THE IMPACT OF NON-EMERGENCY MEDICAL USE ON THE UNITED STATES HEALTHCARE SYSTEM: A RETROSPECTIVE STUDY

By

Patrick Casimir

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Final Dissertation Approval Form

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BY

Patrick Casimir

Dissertation Committee:

Shankar Srinivasan, PhD, Committee Chair
Syed Haque, PhD, Committee Member Dinesh P. Mital, PhD, Committee Member
Arif M. Rana, PhD, Committee Member

Approved by the Dissertation Committee:

____________________ Date: __________

____________________ Date: __________

____________________ Date: __________

ABSTRACT

The Use of Informatics to Determine the Impact of Non-Emergency Medical Use on the United States Healthcare System and Find Viable Solutions: A Retrospective Study

By

Patrick Casimir

For the last three decades, non-emergency medical use, regarded as the utilization of emergency medical services for conditions that are considered non-emergent, has grown rapidly and continues to be an alarming issue for health authorities, private and public hospitals and a much debated and studied subject by researchers and experts in the field. Correspondingly, this retrospective study was used to analyze the 2010 NEDS data set by investigating and distinguishing the characteristics of non-emergency visits compared to emergency visits. Additionally, this retrospective study identified the percentage of emergency visits made for non- emergency conditions, determined the impact of non-emergency medical use on patient outcomes of inpatient mortality, emergency department waiting time, and total emergency department charges, and made viable recommendations to the ongoing problem of non- emergency medical use. Throughout this study, five main methods of data analysis are used: descriptive statistical analysis, ED CPT severity level analysis, NYU ED classification algorithm analysis, analysis of variance, and logistic regression analysis. First, descriptive statistical analysis is conducted to detect numerical observations that are statistically significant enough to indicate non-emergency medical utilization. Second, ED CPT severity level analysis and NYU

ED classification algorithm analysis are applied to the 2010 NEDS data set to probe whether diagnostic and procedural methods are statistically effective to help differentiate non-emergency visits from emergency visits. Third, analysis of variance is performed using the statistical model ANOVA in an effort to expose and uncover differences that are statistically significant between non-emergency visits and emergency visits. Fourth, the probabilistic statistical method of analysis, logistic regression, is employed to determine if patient's demographic characteristics are statistically significant to predict emergency visits. Consequently, results of descriptive statistics show that between 54.02 to 82.7 percent of all emergency department visits were made for conditions found to be either routine, low-severity, or non-emergent and that there are statistically convenient methods to distinguish non-emergency visits from emergency visits. Also, other results of analysis of variance show significant statistical differences between the means of non-emergency visits and emergency visits. Finally, results of logistic regression suggest that there are statistically significant predictive relations between patients' demographic characteristics and outcomes of emergency visits in 76.5% of all cases. Hence, the results of this study lead to the conclusions that a significant number of emergency department visits are made for non-emergency conditions, which can be depicted as the main basis for non-emergency medical use as to negatively impact patient outcomes of inpatient mortality, emergency department waiting time, and total emergency department charges.

Keywords: emergency department, emergency department waiting time, emergency visits, inpatient mortality, low-severity, non-emergent, non-

emergency conditions, non- emergency medical use, non-emergency visits, patient outcomes, routine, total emergency department charges

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Biomedical Informatics at Rutgers University. Further, I must acknowledge Michael De Lucca, President and CEO of the Broward Regional Health Planning Council, Inc. for his insight on Non-Emergency Medical Use in the United States, which has become the major theme of this dissertation study. Additionally, I would like to acknowledge Dr. Tod Mijanovich, Research Assistant Professor at New York University, for his input and help on modifying and adjusting the NYU ED Algorithm to be applied to the 2010 NEDS data set. Also. I would like to acknowledge the great staff of the Biomedical Informatics Program at the School of Health Related Professions of Rutgers University, in particular Ms. Yvonne Rolley, the Administrative Coordinator for her hard work and professionalism in managing all the crucial activities, supporting the needs of students, and being the bridge between students and faculty. Finally, I would like to acknowledge all my professors, colleagues, co-workers, and individuals, whose names are not individually listed here, who have given me support, advices, encouragement, and useful ideas that have made this dissertation a successful project.

DEDICATION

I would like to dedicate this dissertation to my late mother, Charite Magloire. Although she was not an educated woman, her commitment to the education of her 10 children and tremendous strength and devotion in raising them have always given me the inspiration to work hard, be focused, and thrive for success in life. Without the inspiration from my mother, there is no way I would have been the dedicated and highly motivated human being that I am today. I would also like to dedicate this dissertation study to my late son, Patrick Harmel, whom I will continue to love and miss until my last breath. The forever painful tragedy that has deprived me of my son has also impelled me to be the strongest human being that I can be and to always appreciate and face every day of my life with great focus, motivation, appreciation, gratefulness, discipline, and toughness. Additionally, I want to dedicate this dissertation to my wife, Carmelle Alexis. For the last 27 years, her love, support, patience, forgiveness, friendship, advices, and companionship have positively changed my life and allowed me to reach family and personal goals and be successful in my endeavors. An equal dedication goes to my daughter, Steffi for bringing joy to my life and always making me proud as a father with the hope and expectations that she will grow up to become a wonderful, smart, educated, hard-working, and successful human being. Furthermore, I want to dedicate this dissertation to the rest of my family, my father Lemercier, my brothers and sisters, Maude, Gladyss, Nicole, Annie, Madeleine, Jude, and Willy for their love, support, and help throughout my life. Lastly, I would like to dedicate this dissertation to all those who have positively impacted my life and helped me at some point in my life.

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CHAPTER I

INTRODUCTION

1.1 Problem Statement

The delivery of emergency medical services in the United States has been a controversial and troubling issue for more than three decades. Although emergency department rooms are primarily designed to provide urgent, critical, and emergent medical care services, millions of Americans use emergency department (ED) rooms to seek treatment for non-emergency medical conditions as they successfully bypass the need to visit a primary care physician by using ED rooms as alternatives to primary medical care providers. Throughout this dissertation, non- emergency medical use will refer to the common practice of receiving emergency medical services for health conditions that are neither emergent nor life threatening. Predominantly, such utilization results in a non-emergency visit, a visit for which treatment is not critically urgent, not lifesaving, and not required within less than 60 minutes. In today's literature, various terms have been used to describe non-emergency visits. Non-emergency visits are often labeled as non- urgent, avoidable, or preventable. While all those terms do not have a precisely similar definition, they all bear the common understanding that such visits were not truly emergent and that they could have been handled elsewhere such as in a primary care setting or in a urgent care center. Even though a consensus on the definition of an emergency medical condition is nonexistent, the Emergency Medical Treatment and Active Labor Act (EMTALA) provides a legal definition as, a medical condition manifesting itself by acute symptoms of sufficient severity (including severe pain) such that the absence of immediate medical attention could reasonably be expected to result in: (i) placing the health of the individual (or, with respect to a pregnant woman, the health of her unborn child) in serious jeopardy, (ii) serious impairment to bodily functions, or (iii) serious dysfunction of any bodily organ or part.[1]

As shown in Table 1, an increasing number of patients are using emergency department rooms to receive care for non-emergency medical conditions. The percentage of emergency care services rendered for non-emergency conditions often varies depending on the methods of assessment. Some studies, using diagnosis at triage, suggested that the overall percentage of utilization of emergency rooms for non-emergency conditions totaled 13% in 2006.[2]

Table 1: Estimated number of non-emergency visits from 1991 to 2009 (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009 and U.S Population by Year according to Census records. Based on assumptions that 48% of all ED visits are for non-emergency conditions)

Year	Non-emergency Visits (Millions)	Non-emergency	U.S. Population (Millions)
1991	**42.5**	168	252.98
1992	**43.6**	171	256.51
1993	**44.4**	172	259.92
1994	**43.4**	167	263.13
1995	**45.5**	173	266.28
1996	**44.7**	168	269.39
1997	**44.5**	167	272.65
1998	**45.5**	168	275.85
1999	**47.8**	175	279.04
2000	**49.5**	176	282.16
2001	**50.9**	179	284.97
2002	**52.8**	183	287.63
2003	**53.3**	183	290.11
2004	**54.0**	184	292.81
2005	**55.1**	186	295.52
2006	**56.8**	190	298.38
2007	**58.0**	192	301.23
2008	**59.0**	194	304.09
2009	**61.1**	199	306.77

Another study, using discharge diagnosis based on the ED use profiling algorithm known as the New York University (NYU) ED Algorithm, revealed that 56% of all emergency department visits in 2010 were for non-emergency conditions deemed avoidable.[3] Correspondingly, business intelligence and clinical analytics coupled with statistical methods of analysis will be used throughout this doctoral research to assess the problem of using emergency rooms for non-emergency medical care and make recommendations that can be helpful in improving emergency care delivery and quality of care in general.

1.2 Historical Background

On April 7, 1986, President Ronald Reagan signed EMTALA into law. EMTALA mandates hospitals to perform an emergency medical screening (EMS), determine if an emergency medical condition (EMC) exists, stabilize the EMC if possible and/or transfer, and accept EMC's transfer for all patients who come to emergency rooms to seek treatment regardless of patients' ability to pay for those emergency care services received. The primary intent of EMTALA was to guarantee emergency medical services for all ED patients and to stop hospitals from the usual practice of dumping patients because of their inability to pay or lack of health insurance coverage. However since the passage of EMTALA, utilization of ED rooms has considerably increased, which has created a lot of controversies leading many to blame EMTALA for the rise in emergency medical use. Despite EMTALA's revisions in 2003 by the Centers for Medicare and Medicaid Services (CMS) which were intended to clarify and simplify its obligations and limitations, the utilization of ED rooms for both emergency and non- emergency conditions has continued to increase beyond capacity (Figure 1).

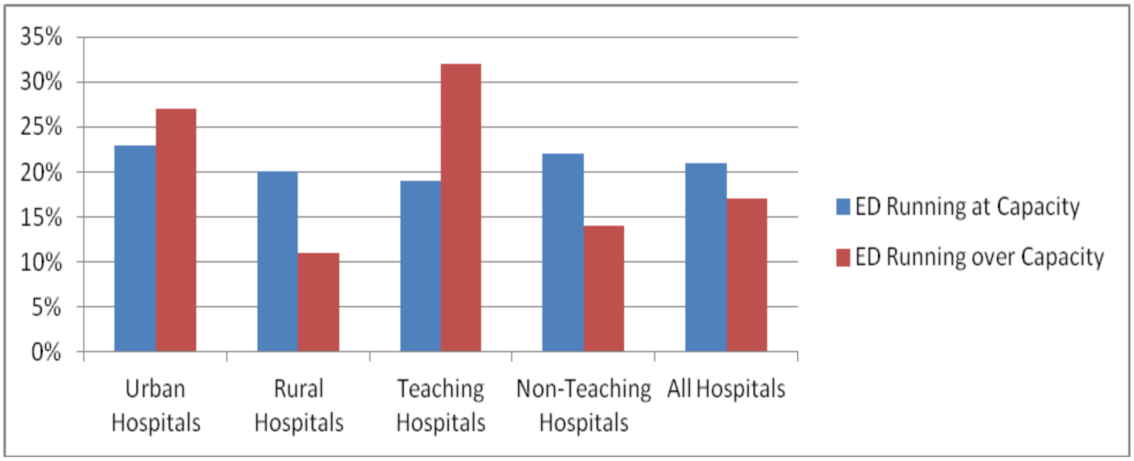

Figure 1: Percent of Hospitals Reporting ED Capacity Issues, March 2010. (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009)

1.3 Study Purpose

This dissertation is a retrospective study designed to analyze the 2010 National Emergency Department Sample (NEDS) data set of the Healthcare Cost and Utilization Project (HCUP) to investigate and distinguish the characteristics of non-emergency visits, estimate the number of ED visits made for non-emergency conditions, determine the impact of non- emergency medical use on patient outcomes of mortality, ED waiting time, and total ED charges, and make viable recommendations that can help unravel the ongoing and increasing problem of non-emergency medical use. The 2010 NEDS data set was used for this retrospective study because it was the most recent and latest data set available from HCUP when this study was initiated. Analyses and interpretations will be made from a number of sources including business intelligence, clinical analytics, and statistical modeling tools. Specifically, descriptive and inferential statistical analyses will be performed on the HCUP's 2010 NEDS dataset to find differences among ED visits in order to determine whether those ED visits were due to emergency or non-emergency conditions.

The 2010 NEDS is a data set made of a sampling population of over 28 million records of ED visits collected at 961 hospitals across the nation and stratified at almost 20% of hospital- based ED visits, which makes this dissertation an empirical research since no other previous known studies have been conducted to use the 2010 NEDS data set to investigate ED utilization for non-emergency conditions. Because of the enormous size of the 2010 NEDS data set, data records from previous years and/or other data sources will not be used in this dissertation. This dissertation will attempt to investigate the impact of non-emergency medical on the healthcare system in the United States. Although previous studies have researched the utilization of ED medical services at specific hospitals, states, regions, and for particular diagnoses, no study has been done to investigate and determine the negative impact of non-emergency medical use on outcomes of ED waiting time, ED cost per visit, and inpatient mortality.

1.4 Study Hypotheses

Study hypotheses, based on descriptive and inferential statistical analysis of the 2010 NEDS data set from HCUP, predominantly investigate whether an important number of ED visits in 2010 were made for non-emergency conditions compared to emergency conditions. In all, descriptive and inferential statistics will be used to analyze ED visits records within the 2010 NEDS data set as units of analysis to distinguish non-emergency visits from emergency visits by uncovering variations and making comparisons between emergency and non-emergency visits within the 2010 NEDS data set. In doing so, differences and patterns will emerge among ED visits that will help determine whether those ED visits are due to emergency or non-emergency conditions. As previously explained, the HCUP's 2010 NEDS data set is made of a collection of over 28 million ED visits recorded at 961 hospitals across the United States and stratified at almost 20% of hospital-based ED visits. So far, hypotheses for this dissertation are:

1. Are there statistically significant numerical observations within the 2010 NEDS indicative of non-emergency medical use?
2. Are there statistically effective diagnostic and procedural methods in differentiating non- emergency visits from emergency visits?
3. Are emergency visits within the 2010 NEDS statistically significantly different from non- emergency visits?
4. Are there statistically significant relations between patients' demographic characteristics and outcomes of emergency visits?

1.5 Intended Results

Intended results from statistical modeling analyses described in the previous section of this dissertation will demonstrate that a considerable amount of ED visits in 2010 were made for non-emergency conditions. Also this research study intends to show that non-emergency visits have a negative impact on healthcare in terms of impeding quality, increasing cost, hindering access, and diminishing efficiency.

Intended results of this dissertation will show that:

- Percentage and frequency counts of non-emergency visits among 2010 NEDS statistical data sample population are statistically significant.
- Diagnostic and procedural methods are statistically effective to differentiate non- emergency visits from emergency visits.
- Non-emergency visits within the 2010 NEDS are statistically and significantly different from emergency visits.
- Predictive relations between patient's demographic characteristics and outcomes of emergency visits are statistically significant.
- Non-emergency medical use can negatively impact inpatient mortality.
- Non-emergency medical use can raise the total cost of ED charges.
- Non-emergency medical use can obstruct access to emergency medical care.
- Non-emergency medical use can adversely affect ED waiting time.

1.6 Study Significance

This study will be significant to the healthcare practice in general for a number of reasons. Study results can help in the reduction of non-emergency visits through critical revisions of EMTALA and new initiatives, aid in the design of new triage systems that will effectively identify non-emergency visits, lead to the implementation of highly effective ED management programs as they relate to patient's demographics and ED visit's characteristics and allow policymakers to take critical measures that can ultimately tackle the ongoing and increasing non-emergency medical use crisis.

CHAPTER II

RELATED LITERATURE

2.1 Role of Business Intelligence and Clinical Analytics in Healthcare

The healthcare industry has been making significant changes to the way healthcare services are delivered in the United States. One such important change is the increasing application of new technologies within healthcare facilities across the country to provide higher quality, safer, and cheaper healthcare services. Healthcare organizations are implementing new information systems and technologies that combine the use of computers for storing patient's data, sharing information, and giving advice to clinicians in diagnosing patients, ordering medications, and solving other clinical problems. Yet healthcare organizations are facing critical challenges to integrate newly emerging data processing technologies such as business intelligence (BI) and clinical analytics into their daily operations, both of which can be used to transform data into a competitive array of knowledge needed to enhance quality, reduce cost, improve productivity, and gain market share. Business intelligence is often depicted as the "ability to convert data into actionable information for decision making and critical to demonstrating improved value…as has been the conclusion of these authors."[4] On the other hand, clinical analytics is defined as "a tool that provides information and context to physicians as they make decisions about the care of their patients or aid in better understanding the health of their covered populations…as has been the conclusion of this author."[5]

The application of BI and clinical analytics in healthcare is increasingly being accepted as a technological and scientific requirement for greater performance and increased financial revenues. The implementation of BI and clinical analytics within health care organizations has been known to be critically significant. BI is useful to healthcare organizations and help them gain "valid, comprehensive views of organizational data and understand complex processes and relationships by means of easily assimilated, customized, visual reports that help users to make timely and informed decisions, take actions that will improve performance, and understand how their actions affect the entire organization…as has been the conclusion of these authors."[6] Moreover, it was recognized that the implementation of BI will aid healthcare organizations in "providing actionable information that can be used to make better decisions. The healthcare industry is increasingly embracing BI with the goal of improving business processes in order to increase revenue, reduce costs and improve patient satisfaction… as has been the conclusion of this author."[7] In the same light, in a 2010 research consortium of Chief Medical officers (CMOs) and Chief Medical Information Officers (CMIOs) sponsored by Anvita Health, it was acknowledged that clinical analytics was being used in "collecting and/or leveraging clinical and/or claims data to enhance patient care cost, safety, and efficiency…as has been the conclusion of these authors".[5(3)] Additionally, Statistical Analysis Software (SAS) researchers indicated that health analytics can help healthcare organizations "simplify data integration across the extended enterprise, understand and manage financial risks and incentives, proactively improve care quality and outcomes, drive greater efficiency of care delivery, engage patients as unique individuals…as has been the conclusion of these authors."[8]

This evolving trend of utilizing BI and clinical analytics by healthcare organizations has led to a common quest for higher quality, efficiency, and productivity. In the same context, this dissertation will analyze data records from the 2010 NEDS sample to generate informative results and statistical findings that depict the harmful impact of non-emergency visits on the healthcare system in terms of quality, safety, cost, and efficiency. Furthermore those findings will be used to make practical recommendations to improve quality, enhance safety, reduce cost, and heighten efficiency as they relate to the healthcare practice.

2.2 Major Causes of Non-Emergency Medical Use

The current literature on major causes of non-emergency visits varies significantly depending on expert's affiliation, data sources, hospital's location, assessment methods, and populations. To better understand the impact of non-emergency medical use on quality of care and find solutions for improvement, it is critical to identify the causes associated with this problem. Most experts and researchers point out the major causes of non-emergency visits as either primary care, financial, legal, or capacity constraints.

2.2.1 Primary Care Constraints

Adequate access to primary care services has always been linked to the improvement of overall quality of care and the reduction of mortality rate. Variably, primary care constraints are often mentioned as one of the major reasons for non-emergency visits. In general, primary care constraints refer to lack of access to primary care due to difficulties to maintain health insurance coverage, a primary care provider, and a regular healthcare facility to seek treatment. Accordingly, a 2012 study of patients and health professionals revealed that lack of access to primary care services was the main "reasons for using EDs for non-urgent complaints...as has been the conclusion of these authors."[9] Moreover, research findings from a New England Healthcare Institute's (NEHI) report have shown that "experts believe that for patients the ED simply cannot provide the continuity of care that the primary care system offers…as has been the conclusion of these authors."[10] Finally, another 2006 study reported that "non-emergent and primary care preventable conditions account for a large percentage of total ED volume, which suggests many patients experience primary care access barriers or dissatisfaction with primary care providers...as has been the conclusion of this author."[11] As shown in the literature being reviewed here, there is growing and suitable evidence on the use of ED rooms for non-emergency purposes by patients lacking access to primary care. Nonetheless, lack of access to primary care is far from being a significant cause of non-emergency medical use. It is not always the case that patients who lack access to primary care seek treatments in hospital's ED rooms because of non-emergency events. Individuals with access to traditional primary care services also make regular visits to ED rooms for non-emergency medical conditions.

