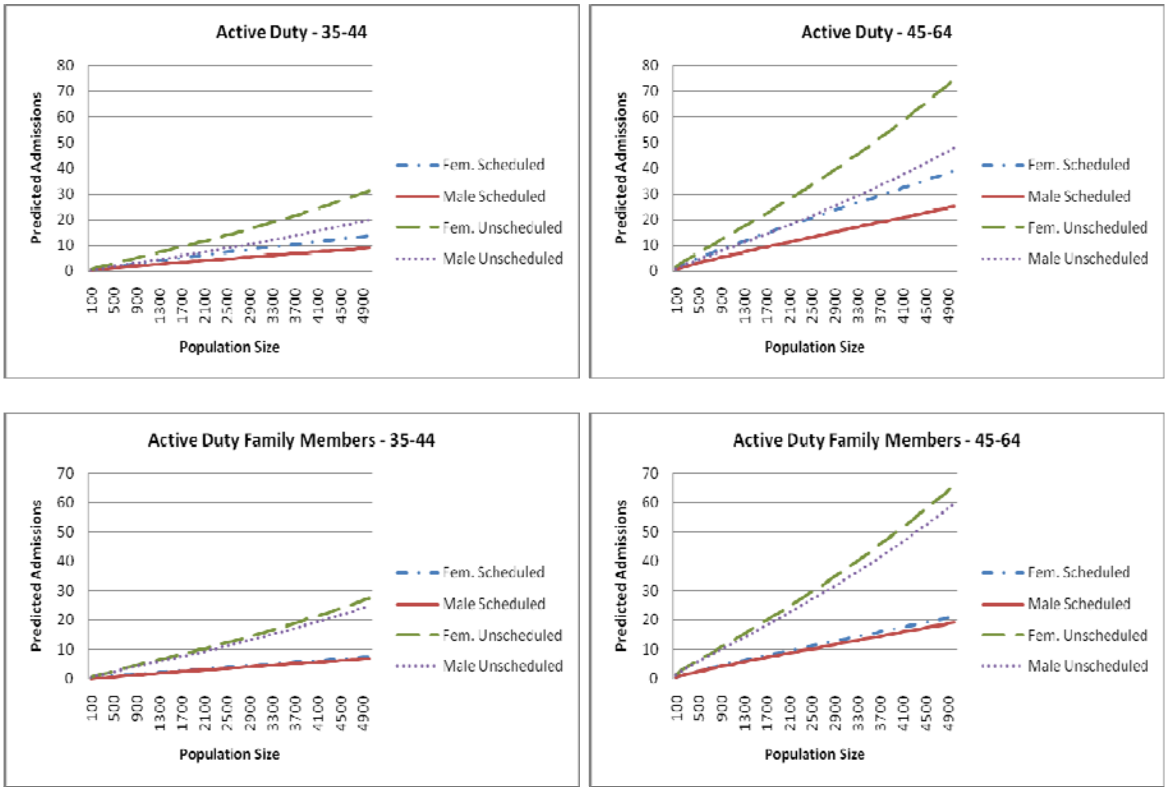

Figure 17. Expected Active Duty/Active Duty Family Members Admissions by Age Group

Figure 18 shows that expected admissions of retirees and family members of retirees increase as age increases. The categories with the highest number of expected admissions correspond to the size of the population with male retirees, having higher expected admissions than females and female retired family members having higher expected admissions than males.

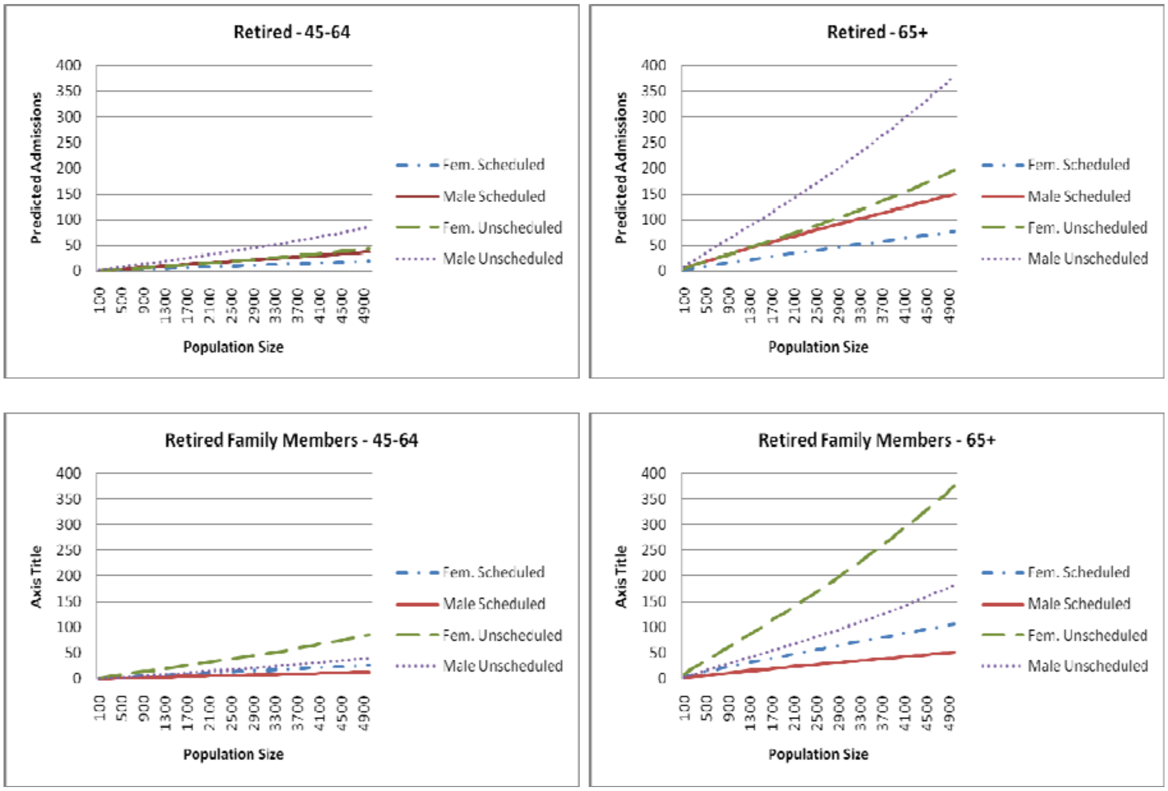

Figure 18. Expected Retired/Retired Family Member Admissions by Age Group

4. Four West Un-enrolled Beneficiaries

Active duty males, ages 18-24, have highest number of expected admissions and the expected male admissions show a decrease for the age group 25-34 as shown in Figure 19. The expected admissions then begin to increase again with age. The expected number of female admissions shows almost no difference across age groups.