2.2.2 Financial Constraints

Earlier we referred to primary care constraints as one of the major causes of non- emergency medical use for the delivery of emergency medical care services. Another theme agreed upon by researchers and experts as a critical cause of such misusage is financial constraints. In terms, financial constraints are caused by the inability of people to pay for medical care. Financially constrained individuals are primarily those of low income and underserved populations. A review of literature indicated that financial constraints can play a significant role in the decision of individuals to use ED rooms to receive care for events of non-emergency nature. Findings from different studies have shown an increase in the likelihood of using emergency rooms for non-emergency care among low-income individuals. A 2006 study on the use of ED for potentially avoidable conditions in New Jersey recognized that "ED patients most likely to have their visits (without admission) classified as potentially avoidable include children ages 4 and under and traditionally underserved populations – i.e., charity care, self-pay, Medicaid, non-Hispanic blacks, and Hispanics…as has been the conclusion of this author."[12] Another report from the Division of Health Care Finance and Policy (DHCFP) of Massachusetts explained that "designated medically underserved populations (low income) consistently exhibited higher rates of preventable or avoidable ED visits compared to the state average…as has been the conclusion of this author."[13] Although current literature findings[12, 13(26)] validate the non-emergency use of ED rooms by low income and underserved populations, nonetheless financial constraints are not commonly perceived as primary causes of such practice. It is also known that people in high income brackets with ability to pay for care are frequent users of ED rooms for non-emergency conditions (Figure 2).

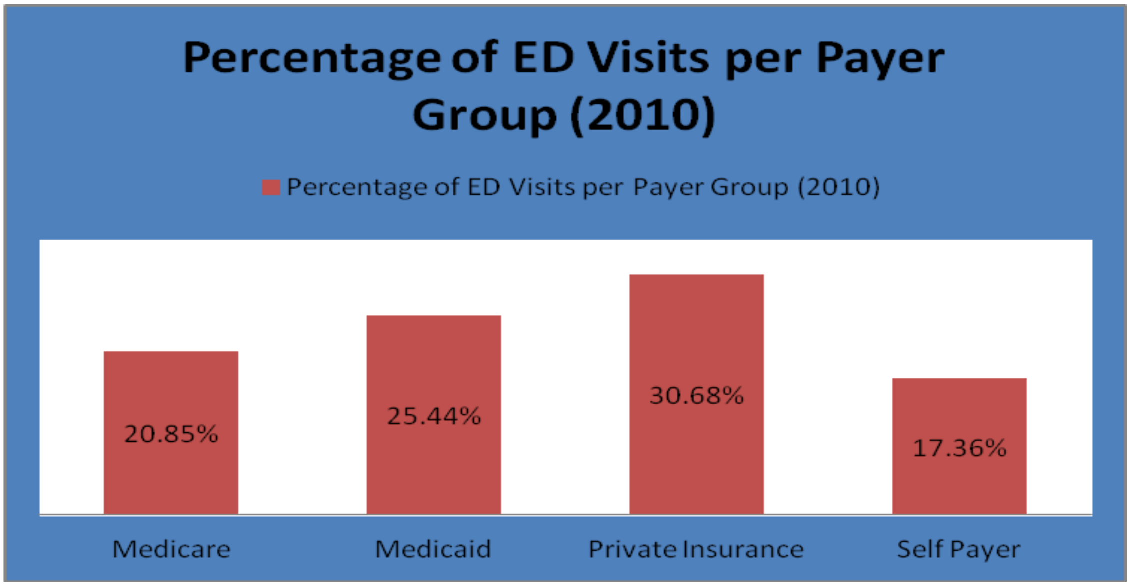

Figure 2: Percentage of ED Visits by Payer Group 2010 (Source: NEDS's 2010 Data set from HCUP)

2.2.3 Legal Constraints

When Congress voted EMTALA into law in 1986, the intent was to alleviate the practice of dumping patients in hospital's ED rooms and guarantee nondiscriminatory emergency medical care services for the general public. As noted earlier, EMTALA mandates hospitals that are part of CMS to provide care to all patients with an emergency medical condition regardless of their ability to pay. Enacted in 1986, EMTALA has contributed to significant increases in non-emergency medical use and reductions in quality of care, according to results and findings of numerous studies. It was reported that since the implementation of EMTALA, overall ED use has significantly increased from "77 million visits in 1986 to 127 million visits in 2009 …as has been the conclusion of this author,"[14] a 65% increase. Because of the growing increase of emergency medical use for non-emergency conditions, EMTALA has been cited as a possible cause. It was stated that EMTALA is responsible for the "escalating use of the emergency department for non-urgent conditions and patient waits for care, according to a comprehensive new report from a federal watchdog agency...as has been the conclusion of this author."[15] As supported in current literature, an increasing number of ED visits for non-emergency health conditions are caused by EMTALA. Correspondingly, EMTALA can be considered as an open door policy that encouraged millions of patients to gain emergency care for non-emergency conditions. While it holds true that non-emergency visits have increased considerably since the enactment of EMTALA, it is unfounded and superficial to affirm that individuals make non- emergency visits primarily because of EMTALA's legal mandate on hospitals. The rise of non- emergency visits since 1986, the year EMTALA was enacted, has been nothing but circumstantial. There is a consensus that other factors not related to EMTALA have more crucially influenced the decision of people to use ED rooms for non-emergency health issues.

2.2.4 Capacity Constraints

So far the literature review on the causes of non-emergency medical use has identified many factors that can lead to different interpretations. In general, there is a greater consensus and common understanding among experts that capacity constraints in the ambulatory care sector are responsible for non-emergency medical use in ED rooms across the nation, though it is often easier to point out less imperative factors. Ordinarily, capacity constraints within the healthcare sector have been attributed the overall rise in ED utilization regardless of the urgency of the health problems. It has been known that capacity constraints are the primary factors associated with non-emergency medical use. While the U.S population continues to grow at a steady pace, the number of community hospitals and ED rooms has considerably decreased. From 1989 to 2009, the number of community hospitals across the nation has trimmed down 10% (Figure 3).

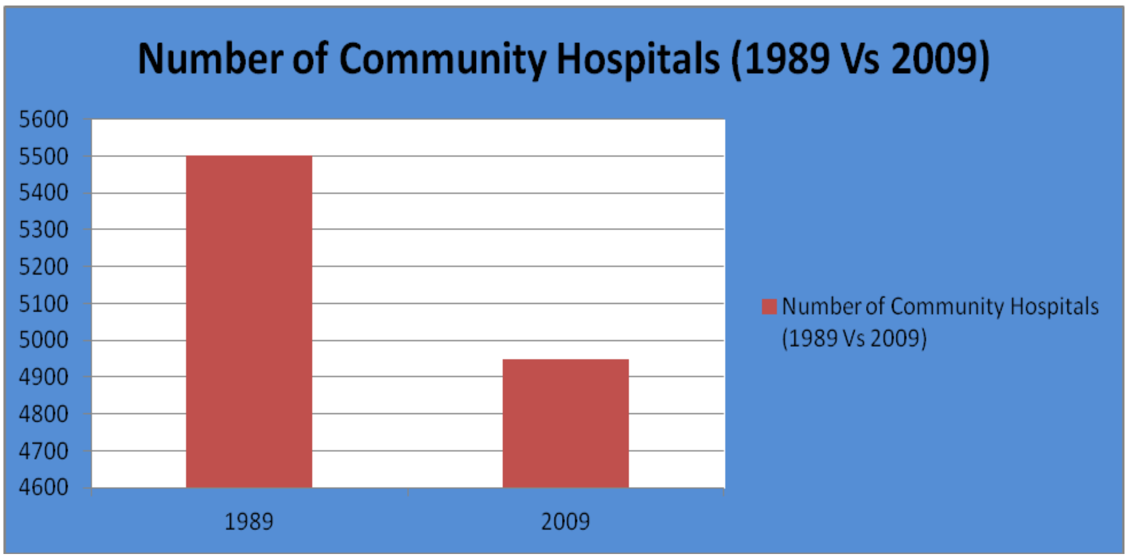

Figure 3: Decrease in number of Community Hospitals (1989 vs 2009) (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009, for community hospitals)

Correspondingly, the total number of inpatient beds has seen a reduction of 20% (Figure 4). A 2011 study noted,

> This suggests that as demand for medical care increases over time and the capacity of office – based physicians is squeezed, some of the excess demand for ambulatory care will spill over to hospital emergency departments. At the same time, many patients prefer to use hospital emergency departments even if they believe that their health problem could have been handled by a primary care physician outside of the emergency department.[16]

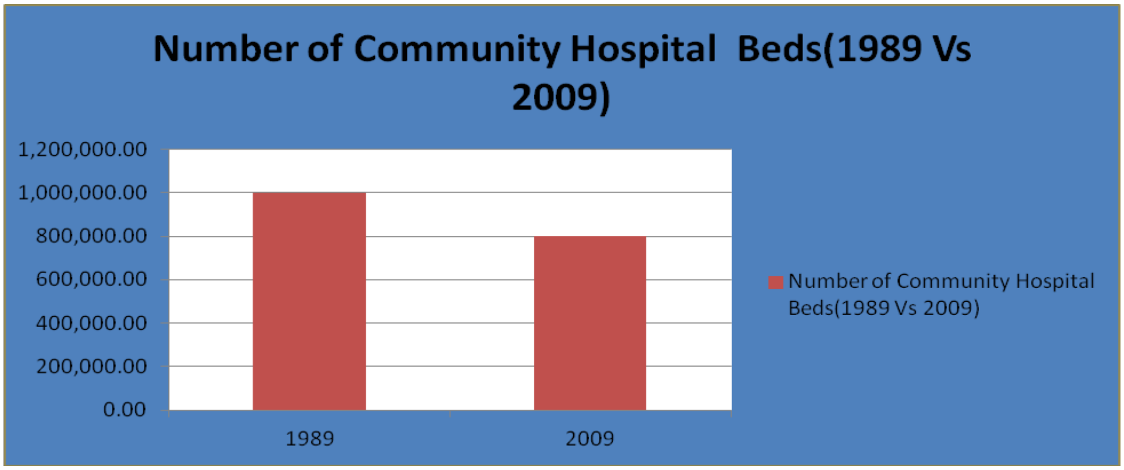

Figure 4: Decrease in number of Hospital Beds (1989 vs 2009) (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009, for community hospitals)

Moreover, a 2007 study on the utilization of ED for non-emergency pediatric care demonstrated that strained capacity on health care settings due to insufficiency accounted for 18% of all non-emergency visits[17] (Figure 5). Similarly, a Community Tracking Study of 12 metropolitan communities conducted by Health System Change (HSC) recognized causal relationship between capacity constraints and the utilization of ED for non-urgent care and advanced,

> Community health centers have expanded access to care in underserved areas but still struggle to respond to growing demand for primary care. Many safety net hospitals— the public and not-for-profit hospitals serving large proportions of low-income, uninsured and Medicaid patients—have primary and specialty care clinics that are key sources of care for low-income people, yet they too face Capacity constraints, and waits for appointments can be several months.[18]

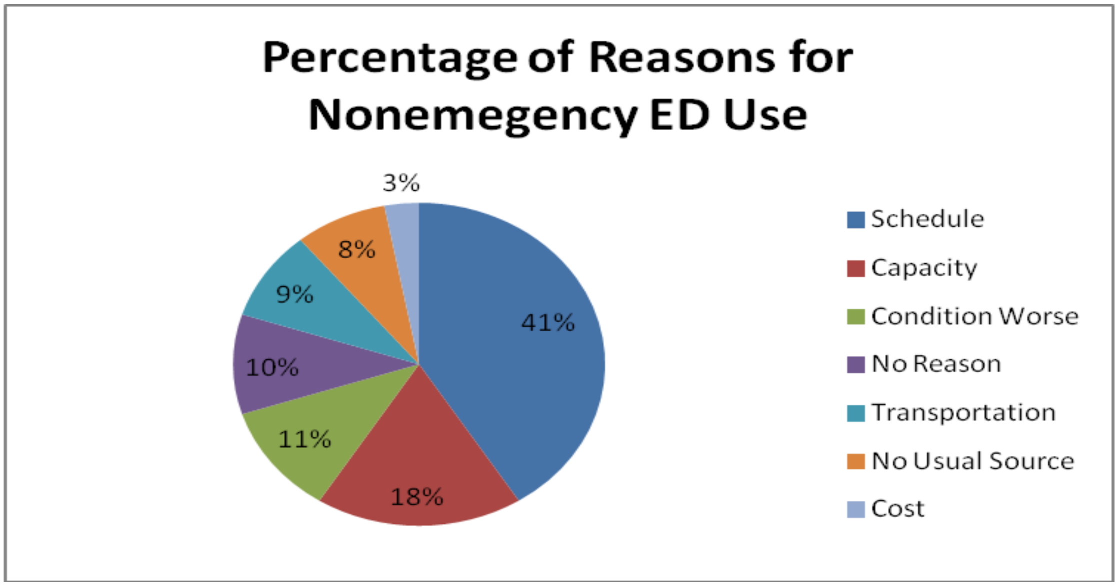

Figure 5: Causes of Non-emergency Visits, 2007
Source: Emergency Department Use for Non-Urgent Care: Patient Perspectives and Possible Solutions (2007)

Finally, findings from a study by New Jersey Hospital Association (NJHA) researchers concluded that lack of capacity from traditional healthcare facilities plays an important role in the use of hospital's ED for non-emergency care.[11(5)] It is clear that increases in population have outgrown the available capacity of inpatient beds in hospitals and other healthcare settings, which created a severe imbalance in terms of "supply and demand" for basic healthcare services. Thus, those findings are consistent with implications, made earlier in this research, showing that although primary care, financial, and legal constraints play a role in non-emergency medical use, insufficient and strained capacity is a more significant determinant of this practice.

2.3 Major Consequences of Non-Emergency Medical Use

Earlier we reviewed the literature that covered many factors leading to the utilization of ED rooms for non-emergency health conditions. While the practice of using ED rooms for non- emergency care is attributed to various causes, it also has consequences that need to be examined here if we are to shed light on their impact on the healthcare system. Seemingly, the literature on consequences of non-emergency medical use is vast and at times contradictory. In all, we will focus on the literature that depicts four main consequences such as ED closing, ED overcrowding, financial losses, and diminished outcomes.

2.3.1 ED Closing

While many studies have attempted to investigate ED closures as a consequence of surging increases in ED utilization, only few of those studies have attributed such consequences to strictly non-emergency visits. Over the last two decades, significant increases in populations and the number of ED visits across the United States have not been matched by the expansion of the number of ED rooms. As the overall number of ED visits continues to rise, the number of ED rooms is continuously declining. From 1991 to 2009, the number of ED rooms in operation has decreased from 5108 to 4594, a decrease of 11%. It is important to note that during that same period, the overall number of ED visits and the number of ED visits per 1000 people have augmented respectively from 351 to 415, an increase of 18% (Table 2). In a 2011 study on ED closures, the authors associated ED closures with ED utilization for non-emergency conditions and proclaimed,

> These community-characteristic findings are especially compelling given that vulnerable populations, including those in minority groups and both uninsured and underinsured patients, use EDs for acute care at greater rates than other populations. As more of these patients lose access to primary care, an increasing number of EDs are meeting criteria as safety-net facilities, which suggests that more EDs may be at risk of closing in the future.[19]

Clearly, the current literature on recent ED closures does not provide a percentage on the number of those closures directly influenced by non-emergency medical use. Yet, those observations are in line with our argument that the use of ED for non-emergency health issues is somehow linked to recent ED closures.

Table 2: Increase in number of ED Visits and decrease in number of ED Departments from 1991 to 2009 in Community Hospitals. (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009 and U.S Population by Year according to Census records.)

Year	Number of ED Visits (Millions)	Number of ED Departments	Number of ED Visits
1991	88.5	**5,108**	351
1992	90.8	**5,035**	356
1993	92.6	**4,998**	359
1993	90.5	**4,960**	348
1995	94.7	**4,923**	360
1996	93.1	**4,884**	351
1997	92.8	**4,813**	347
1998	94.8	**4,771**	351
1999	99.5	**4,679**	365
2000	103.1	**4,650**	366
2001	106.0	**4,621**	372
2002	110.0	**4,620**	382
2003	111.0	**4,570**	382
2004	112.6	**4,595**	383
2005	114.8	**4,611**	388
2006	118.4	**4,587**	395
2007	120.8	**4,565**	401
2008	127.3	**4,613**	405
2009	127.2	**4,594**	415

2.3.2 ED Overcrowding

In addition to ED closing, ED overcrowding has been seen as another consequence of people using ED rooms for non-emergency medical events. In the last decade, ED overcrowding has reached alarming proportions, which has fueled the controversial debate on the factors associated with such an epidemic phenomenon. ED overcrowding occurs when the need for emergency care exceeds the availability of emergency services to be offered, which creates a problematic situation in which ED rooms are running at either maximum or over capacity. A considerable number of studies that examined the determinant factors of ED overcrowding have recognized a consequential relation between ED overcrowding and non-emergency medical use. A 2010 report cited the use of ED for non-emergency conditions as a consequence of ED overcrowding.[20] Moreover, the authors of this report perceived that,

> A common proposed solution by many researchers has been to initiate programs for uninsured ED users, such as eligible CHAP enrollees, because they are part of and contribute to the overcrowding of EDs through their non-urgent utilization. An ancillary issue is that any insured individuals who also utilize the ED for non-urgent care could be sources of ED overcrowding.[20(7)]

Also, a 2011 report suggested that the excess utilization of ambulances for non-urgent events plays a role in ED overcrowding and acknowledged “the potential adverse consequences of non-urgent ambulance use include increased hospital crowding, and limits to rapid ambulance response for patients whose condition requires immediate care...as has been the conclusion of these authors”[21]

2.3.3 Financial Losses

The use of ED for non-emergency conditions can be financially devastating to hospitals because such a practice forces hospitals to squander resources that could have been allocated to resolve emergency issues. Again, it is important to note that EMTALA's mandate, without provision for reimbursement, requires hospitals to provide emergency care to people who come to the ED to seek care regardless of their ability to pay. Thereby, many experts consider the utilization of ED rooms for non-emergency care as a financial waste because those conditions can be treated at a much cheaper cost at physician offices, clinics, and urgent care centers (Table 3). As in related literature, a study by NEHI estimated that the financial losses due to avoidable ED visits amounted to $38 billion for just the year 2007.[10(6)] Those estimations were based on the argument that, in 2007, the average cost of an ED visit was $767 compared to $187, the cost of an office visit, for a difference of $580 per visit.[10(6)] Next, we multiplied $580 by 65.4 million, which represented 56% of the total number of avoidable ED visits in 2007.[10(6)] Another 2007 study provided the evidence for financial losses due to non-emergency visits and advanced,

> over $18 billion dollars are wasted annually for ED visits that are non-urgent or primary care treatable and could have been treated in a health center. This figure takes into account the total number of ED visits by state and assumes that 35% of all ED visits are avoidable.[22]

Table 3: Potential Financial Losses Due to Non-emergency Visits from 1991 to 2009 (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009, U.S Population by Year according to Census records. Estimations were made that 48% of all ED visits were for non-emergency conditions and that each visit accounts for a loss of $580.)

Year	Non-emergency Visits (Millions)	Non-emergency Visits Per 1000	Potential Financial Losses due to
1991	42.5	168	**24.65**
1992	43.6	171	**25.29**
1993	44.4	172	**27.75**
1994	43.4	167	**25.17**
1995	45.5	173	**26.39**
1996	44.7	168	**25.93**
1997	44.5	167	**25.81**
1998	45.5	168	**26.39**
1999	47.8	175	**27.72**
2000	49.5	176	**28.71**
2001	50.9	179	**29.52**
2002	52.8	183	**30.62**
2003	53.3	183	**30.91**
2004	54.0	184	**31.32**
2005	55.1	186	**31.96**
2006	56.8	190	**32.94**
2007	58.0	192	**33.64**
2008	59.0	194	**34.22**
2009	61.1	199	**35.44**

2.3.4 Diminished Outcomes

Besides the consequences listed above, another consequence of non-emergency medical use is the decline in patient outcomes. It has been widely reported that non-emergency visits can lessen quality of care and diminish health care outcomes such as ED wait time, patient's safety, length of stay, patient satisfaction, and cost per discharge among others. When people visit ED rooms to seek care, hospitals are required by law to perform an emergency medical screening to determine if an emergency medical condition is present. To do so, critical resources can be wasted in the triage and medical screening of those patients prior to uncover that their conditions are of non-emergency and could have been treated elsewhere. A 2007 report findings supported our argument that non-emergency visits can lead to a worsening of patient outcomes.[9(7)] The authors declared that,

> ED health professionals considered that non-urgent patients decreased ED access for real emergency cases, reduced the quality of care (prolonged waiting times, delayed diagnoses and treatments, delayed care for seriously ill patients), and produced negative spillover effects. Moreover, non-urgent ED visits caused disproportionate frustration among staff, because ED health professionals had the impression that they were no longer practicing the kind of medicine that they trained for.[9(7)]

In another related study published in 2011, the author explained the impact of non- emergency visits on health outcomes. Subsequently, he suggested "growing use of the ED for non-urgent medical problems can also increase health care costs and negatively affect quality of, continuity of, and patients' satisfaction with care…as has been the conclusion of these authors."[23] Furthermore, a 2007 research study from the New England Healthcare Institute (NEHI) pointed out the negative impact of non-emergency visits on health care and mentioned "avoidable ED use diminishes the quality of ED care; crowding, long waits and added stress on staff take away from patients in need of true emergency care...as has been the conclusion of the author".[10(2)] Lastly, it has been known that ED overuse can increase mortality rate among patients in the ED, there is no available data on the amount that directly resulted from non- emergency visits. As noted by studies previously cited in this section on the dissertation, non- emergency medical use has the potential to negatively affect health care outcomes and the quality of care as a whole, which more effectively matches the idea of our research that the utilization of ED rooms for non-emergency health problems represents a relevant threat to the quality and safety of medical care services.

2.4 Potential Solutions to Non-Emergency Medical Use

So far we have reviewed related literature on the causes and consequences of non- emergent use of ED care services. Nevertheless, it is still unclear as to what steps must be taken to considerably reduce or thwart that practice. Because of the controversy and intense debate generated by the surging increase of non-emergency visits, many experts have designed studies intended to formulate potential solutions to this growing problem. Those suggested solutions, although divergent and contentious, bring forward some ideas that need to be investigated more thoroughly. Overall, a literature review on solutions to curb non-emergency visits reveals a myriad of potential solutions among which we will select the ones later discussed in this section of this dissertation: patient education, financial incentives, disease management programs, urgent care centers' reform, primary care provider's expansion.

2.4.1 Patient Education

Patient education has always been regarded as one of the fundamental pillars of an improved and proficient healthcare system. In that same context, many experts have suggested that educating patients has the potential to deter some of them from abusing emergency care services. It has been widely suggested that some initiatives can be taken to educate the general public on the danger of utilizing ED rooms for non-emergency conditions. Many have investigated the perception of patients on emergency health issues and their understanding of EMTALA's requirement. As a result, it has been agreed upon that patients who understand the significance and restrictions of an emergency medical condition as mandated by EMTALA are less likely to make non-emergency trips to the ED. As an example, individuals can visit websites such as WebMD to seek information about symptoms and make decisions in terms of needed care services. For example when individuals with diarrhea understand that it can often be a non-serious condition that is treatable with over the counter medications, it is highly unlikely they will go to the emergency room to seek care. Lately, some hospitals have crafted patient education programs aimed at revising ED frequent user's perception and deterring them from future non-emergency visits. In accordance, a 2010 NEHI research study confirmed,

> Providing patients with educational materials and empowering them to manage their own conditions, where appropriate, is another way to reduce ED visits. For instance, providing new mothers with health information on caring for their infants may prevent mothers from seeking non-urgent care or reassurance regarding their infant's health status in the emergency department.[10(8)]

In addition to direct patient education, the NEHI study recommended that hospitals help patients find alternative source of health education through web-based patient education tool such as HeartHub, MedlinePlus, Healthwise, and Family Doctor.[10(11)] Finally, a study sponsored by a partnership of health organizations shared the idea that patient education can be significant in reducing non-emergency visits through "culturally appropriate health education materials and services to improve health literacy...as has been the conclusion of these authors"[17(16)]

2.4.2 Financial Initiatives

Observations made in Section 2.2.2, supported by findings within current literature, suggested that financial constraints can lead to the practice of non-emergency medical use, which consequentially results in financial losses for hospitals and the healthcare sector. While various studies have looked at financial factors as causal and consequential determinants of non- emergency visits, there have been suggestions to implement financial initiatives designed at increasing cost-sharing from individuals for emergency care services and utilizing a special reimbursement system based on pay-for-performance, which will reward hospitals for reducing non-emergency medical use. A 2009 report explained that an increase of cost-sharing from patients led to significant reduction of ED use for non-emergency conditions.[11(9)] In that same regard, the report concurred "Many of these findings are consistent with the RAND Health Insurance Experiment, which found that cost-sharing reduced overall ED use and more rapidly for conditions defined as "less serious"...as has been the conclusion of these authors".[11(9)] Also, a 2010 NEHI report made a similar observation and informed that,

> Research has shown that increasing co-payments for visits classified as non- urgent will reduce the use of the ED for such visits. For example, one study found that among commercially insured subjects, ED visits decreased 12 percent following the enactment of a $20-$35 co-payment for emergency services, and decreased by 23 percent with a $50-$100 co-payment.[10(12)]

Furthermore, in the NEHI research study, considerations were made that an improved payment system for emergency medical services could alleviate financial losses for health care providers and provide enticement for reducing non-emergency visits.[10(13)] The NEHI report recommended that "reformed payment systems, such as global service payments, would give providers the resources to offer additional services to their patients such as extended hours and telephone and email correspondence. Also, under a pay-for-performance system, nonurgent and avoidable ED use could be used as a metric to measure physician performance, with rewards for physicians who reduce ED overuse by their patients”.[10(14)]

2.4.3 Disease Management Programs

Literature review on potential methods to prevent non-emergency medical use is extensive because various efforts to solve that practice have yet to be successful. While many initiatives have been proposed and undertaken, non-emergency visits have continued to grow at a considerable pace. According to NEHI researchers, one such initiative is for hospitals to develop new disease management programs to help patients manage their health care conditions and improving their overall quality of health.[10(11)] Disease management programs have shown to enhance patient’s health outcomes by allowing them to efficiently monitor health conditions and associated risks. Commonly, it was found that patients who are involved in a disease management program of any kind have a much lower rate of non-emergency medical use compared to those who are not. As such, findings from a 2010 NEHI report implied that,

> making follow-up calls to patients is another, similar management strategy that shows promise in preventing avoidable ED visits. These follow-up calls may occur after a doctor’s visit at which a chronic condition was discussed or shortly after a patient has been discharged from the hospital.[10(11)]

Likewise, it was reported that the number of ED visits among regular ED patients can drop up to 75% per year after adhering to a disease management program.

2.4.4 Urgent Care Centers Reform

The ongoing crisis in which ED rooms are being used for the delivery of non-emergency healthcare services presents both private healthcare providers and governmental health authorities with the challenging task of finding solutions for reducing such practice. One potential solution, widely recommended, is the creation of a national plan to reform and expand the urgent care sector, which will allow people to have access to some alternative options when facing health issues of non-emergency characteristic. Generally, urgent care centers are regarded as medical facilities where patients are treated for health conditions that are immediate but not life-threatening, urgent, or serious. Although there lacks a formally recognized definition, the Urgent Care Association of America (UCAOA) defines urgent care as "the delivery of ambulatory medical care outside of a hospital emergency department on a walk-in basis without a scheduled appointment…as has been the conclusion of this author."[24] Others describe urgent care centers as healthcare facilities "that are not emergency departments, but typically (a) provide care primarily on a walk-in basis; are open (b) every evening Monday through Friday and (c) at least one day over the weekend; (d) provide suturing for minor lacerations, and (e) provide onsite x-rays…as has been the conclusion of these authors".[25] It is estimated that between 40 to 50 percent of all ED visits are for non-urgent conditions that are more appropriate for urgent care settings. Based on those estimations a number of 10.18 to 72.56 million of ED patients could have been treated in urgent care centers instead of hospital's ED rooms in 2009. According to NEHI, a significant reduction of ED visits for non-urgent events among patients is feasible with recent access to urgent care centers.[10(10)] NEHI reported that urgent care centers can provide,

> alternative to the emergency department. One study found that among patients who had previously used the ED for non-urgent reasons, using an urgent care clinic resulted in a 48 percent decrease in their subsequent emergency department use, while subsequent urgent care clinic visits increased 49 percent.[10(10)]

Moreover, a 2010 study collected data from the 2006 National Hospital Ambulatory Medical Care Survey (NHAMCS) using a sampling of 31,197 visits, representing an estimated 104 million visits nationally.[26] Based on the study results, some authors agreed that urgent care centers can be used as alternative facilities in treating non-emergency conditions as shown in Figure 6. Accordingly, they advanced,

> Americans seek a large amount of non-emergency care in emergency departments, where they often encounter long waits to be seen. Urgent care centers and retail clinics have emerged as all alternatives to the emergency department for non- emergency care. We estimate that 13.7–27.1 percent of emergency department visits could take place at one of these alternative sites.[26(6)]

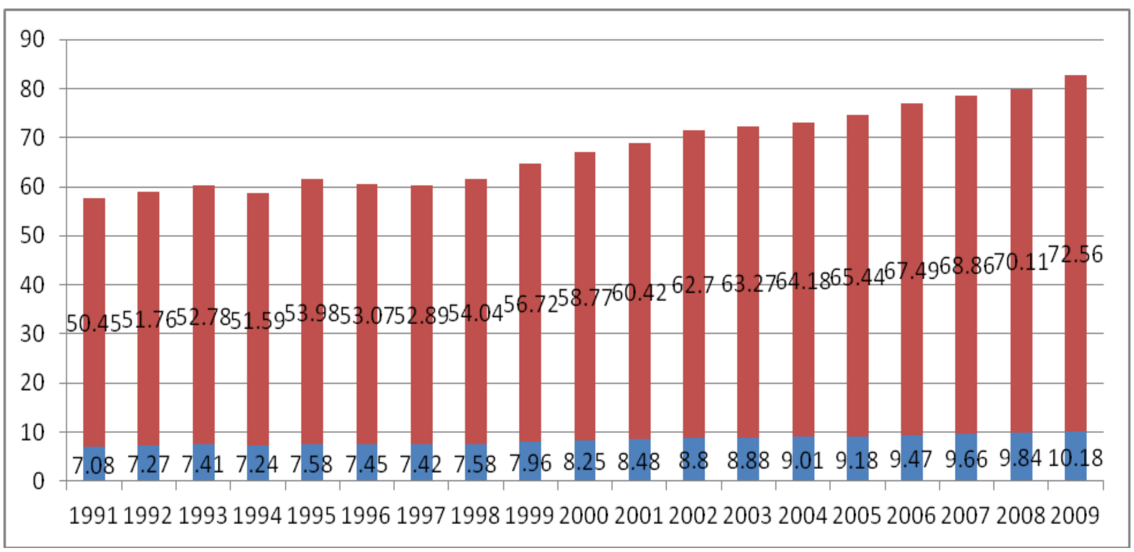

Figure 6: Potential Low Number of ED visits treatable at Urgent Care Centers 8% (Millions) and Potential High Number of ED visits treatable at Urgent Care Centers 57% (Millions)

(1991 – 2009) (Source: Avalere Health analysis of American Hospital Association Annual Survey data, 2009). Based on assumptions that between 8% to 57% of all ED visits are Treatable at Urgent Care Centers.

As explained in current literature, proficient access to urgent care centers can deter individuals from non-emergency visits. However, in order for urgent care centers to become considerable solutions to reducing non-emergency medical use there must be a national effort to significantly expand the number of urgent care centers and improve the quality of care services available at those facilities. Such effort, if part of a renewed national health program, will alleviate capacity constraints that plague the healthcare system and compel millions of individuals to make non-emergency visits.

2.4.5 Primary Care Providers Expansion

Previously, we pointed out findings from many studies that implied a lack of access to primary care providers is related to the increase of non-emergency visits. Perceived as one the major cause of non-emergency medical use, the ongoing lack of access to primary medical care has been a problematic issue in healthcare for more than three decades and has also been linked to the rise of mortality rate among populations and other negative public health outcomes. Evidently, a durable and long-term solution to reduce non-emergency medical use must encompass measures and a new approach aimed at increasing access to primary care services. A somehow similar observation was made that "increasing non-ED capacity in the health care system, as well as expanding the availability of CHCs and HMOs for low-income people, might lead to some marginal reductions in ED use…as has been the conclusion of this author".[23(12)] As long as there is an imbalance between demands for primary healthcare services and supplies of such services, individual will continue to seek alternative ways to obtain ambulatory care. Usually, a popular alternative is to simply go to nearest emergency room. In addition to increasing the number of primary care providers considerably, other initiatives have been proven successful at routing non-emergency patients away from ED rooms. One strategy proposed in a 2008 study is,

> to help patients establish “medical homes” that provide preventive and primary care for both episodic medical needs and chronic conditions, with coordination of follow- up visits and tests. Such providers, which include hospital outpatient clinics, community health centers and individual primary care practitioners, may provide less costly care, reduce reliance on the ED for non-urgent conditions and diminish the likelihood of a non- urgent problem going untreated and becoming more severe.[18(2)]

Another promising approach published in a project study of the NJHA has been to work with a patient following a non-emergency visit and “refer the patient for a follow-up visit with a primary care provider, or if the patient had no regular physician, immediately scheduled an appointment at the partnering federally qualified health center. The ED staff also educated the patient on the appropriate site of care for various healthcare needs and the importance of having a "medical home" for primary care needs…as has been the conclusion of this author.”[27] In truth, expansion in capacity of primary care services, coupled with new strategies similar to those cited earlier, is viewed as the preeminent solution to limit non-emergency medical use. While some solutions, mentioned in previous sections of this dissertation, can play a role in reducing non-emergency medical use, reform in the primary care sector to enhance access is regarded here as the leading solution to non-emergency medical use. As shown in Table 4, solely capacity increase in the primary care sector could have eliminated at least 11 million non-emergency visits in 2009, an 18% reduction.

Table 4: Potential reduction of non-emergency visits from 1991 to 2009 due to capacity increase (Using Avalere Health analysis of American Hospital Association Annual Survey data, 2009, U.S Population by Year according to Census records. Assumptions were made that 48% of all ED visits were for non- emergency conditions and that of those non-emergency visits are caused by lack of capacity in healthcare)

Year	Non-emergency Visits (Millions)	Non-emergency Visits Per 1000	Potential Reduction due to
1991	42.5	168	**7.65**
1992	43.6	171	**7.85**
1993	44.4	172	**7.99**
1994	43.4	167	**7.81**
1995	45.5	173	**8.19**
1996	44.7	168	**8.05**
1997	44.5	167	**8.01**
1998	45.5	168	**8.19**
1999	47.8	175	**8.6**
2000	49.5	176	**8.91**
2001	50.9	179	**9.16**
2002	52.8	183	**9.5**
2003	53.3	183	**9.59**
2004	54.0	184	**9.72**
2005	55.1	186	**9.92**
2006	56.8	190	**10.22**
2007	58.0	192	**10.44**
2008	59.0	194	**10.62**
2009	61.1	199	**10.99**

CHAPTER III

METHODS OF DATA ANALYSIS

3.1 2010 NEDS Data Set Overview

The 2010 national emergency department sample data set, used for this dissertation, is a compilation of emergency department visits records that derive from the HCUP NEDS database. The 2010 NEDS data set was purchased from the Agency for Healthcare Research & Quality (AHRQ) for a discounted price for students and received in a DVD disk with 4 files made of compressed data in comma-separated value (CSV) format. It is important to note that users of the 2010 NEDS data must be aware of and comply with the data use limitations, which requires all users to complete the Data Use Agreement (DUA) training, sign and return a copy of the DUA to the Agency for Healthcare Research & Quality (AHRQ) (Appendix A). Under Federal law, violators of the DUA can be fined up to $10,000 and imprisoned for up to 5 years. The 2010 NEDS contains ED visits records originated from the State Emergency Department Database (SEDD) and the State Inpatient Databases (SID) collected across 961 hospitals nationwide during that same calendar year. According to HCUP, "the NEDS is the largest all-payer emergency department (ED) database in the United States, yielding national estimates of hospital-based ED visits. Unweighted, it contains data from approximately 29 million discharges each year. Weighted, it estimates roughly 130 million ED visits…as has been the conclusion of this author."[28] The 2010 NEDS data set consists of four main files structured as tables: the NEDS Core File, the NEDS Supplemental ED File, the

NEDS Supplemental Inpatient File, and the NEDS Hospital Weights File. The 2010 NEDS Core File is the largest of the four files and includes 28,584,301 million ED visits records or 100% of the sampling population whether s u c h visits

Table 5: List of data elements in the 2010 NEDS Core file

Data Element	Type	Description
AWEEKEND	Categorical	Admission Day: (0) Monday - Friday, (1) Saturday - Sunday
AMONTH	Numeric	Admission Month: (1) January - (12) December
AGE	Numeric	Age at admission: 0 - 124 years
DX1 - DX15	Character	ICD-9-CM Diagnosis Codes
DXCCS1 - DXCCS15	Numeric	Clinical Classification Software for all diagnosis
CHRON1 - CHRON15	Numeric	Chronic condition indicator: (0) not chronic, (1)
NDX	Numeric	Number of diagnosis codes up to 15 codes are
DQTR	Categorical	Quarter of discharge: (1) Jan - Mar, (2) Apr - Jun, (3) Jul - Sep, (4) Oct - Dec
YEAR	Numeric	Calendar year: 2010
DISP_ED	Categorical	Disposition from ED: (1) routine. (2) transfer, (5) other transfers, (6) home health care, (7) against medical advice, (9) admitted, (20) died in ED, (21) law
DIED_VISIT	Categorical	Died in Ed: (0) did not die, (1) died in Ed, (2) died in hospital
EDevent	Categorical	Type of ED event: (1) treated and released. (2) admitted, (3) transferred, (9) died in ED, (98) not admitted, destination unknown (99)
INJURY	Categorical	Presence of injury: (0) no injury, (1) injury in 1st diagnosis, (2) injury in a
MULINJURY	Categorical	Number of injuries: (0) 1 or no injury, (1) more than 1 injury reported
INJURY_SEVERITY	Categorical	Injury severity: (1) the least - (75) the most
ECODE1 - ECODE4	Character	External cause of injury poisoning diagnosis codes (ICD-9- CM)
E_CCS1 - E_CCS4	Numeric	CCS external cause of injury poisoning diagnosis
NECODE	Numeric	Number of external cause of injury poisoning diagnosis codes, up to 4 are recorded
INTENT_SELF_HARM	Categorical	Diagnosis coded for injury with self harm intent: (0) no self harm, (1) self harm

INTENT_UNIN TENTIONAL	Categorical	Diagnosis coded for injury with unintentional intent: (0) no unintentional, (1) unintentional
INTENT_ASSA ULT	Categorical	Diagnosis coded for injury by assault: (0) not by assault,
INJURY_CUT	Categorical	Diagnosis coded for injury by cut: (0) not by cut,
INJURY_DRO	Categorical	Diagnosis coded for injury by drowning: (0) not by
WN		drowning, (1) by drowning
INJURY_FALL	Categorical	Diagnosis coded for injury by fall : (0) not by fall, (1) by fall
INJURY_FIRE	Categorical	Diagnosis coded for injury by fire : (0) not by fire, (1) by fire
INJURY_FIRE ARM	Categorical	Diagnosis coded for injury by firearm : (0) not by firearm,
INJURY_MAC HINERY	Categorical	Diagnosis coded for injury by machinery : (0) not by machinery, (1) by machinery
INURY_MVT	Categorical	Diagnosis coded for injury by Motor Vehicle Traffic : (0) not by MVT, (1) by MVT
INJURY_NATU RE	Categorical	Diagnosis coded for injury by natural events: (0) not by natural events, (1) by natural events
INJURY_POIS ON	Categorical	Diagnosis coded for injury by poison : (0) not by poison,
INJURY_STRU CK	Categorical	Diagnosis coded for injury by being struck : (0) not by being struck, (1) by being struck
INJURY_SUFF OCATION	Categorical	Diagnosis coded for injury by suffocation: (0) not by suffocation (1) by suffocation
FEMALE	Categorical	Gender: (0) male, (1) female
PL_NCHS2006	Categorical	Urban-rural residency: (1) large central metropolitan, (2) large fringe metropolitan, (3) medium metropolitan, (4) small metropolitan, (5) micropolitan, (6) not metropolitan or
ZIPINC_QRTL	Categorical	Median household income quartiles: (1) $1 - $40999, (2) $41000 - $50999, (3) $51000 - $66999, (4) $67000
PAY1	Categorical	Primary payer: (1) Medicare, (2) Medicaid, (3) Private Insurance including HMO, (4) Self Pay, (5) No Charge, (6) Other
PAY2	Categorical	Secondary payer: (1) Medicare, (2) Medicaid, (3) Private Insurance including HMO, (4) Self Pay, (5) No Charge, (6) Other
TOTCHG_ED	Numeric	Total charges for ED services rendered
HCUPFILE	Character	origin of HCUP record: (SEDD) from SEDD file, (SID) from SID file
DISCWT	Numeric	Discharge weight
HOSP_ED	Categorical	Unique HCUP NEDS hospital number

HOSP_REGION	Categorical	Hospital region: (1) Northeast, (2) Midwest, (3) South, (4) West
NEDS_STRATUM	Numeric	Stratum used to sample hospitals
KEY_ED	Numeric	Unique HCUP NEDS record number

resulted in patient's admission to an hospital or not. The 2010 NEDS Core File contains over 40 data elements. Table 5 details the data elements along with their description.