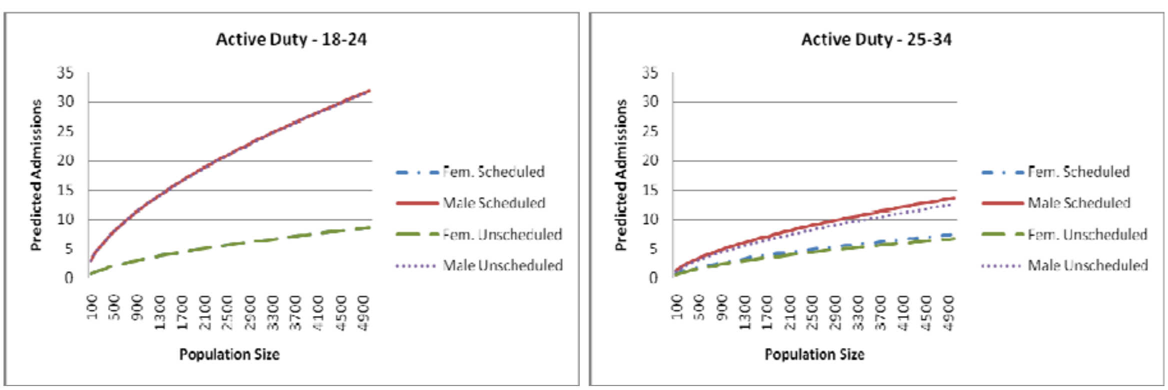

Figure 19. Expected Active Duty Admissions by Age Group

Figure 20 illustrates that active duty family members have a low number of expected admissions across age groups and that there is the trend of increased expected admissions with increased age.

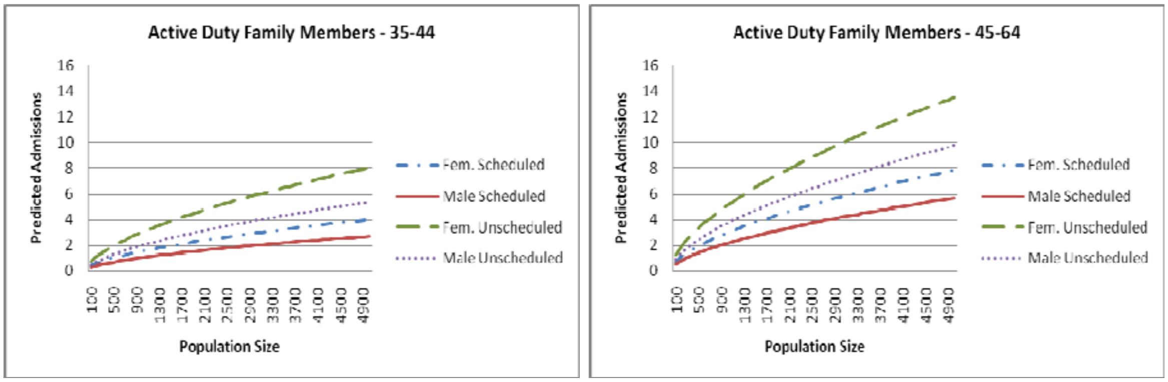

Figure 20. Expected Active Duty Family Member Admissions by Age Group

Figure 21 shows that expected admissions increase with age for both retirees and retired family members, with males having the highest expected number of admissions for retirees.

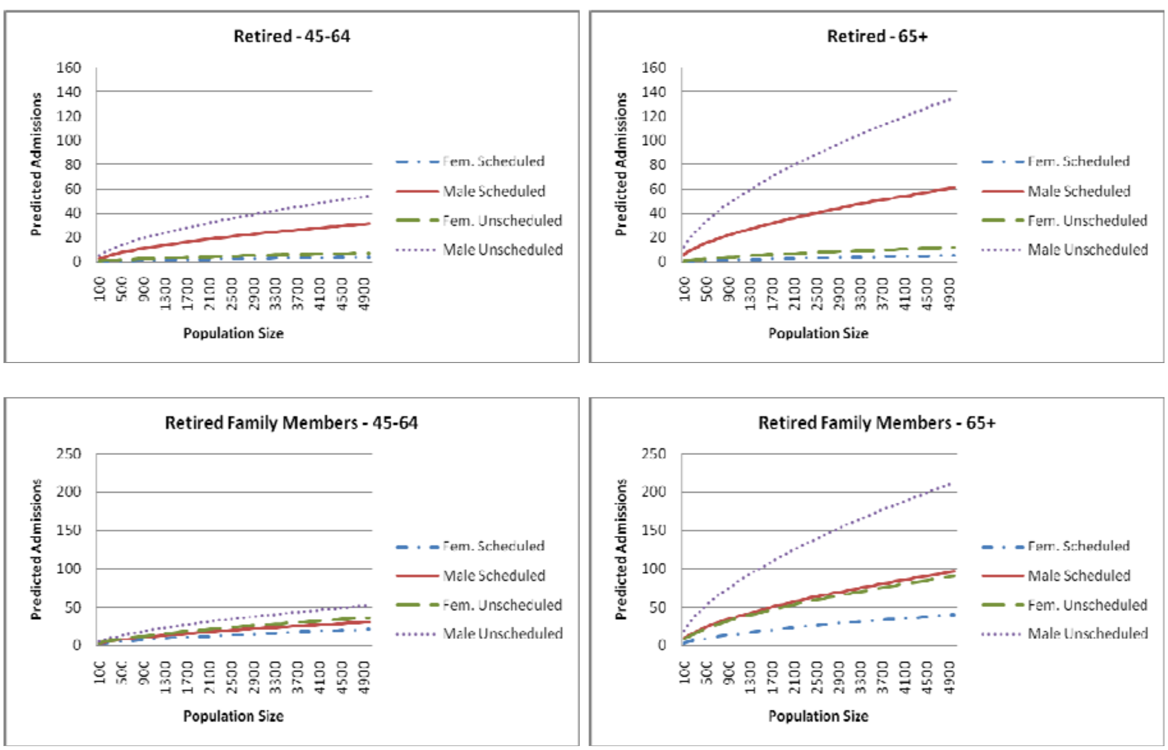

Figure 21. Expected Retired/Retired Family Member Admissoins

B. PREDICTIONS FROM VARIED AVERAGE POPULATION SIZES

1. Comparison to Actual Population

In this section, the average population totals for each enrolled and un-enrolled beneficiary category resulting in admissions to Four East or Four West are increased and decreased by 10 and 25 percent. The new populations are used to observe how changes from the current population might impact the volume of admissions to each location.

a. Four East (Enrolled)

When the populations for enrolled patients admitted to Four East are increased or decreased by a percentage, the percentage of change in the predicted values is proportionate for all patient categories as illustrated in Figure 22.