The 2010 NEDS Supplemental ED File includes 24,192,665 million records of ED visits in which patients were not directly admitted to the hospital. The 2010 NEDS Supplemental ED File mainly contains procedural data elements such as CPT1 for Current Procedural Terminology (CPT) and PR_ED1 for ICD-9-CM procedures performed during ED visits (Table 6).

Table 6: List of data elements in the 2010 NEDS Supplemental ED file

Data Element	Type	Description
CPT1 - CPT15	Character	CPT codes for procedures performed during ED visits
CPTCCS1 - CPTCSS15	Numeric	Clinical classifications Software for all CPT procedures
NCPT	Numeric	Number of procedures on the original record. Can be up to 15
PR_ED1 - PR_ED9	Character	ICD-9-CM procedures performed in ED
PRCCS_ED1 - PRCCS_ED9	Numeric	Clinical Classification Software for all ICD-9-CM procedures
PCLASS_ED1 - PCLASS_ED9	Categorical	Procedure class for all ICD-9-CM procedures: (1) Minor diagnostic, (2) Minor therapeutic, (3) Major diagnostic,
NPR_ED	Numeric	Number of procedures recorded on the original record. Can be up to 9.
HCUPFILE	Character	Origin of HCUP record: (SEDD) from SEDD file, (SID) from SID file
DISCWT	Numeric	Discharge weight
HOSP_ED	Categorical	Unique HCUP NEDS hospital number
KEY_ED	Numeric	Unique HCUP NEDS record number

The 2010 NEDS Supplemental Inpatient File includes 4,391,636 million records of ED visits that resulted in admission to the same hospital. The 2010 NEDS Supplemental Inpatient File contains data elements such as length of stay (LOS) during inpatient stay, total charges during inpatient stay, discharge information during inpatient stay, and Diagnosis Related Group (DRG) used on discharge date and calculated without presence of admission (POA) (Table 7).

Table 7: List of data elements in the 2010 NEDS Supplemental Inpatient file

Data Element	Type	Description
DISP_IP	Categorical	Disposition from inpatient: (1) routine, (2) transfer to short-term hospital, (5) other transfers, (6) home health care, (7) against medical advice, (20) died in hospital,
DRG	Numeric	Diagnosis related group used on discharge date
DRG_NoPOA	Numeric	DRG used without the use of present on admission flags for diagnosis codes
DRGEVER	Numeric	Grouper version used on discharge date
MDC	Numeric	Major diagnosis category 9MDC) used on discharge date
MDC_NoPOA	Numeric	MDC used without the use of present on admission flags for diagnosis codes
LOS_IP	Numeric	Length of inpatient stay
TOTCHG_IP	Numeric	Total charges for inpatient stay
PR_IP1 - PR_IP9	Character	ICD-9-CM procedures performed in ED or during inpatient stay
PRCCS_IP1 - PRCCS_IP9	Numeric	Clinical Classification Software for all ICD-9-CM procedures
PCLASS_IP1 - PCLASS_IP9	Categorical	Procedure class for all ICD-9-CM procedures: (1) Minor diagnostic, (2) Minor therapeutic, (3) Major diagnostic,
NPR_IP	Numeric	Number of procedures recorded on the original record. Can be up to 9.
HCUPFILE	Character	Origin of HCUP record: (SEDD) from SEDD file, (SID) from SID file
DISCWT	Numeric	Discharge weight
HOSP_ED	Categorical	Unique HCUP NEDS hospital number
KEY_ED	Numeric	Unique HCUP NEDS record number

Finally, the 2010 NEDS Hospital Weights File includes 961 records of hospitals used for the collection of ED visits. The 2010 NEDS Hospital Weights File contains data elements such as number of ED visits per hospital, hospital's ownership and governance, hospital's region, hospital's trauma level designation, hospital's teaching status, and hospital's urban-rural designation. All four files comprise the unique key identifiers HOSP_ED and KEY_ED that can be used to perform record linkage and cross join among the four main files or tables. (Table 8).

Table 8: List of data elements in the 2010 NEDS Hospital Weights File

Data Element	Type	Description
N_DISC-U	Numeric	Number of AHA universe ED visits in the
S_DISC-U	Numeric	Number of sampled ED visits in the stratified
TOTAL_EDvisits	Numeric	Total number of ED visits for the particular
DISCWT	Numeric	Discharge weight
YEAR	Numeric	Calendar year of discharge
N_HOSP_U	Numeric	Number of AHA universe hospital-based EDs in
S_HOSP_U	Numeric	Number of sampled hospital-based EDs in the
HOSP_ED	Numeric	Unique HCUP NEDS hospital number
HOSP_URCAT4	Categorical	Hospital urban-rural location: (1) large metropolitan areas, (2) small metropolitan areas, (3) micropolitan areas, (4) not metropolitan or micropolitan,
HOSP_CONTROL	Categorical	Hospital control/ownership: (0) government or private, (1) Government, non federal, public, (2) private, non-profit, voluntary, (3)
HOSP_REGION	Categorical	Hospital Region: (1) Northeast, (2) Midwest, (3) South, (4) West
HOSP_TRAUMA	Categorical	Trauma center level: (0) non-trauma center, (1) trauma level I, (2) trauma level II, (3) trauma level III, (8) trauma level I, or II, (9) trauma
HOSP_UR_TEACH	Categorical	Teaching status: (0) metropolitan non-teaching, (1) metropolitan teaching,
NEDS_SRATUM	Numeric	Stratum used to sample EDs
HOSPWT	Numeric	Weight to hospital-based EDs in AHA universe

In all, the 2010 NEDS consists of more than 100 clinical and non-clinical variables such as those previously listed. Lastly, the 2010 NEDS dataset had to abide by various restrictions imposed by states such as the number and type of hospitals (Appendix B). Also, due of confidentiality laws, discharge records for conditions such HIV/AIDS and behavior health were not provided as ED visits data to the HCUP.

3.2 2010 NEDS Sampling Framework

The overall sampling population of the 2010 NEDS data set is made of 20% of all ED visits that occurred at community hospitals across 28 states in the United States in 2010. HCUP has partnered with organizations within those 28 states that collected and maintained statewide data set of ED visits (Table 9).

Table 9: List of state organizations partners with HCUP for the 2010 NEDS (Source: HCUP)

State	Website of HCPU's State Partner
Arizona	http://www.azdhs.gov/plan/crr/ddr/index.htm
California	http://www.oshpd.ca.gov
Connecticut	http://www.chime.org
Florida	http://ahca.myflorida.com/SCHS/index.shtml
Georgia	https://www.gha.org/
Hawaii	http://www.hhic.org
Illinois	http://www.idph.state.il.us
Indiana	http://www.ihaconnect.org
Iowa	http://www.ihaonline.org
Kansas	http://www.kha-net.org
Kentucky	http://www.chfs.ky.gov
Maryland	http://www.hscrc.state.md.us
Massachusetts	http://www.mass.gov/chia
Minnesota	http://www.mnhospitals.org
Missouri	http://www.mhanet.com
Nebraska	http://www.nhanet.org
Nevada	http://chia.unlv.edu
New Jersey	http://www.nj.gov/health/healthcarequality
New York	http://www.health.state.ny.us/nysdoh/sparcs/sparcs.htm
North Carolina	http://www.shepscenter.unc.edu/data/nc-hospital-discharge-data/
Ohio	http://www.ohanet.org
Rhode Island	http://www.health.ri.gov
South Carolina	http://ors.sc.gov
South Dakota	http://www.sdaho.org
Tennessee	http://www.tha.com
Utah	http://health.utah.gov/ems/
Vermont	http://www.vahhs.org
Wisconsin	http://www.dhs.wisconsin.gov/

As long as those hospitals were included in the American Hospital Association (AHA) Annual Survey Database and have collected more than 10 ED visits with no more that 90% of those visits resulted in admission. The 2010 NEDS sampling frame is made of 20% of the general or universe population and stratified by U.S region, trauma center designation, urban- rural location of the hospital, ownership of the hospital, and teaching status of the hospital. Each stratum is a 5-digit number composed of five stratifiers, with each stratifier represented by a single digit. The 2010 NEDS sampling population was stratified in order to guarantee that the sampling is fully representative of the target universe. Strata that included less than two hospitals were incorporated with the adjoining stratum depending on urban-rural location, trauma center designation, and ownership. As previously mentioned, only data records from the 2010 NEDS will be used for this research. The large sampling size of more than 28 million records, a 20% make up of all ED visits nationwide, makes this data set a very reliable and valid sampling population.

3.3 2010 NEDS Unit of Analysis

In the 2010 NEDS data set, each ED visit is represented by a single record or unit of analysis. The NEDS is an event-record type database instead of patient-record. Within the NEDS data set, multiple ED visits from a single patient are considered as multiple records as long as: there is a revenue code that indicates ED services were performed, the charges for ED services are greater than zero, a CPT code of 99281, 99282, 99283, 99284, and 99285 was used to report ED procedures performed, and the ED visit was registered by the admission source. In other words, if a patient makes 10 ED visits in 2010, those 10 ED visits were accounted for 10 different ED data records or units of analysis. The 2010 NEDS does not contain any patient-level identifier such as medical record number or encounter number, which makes it impossible to perform analysis at a patient-level. Each ED visit has a unique 14-digit identifier or record number to be used as unit of analysis. The 2010 NEDS does not contain any state-characteristic information, which prohibits analyses at the state-level. In order to calculate national estimates, the discharge weight variable DISCWT must be used with ED visit as unit of analysis.

3.4 Statistical Modeling Analysis

In this section, statistical modeling analysis of the 2010 NEDS data set will be conducted. Statistical modeling analysis was performed using SAS software 9.3 within a Windows 7 environment. Statistical modeling analysis includes descriptive statistical analysis, ED CPT severity level analysis, New York University (NYU) ED classification algorithm analysis, recategorization, analysis of variance, simple logistic regression analysis, and multiple logistic regression analysis. The enormous size of the 2010 NEDS sampling makes it a very complex, ambitious, and challenging endeavor to perform statistical data analysis of such an extensive data set, which raises the empirical significance of this dissertation. No previous studies have used such a large data set with the purpose being sought in this dissertation.

3.4.1 Descriptive Statistical Analysis

Overall, the objective of the descriptive statistical analysis is to produce a well detailed summary and make up of the 2010 NEDS Core file in terms of frequencies and percentage counts and uncover general trends and variations among different groups and categories of ED visits. Historically, descriptive statistics, which originated from England as far back as 1770, are a combination of methods, processes, and decisions used in making statistical observations of samples or populations.[29] In this dissertation, descriptive statistical analysis will test whether there are statistically significant numerical observations within the 2010 NEDS data set indicative of non-emergency medical use. First, data elements were statistically analyzed with the emphasis to determine the frequency and percentage of ED visits per individual statistical category or grouping such as injury severity, income, death in the ED, chronicity, quarter of discharge, age, region, presence of injury, disposition from the ED, type of injury, gender, location of residency, month, day, ED charges, intent of injury, payer, and the type of ED event using basic SAS functions such as PROC SORT, PROC SQL, PROC MEANS, PROC TABULATE, PROC UNIVARIATE, PROC FREQ. Second, extensive descriptive statistical analysis was carried out to compare ED visits per payer group, region, age group, income group, gender, and location of residence.

Table 10: Descriptive analysis per sub-categorical data elements types

EDevent	AGE					
ROUTINE	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
ADMIT/TRANSFER	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
INJURY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
NO INJURY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
INJURY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
INJURY_SEVERITY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
LOW	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
HIGH	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
CHRON1	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
CHRONIC	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	75 -
NOT CHRONIC	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	>89
MULTINJURY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	>89
1 OR NO INJURY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	>89
> 1 INJURY	0 - 14	15 - 29	30 - 44	45 - 59	60 - 74	>89

For each of those groupings, ED visits were compared and analyzed across the type of ED event, presence of injury, chronicity, number of injury, and severity of injury. Such analyses were necessary to illustrate variations among sub-categorical variables. As an example, those analyses made it possible to differentiate the types of ED events per sub-categories of payer, age, region, gender, income, and location. Payer, age, region, gender, income, location were divided in various sub-categories. Each of those sub-categories was analyzed across types of ED events in terms of routine visit or admission, presence of injury, number of injury, severity of injury, and chronicity of conditions as depicted in Table 10.

As shown in Table 10, various sub-categories of data elements (i.e., EDevent, INJURY, INJURY_SEVERITY, CHRON1, MULTINJURY) were statistical analyzed and compared to 7 sub-categories of the AGE data element. All together, similar analyses and comparisons were made for data elements EDevent, INJURY, INJURY_SEVERITY, CHRON1, MULTINJURY and all sub-categories of data elements AGE, FEMALE, PAY1, HOSP_REGION, PL_NCHS2006, ZIPINC_QRTL (Table 11).

Table 11: Descriptive analysis per sub-categorical data elements groups

AGE	PAY1	HOSP_REGION	FEMALE	ZIPINC_QRTL	PL_NCHS
AGE	**PAYER**	**REGION**	**GENDER**	**INCOME**	**LOCATION/RE**
0 - 14	Medicare	Northeast	Male	1 - 40999	L a
15 - 29	Private	Midwest	Female	41k - 50999	Large Fringe
30 - 44	Medicaid	South		51k - 66999	Medium
45 - 59	Self	West		67k >	Small
60 - 74					Micropol
75 - 89					Not Metro or
>89					

3.4.2 ED CPT Severity Level Analysis

In this section, we will perform an analysis of ED severity level based on CPT codes used in order to test the hypothesis that there exist statistically effective procedural methods to differentiate non-emergency visits from emergency visits. Lately, some CPT codes, used in the recording of procedures performed in emergency departments, have also been utilized by payers to pinpoint the severity level of ED events, which has increasingly been drawn on as a condition for reimbursement of insurance claims. CPT severity coding originated from the Emergency Severity Index (ESI), which was a triage tool for emergency departments. According to the AHRQ, ESI was developed around 1999 by “ED physicians Richard Wuerz and David Eitel in the United States to facilitate the prioritization of patients based on the urgency of treatment for the patients' conditions…as has been the conclusion of this author.”[30]

Table 12: Classification of ED services based of CPT level coding severity

CPT Codes	Description and Requirements
99281	**For problems that are self-limited or minor with:**
	a) a focused history
	b) a focused examination
	c) a straightforward medical decision making
99282	**For problems that are of low to moderate severity with:**
	a) an expanded focused history
	b) an expanded focused examination
	c) a low complexity medical decision making
99283	**For problems that are of moderate severity with:**
	a) an expanded focused history
	b) an expanded focused examination
	c) a moderate complexity medical decision making
99284	**For problems that require urgent evaluation and are of high**
	a) a detailed history
	b) a detailed examination
	c) a moderate complexity medical decision making
99285	**For problems that pose immediate threat to life and physiologic**
	a) a comprehensive history
	b) a comprehensive examination
	c) a high complexity medical decision making

The Florida Center for Health Information and Policy Analysis of the Agency for Health Care Administration concurred that "Current Procedural Terminology Evaluation and Management codes can be used to categorize ED ambulatory visits. The codes delineate the relative severity, low to high, of the person's condition upon arrival at the ED…as has been the conclusion of this author."[31] Generally, five main CPT codes are used to report ED services: 99281, 99282, 99283, 99284, and 99285. Based on guidelines that govern reporting of ED services, those CPT codes are described and classified in Table 12. Afterward, those CPT codes are reclassified in 2 main groups:

a) **Low Acuity/Severity**

- 99281: for problems that are self-limited or minor

- 99282: for problems that are of low to moderate severity

b) **High Acuity/Severity**

- 99283: for problems that are of moderate severity
- 99284: for problems that require urgent evaluation and are of high severity
- 99285: for problems that pose immediate threat to life and physiologic function

Commonly, CPT level coding of low acuity/severity is considered as non-emergent or for non-urgent conditions and CPT level coding of high acuity/severity is considered as emergent or for urgent conditions. In this dissertation, CPT severity level analysis is applied to the 2010 NEDS with the intent to establish the usefulness of this method in investigating ED visits of non-emergency and emergency attributes. In this dissertation, data elements CPT1 – CPT15 are statistically analyzed and grouped in two categories of non-emergency and emergency visits. Unlike the traditional classification analysis, in which ED services with CPT coding 99283 are defined as of high acuity and severity, services with CPT coding of 99283 are analyzed and grouped depending on the association with or the presence of injury. ED services with CPT coding 99283 without the presence of injury are classified as non-emergent and ED services with CPT coding 99283 with the presence of an injury diagnosis are classified as emergent (Table 13). Because the data elements CPT1 – CPT15 and INJURY are part of two different data files, it was necessary to link the 2010 NEDS Core File to the 2010 NEDS Supplemental ED File to make it possible to analyze CPT codes with the diagnosis of injury. The decision to reclassify various 99283 CPT codes was based on the understanding that many of the symptoms attributed to 99283 CPT codes can be of minor severity and complexity unless if they are associated with some types of injuries. By example, symptoms such as eye pain, fever, headache, mild dyspnea, abdominal pain, and cellulitis all require treatments and procedures that can be handled effectively and safely either at urgent care centers or physician's offices. While some conditions linked to 99283 CPT codes can require emergency medical services, others do lack the level of severity and urgency needed to be accepted as emergency conditions.

Table 13: Final classification of ED services based on CPT level coding severity and presence of injury

NON-EMERGENCY VISITS
99281
99282
99283 Without Injury
EMERGENCY VISITS
99283 With Injury
99284
99285

3.4.3 NYU ED Classification Algorithm Analysis

In this section, the New York University (NYU) ED algorithm will be used as statistical method of analysis of the 2010 NEDS to test the hypothesis that statistically effective diagnostic methods can help differentiate non-emergency visits from emergency visits. The NYU ED algorithm, widely recognized and accepted in ED utilization analysis, is a profiling algorithm designed by the NYU Center for Health and Public Service Research to classify utilization of ED services depending on the patient' principal ICD-9-CM diagnosis code. Originally, the NYU ED algorithm was developed with the aid of a panel of ED physicians using a sample of 6000 ED complete records. Designers of the NYU ED algorithm have cautioned that it “is not intended as a triage tool or a mechanism to determine whether ED use in a specific case is "appropriate" (e.g., for reimbursement purposes)…as has been the conclusion of these authors.”[32] As shown in Table 14, they also explained that “Since few diagnostic categories are clear-cut in all cases, the algorithm assigns cases probabilistically on a percentage basis, reflecting this potential uncertainty and variation…as has been the conclusion of these authors”.[32(1)]

Table 14: Partial list of diagnoses and proportions used in the classification of categories in the NYU ED Algorithm. The complete file contains 659 records. (Source: EDDXS File NYU – Wagner)

	prindx	nonemerg	emergpc	emedpa	emednpa
1	0030	0	1	0	0
2	0059	0.3714285714	0.4571428571	0	0.1714285714
3	0090	1	0	0	0
4	01190	0	0	1	0
5	03400	0	1	0	0
6	0341	0.3333333333	0.6666666667	0	0
7	035	0	1	0	0
8	0381	0	0.2307692308	0	0.7692307692
9	03810	0	1	0	0
10	042	0.0666666667	0	0	0.9333333333
11	0529	0.4666666667	0.4666666667	0	0.0666666667
12	0539	0.75	0.25	0	0
13	05410	0	0.5	0	0.5
14	0549	0.75	0	0	0.25
15	0569	1	0	0	0
16	05700	0.2857142857	0.7142857143	0	0
17	0709	1	0	0	0
18	0743	0.5	0.5	0	0
19	075	0.4621848739	0.4369747899	0	0.1008403361
20	0779	0.6744186047	0.2325581395	0	0.0930232558

Based on the primary ICD-9-CM code on the patient’s record, the NYU ED algorithm generates a classification of ED events in 5 main categories (Figure 7):

1) **Non-emergent**: Conditions for which immediate medical care was not required

within 12 hours

2) **Emergent/Primary Care Treatable**: Conditions for which treatment was required within 12 hours

3) **Emergent - ED Care Needed - Preventable/Avoidable**: Conditions for which emergency care was needed but could have been avoided and prevented

4) **Emergent - ED Care Needed - Not Preventable/Avoidable**: Conditions for which emergency care was needed and that could not have been avoided and prevented

5) **Others**: Conditions that relate to mental health issues, alcohol, substance abuse, injury, and conditions deemed unclassified because they do not fit any of the classification scheme

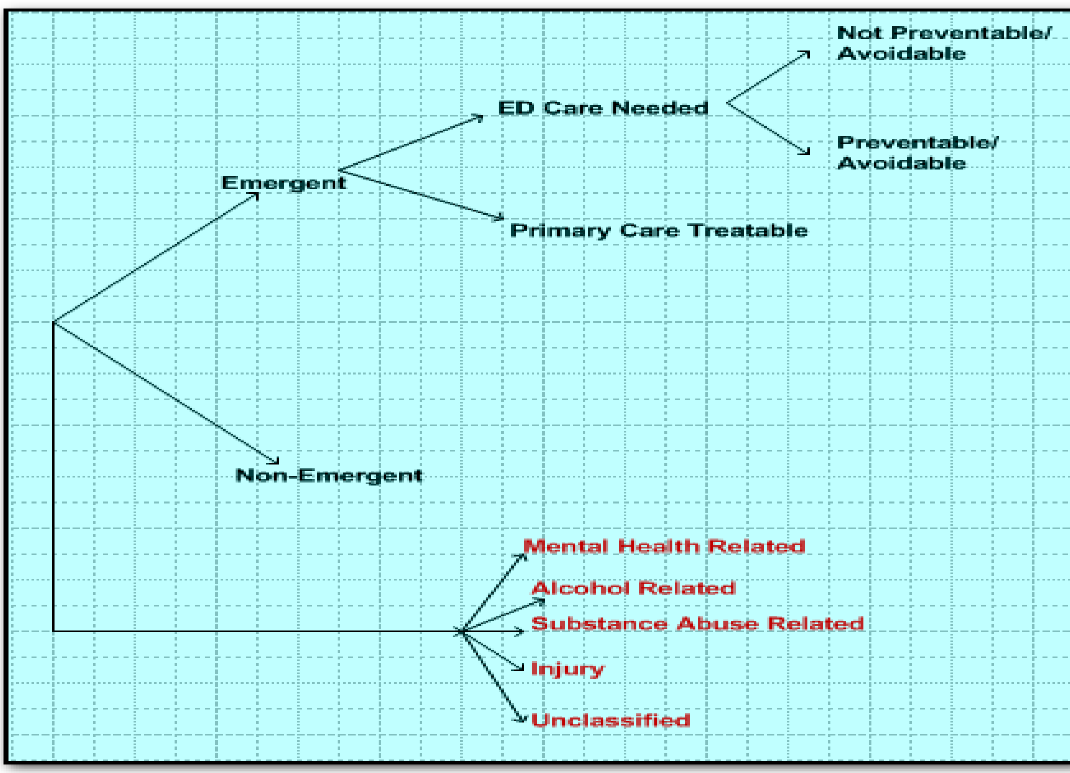

Figure 7: NYU ED Algorithm Classification. (Source NYU – Wagner)

According to designers, when applying the NYU ED algorithm to an ED data set, investigators need to understand that the above classification within the output data is calculated as follow:

> For each ED encounter, the numbers in the new fields represent the relative percentage of cases for that diagnosis falling into the various classification categories. For example, in the case of urinary tract infections (ICD-9-CM code 599.0), each case is assigned 66% "non-emergent", 17% “emergent/primary care treatable”, and 17% "emergent - ED care needed - preventable/avoidable". The sum of the data new data fields will always total 1", and the injury, psych, alcohol, drug, and unclassified fields are always binary (equal to 1" or 0").[32(1)]

Over the last decade, the NYU ED algorithm has been used as a method to analyze and investigate ED utilization in much smaller sampling populations that contain ED records for a specific database, hospital, county, or state. Yet, no other known study has applied the NYU ED algorithm to assess a data set of such a large and extensive size as it is being done in this dissertation to analyze a data set of over 28 million ED records. Accordingly, a panel of physicians from the Utah Department of Health used the NYU ED algorithm to analyze ED visits in Utah and acknowledged “With a better understanding of the method of the NYU algorithm, the physician panel endorsed to use the NYU algorithm and the assigned weights, without any modification…as has been the conclusion of these authors.[35] Instructions on the use of the NYU ED Algorithm (Appendix C) and the SAS software tool available at the NYU web site were downloaded and used to analyze the 2010 NEDS data set. Furthermore, due to issues linked to the 2010 NEDS data set and the fact that the NYU ED algorithm was designed to work with SAS 7 or 8, modifications were made so that the NYU ED algorithm can be used with SAS 9.3. Prior to performing the NYU ED algorithm analysis, DX1, the data element for the principal diagnosis, was cleaned of all data records that were either missing or valued as invl and incn (for invalid and inconclusive). A total of 8881 amongst 28,584,301 the ED records were excluded from the analysis. Within DX1 of 2010 NEDS, a total of 10439 different primary diagnosis codes were used for the NYU ED algorithm analysis. Although we will use the same classification schemes, our analysis will only consider two main categories of ED visits, which makes this method of analysis very complex and time-consuming. In one hand, ED visits, within groups 1 - 2, classified as non-emergent and emergent primary care treatable will be considered as non-emergency visits. In another hand, ED visits, within groups 3 - 4, classified as emergent with ED care needed and preventable/avoidable and emergent with ED care needed and not preventable/avoidable will be considered as emergency visits. The basis for such an analysis to classify ED visits depends on whether emergency medical care services were emergent or non- emergent at the time of the ED visit, instead of consideration that the condition that led to the ED visit was either avoidable or preventable (Table 15).

Table 15: Final classification of ED services after NYU ED Algorithm analysis

NON-EMERGENCY ED VISITS
1. Non-emergent
2. Emergent Primary Care Treatable
EMERGENCY ED VISITS
3.Emergent - ED Care Needed - Preventable/Avoidable
4.Emergent - ED Care Needed - Not Preventable/Avoidable

3.4.4 Analysis of Variance

This section of the dissertation shows how ANOVA, a statistical method of analysis of variance, is used to study and evaluate differences among means of data sets by comparing the value of *F ratio* to the *F crit*. In statistics, *F ratio* is the ratio of the variance between groups to the variance within groups and *F crit* is the threshold value that determines when the test is to be rejected. In this dissertation, the utilization of ANOVA Single Factor from Excel 2007 will be necessary to test the hypothesis that emergency visits within the 2010 NEDS data set are statistically significantly different from non-emergency visits by comparing differences between means of numbers of ED visits that resulted in admission and those that did not, ED visits associated with injury and ED visits not associated with injury, ED visits with one injury or less and those with multiple injuries, ED visits for high severity injury and those for low severity injury, and ED visits for chronic conditions and those for non chronic conditions. The goal of using ANOVA to estimate differences among scores of ED visits within the 2010 NEDS data set is to test the hypothesis that those five critical criteria of admission, presence of injury, severity of injury, number of injuriy, and chronicity can be indicators of whether ED visits are made for emergency or non-emergency conditions. In fact, the ANOVA analysis will help us test the underlying probability that ED visits recorded as routine, no injury, low injury severity, non chronic, and with one injury or less are more likely to result in non-emergency visits.

Table 16: Partial table of the format of the aggregate data used for ANOVA analysis

	ED EVENT		INJURY		INJURY SEVERITY	
AGE	ROUTINE	ADMIT	NO INJURY	INJURY	LOW	HIGH
0 - 14	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
15 - 29	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
30 - 44	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
45 - 59	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
60 - 74	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
75 - 89	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
>89	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
PAYER	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
Medicare	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
Private	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
Medicaid	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
Self	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
GENDER	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
Male	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency
Female	Frequency	Frequency	Frequency	Frequency	Frequency	Frequency

To do the analysis of variance, first, aggregate data from descriptive analysis were used to design five groups of data sets based on the criteria previously mentioned. Second, the SAS tool was used to perform a single factor ANOVA. Each group of data set is made of 2 sets of data to be compared by ANOVA based on the format shown in Table 16. For each analysis, when the value of *F ratio* is greater than *F crit*, the underlying hypothesis will be confirmed. Yet, if the value of *F ratio* is smaller than the *F crit*, which will indicate that the underlying hypothesis can only be explained by chance.

3.4.5 Recategorization

In order to perform logistic regression analysis on the 2010 NEDS data set, some data elements with numerical variables were recategorized into data elements with categorical variable and data elements with categorical variables into data elements with binary variables. First, the data element AGE made of numerical variables ranging from 0 to 124 was converted into a new categorical data element AGECAT with 7 main categories grouped as such: ages from 0 – 14 = 1; ages from 15 – 29 = 2; ages from 30 – 44 = 3; ages from 45 – 59 = 4; ages from 60 – 74 = 5; ages from 75 – 89 = 6; and ages greater than 89 = 7. Second, the data element TOTCHG_ED was converted into a new data element ED_CHG with 4 main categories grouped as follow: charges from 0 – 2500.99 = 1; charges from 2501 – 5000.99 = 2; charges from 5001 – 7500.99 = 3; charges greater than 75001 = 4. Because of the large size of the 2010 NEDS data set, recategorizion of those data elements enhances the method of regression analysis by speeding up the process and making it easier to analyze and study odds ratio per sub-categories instead of every unit of change. It would have been extremely challenging to understand how the patient's age and ED charges influence ED events if the regression analysis had to be conducted for ages raging from 0 to 124 and charges from 0 to 14000 were used to analyze the relation of all the classes' age and charges on the outcome of ED visits. Finally, the data element EDevent, a categorical variable, was recategorized as a binary or dichotomous data element called EMERGENCY with only 0 and 1 as values. Originally, EDevent was classified as follow: (1) for patients treated and released, (2) for patients admitted, (3) for patients transferred to another hospital, (9) for patients who died in ED, (98) for patients not admitted and unknown destination, and (99) for patients discharged alive and unknown destination. In order to study outcomes of ED events and the likelihood that ED visits are influenced by other variables such as age, gender, we made the interpretation that all ED visits not resulted in either admission or transfer were of non-emergency and classified them as 0, ED visits for which patients were admitted or transferred to another hospital were of emergency and classified as 1. Moreover, the data elements NECODE and NDX were recategorized into NECODE_CAT and NDX_CAT. As such, simple regression analysis and multiple regression analysis can be performed to predict how a specific or multiple data elements affect the outcomes of ED visits with 1 for emergency and 0 for non-emergency. Thus, variables such as AGECAT, FEMALE, ED_CHG, NECODE_CAT, NDX_CAT and will be used as independent variables and EMERGENCY as dependent variable.

3.4.6 Logistic Regression Analysis

Earlier we explained why the recategorization of various data elements was conducted as a requirement to the application of logistic regression analysis method. Commonly, logistic regression is used to analyze and evaluate the relationship between independent or predictor variables and dichotomous outcomes or dependent variables. Accordingly, a 2002 report declared “Generally, logistic regression is well suited for describing and testing hypotheses about relationships between a categorical outcome variable and one or more categorical or continuous predictor variables ...as has been the conclusion of these authors.”[34] Moreover, it was explained that “logistic regression calculates the probability of success over the probability of failure; the results of the analysis are in the form of an odds ratio...as has been the conclusion of this author.”[35] The usage of logistic regression model was acknowledged going back in the late 1960s and early 1970s as alternative to ordinary least square (OLS) regression or linear discriminant function analysis, because both of which were not suitable in predicting dependent variables with dichotomous outcomes.[34(1)] In this section, logistic regression analysis will be used to test the hypothesis that there are statistically significant relations between patient's demographic characteristics and emergency visits. Logistic regression analysis will be useful in predicting the probability that outcomes of ED visits, represented by the newly created data element EMERGENCY a dichotomous dependent variable with value of 1 for an emergency visit and value of 0 for a non-emergency visit, are influenced by a single or multiple independent or predictor variables such as age, gender, injury, income, payer type, and location of residence. The dichotomous variable EMERGENCY was created from the recategorization of EDevent variable. By default, the SAS software models the probability that the outcome variable equals 0. In this analysis, we will model the probability that the response or outcome EMERGENCY equals 1 by adding the option "descending" to all logistic regression analysis coding. Our analysis will model a positive response variable that predicts the odds ratio that an emergency visit occurs. No additional steps were taken to clean the data from missing values because the SAS application performs such deletions automatically.

In this dissertation, logistic regression analysis, in its simple terms, will be used to test or investigate the likelihood of an emergency visit as a function of one or multiple predictors. Simple logistic regression will be used to investigate the relation between one binomial outcome and one predictor or independent variable. Multiple logistic regression will be used to investigate the relation between one binomial outcome and multiple predictors or independent variables. Consequently, multiple regression analysis allows investigators to assess how the relationship between the outcome variable and independent variable is influenced by the addition of one or multiple independent variables. As an example, age can be added to a simple regression analysis in which gender was initially used as independent variable to predict the likelihood of an emergency visit. In doing so, it is now possible to determine whether age has affected the association between gender and the outcome either positively or negatively. If that ED visit is represented by Y and one predictor X_1, Equation 1 is representative of a simple logistic regression model:

$$Y = \alpha + \beta_1 X_1 \qquad \text{(Equation 1)}$$

An example of this model to test the relation between a positive ED visit and gender can be formulated as shown in Equation 2:

$$EMERGENCY = \alpha + \beta_1(FEMALE) \qquad \text{(Equation 2)}$$

If that ED visit is represented by Y and more than one predictor, X_1, X_2, X_n. Equation 3 is representative of a multiple logistic regression model:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n \qquad \text{(Equation 3)}$$

An example of the same model to test the relation between a positive ED visit and gender and age can be shown as in Equation 4:

$$EMERGENCY = \alpha + \beta_1(FEMALE) + \beta_2(AGECAT) \qquad \text{(Equation 4)}$$

In those equations, Y represents the dichotomous dependent or outcome variable, X represents the predictor or independent variable (s), α represents the Y intercept or constant of the equation, β represents the coefficient of the predictor or independent variable (s), and n represents the number of the subscript of the last predictor or independent variable. A more complex and alternative formula of the logistic equation 1 or 3 can be written as shown below in Equation 5:

$$\text{Logit}(Y) = \text{natural log (odds)} = \ln(\pi/1 - \pi) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n \quad \text{(Equation 5)}$$

In the latest equation 5, $\boldsymbol{\pi}$ represents the probability of the event Y = 1 (i.e., a patient goes to the ED for emergency condition), $1 - \boldsymbol{\pi}$ represents the probability of Y = 0 (i.e., a patient goes to the ED for a non-emergency condition).

So far, we have explained how the logistic regression model will be used in this dissertation to perform data analysis of the 2010 NEDS. However, it is also critical to validate the logistic regression analysis by demonstrating the effectiveness of the model used in equation 1, 2, and 3. Various studies suggested different assessment methods of logistic regression model. Some studies emphasized odds ratios[35(3)], others favored β coefficients[36], and finally others recommended c-statistic as the statistical measure of primary interest.[37] In this dissertation, we will justify all logistic regression analyses using tables that contain results and output data from SAS 9.3 for four statistical measures: overall model evaluation, statistical tests of individual predictors, goodness-of-fit statistics, and validations of predicted probabilities.[34(7)]

First, overall model evaluation, which is a test of the null hypothesis, will be validated using the related p-values of three statistical tests: likelihood ratio test, score test, and Wald test. If needed, Wald confidence limits or Wald confidence interval of 95% can be used to test the null hypothesis. All three values are part of the ***Testing Global Null Hypothesis: BETA=0*** table, one of the many results of any logistic regression procedure in SAS 9.3. The goal of the null hypothesis test is to determine if the logistic model in equation 1, 2, or 3 is an improvement over the null model. A null model only contains the constant or intercept α without predictor variable (i.e., the hypothesis that any of the predictor's regression coefficient β is not equal to 0). It is to be written as Y = α. Generally, very small p-values less than 0.0001 suggest that the null hypothesis is satisfactory and that the overall model evaluation is validated.

Second, statistical tests of individual predictors will be conducted using the values of β coefficients contained in the ***Analysis of Maximum Likelihood Estimates*** table as a result of logistic regression analysis in SAS 9.3. In our logistic regression analysis, β coefficients are critically important because their values represent the amount by which the outcome variable will be altered for one categorical change. Here, we define one categorical change as the difference between categorical predictor variables (i.e., men and women, Medicare and Medicaid payers, low income and high income patients, 0 – 14 age group and 15 – 29 age group).

Third, goodness-of-fit statistics will be tested using ***Model Fit Statistics*** table. The Model Fit Statistics table includes three measurements: Akaike Information Criterion (AIC), Schwarz Criterion (SC), -2 Log L. Those measurements are used to appraise the "fitness" of the model. Although their values are insignificant, according to the UCLA Statistical Consulting Group, "AIC and SC penalize the log-likelihood by the number of predictors in the model"[37(1)] and -2 Log L is helpful in testing hypothesis of nested models.

Fourth, validations of predicted probabilities will be performed using four measurements within the ***Association of Predicted Probabilities and Observed Responses*** table. Those four measurements are: Somers' D, Gamma, Tau-a, and *c*. Somers' D, Gamma, Tau-a, and *c* are useful in validating whether high probabilities are associated with outcome events being true and low probabilities with outcome events being false.[34(5)] Of those four measures, *c*, often described as c-statistic or concordance index, can be used to assess how well the model predicts the outcome. *c*, accepted as an equivalent of the receiver operating characteristic (ROC), can be valued from 0.5 to 1. While a value of 0.5 indicates that the model only predicts the outcome by chance, a value of 1 implies that the model perfectly predicts the outcome. As such, it will be preferable that our logistic regression analyses produce a higher value for *c*. By example, a *c* statistic of 0.8 for a model using gender as independent variable would mean that for 80% pairs of ED visits (1 for emergency and 0 for non-emergency), the model correctly predicts the outcome.