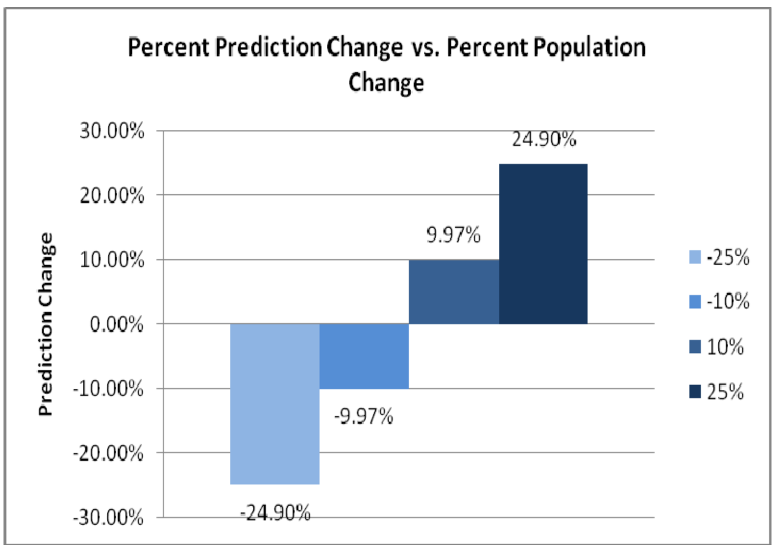

Figure 22. Four East Enrolled Percent Prediction Change vs. Percent Population Change

b. Four East (Un-enrolled)

The predictions for un-enrolled patients admitted to Four East do not change at the same rate as the percentage of change to the total population. When the population size is decreased by 10 percent, the predicted values decrease anywhere from 4.8 to 8.2 percent. When the population size is decreased by 25 percent, the predicted admissions decrease by the range of 12.8 to 20.2 percent. A 10 percent increase in population results in prediction increases between 4.5 and 8.3 percent while a 25 percent increase results in predictions ranging from 10.8 to 21.2 percent increase. The highest and lowest predictions for the changed populations resulted from active duty males between the ages 25-34 with scheduled and unscheduled admissions as shown in Table 5.

Type of Admission	Pop. Decrease of 25%	Pop. Decrease of 10%	Pop. Increase of 10%	Pop. Increase of 25%
Scheduled	- 20.2	-8.2	+8.3	+12.2
Unscheduled	- 12.8	-4.8	+4.5	+10.8

Table 5. Percent Prediction Changes for Active Duty Males Ages 25-34 by Admission Type

c. Four West (Enrolled)

Like Four East (un-enrolled), the predictions for enrolled patients admitted to Four West do not change at the same rate as the percentage of change in the total population. The range of change in predictions is also broader. When the population size is decreased by 10 percent, the predicted values decrease anywhere from 8.5 to 15.2 percent. When the population size is decreased by 25 percent, the predicted admissions decrease by the range of 25.6 to 35.1 percent. A 10 percent increase in population results in prediction increases between 8.4 and 16.9 percent while a 25 percent increase results in predictions ranging from 20.8 to 46.0 percent increase. In this case, half highest and lowest predictions are attributable to active duty males between the ages 25-34 with unscheduled admissions and the other half are attributable to active duty females ages 65+ with scheduled admissions ad shown in Table 6.

Beneficiary Type	Type of Admission	Pop. Decrease of 25%	Pop. Decrease of 10%	Pop. Increase of 10%	Pop. Increase of 25%
AD Male, age 25-34	Unscheduled	-21.6	-8.5	+16.9	+46.0
AD Female, age 65+	Scheduled	-35.1	-15.2	+8.4	+20.8

Table 6. Percent Prediction Changes for Active Duty Males Ages 25-34 and Active Duty Females Ages 65+

d. Four West (Un-enrolled)

As with Four East, there is no variation across patient categories for predictions of admissions of un-enrolled patients to Four West. There is, however, a difference between the percentage of change to the total population and the percentage of change to the predicted admissions. When the population decreases by 10 and 25 percent, the resulting decrease in admissions is only 6.1 and 16 percent respectively. When the population increases by 10 and 25 percent, the resulting increase in admissions is 5.9 and 14.5 percent respectively as shown in Figure 23.

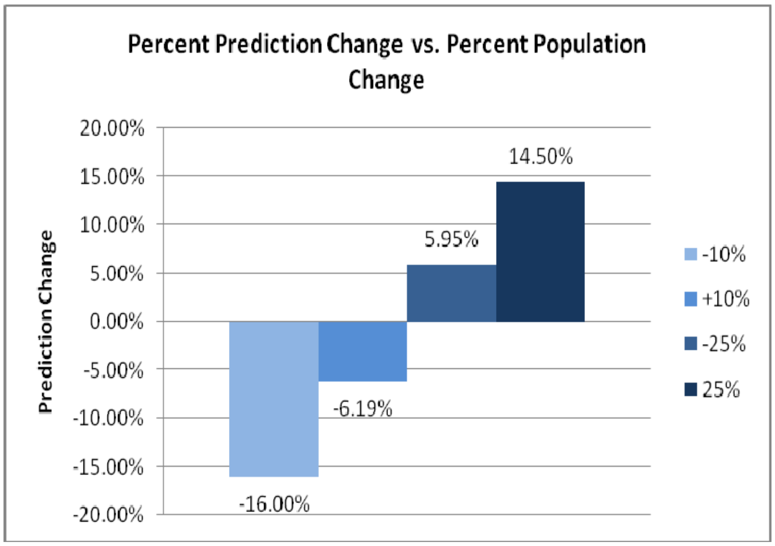

Figure 23. Four West Unenrolled Percent Prediction Change vs. Percent Population Change

2. Examination of Largest Beneficiary Categories

The four largest beneficiary categories that contribute to the patient population at NMCSD are active duty males, retired males, active duty family member females and retired family member females. Scheduled and unscheduled admission predictions are calculated by age group across the range of population sizes for each category and plotted for observation. It is assumed that if the populations change at NMCSD, the changes will be reflected in the enrolled portions of the population.

a. Four East

The actual population sizes of active duty males by age group categories enrolled to NMCSD range from approximately 4,000 to 44,000. The plot in Figure 24 shows that as the population increases for each age group, 45-64 year-olds see the most rapid increase in scheduled admissions to Four East while the slowest increase in admissions is for the age groups 18-24 and 25-34. Figure 24 also shows that the age group 18-24 has the largest number of unscheduled admissions as well as the greatest increase in admissions as the population increases. There is very little difference in the admission rates for the age groups 25-34 and 35-44 and the rate of change in admissions increases slowly with an increase in population size.