CHAPTER IV

RESULTS OF DATA ANALYSIS

In this chapter, results of various statistical modeling analyses performed in the previous section will be detailed. Results of descriptive statistical analysis, ED CPT severity level analysis, NYU ED classification Algorithm analysis, analysis of variance, and logistic regression analysis will be reviewed and discussed.

4.1 Results of Descriptive Statistical Analysis

In the following section, results of descriptive statistical analysis will provide readers with a clear and numerical representation of the 2010 NEDS data set. In general, tables and figures will be used to show numerical and statistical observations within such a large data set, which is a critical requirement for further analyses. The next table shows the distribution of ED visits per type of ED event. The data shown in Table 17 is critical as it shows that 82.78% of all ED visits are for routine conditions in which the patients were treated and released without being admitted, 15.36% of ED visits resulted in admission, and 1.45% of ED visits led to patients being transferred to another short term hospital.

Table 17: Distribution of ED visits per type of ED event in 2010

EDEVENT TYPE	FREQUENCY	PERCE
Routine (Treat & Release)	23,660,997	82.7
Admitted to Inpatient	4,391,636	15.3
Transferred to Short Term Hospital	413,496	1.45%
Died during ED visit	44,418	0.16%
Not admitted, destination unknown	73,592	0.26%
Discharged alive, destination unknown	162	0.00%
	28,584,301	**100.0**

The next table depicts ED visits in terms of the presence of injury. While injuries are primary causes of ED visits, the data in Table 18 shows that 76.77% of ED patients in 2010 did not have a single injury diagnosis.

Table 18: Distribution of ED visits per presence of injury in 2010

INJURY RELATED	FREQUENCY	PERCENT
No Injury	21,928,612	76.72%
Injury in 1st Diagnosis	6,000,201	20.99%
Injury in 2nd Diagnosis	655,488	2.29%
	28,584,301	**100.01**

In Table 19, ED visits are explored as per the chronicity of conditions that cause patients to make those visits. Again, the data in Table 18 shows similar trends with previous statistical observations that more than 75% of all ED visits were either for routine conditions or lack the presence of injury. The current table reveals that 83% of ED visits were for conditions that were not chronic. As in related literature, it is generally accepted that patients with non chronic conditions are more likely to make non-emergency visits compare to patients with chronic conditions.

Table 19: Distribution of ED visits per chronicity in 2010

CHRONICITY	FREQUENCY	PERCE
Non Chronic Condition	2,3742,567	83.0
Chronic Condition	4,832,873	16.9
Missing	8,861	0.03%
	28,584,301	**100.0**

Table 20 exhibits the distribution of ED visits per severity of injury. Earlier we explained that less than 25% of ED visits were associated with some type of injury. The data in Table 20 further demonstrates that even when injuries were present, almost all of those injuries were not severe.

Table 20: Distribution of ED visits per injury severity in 2010

INJURY SEVERITY	FREQUENCY	PERCENTAGE
Not Severe (0 - 5)	28,192,481	98.63%
Severe (6 - 75)	297,665	1.04%
Unknown	94,145	0.33%
Missing	10	0.00%
	28584301	**100%**

Tables 21 through 27 contain demographical and financial data of ED patients. These tables will portray statistical observations about age, gender, region, income, payer, location of residency, and charges as they relate to ED patients and visits. Distribution of ED visits per age (Table 21) does not provide any unexpected results. The results appear consistent with number of people per age group. By example, while 23.67% of ED visits are made by individuals between the age of 15 and 29 and only 11.14% by people between the age of 60 and 74, it is also clear that a larger number of people are aged between 15 and 29 than 60 and 74. According to the US Census, in 2010, 21.5% of the US population were between 15 and 29 years old when only 11.4% were between 60 and 74 years old[38].

Table 21: Distribution of ED visits per age in 2010

AGE	FREQUENCY	PERCENTAGE
0 - 14	4,785,306	16.74%
15 - 29	6,767,314	23.67%
30 - 44	5,738,766	20.08%
45 - 59	5,205,218	18.22%
60 - 74	3,186,238	11.14%
75 - 89	2,468,361	8.64%
>89	431,314	1.51%
Missing	1,784	0.00%
	28,584,301	**100.00%**

Similarly, the data in Table 22 does not reveal any significant discrepancy in the distribution of ED visits among men and women. In total, 55.52% of ED visits were made by women compared to 44.47% by men. At the same time, women made 50.8% of the general population compared to 49.2% for men. Generally, women made more ED visits than men due to complications associated with prenatal care, labor and delivery.

Table 22: Distribution of ED visits per gender in 2010

GENDER	FREQUENCY	PERCENTAGE
Male	12,711,893	44.47%
Female	15,869,903	55.52%
Missing	2,505	0.01%
	28,584,301	**100.00%**

In terms of region, Table 23 shows that 43.53% of all ED visits occurred in the South. This greater distribution of ED of visits in the South is not primarily caused by the percentage of the total US population. In 2010, the southern states that participated in the HCUP accounted for 43.53% of all ED visits compared to 17.42% for western states. Yet, those same southern states only represented 17.28% of the overall US population compared to 15.91% for those western states. Further analysis will be necessary to detect why such a large percentage of ED visits was concentrated in the South in 2010.

Table 23: Distribution of ED visits per region in 2010

REGION	FREQUENCY	PERCENTAGE
Northeast	5,203,928	18.20%
Midwest	5,959,846	20.85%
South	12,442,544	43.53%
West	4,977,983	17.42%
	28,584,301	**100.00%**

The data in Table 24 displays the distribution of ED visits per income group. As expected, the data shows that individuals in the low lower income brackets account for greater percentages of ED visits made in 2010. Seemingly, the general assumption is that the less money people make the more likely they are to make non-emergency visits. Nonetheless, one must also take in consideration that a much larger number of people were earning between $1 to $40,999 compared to $67,000 or more. The point we are trying to make here is that financial constraints solely do not explain why 32.16% of ED visits were made by people in the lowest income bracket while 16.78% by people in the highest income bracket.

Table 24: Distribution of ED visits per income in 2010

INCOME	FREQUENCY	PERCENTAGE
1 - 40999	9,191,628	32.16%
41k - 50999	7,777,215	27.21%
51k - 66999	6,174,088	21.60%
67k >	4,795,462	16.78%
Missing	645,908	2.26%
	28,584,301	**100.01%**

Contrary to popular belief, the data in Table 25 implies that payers with private health insurance accounted for a greater percentage of ED visits than those with Medicare, Medicaid, and self payers. The data in Table 25 is significant as it refutes the notion that the lack of health is the primary cause of ED visits. In all, only 17.36% of visits were initiated by uninsured patients in 2010.

Table 25: Distribution of ED visits per payer in 2010

PAYER	FREQUENCY	PERCENTAGE
Medicare	5,958,702	20.85%
Medicaid	7,273,121	25.44%
Private	8,770,514	30.68%
Self	4,962,839	17.36%
No Charge	194,677	0.70%
Other	1,304,714	4.56%
Missing	119,734	0.41%
	28,584,301	**100.00%**

Results of the distribution of ED visits in 2010 per patient's location of residency, as shown in Table 26, are fairly consistent with assumptions that more ED visits take place in large metropolitan areas where most of the US population resides.

Table 26: Distribution of ED visits per residency in 2010

RESIDENCY	FREQUENCY	PERCEN
Large Central Metropolitan	7,909,519	27.67
Large Fringe Metropolitan	6,086,459	21.29
Medium Metropolitan	6,442,332	22.54
Small Metropolitan	2,742,441	9.59%
Micropolitan	3,177,713	11.11
Not Metro or Micropolitan	2,045,443	7.16%
Missing	180,394	0.63%
	28,584,301	**99.99**

The data in Table 27 represents the distribution of ED visits per charges incurred in 2010. In addition to frequency and percentage, Table 27 contains information on the means of charges depending on the types of ED events. Considering that the data being analyzed is a sampling representing 20% of all ED visits nationwide, it is reasonable to suggest that making ED visits is a very expensive activity. Charges for routine ED visits totaled $43,888,525,841 U.S. dollars with a mean of $2128. The total amount of charges for ED visits that resulted in admission was $5,217,557,465 U.S. dollars with a mean of $1,593.

Table 27: Distribution of ED visits per charges in 2010

ED CHARGES	FREQUENCY	PERCENTAGE	I
Routine (Treat & Release)	43,888,525,841	86.08%	
Admitted to Inpatient	5,217,557,465	10.23%	
Transferred to Short Term Hospital	1,478,434,779	2.90%	
Died during ED visit	164,669,019	0.32%	
Not admitted, destination unknown	230,508,038	0.45%	
Discharged alive, destination unknown	479,254	0.00%	
	50,980,174,396	**99.98%**	

The next two tables contain data on the distribution of ED visits per month and day of admission. No significant differences are worth reporting. Distribution of ED visits per calendar month varies from 6.38% to 7.39%. Distribution of ED visits was also similar across week days and weekends. In all, 71.36% of ED visits in 2010 took place during the five days of the week (i.e., 14.272% per single day) while 28.52% of ED visits happened between Saturday and Sunday (i.e., 14.26% per each single day). Once again, the results of descriptive statistical analysis produce statistical observations contradictory to the idea that most ED visits occur during weekends.

Table 28: Distribution of ED visits per month of admission in 2010

MONTH OF ED VISIT	FREQUENCY	PERCENTAGE
January	1,977,634	6.92%
February	1,824,448	6.38%
March	2,041,734	7.14%
April	1,984,235	6.94%
May	2,111,381	7.39%
June	2,045,554	7.16%
July	2,094,182	7.33%
August	2,076,968	7.27%
September	2,020,600	7.07%
October	2,017,148	7.06%
November	1,931,291	6.76%
December	1,969,262	6.89%
Missing	4,489,864	15.70%
	28,584,301	**100.01%**

Table 29: Distribution of ED visits per day of admission in 2010

DAY OF ED VISIT	FREQUENCY	PERCENTAGE
Mon - Friday	20,397,665	71.36%
Sat - Sunday	8,151,130	28.52%
Missing	35,506	0.00120%
	28,584,301	**100.00%**

Finally, the next five tables and five graphs contain aggregate data that summarize the results of descriptive statistical analysis of ED visits in the 2010 NEDS. Distribution of percentages of ED visits were grouped and graphed per age, payer, gender, region, income, and location and compared across routine versus admission ED visits (Table 30 & Figure 8), no injury versus injury ED visits (Table 31 & Figure 9), low severity versus high severity ED visits (Table 32 & Figure 10), not chronic versus chronic ED visits (Table 33 & Figure 11), and single or no injury versus multiple injuries ED visits (Table 34 & Figure 12).

Table 30: Distribution of percentages of ED visits per Routine vs Admit/Transfer across age, payer, gender, region, income, and location groups in 2010

	ED EVENT	
AGE	**ROUTINE**	**ADMIT/TRANSFER**
0 - 14	94.8	3.74
15 - 29	93.17	5.7
30 - 44	89.2	9.53
45 - 59	79.59	18.36
60 - 74	64.65	32.23
75 - 89	52.86	43.89
>89	46.63	49.47
PAYER		
Medicare	59.53	37.25
Private	87.22	11.22
Medicaid	88.93	9.58
Self	92.3	6.45
GENDER		
Male	81.83	15.98
Female	83.53	14.87
REGION		
Northeast	81.63	17.27
Midwest	82.6	14.22
South	83.55	14.88
West	82.26	15.95
INCOME		
1 - 40999	84.48	15.01
41k - 50999	83.63	15.99
51k - 66999	82.14	17.5
67k >	79.79	19.87
LOCATION		
Large Central Metropolitan	81.4	18.34
Large Fringe Metropolitan	81.1	18.52
Medium Metropolitan	84.29	15.39
Small Metropolitan	84.38	15.35
Micropolitan	84.11	14.68
Not Metro or Micropolitan	84.31	15.35

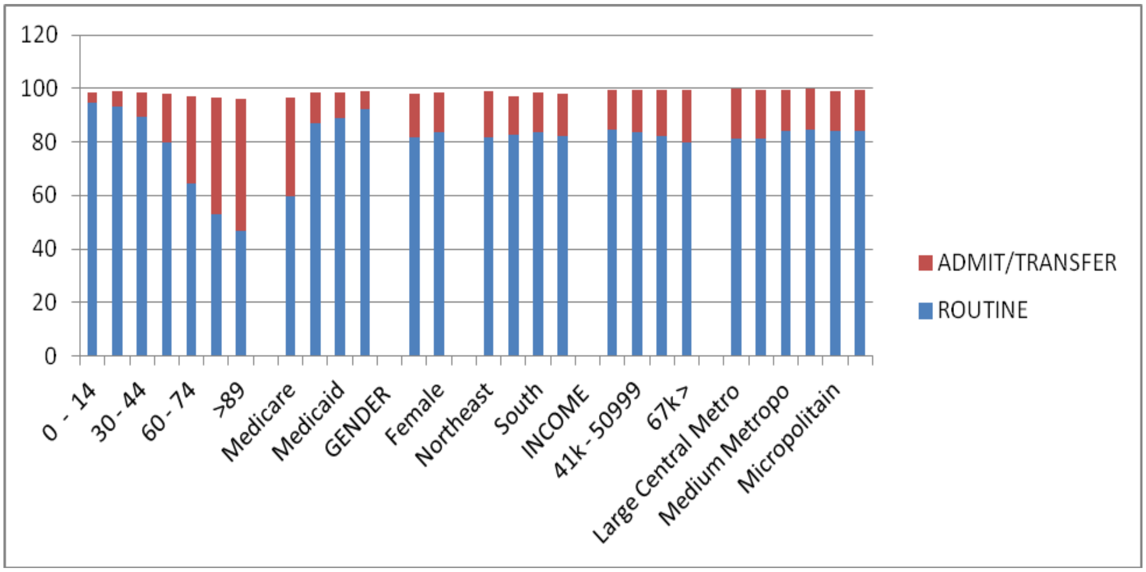

Figure 8: Percentages of ED visits per Routine vs Admit/Transfer across age, payer, gender, region, income, and location groups

Table 31: Distribution of percentages of ED visits per No Injury vs Injury across age, payer, gender, region, income, and location groups in 2010

	INJURY	
AGE	**NO INJURY**	**INJURY**
0 - 14	72.39	27.61
15 - 29	74.11	25.89
30 - 44	77.27	22.73
45 - 59	78.78	20.93
60 - 74	81.77	18.23
75 - 89	80.31	19.69
>89	74.44	24.56
PAYER		
Medicare	81.96	18.04
Private	72.68	27.31
Medicaid	80.58	19.43
Self	75.94	24.07
GENDER		
Male	72.78	27.22
Female	79.86	20.13
REGION		
Northeast	75.39	24.61
Midwest	75.64	24.36
South	77.47	22.53
West	77.49	22.51
INCOME		
1 - 40999	78.91	21.09
41k - 50999	76.91	23.1
51k - 66999	75.79	24.21
67k >	73.2	26.9
LOCATION		
Large Central Metropolitan	79.11	20.99
Large Fringe Metropolitan	75.79	24.21
Medium Metropolitan	75.43	24.57
Small Metropolitan	76.84	23.16
Micropolitan	75.79	24.21
Not Metro or Micropolitan	75.43	24.57

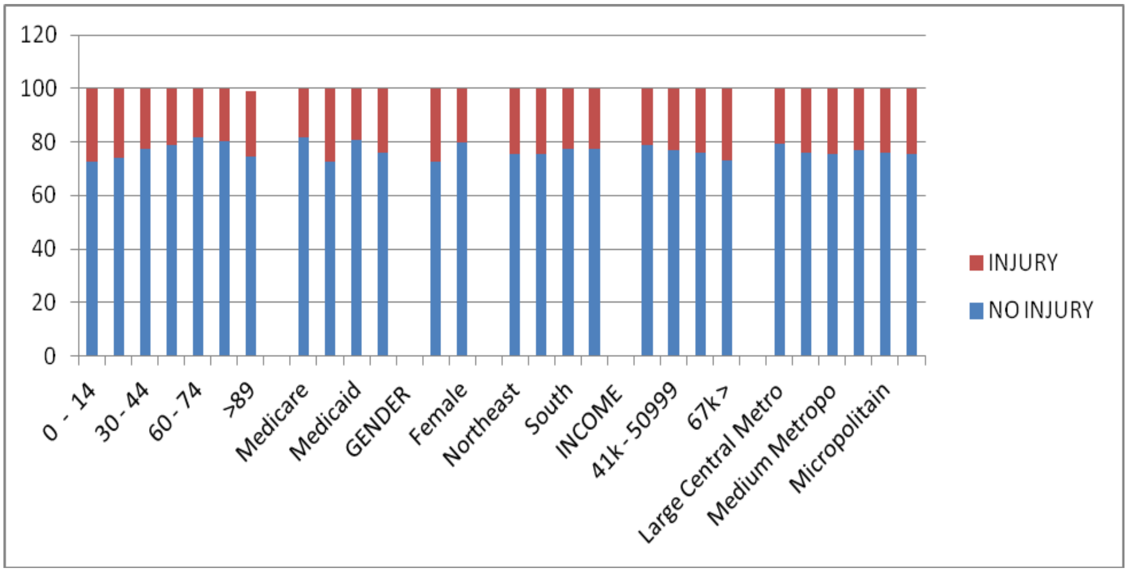

Figure 9: Percentages of ED visits per Injury vs No Injury across age, payer, gender, region, income, and location groups

Table 32: Distribution of percentages of ED visits per Low Injury Severity vs High Injury Severity across age, payer, gender, region, income, and location groups in 2010

	INJURY SEVERITY	
AGE	**LOW**	**HIGH**
0 - 14	99.15	0.85
15 - 29	98.88	1.12
30 - 44	98.97	1.03
45 - 59	98.76	1.24
60 - 74	98.37	1.63
75 - 89	96.81	3.19
>89	95.05	4.95
PAYER		
Medicare	97.78	2.22
Private	98.69	1.31
Medicaid	99.22	0.78
Self	98.90	1.10
GENDER		
Male	98.37	1.63
Female	98.84	1.16
REGION		
Northeast	98.75	1.25
Midwest	98.57	1.43
South	98.66	1.34
West	98.50	1.50
INCOME		
1 - 40999	98.82	1.18
41k - 50999	98.63	1.37
51k - 66999	98.54	1.46
67k >	98.40	1.60
LOCATION		
Large Central Metropolitan	98.79	1.21
Large Fringe Metropolitan	98.59	1.41
Medium Metropolitan	98.59	1.41
Small Metropolitan	98.61	1.39
Micropolitan	98.53	1.47
Not Metro or Micropolitan	98.46	1.54

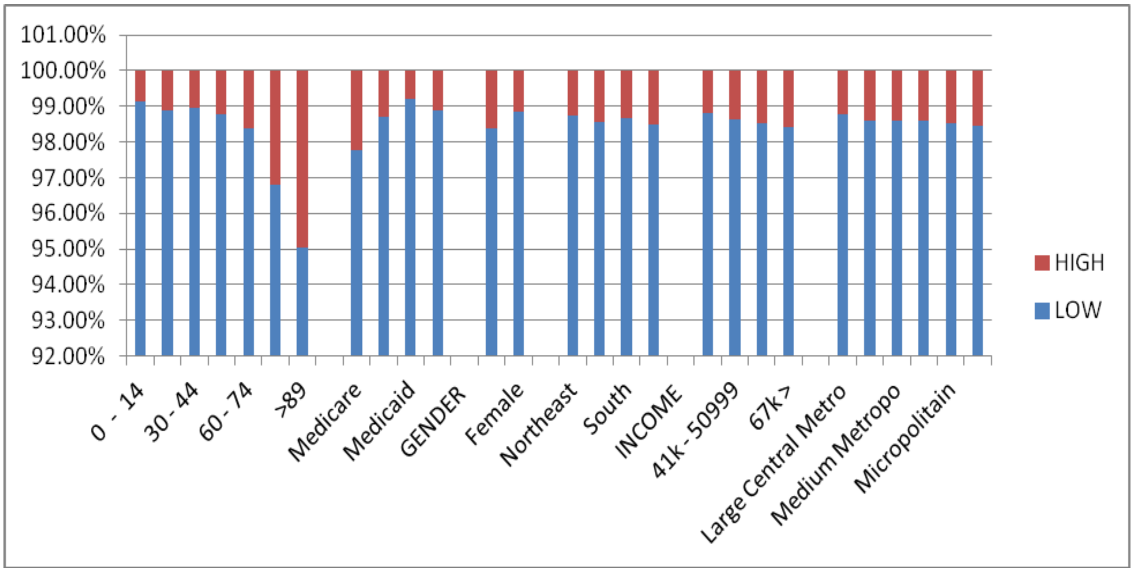

Figure 10: Percentages of ED visits per Low Injury Severity vs High Injury Severity across age, payer, gender, region, income, and location groups

Table 33: Distribution of percentages of ED visits per Non Chronic vs Chronic across age, payer, gender, region, income, and location groups in 2010

	CHRONICITY	
AGE	NON CHRONIC	CHRONIC
0 - 14	93.63	6.35
15 - 29	88.56	11.4
30 - 44	83.89	16.07
45 - 59	77.47	22.5
60 - 74	72.9	27.07
75 - 89	71.98	28
>89	74.53	25.44
PAYER		
Medicare	71.95	28.03
Private	86.21	13.77
Medicaid	86.21	13.76
Self	85.1	14.82
GENDER		
Male	82.11	17.86
Female	83.82	16.15
REGION		
Northeast	81	19
Midwest	83.86	16.06
South	83.46	16.49
West	83.24	16.76
INCOME		
1 - 40999	82.65	17.31
41k - 50999	83.66	16.31
51k - 66999	83.56	16.41
67k >	82.86	17.12
LOCATION		
Large Central Metropolitan	82.1	17.86
Large Fringe Metropolitan	83.03	16.94
Medium Metropolitan	83.85	16.14
Small Metropolitan	83.37	16.61
Micropolitan	83.71	16.24
Not Metro or Micropolitan	83.72	16.24

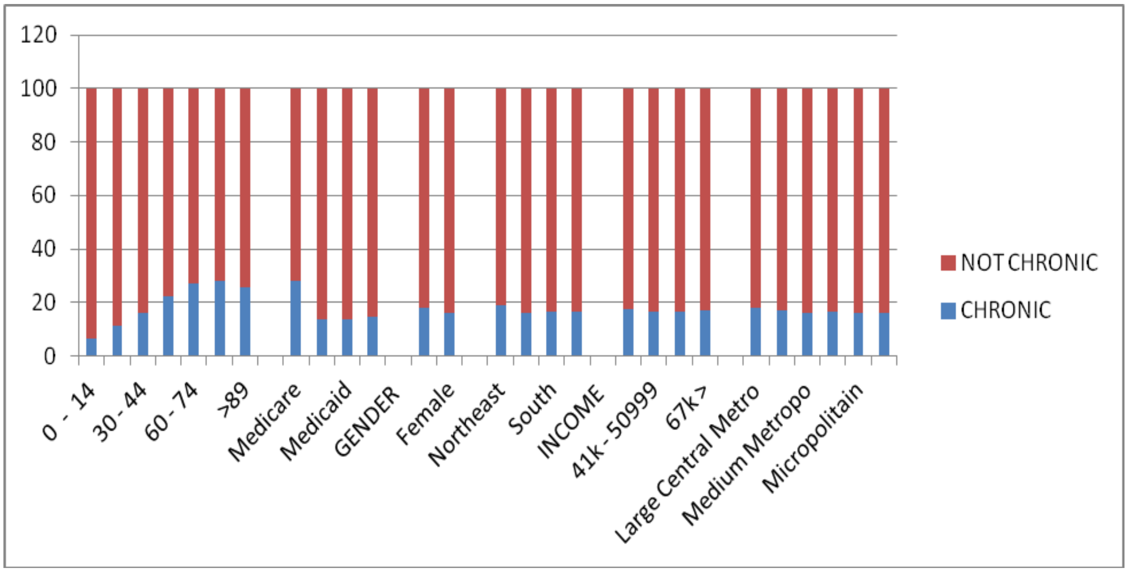

Figure 11: Percentages of ED visits per Non Chronic vs Chronic across age, payer, gender, region, income, and location groups

Table 34: Distribution of percentages of ED visits per 1 Injury or less vs Multiple Injuries across age, payer, gender, region, income, and location groups in 2010

	MULTINJURY	
AGE	**1 OR NO INJURY**	**MORE THAN 1**
0 - 14	95.5	4.5
15 - 29	93.44	6.56
30 - 44	94.31	5.68
45 - 59	94.33	5.66
60 - 74	94.76	5.24
75 - 89	93.55	6.45
>89	91.55	8.55
PAYER		
Medicare	94.7	5.3
Private	93.25	6.75
Medicaid	96.08	3.92
Self	93.92	6.08
GENDER		
Male	93.39	6.61
Female	94.94	5.06
REGION		
Northeast	94.63	5.37
Midwest	94.12	5.88
South	94.14	5.86
West	94.28	5.72
INCOME		
1 - 40999	94.93	5.07
41k - 50999	94.33	5.67
51k - 66999	93.97	6.02
67k >	93.21	6.79
LOCATION		
Large Central Metropolitan	94.88	5.12
Large Fringe Metropolitan	93.75	6.25
Medium Metropolitan	94.03	5.97
Small Metropolitan	94.38	5.61
Micropolitan	94	6
Not Metro or Micropolitan	94.29	5.71

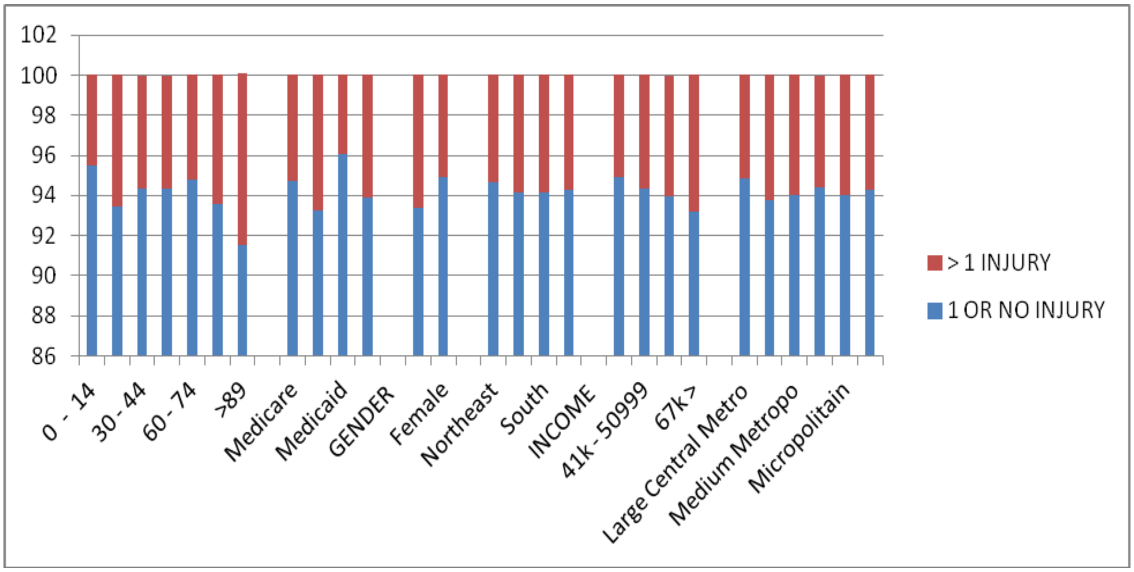

Figure 12: Percentages of ED visits per 1 Injury or less vs Multiple Injuries across age, payer, gender, region, income, and location groups

Overwhelmingly, results of descriptive statistical analysis of the 2010 NEDS confirm previously made hypotheses that statistically significant numerical observations within the 2010 NEDS data set are indicative of non-emergency medical use. Such numerical observations are that 82.78% of ED visits were routine whilst 16.91% resulted in admission, 76.72% of ED visits were not injury related whilst 23.28% had an injury diagnosis, 83.06% of ED visits were for non- chronic conditions whilst 16.91% were not, 98.63% of ED visits were for non-severe injuries whilst 1.04% was not, and mean of ED charges for routine ED visits were $2128 whilst mean of ED charges for ED visits that resulted in admission were $1593. These results are a clear indication that a significant percentage of ED visits were made for non-emergency events. Even though not all routine ED visits are made for non-emergency conditions, a substantial amount of routine ED visits are driven by non-emergency events. Although the use of descriptive statistical analysis of the 2010 NEDS data set does not permit to calculate the number nor the percentage of ED visits made for non-emergency conditions, further statistical methods of ED CPT Severity level analysis and NYU ED Algorithm classification analysis will provide us with better numerical estimations of such values.

4.2 Results of ED CPT Severity Level Analysis

This section will encompass results of the ED CPT severity level analysis explained and introduced earlier. Data in the next tables and graphs will depict statistical observations of CPT codes 99281, 99282, 99283, 99284, and 99285 across all fifteen data elements CPT1 – CPT15. Table 35 shows frequencies and overall percentages for CPT codes used in the 2010 NEDS. The data in Table 35 shows that a total of 16,730,607 million CPT codes were used among which 99281 accounted for 8.76%, 99282 for 17.07%, 99283 for 40.25%, 99284 for 25.88%, and 99285 for 8.04%. In Table 36, ED visits with CPT coding 99283 were reclassified in two groups: 99283NI and 99283I. Data in the 99283NI column represent ED visits for which the CPT coding 99283 was used while the diagnosis of injury was not present. Data in the 99283I represent ED visits for which the CPT coding 99283 was used while the diagnosis of injury was present. Finally, Table 37 shows the final classification and distribution of ED visits according to the ED CPT Severity analysis and whether CPT coding 99283 is associated with the presence of injury or not. As we explained earlier, ED visits with CPT codes 99281, 99282, and 99283NI were classified as non-emergency and 99283I, 99284, 99285 were classified as emergency. According to the analysis scheme used, the results in Table 37 and Figure 13 show that 54.02% of the ED visits were of non-emergency characteristic and 45.98% were severe enough to be considered as emergency visits.

Again, results of ED CPT severity level analysis of the 2010 NEDS corroborate our hypotheses that there are statistically effective procedural methods in differentiating non- emergency visits from emergency visits. Those procedural methods show that 54.02% of ED visits were of low severity or made for non-emergency conditions whilst 45.98% were of high severity or made for emergency conditions.

Table 35: Distribution of CPT codes in the 2010 NEDS

	99281	99282	99283	99284	99285	TOTAL
CPT1	666,014	2,164,603	4,697,135	2,536,082	732,235	10,796,069
CPT2	357,376	426,503	933,215	526,296	171,663	2,415,053
CPT3	205,242	139,718	428,934	380,993	108,357	1,263,244
CPT4	115,395	56,710	208,235	163,415	48,486	592,241
CPT5	54,218	25,027	118,330	108,412	31,168	337,155
CPT6	28,247	14.903	82,813	88,462	26,211	240,636
CPT7	15,082	9,082	60,625	78,785	23,926	187,500
CPT8	8,163	6,036	47,321	75,241	25,935	162,696
CPT9	5,010	4,066	38,177	72,887	26,792	146,932
CPT10	3,318	2,871	32,301	67,324	26,415	132,229
CPT11	2,314	1,957	26,869	62,716	27,049	120,905
CPT12	1,568	2,055	33,549	88,276	51,340	176,788
CPT13	1,170	761	11,832	33,368	16,967	64,098
CPT14	943	580	8,973	27,037	15,186	52,719
CPT15	778	430	6,595	21,449	13,090	42,342
TOTAL	1,464,838	2,855,302	6,734,904	4,330,743	1,344,820	16,730,607
PERCENTAG	8.76	17.07	40.25	25.88	8.04	100%

Table 36: Distribution of CPT codes in the 2010 NEDS associated with presence of injury

	99281	99282	99283NI	99283I	99284	99285	
CPT1	666,014	2,164,603	3,377,035	1,320,100	2,536,082	732,235	
CPT2	357,376	426,503	584,070	349,145	526296	171,663	
CPT3	205,242	139,718	256,218	172,716	380,993	108,357	
CPT4	115,395	56,710	108,952	99,283	163,415	48,486	
CPT5	54,218	25,027	84,047	34,283	108,412	31,168	
CPT6	28,247	14,903	66,578	16,235	88,462	26,211	
CPT7	15,082	9,082	51,239	9,386	78,785	23,926	
CPT8	8,163	6,036	41,783	5,538	75,241	25,935	
CPT9	5,010	4,066	34,307	3,870	72,887	26,792	
CPT10	3,318	2,871	29,641	2,660	67,324	26,415	
CPT11	2,314	1,957	24,953	1,916	62,716	27,049	
CPT12	1,568	2,055	31,603	1,946	88,276	51,340	
CPT13	1,170	761	11,013	819	33,368	16,967	
CPT14	943	580	8,376	597	27,037	15,186	
CPT15	778	430	,6126	469	21,449	13,090	
TOTAL	1,464,838	2,855,302	4,715,941	2,018,963	4,330,743	1,344,820	
PERCENTAGE	8.76	17.07	28.19	12.06	25.88	8.04	

Table 37: Final classification of ED visits per ED CPT Severity associated with presence of injury in the 2010 NEDS

NON-EMERGENCY	FREQUENCY	PERCENTAG
99281	1,464,838	8.76
99282	2,855,302	17.07
99283NI	4,715,941	28.19
TOTAL	**9,036,081**	**54.02**
EMERGENCY		
99283I	20,189,63	12.06
99284	4,330,743	25.88
99285	1,344,820	8.04
TOTAL	**7,694,526**	**45.98**
	16,730,607	**100**

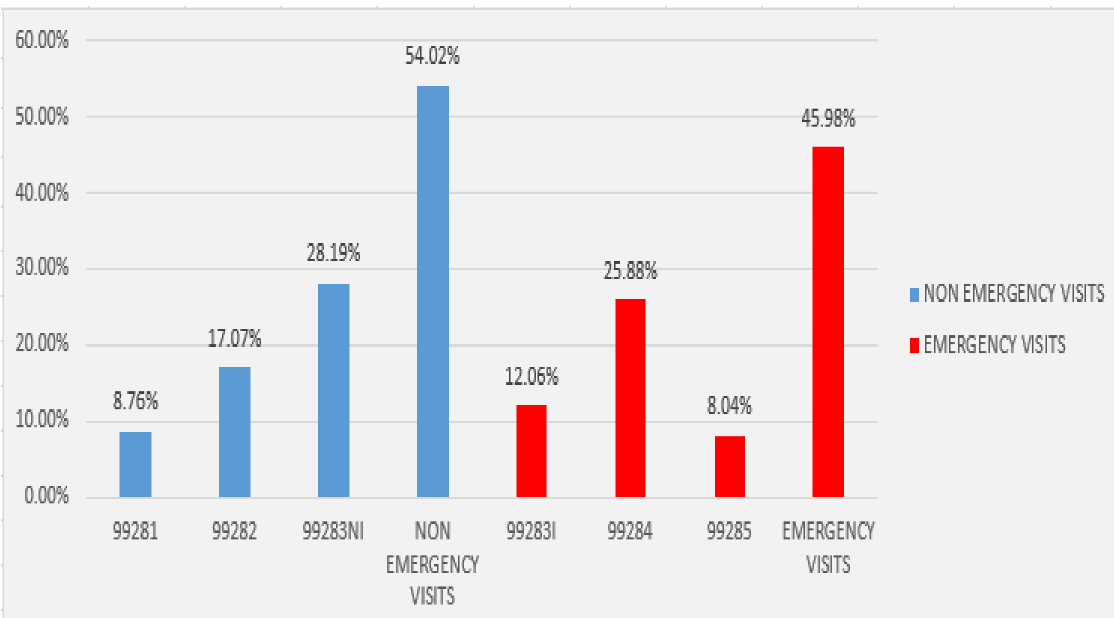

Figure 13: Distribution of percentages of CPT codes in the 2010 NEDS associated with presence of injury

4.3 Results of NYU ED Classification Algorithm Analysis

In this section of the dissertation, results of the NYU ED classification algorithm analysis of the 2010 NEDs will be put on display. The results were derived from the output of NYU ED classification algorithm applied to the 2010 NEDS, in which percentages of all diagnoses for each of those categories were sorted and computed as per the following instructions from designers (Table 38), "To profile a hospital, payor group, zip code area, patient type, etc., simply aggregate these values to find the total percentage of cases falling into each of the categories…as has been the conclusion of these authors."[32(1)]

Table 38: Partial list of results of ED visits in the 2010 NEDS by the NYU ED Algorithm analysis in SAS 9.3 (The complete file contains 28,575,420 million valid records)

	dxgroup	ne	epct	edcnpa	edcnnpa
19850193	7870	0.5882352941	0.2352941176	0	0.1764705882
19850194	7870	0.5882352941	0.2352941176	0	0.1764705882
19850195	7870	0.5882352941	0.2352941176	0	0.1764705882
19850196	7870	0.5882352941	0.2352941176	0	0.1764705882
19850197	7870	0.5882352941	0.2352941176	0	0.1764705882
19850198	7870	0.5882352941	0.2352941176	0	0.1764705882
19850199	7870	0.5882352941	0.2352941176	0	0.1764705882
19850200	7870	0.5882352941	0.2352941176	0	0.1764705882
19850201	7870	0.5882352941	0.2352941176	0	0.1764705882
19850202	7870	0.5882352941	0.2352941176	0	0.1764705882
19850203	7870	0.5882352941	0.2352941176	0	0.1764705882
19850204	7870	0.5882352941	0.2352941176	0	0.1764705882
19850205	7870	0.5882352941	0.2352941176	0	0.1764705882
19850206	7870	0.5882352941	0.2352941176	0	0.1764705882
19850207	7870	0.5882352941	0.2352941176	0	0.1764705882
19850208	7870	0.5882352941	0.2352941176	0	0.1764705882
19850209	7870	0.5882352941	0.2352941176	0	0.1764705882
19850210	7870	0.5882352941	0.2352941176	0	0.1764705882
19850211	7870	0.5882352941	0.2352941176	0	0.1764705882
19850212	7870	0.5882352941	0.2352941176	0	0.1764705882
19850213	7870	0.5882352941	0.2352941176	0	0.1764705882
19850214	7870	0.5882352941	0.2352941176	0	0.1764705882
19850215	7870	0.5882352941	0.2352941176	0	0.1764705882
19850216	7870	0.5882352941	0.2352941176	0	0.1764705882
19850217	7870	0.5882352941	0.2352941176	0	0.1764705882

Consequently, the final classification of ED visits following the application of NYU ED classification algorithm will be similar to the one shown earlier in Figure 7. Based on that classification, since we are only using the four main categories of non-emergent, emergent primary care treatable, emergent - ED care needed - preventable/avoidable, and emergent - ED care needed - not preventable/avoidable to classify ED visits in the 2010 NEDS, our expectations are that the final results will demonstrate that a very large percentage of ED visits will be classified as either non-emergent or emergent primary care treatable instead of emergent - ED care needed - preventable/avoidable or emergent - ED care needed - not preventable/avoidable because ED visits for which diagnoses were related to injury, mental health, substance abuse are excluded by the NYU ED algorithm. In total, 23.00% of all ED visits in 2010 NEDS resulted of some type of injury. The model explained above can be written as per Equation 6 below:

Total of ED Visits = Percentage of Non-Emergent + Percentage of Emergent Primary Care Treatable + Percentage of Emergent/ED Care Needed/Preventable/Avoidable + Percentage of Emergent/ED Care Needed/Not

The data in the tables and graphs below is indicative of the results of the NYU ED algorithm analysis of the 2010 NEDS. As expected, Table 39 shows that a great majority of ED visits were classified as non-emergent or emergent primary care treatable following analysis by the NYU ED algorithm for the ED visits included in the primary classification. Table 39 includes a total of 16,594,706 million or around 58.07% of the 28,575,420 million of ED visits used for the analysis. Table 38 shows the data for ED visits excluded from the primary classification or special categories, a total of 11,980,718 million ED visits or around 41.93% that were related to mental health, alcohol, injury, or unclassified, of which partial list of the results is shown in Table 38. Finally, using our own reclassification scheme announced and explained earlier in Table 15, ED visits were grouped as non-emergency or emergency. A percentage of 65.78% was reclassified as non emergency while 34.22%

as emergency as shown in Table 42 and Figure 14.