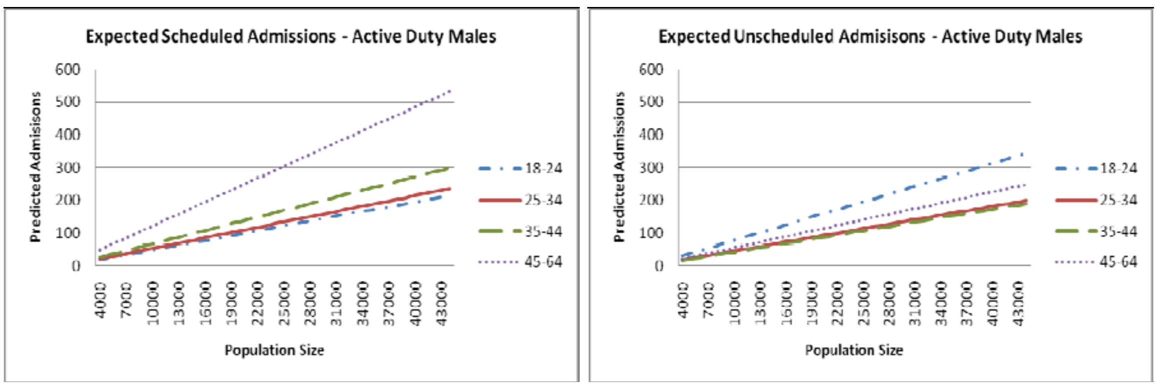

Figure 24. Four East, Active Duty, Male, Scheduled/Unscheduled Admissions

The population sizes of retired males by age group categories range from approximately 4,000 to 42,000. Figure 25 shows that scheduled admissions for retired males belonging to the age groups 25-34 and 65+ have the most rapid rate of increase as the population size increases. However, based on actual population size, these categories are not likely to increase as rapidly because most retirements occur within the age groups 35-44 and 45-64. A similar trend is shown for unscheduled admissions.

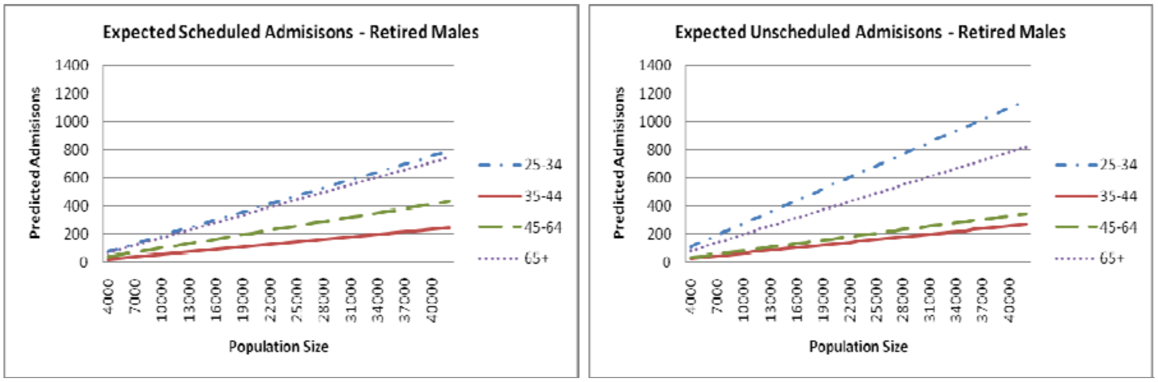

Figure 25. Four East, Retired, Male, Scheduled/Unscheduled Admissions

The population sizes of female active duty family members by age group categories range from approximately 4,000 to 37,000. This beneficiary category shows a trend of increased scheduled and unscheduled admissions by age group. The lowest rate of expected admissions is with the age group 18-24 and as the range of the age groups increases, so does the number of expected admissions as shown in Figure 26. The most significant difference between the plots is that there is greater variance between age groups for the expected scheduled admissions than expected unscheduled admissions.

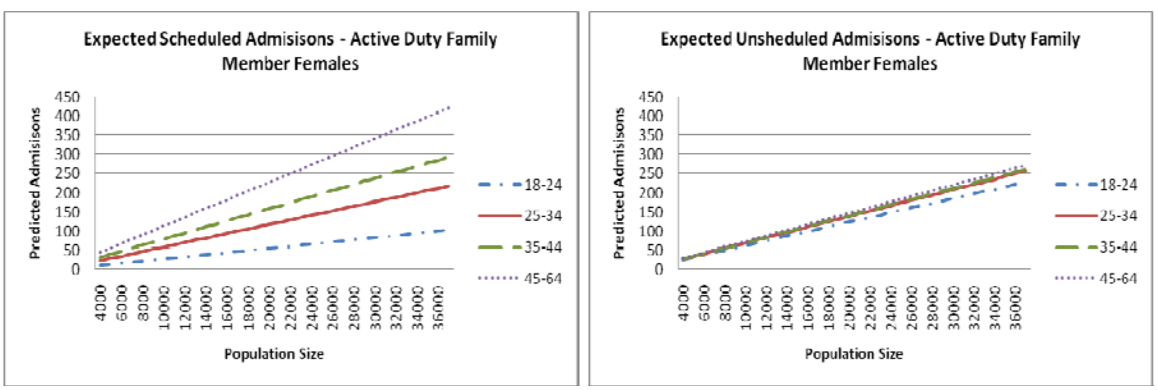

Figure 26. Four East, Active Duty Family Member, Female, Scheduled/Unscheduled Admissions

The population sizes of female retired family members by age group categories range from approximately 1,000 to 40,000. Figure 27 shows a trend of increased admissions by age group nearly identical to the one in Figure 26 for female family members of retirees.

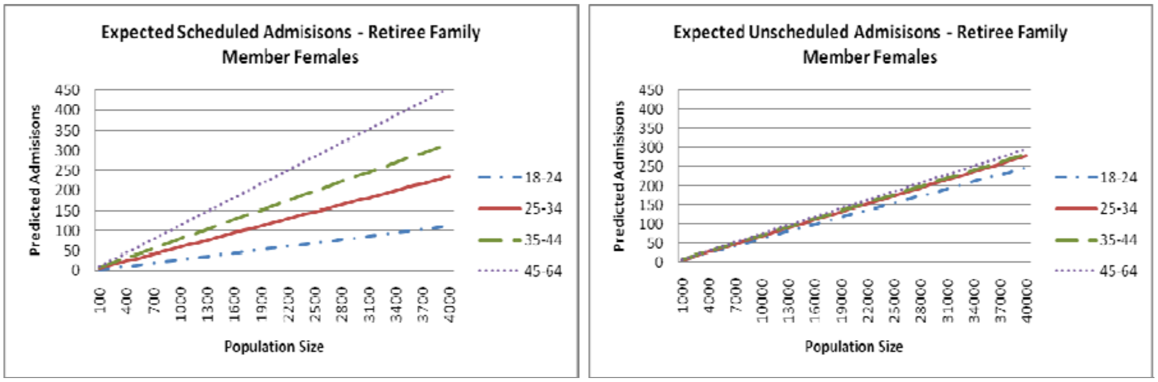

Figure 27. Four East, Retired Family Member, Female, Scheduled/Unscheduled Admissions

b. Four West

The ranges of population size provided for Four East also apply to the beneficiary categories in Four West. Figure 28 shows that expected scheduled admissions for active duty males are almost flat across all age groups and as the population increases. The rates of increase for expected unscheduled admissions are nearly identical for age groups 18-24 and 25-34 while the older age groups show a more rapid increase as the population size grows.

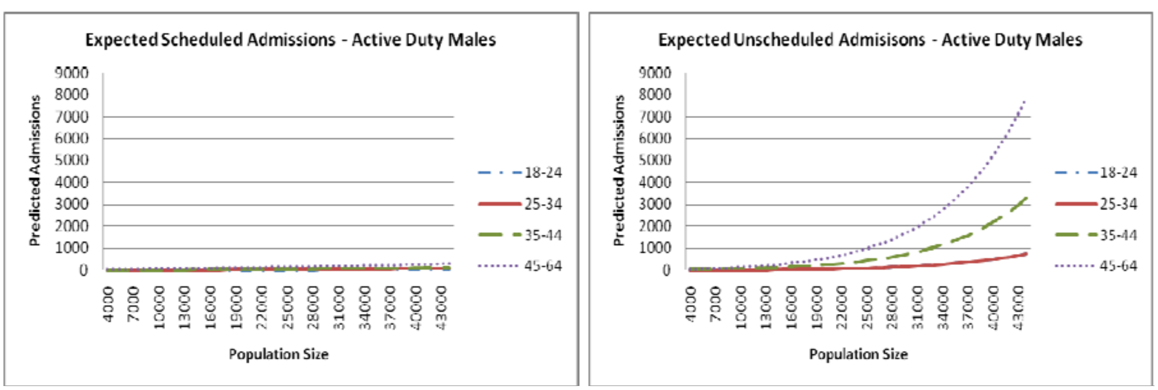

Figure 28. Four West, Active Duty, Male, Scheduled/Unscheduled Admissions

Figure 29 shows that the increasing trends in expected unscheduled admissions for retired males by age group are nearly identical to there of active duty males.

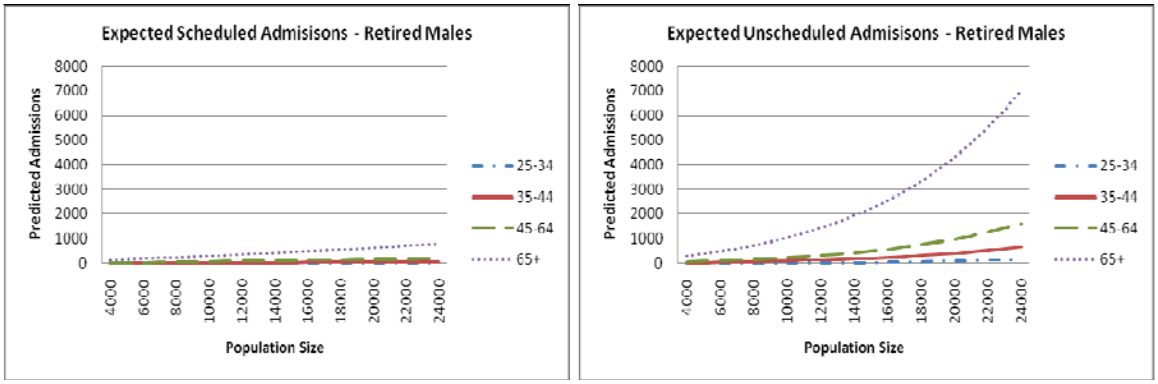

Figure 29. Four West, Retired, Male, Scheduled/Unscheduled Admissions

Female active duty family members show a trend of increased unscheduled admissions by age group. The lowest rate of expected admissions is with the ages 18-34 and as the range of the age groups increases, so does the number of expected admissions as shown in Figure 30. Again, the number of scheduled admissions remains low across all age groups and population sizes.

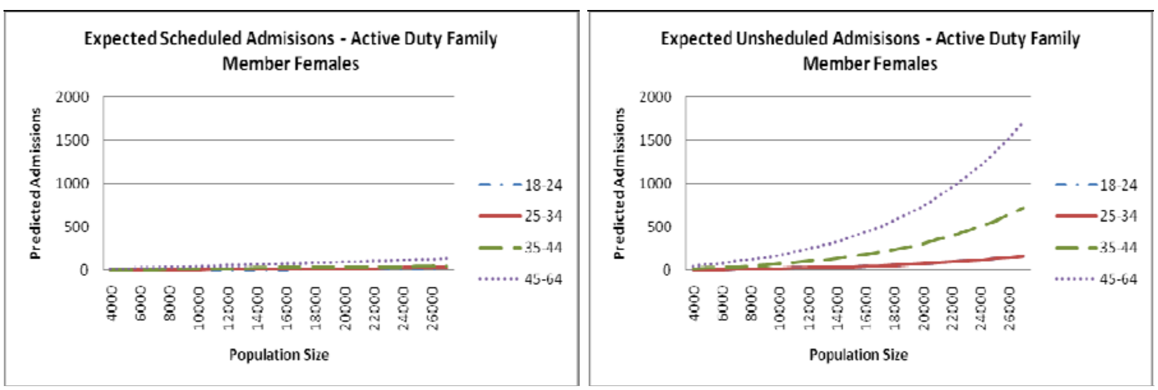

Figure 30. Four West, Active Duty Family Member, Female, Scheduled/Unscheduled Admissions

Figure 31 shows a trend of increased admissions by age group for female family members of retirees, which is nearly identical to that of female active duty family members.

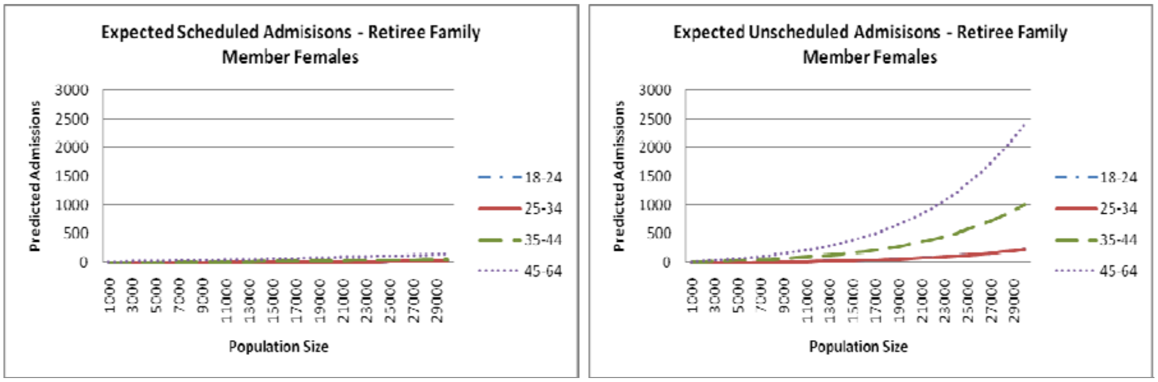

Figure 31. Four West, Retired Family Member, Female, Scheduled/Unscheduled Admissions

c. Summary

The most noticeable difference between admission patterns on Four East and Four West is that the vast majority of expected admissions to Four West are unscheduled. In most cases, the expected number of scheduled admissions to Four East exceeds the expected number of unscheduled admissions.

3. Confidence Intervals on Largest Beneficiary Categories

Confidence Intervals are calculated across the range of the population size for each of the largest beneficiary categories. Tables 7 and 8 provide a snapshot of how the confidence intervals can change as the age group and population size for the predictions are adjusted. The 45-64 year-old age group has the smallest proportion of the active duty population and whether the population size is at its largest or smallest, this age group has the widest confidence interval range. When using the population size of 4,000 the confidence intervals for predictions across all age groups are narrower than the calculated intervals when using the population size of 44,000. In both population cases, the age group 25-34 has the smaller confidence intervals than those of other age groups with the same population size.

Four East Active Duty Males – Scheduled Admissions

	Population = 4,000		**Population = 44,000**	
Age Groups	**Predicted Admissions**	**95% CI**	**Predicted Admissions**	**95% CI**
18-24	19.8	(16.6, 23.7)	216.3	(171.7, 272.4)
25-34	21.7	(18.9, 25.0)	237.2	(199.8, 281.6)
35-44	27.4	(23.6, 31.9)	299.3	(245.3, 365.1)
45-64	48.7	(38.5, 61.7)	531.8	(391.3, 722.8)

Table 7. Confidence Intervals for Active Duty Male Admission Predictions

Four West Active Duty Males – Scheduled Admissions

	Population = 4,000		**Population = 4,000**	
Age Groups	**Predicted Admissions**	**95% CI**	**Predicted Admissions**	**95% CI**
18-24	3.1	(2.2, 4.4)	47.2	(7.9, 281.1)
25-34	4.4	(3.3, 5.8)	65.9	(7.9, 281.1)
35-44	7.3	(5.8, 9.2)	110.2	(13.0, 335.3)
45-64	20.5	(15.9, 26.3)	309.3	(57.1, 1675.5)

Table 8. Confidence Intervals for Active Duty Male Admission Predictions

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V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

Regression analysis provides an approach to predicting inpatient volume that can enhance decision-making ability when trying to anticipate future needs of the patient population. One might argue that the “common sense” approach works just as well, but there are some trends that are shown in the regression predictions that are not necessarily intuitive.

Through the findings of regression analysis, scenarios that might not have otherwise have been considered are brought forward. Important findings include the fact that when the population at NMCSD increases or decreases, the rate of change in admissions will lag behind the change in population. It is also important to note that although age appears to be a strong indicator for the likelihood of being admitted to the hospital, there are circumstances where this is not the case.

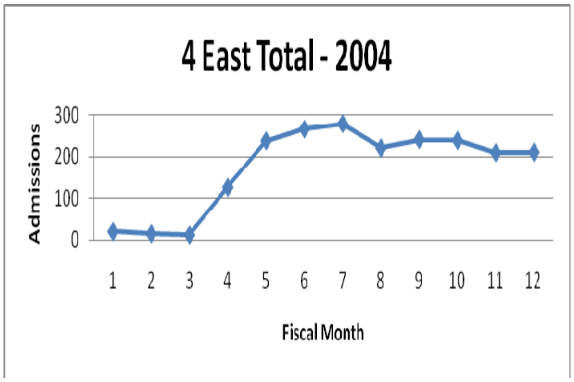
There is, however, one noticeable trend that regression analysis cannot address. It appears when Four East and Four West are up and running, the number of admissions remains relatively stable no matter how many unscheduled admissions there are. This could imply that the staff in charge of managing the surgical schedules keeps the schedule balanced and consistent no matter what unexpected events take place.

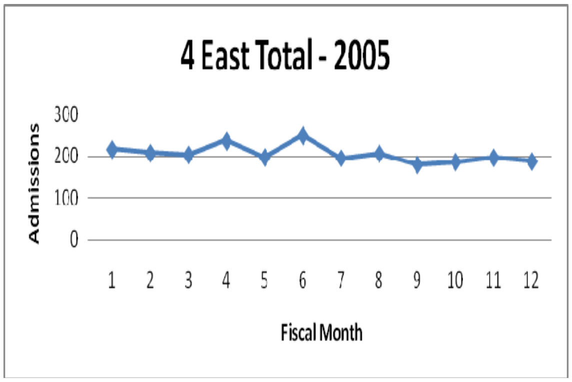
B. RECOMMENDATIONS FOR FUTURE RESEARCH

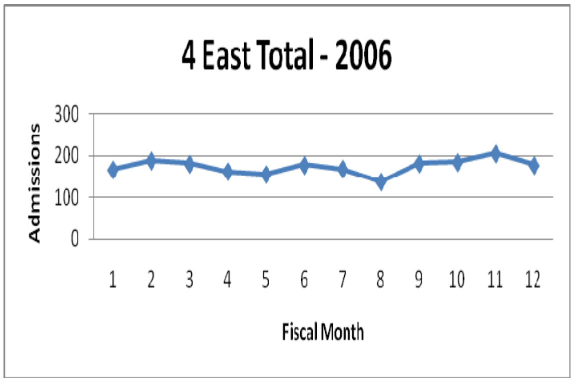
Throughout this thesis, several additional opportunities for additional research became clear. Because it appears that the schedules are so closely managed by the surgical staff, it is recommended that a future study focus on actual requests for service. A comparative analysis could be conducted to see if there is a significant difference between surgical services requested and surgical services provided at NMCSD, or a study could be conducted on the amount of time that patients generally wait for elective surgeries. There is also the opportunity to delve deeper into the study of admissions by incorporating expected length of stay. Woodruff [12] discusses modeling expected lengths of stay so that predictions can be made on the probability of an inpatient bed being available to meet daily demand. This study would involve determining the average daily census as well as peak census. With that, one can determine the total number of inpatient beds that are required to meet the desired level of bed availability with a certain probability.

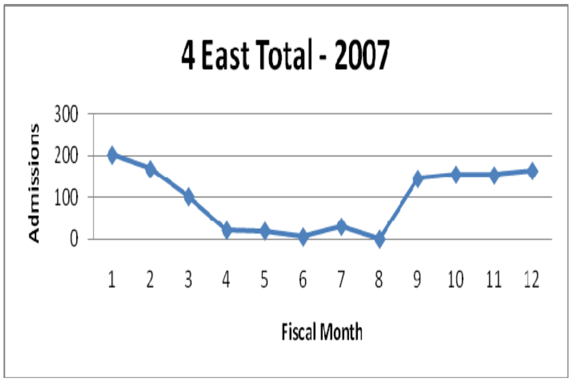
APPENDIX A

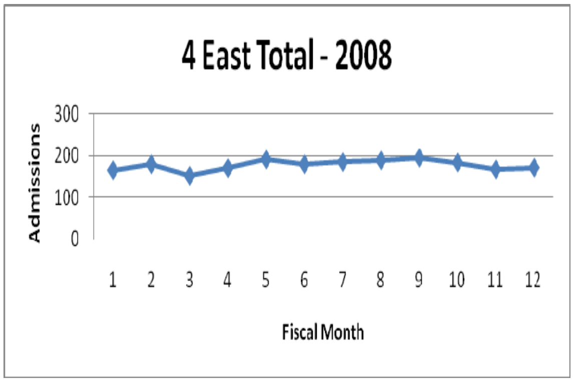
Four East Admission Plots by Fiscal Month











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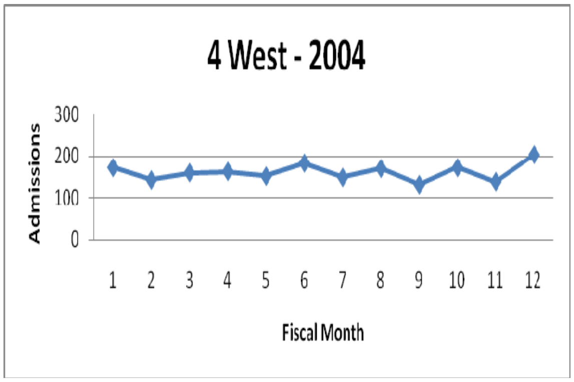
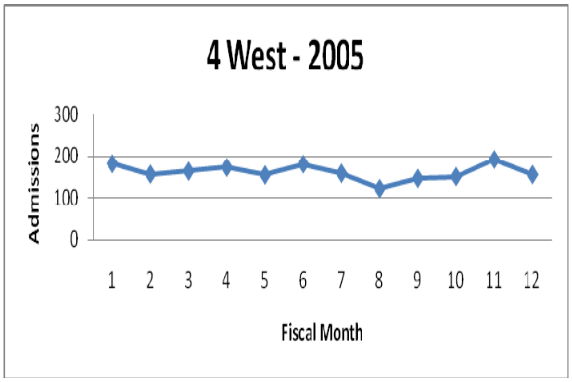
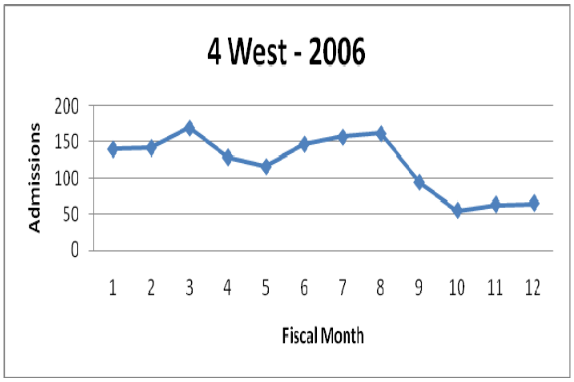
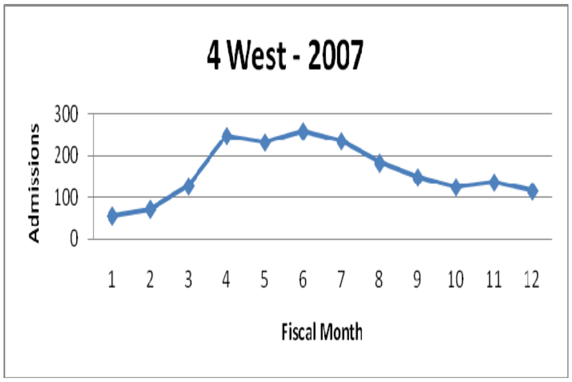
APPENDIX B

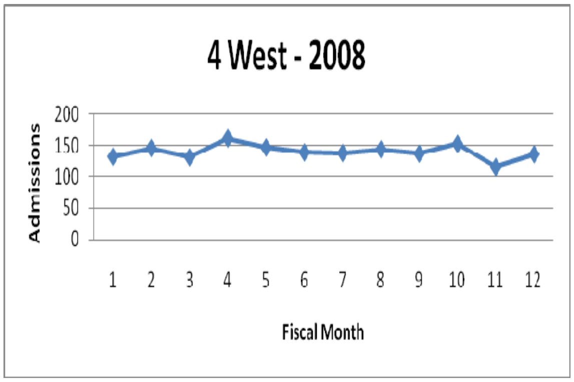
Four West Admission Plots by Fiscal Month











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APPENDIX C

<u>Four East (enrolled) Final Model</u>

Variable	**Coefficient**	**S. E.**	**Variable**	**Coefficient**	**S. E.**
Intercept	-14.6376	368.8402	BenCat (Ret.FM)*Age (18-24)	-8.6204	-8.6204
AdmitSource	-1.0858	0.5607	BenCat (ADFM)*Age (18-24)	-7.9062	-7.9062
FM (Jan)	-0.0058	0.0441	BenCat (Ret.)*Age (18-24)	-9.2121	-9.2121
FM (Jul)	0.1187	0.0431	BenCat (Ret.FM)*Age (25-34)	-7.5230	-7.5230
FM (Oct)	-0.1560	0.0462	BenCat (ADFM)*Age (25-34)	-7.2564	-7.2564
BenCat (Ret.FM)	7.8167	368.8404	BenCat (Ret.)*Age (25-34)	-9.5159	-9.5159
BenCat (ADFM)	7.6733	368.8404	BenCat (Ret.FM)*Age (35-44)	-7.4022	-7.4022
BenCat (Ret.)	11.3046	444.1658	BenCat (ADFM)*Age (35-44)	-7.1922	-7.1922
AGC (18-24)	9.7046	368.8403	BenCat (Ret.)*Age (35-44)	-10.9131	-10.9131
AGC (25-34)	9.1678	368.8403	BenCat (Ret.FM)*Age (45-64)	-7.3655	-7.3655
AGC (35-44)	9.1185	368.8403	BenCat (ADFM)*Age (45-64)	-7.4041	-7.4041
AGC (45-64)	9.3751	368.8403	BenCat (Ret.)*Age (45-64)	-10.9237	-10.9237
AGC (65+)	-0.6826	577.3442	BenCat (Ret.FM)*Age (65+)	3.4057	3.4057
log(Avg. Tot. Pop)	0.9967	0.0284	BenCat (ADFM)*Age (65+)	-9.3754	-9.3754
AdmitSource*AGC(18-24)	0.6198	0.5641	BenCat (Ret.)*Age (65+)	NA	NA
AdmitSource*AGC(25-34)	1.2489	0.5610	AdmitSource*BenCat.(Ret.FM)	-0.5154	-0.5154
AdmitSource*AGC(35-44)	1.5306	0.5604	AdmitSource*BenCat (ADFM)	-0.3268	-0.3268
AdmitSource*AGC(45-64)	1.8489	0.5587	AdmitSource*BenCat (Ret)	-0.5407	-0.5407
AdmitSource*AGC(65+)	1.5236	0.5619			

Four East (un-enrolled) Final Model

Variable	Coefficient	S. E.	Variable	Coefficient	S. E.
Intercept	-2.5295	0.7447	BenCat (Ret.)*Age (35-44)	-3.0212	1.1607
AdmitSource	0.1913	0.4755	BenCat (Ret.FM)*Age (45-64)	3.4971	0.8473
FM (Jan)	-0.0936	0.0402	BenCat (ADFM)*Age (45-64)	1.8180	0.9054
FM (Jul)	0.1196	0.0382	BenCat (Ret.)*Age (45-64)	-1.5992	1.1256
FM (Oct)	-0.1147	0.0407	BenCat (Ret.FM)*Age (65+)	5.0135	1.2145
Gender	2.2024	0.5894	BenCat (ADFM)*Age (65+)	3.9186	1.4098
BenCat (Ret.FM)	-2.2447	0.8794	BenCat (Ret.)*Age (65+)	NA	NA
BenCat (ADFM)	-1.5867	0.9051	Gender*BenCat(Ret.FM)	-1.2688	0.2812
BenCat (Ret.)	1.6164	1.1087	Gender*BenCat(ADFM)	-2.8268	0.3216
AGC (18-24)	1.4839	0.9344	Gender*BenCat(Ret.)	0.1898	0.3089
AGC (25-34)	0.8613	0.9527	AdmitSource*BenCat.(Ret.FM)	-0.9153	0.1227
AGC (35-44)	0.2991	0.9399	AdmitSource*BenCat (ADFM)	-0.5792	0.0920
AGC (45-64)	-0.0437	0.9327	AdmitSource*BenCat (Ret)	-0.8812	0.1405
AGC (65+)	-1.5491	1.2796	AdmitSource*AGC(18-24)	0.0159	0.4785
Avg. Tot. Pop	0.0000	0.0000	AdmitSource*AGC(25-34)	0.1477	0.4882
log(Avg. Tot. Pop)	0.5268	0.0659	AdmitSource*AGC(35-44)	0.7122	0.4813
BenCat (Ret.FM)*Age (18-24)	0.9316	0.8148	AdmitSource*AGC(45-64)	0.8557	0.4867
BenCat (ADFM)*Age (18-24)	1.2114	0.8640	AdmitSource*AGC(65+)	0.8880	0.4892
BenCat (Ret.)*Age (18-24)	-4.1468	1.4518	Gender*AGC(18-24)	-0.5586	0.5610
BenCat (Ret.FM)*Age (25-34)	1.5102	0.9473	Gender*AGC(25-34)	-1.0104	0.5648
BenCat (ADFM)*Age (25-34)	2.0512	0.8771	Gender*AGC(35-44)	-1.0814	0.5664
BenCat (Ret.)*Age (25-34)	-3.1315	1.3064	Gender*AGC(45-64)	-1.2630	0.5921
BenCat (Ret.FM)*Age (35-44)	2.6688	0.8788	Gender*AGC(65+)	-0.7469	0.6608
BenCat (ADFM)*Age (35-44)	2.1566	0.8725	AdmitSource*Avg. Tot. Pop	3.94E-05	0.0000

Four West (enrolled) Final Model

Variable	Coefficient	S. E.	Variable	Coefficient	S. E.
Intercept	-6.8035	0.5510	Avg. Tot. Pop	0.0001	0.0000
AdmitSource	0.4220	0.5726	log(Avg. Tot. Pop)	0.8451	0.0557
FM (Jan)	0.0546	0.0419	AdmitSource*BenCat.(Ret.FM)	-0.5087	0.1637
FM (Jul)	0.1522	0.0412	AdmitSource*BenCat (ADFM)	-0.4934	0.1613
FM (Oct)	0.1879	0.0408	AdmitSource*BenCat.(Ret.)	-0.1804	0.1663
Gender	-0.4419	0.1422	Gender*BenCat(Ret.FM)	-0.2779	0.3292
BenCat (Ret.FM)	0.1313	0.161855	Gender*BenCat(ADFM)	0.3437	0.2787
BenCat (ADFM)	-0.1257	0.1510	Gender*BenCat(Ret.)	1.1006	0.2233
BenCat (Ret.)	-0.5142	0.2255	AdmitSource*AGC(18-24)	-0.25404	0.5977
AGC (18-24)	0.9853	0.4044	AdmitSource*AGC(25-34)	0.067061	0.6009
AGC (25-34)	0.9983	0.4091	AdmitSource*AGC(35-44)	-0.89543	0.5744
AGC (35-44)	2.4752	0.3897	AdmitSource*AGC(45-64)	-0.7356	0.5717
AGC (45-64)	3.3474	0.3909	AdmitSource*AGC(65+)	-0.8340	0.5647
AGC (65+)	4.8306	0.3866	AdmitSource*Avg. Tot. Pop.	-0.0001	0.0000

Four West (un-enrolled) Final Model

Variable	**Coefficient**	**S. E.**	**Variable**	**Coefficient**	**S. E.**
Intercept	-1.1192	1.0015	BenCat(ADFM)*Age(35-44)	18.89555	583.7807
AdmitSource	-14.2361	432.1403	BenCat(Ret.)*Age(35-44)	-15.5437	555.9589
FM (Jan)	0.0922	0.0559	BenCat(Ret.FM)*Age(45-64)	20.53619	592.7636
FM (Jul)	0.1465	0.0553	BenCat(ADFM)*Age(45-64)	19.3623	583.7807
FM (Oct)	0.2509	0.0540	BenCat(Ret.)*Age(45-64)	-14.3243	555.9586
Gender	0.6537	1.2248	BenCat(Ret.FM)*Age(65+)	35.3422	812.6858
BenCat (Ret.FM)	-18.9125	592.7638	BenCat(ADFM)*Age(65+)	35.7476	806.1572
BenCat (ADFM)	-18.7197	583.7808	BenCat(Ret.)*Age(65+)	NA	NA
BenCat (Ret.)	14.3810	555.9587	AdmitSource*AGC(18-24)	14.2425	432.1403
AGC (18-24)	-2.0330	1.1527	AdmitSource*AGC(25-34)	14.3271	432.1403
AGC (25-34)	-2.2713	1.1755	AdmitSource*AGC(35-44)	13.5481	432.1403
AGC (35-44)	-2.2806	1.1678	AdmitSource*AGC(45-64)	13.6956	432.1403
AGC (45-64)	-2.2252	1.1381	AdmitSource*AGC(65+)	13.4471	432.1403
AGC (65+)	-16.1155	555.9593	Gender*BenCat(Ret.FM)	-1.0396	0.4975
log(Avg. Tot. Pop)	0.6060	0.0727	Gender*BenCat(ADFM)	-1.7422	0.3352
BenCat(Ret.FM)*Age(18-24)	17.1212	592.7637	Gender*BenCat(Ret.)	0.5565	0.3830
BenCat(ADFM)*Age(18-24)	17.9493	583.7807	Gender*AGC(18-24)	0.6465	1.2410
BenCat (Ret.)*Age(18-24)	-15.8008	555.9599	Gender*AGC(25-34)	-0.0444	1.2450
BenCat(Ret.FM)*Age(25-34)	16.9687	592.7643	Gender*AGC(35-44)	0.6854	1.2533
BenCat(ADFM)*Age(25-34)	18.0880	583.7807	Gender*AGC(45-64)	0.7626	1.2542
BenCat(Ret.)*Age(25-34)	-15.5131	555.9595	Gender*AGC(65+)	1.2414	1.2632
BenCat(Ret.FM)*Age(35-44)	19.1056	592.7638			

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