Accordingly, the results of NYU ED classification algorithm analysis validate our hypotheses that there are statistically effective diagnostic methods to differentiate non- emergency visits from emergency visits. As a diagnostic based statistical method of analysis, the NYU ED algorithm's results show that 65.78% of ED visits were for non-emergency reasons whilst 34.22% were emergency reasons.

Table 39: Distribution and classification of ED visits of the 2010 NEDS based on the NYU ED Algorithm

CATEGORIES	FREQUENCY	PERCENT
Non Emergent	5,466,632	32.94%
Emergent Primary Care Treatable	5,449,610	32.84%
Emergent - ED Care Needed - Preventable/Avoidable	1,958,683	11.80%
Emergent - ED Care Needed - Not Preventable/Avoidable	3,719,781	22.42%
	16,594,706	**100.00**

Table 40: Distribution and classification of ED visits designed as special categories in the 2010 NEDS by the NYU ED Algorithm

CATEGORIES	FREQUENCY
Mental Health Related	729,312
Alcohol/Drug Related	377,451
Injury	6,572,400
Unclassified	4,301,555
	11,980,718

Table 41: Partial list of results of ED visits designed as special categories in the 2010 NEDS by the NYU ED Algorithm

	ne	epct	edcnpa	edcnnpa	injury1	psych	alcohol	drug	unclassified
1	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	1
3	0	0	0	0	0	0	0	0	1
4	0	0	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0	0	1
6	0	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	0	0	1
8	0	0	0	0	0	0	0	0	1
9	0	0	0	0	0	0	0	0	1
10	0	0	0	0	0	0	0	0	1
11	0	0	0	0	0	0	0	0	1
12	0	0	0	0	0	0	0	0	1
13	0	0	0	0	0	0	0	0	1
14	0	0	0	0	0	0	0	0	1
15	0	0	0	0	0	0	0	0	1
16	0	0	0	0	0	0	0	0	1
17	0	0	0	0	0	0	0	0	1
18	0	0	0	0	0	0	0	0	1
19	0	0	0	0	0	0	0	0	1
20	0	0	0	0	0	0	0	0	1
21	0	0	0	0	0	0	0	0	1
22	0	0	0	0	0	0	0	0	1
23	0	0	0	0	0	0	0	0	1
24	0	0	0	0	0	0	0	0	1
25	0	0	0	0	0	0	0	0	1
26	0	0	0	0	0	0	0	0	1
27	0	0	0	0	0	0	0	0	1
28	0	0	0	0	0	0	0	0	1
29	0	0	0	0	0	0	0	0	1
30	0	0	0	0	0	0	0	0	1
31	0	0	0	0	0	0	0	0	1
32	0	0	0	0	0	0	0	0	1
33	0	0	0	0	0	0	0	0	1
34	0	0	0	0	0	0	0	0	1
35	0	0	0	0	0	0	0	0	1

Table 42: Final reclassification of percentages of ED visits of the 2010 NEDS per Emergency and Non- emergency following NYU ED Algorithm application

CATEGORIES	PERCENTAGE
NON-EMERGENCY ED VISITS	
Non Emergent	32.94%
Emergent Primary Care Treatable	32.84%
TOTAL	**65.78%**
EMERGENCY ED VISITS	
Emergent - ED Care Needed - Preventable/Avoidable	11.80%
Emergent - ED Care Needed - Not Preventable/Avoidable	22.42%
TOTAL	**34.22%**

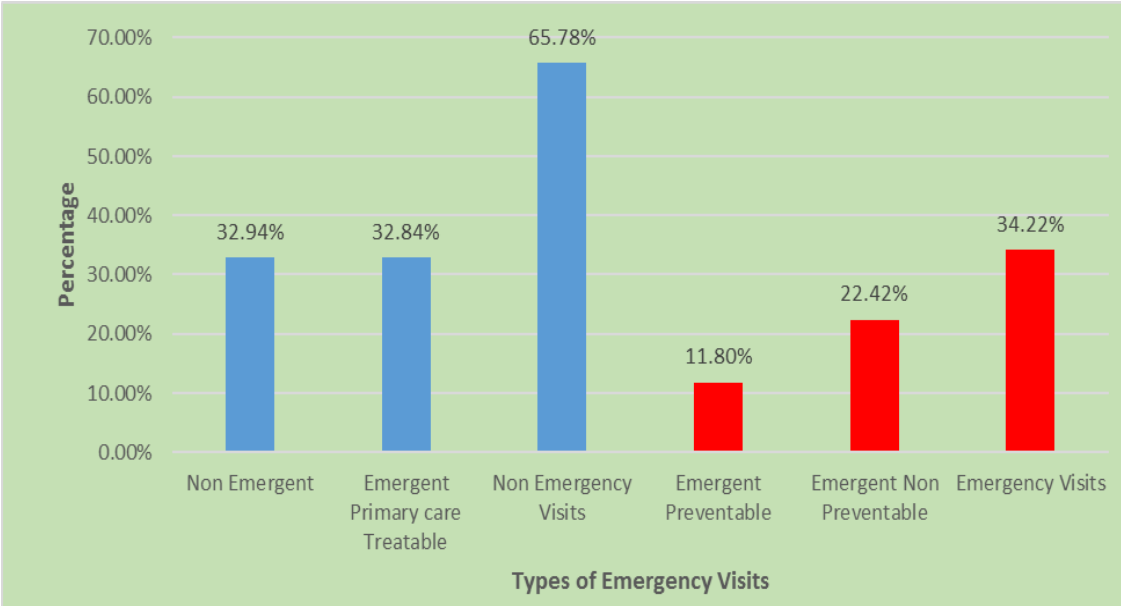

Figure 14: Final reclassification of percentages of ED visits of the 2010 NEDS per Emergency and Non- emergency

4.4 Results of Analysis of Variance

In this section, results of analysis of variance with Anova Single Factor from Excel 2007 will be displayed. As previously explained in Section 3.4.4, the variance analysis will compare data sets in Tables 43, 45, 47, 49, and 51 produced from the aggregation of descriptive statistical observations within the 2010 NED*S* to test the hypothesis that certain categories of ED visits are highly indicative of non-emergency conditions. The results of those analyses shown in Tables 44, 46, 48, 50, and 52 confirm the hypothesis being tested. The results in Tables 44, 46, 48, 50, and 52 show *F ratio* with values of*:* 46.96, 21.15, 88.53, 53.84, and 80.08 are all significantly greater than the value of *F crit* value of 4.03, which corroborates the hypothesis that it is more likely that ED visits, associated to conditions that were routine, without injury, of low severity injury, not chronic, and the absence of multiple injuries, are made for non-emergency reasons compared to ED visits in which patients were either admitted, had injury, suffered a high severity injury, had a chronic condition, and diagnosed with multiple injuries. Results of variance analysis validate our hypotheses that ED visits made for emergency conditions are statistically significantly different of those made for non-emergency conditions because of differences between the means of the ED visits that were routine vs admit, ED visits with no injury vs injury, ED visits with low injury severity vs high severity, ED visits that were not chronic vs chronic, and ED visits with one injury or less vs multiple injuries.

Table 43: Aggregated distribution of ED visits per Routine vs Admit in 2010

	ED EVENT	
AGE GROUP	ROUTINE	ADM
0 - 14	4,536,305	238,1
15 - 29	6,305,112	440,3
30 - 44	5,119,387	599,0
45 - 59	4,143,126	1,038,
60 - 74	2,059,895	1,107,
75 - 89	1,294,861	1,155,
>89	201,120	225,9
PAYER GROUP		
Medicare	3,547,018	2,373,
Private	7,649,813	1,092,
Medicaid	6,467,781	777,3
Self	4,580,959	3,666,
GENDER GROUP		
Male	10,402,002	2,248,
Female	13,256,782	2,556,
REGION GROUP		
Northeast	4,247,866	934,1
Midwest	4,922,690	977,1
South	10,395,712	2,021,
West	4,094,729	872,5
INCOME GROUP		
1 - 40999	7,765,189	1,379,
41k - 50999	6,503,990	1,243,
51k - 66999	5,071,203	1,080,
67k >	3,826,244	952,8
LOCATION GROUP		
Large Central Metropolitan	6,438,049	1,450,
Large Fringe Metropolitan	4,936,331	1,127,
Medium Metropolitan	5,430,055	991,8
Small Metropolitan	2,314,046	420,9
Micropolitan	2,672,755	466,2
Not Metro or Micropolitan	1,724,523	313,8

Table 44: Results of analysis of variance (ANOVA) of Routine vs Admit ED visits

Ano va: Sing

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
ROUTINE	27	139907543	5181760.852	8.59258E+12
ADMIT	27	31752606	1176022.444	6.33803E+11

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*
Between Groups	2.1662E+14	1	2.1662E+14	46.96	8.51 E-
Within Groups	2.39886E+14	52	4.61319E+12		
Total	4.56506E+14	53			

Table 45: Aggregated distribution of ED visits per No Injury vs Injury in 2010

	INJURY	
AGE GROUP	NO INJURY	INJURY
0 - 14	3,463,882	1,321,42
15 - 29	5,015,397	1,751,91
30 - 44	4,434,118	1,304,64
45 - 59	4,100,538	1,104,68
60 - 74	2,605,533	580,705
75 - 89	1,982,427	485,934
>89	325,370	105,944
PAYER GROUP		
Medicare	4,883,895	1,074,80
Private	6,374,689	2,395,82
Medicaid	5,860,601	1,412,52
Self	3,768,571	1,194,26
GENDER GROUP		
Male	9,252,169	12,674,4
Female	3,459,724	3,195,44
REGION GROUP		
Northeast	4,247,866	934,158
Midwest	4,922,690	977,178
South	10,395,712	2,021,21
West	4,094,729	872,592
INCOME GROUP		
1 - 40999	7,253,488	1,938,14
41k - 50999	5,981,218	1,795,99
51k - 66999	4,679,202	1,494,88
67k >	3,510,269	1,285,19
LOCATION GROUP		
Large Central Metropolitan	6,257,216	1,652,30
Large Fringe Metropolitan	4,562,418	1,524,04
Medium Metropolitan	4,909,631	1,532,70
Small Metropolitan	2,107,408	635,033
Micropolitan	2,408,392	769,321
Not Metro or Micropolitan	1,542,900	502,543

Table 46: Results of analysis of variance (ANOVA) of No Injury vs Injury ED visits

Ano va: Sin

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
No INJURY	27	122400053	4533335.296	4.86914E+12
INJURY	27	46537883	1723625.296	5.2104E+12

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*
Between Groups	1.06575E+14	1	1.06575E+14	21.15	2.76 E-
Within Groups	2.62068E+14	52	5.03977E+12		
Total	3.68643E+14	53			

Table 47: Aggregated distribution of ED visits per Low Injury Severity vs High Injury Severity in 2010

	INJURY SEVERITY	
AGE GROUP	LOW	HIG
0 - 14	4,744,642	40,66
15 - 29	6,691,488	75,82
30 - 44	5,679,936	58,83
45 - 59	5,140,914	64,30
60 - 74	3,134,186	52,05
75 - 89	2,389,640	78,72
>89	409,948	21,36
PAYER GROUP		
Medicare	5,826,356	132,3
Private	8,655,636	114,8
Medicaid	7,216,631	56,49
Self	4,908,706	54,13
GENDER GROUP		
Male	12,505,165	206,7
Female	15,684,855	185,0
REGION GROUP		
Northeast	5,138,938	64,99
Midwest	5,874,330	85,51
South	12,275,587	166,9
West	4,903,636	74,34
INCOME GROUP		
1 - 40999	9,082,755	108,8
41k - 50999	7,670,590	106,8
51k - 66999	6,084,173	89,91
67k >	4,718,815	76,64
LOCATION GROUP		
Large Central Metropolitan	7,813,654	95,86
Large Fringe Metropolitan	6,000,546	85,91
Medium Metropolitan	6,351,624	90,70
Small Metropolitan	2,704,369	38,07
Micropolitan	3,130,926	46,78
Not Metro or Micropolitan	2,013,852	31,59

Table 48: Results of analysis of variance (ANOVA) of Low Injury Severity vs High Injury Severity ED visits

Anova:

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
LOW SEVERITY	27	166751898	6175996.222	1.13116E+13
HIGH SEVERITY	27	2304371	85347.07407	2042238928

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-val*
Between Groups	5.00796E+14	1	5.00796E+14	88.53	8.16E-
Within Groups	2.94155E+14	52	5.65683E+12		
Total	7.94951E+14	53			

Table 49: Aggregated distribution of ED visits per Non Chronic Condition vs Chronic Condition in 2010

	CHRONICITY	
AGE GROUP	NON CHRONIC	CHRO
0 - 14	4,480,351	303,
15 - 29	5,992,856	771,
30 - 44	4,814,333	922,
45 - 59	4,032,486	1,171,
60 - 74	2,322,857	862,
75 - 89	1,776,819	691,
>89	321,475	109,
PAYER GROUP		
Medicare	4,287,135	1,670,
Private	7,560,998	1,207,
Medicaid	6,270,235	1,001,
Self	4,223,501	735,
GENDER GROUP		
Male	1,0437,699	2,270,
Female	1,3302,826	2,562,
REGION GROUP		
Northeast	421,4703	989,
Midwest	4,997,741	957,
South	10,386,502	2,052,
West	4,143,621	834,
INCOME GROUP		
1 - 40999	759,7035	1,591,
41k - 50999	6,506,087	1,268,
51k - 66999	5,159,321	1,013,
67k >	3,973,656	820,
LOCATION GROUP		
Large Central Metropolitan	6,493,669	1,412,
Large Fringe Metropolitan	5,053,779	1,030,
Medium Metropolitan	5,402,010	1,039,
Small Metropolitan	2,286,437	455,
Micropolitan	2,660,012	515,
Not Metro or Micropolitan	1,712,502	332,

Table 50: Results of analysis of variance (ANOVA) of Non Chronic vs Chronic ED visits

			Ano va: Sin		
SUMMARY					
Groups	***Count***	***Sum***	***Average***	***Variance***	
NON CHRONIC	27	140410646	5200394.296	8.26438E+12	
CHRONIC	27	28593397	1059014.704	3.36225E+11	
ANOVA					
Source of Variation	***SS***	***df***	***MS***	***F***	***P-valu***
Between Groups	2.31539E+14	1	2.31539E+14	53.84	1.43 E-
Within Groups	2.23616E+14	52	4.3003E+12		
Total	4.55155E+14	53			

Table 51: Aggregated distribution of ED visits per 1 or No Injury vs More than 1 Injury in 2010

	MULTINJURY	
AGE GROUP	1 OR NO INJURY	> 1
0 - 14	4,569,964	215,3
15 - 29	6,323,474	443,8
30 - 44	5,412,554	326,2
45 - 59	4,910,391	294,8
60 - 74	3,019,296	166,9
75 - 89	2,309,056	159,3
>89	394,887	36,4
PAYER GROUP		
Medicare	5,643,037	315,6
Private	8,178,518	591,9
Medicaid	6988,,119	285,0
Self	4,661,192	301,6
GENDER GROUP		
Male	11,872,101	839,7
Female	15,066,826	803,0
REGION GROUP		
Northeast	4,924,357	279,5
Midwest	5,609,601	350,2
South	11,713,846	728,6
West	4,693,463	284,5
INCOME GROUP		
1 - 40999	8,725,667	465,9
41k - 50999	7,335,969	441,2
51k - 66999	5,802,177	371,9
67k >	4,469,928	325,5
LOCATION GROUP		
Large Central Metropolitan	7,504,267	405,2
Large Fringe Metropolitan	5,706,343	380,1
Medium Metropolitan	6,057,713	384,6
Small Metropolitan	2,588,452	153,9
Micropolitan	2,987,047	190,6
Not Metro or Micropolitan	1,928,651	116,7

Table 52: Results of analysis of variance (ANOVA) of 1 or No Injury vs More than 1 Injury ED visits

		Anova: Singl			
SUMMARY					
Groups	***Count***	***Sum***	***Average***	***Variance***	
1 OR NO INJURY	27	159396896	5903588.741	1.03304E+13	
> 1 INJURY	27	9659194	357747.9259	38748952478	
ANOVA					
Source of Variation	***SS***	***df***	***MS***	***F***	***P-value***
Between Groups	4.15211E+14	1	4.15211E+14	80.09	4.16E-
Within Groups	2.69598E+14	52	5.18458E+12		
Total	6.84809E+14	53			

4.5 Results of Logistic Regression Analysis

Finally, results of logistic regression analysis, explained previously in Section 3.4.6, will be presented in this section. First, we will provide the results of a simple logistic regression analysis that predicts the relationship between a patient's age and outcomes of emergency visits. Second, we will review the results of a multiple logistic regression that tests the relation between age, gender, income, method of payment, location of residence, and region and outcomes of ED visits. Using the data of Logistic Regression Results from SAS 9.3 in Table 53 and Table 54, we will analyze the simple and multiple logistic regression models to validate the results and determine if those models are suitable to the analyses being made. For the simple logistic model, the logit formula can be written as:

Predicted Logit of (EMERGENCY) = -3.8274 + (0.6155)*AGECAT (Equation 7)

Following, we will test the validity of this simple logistic model using the parameter estimates. Based on that model, the probability that a patient makes an ED visit for an emergency condition (i.e., EMERGENCY = 1) increases with the increase in age category, which means the higher the age category the more likely that the patient makes an emergency visit. For each increase in age category, the odds ratio of an emergency visit increase by 1.851 times ($e^{0.6155}$ = 1.851). By example, the odds ratio that an 80 year old patient makes an emergency visit are 7.404 times greater than those of a 20 year old patient. Thus, those previous findings confirm the statistical significance of the β coefficient for that model as it positively influences the relation between AGE and EMERGENCY. Additionally, in Table 53, the p values, associated with the likelihood ratio test, score test, and Wald test, are lower than 0.0001, which validates that the overall performance of model to be better than a null hypothesis model explained earlier. The statistical deliberation is that the addition of age as an independent variable makes the model better than an intercept-only model, in which the outcome of an ED visit would be predicted without age. The goodness-of-fit or fitness of the model is validated by AIC, SC, and -2 Log L as they positively adjust the log-likelihood of the model depending on the number of predictor. Finally, the value of the *c* (short for concordance statistic or c-statistic) shows that the predicted probabilities for the model are validated for this model. The value of 0.755 for *c* statistic means that 75.5% of all outcomes pairs are correctly predicted by the model. Also, the high value of 0.755 for *c* statistic suggests that the model does not predict the outcomes randomly but instead predicts a positive outcome 75.5% of the times. Additionally, the concordance statistic *c* is generally used to reveal the predictive value of a logistic regression model. Because the outcome of the logistic model being reviewed here is binary, the concordance statistic c is similar to the area under the receiver operating characteristic (ROC) curve. The ROC curve is a plot of true-positive rate or sensitivity versus false-positive rate or 1 − specificity. Consequently, the concordance statistic c of 0.755 can be used to plot a ROC curve shown in Figure 15. ROC curve analysis of this model confirms its predictive relevance in terms of true-positive rate (sensitivity) and false-positive rate (1 – specificity) for discriminating correctly at a percentage rate of 75.5.

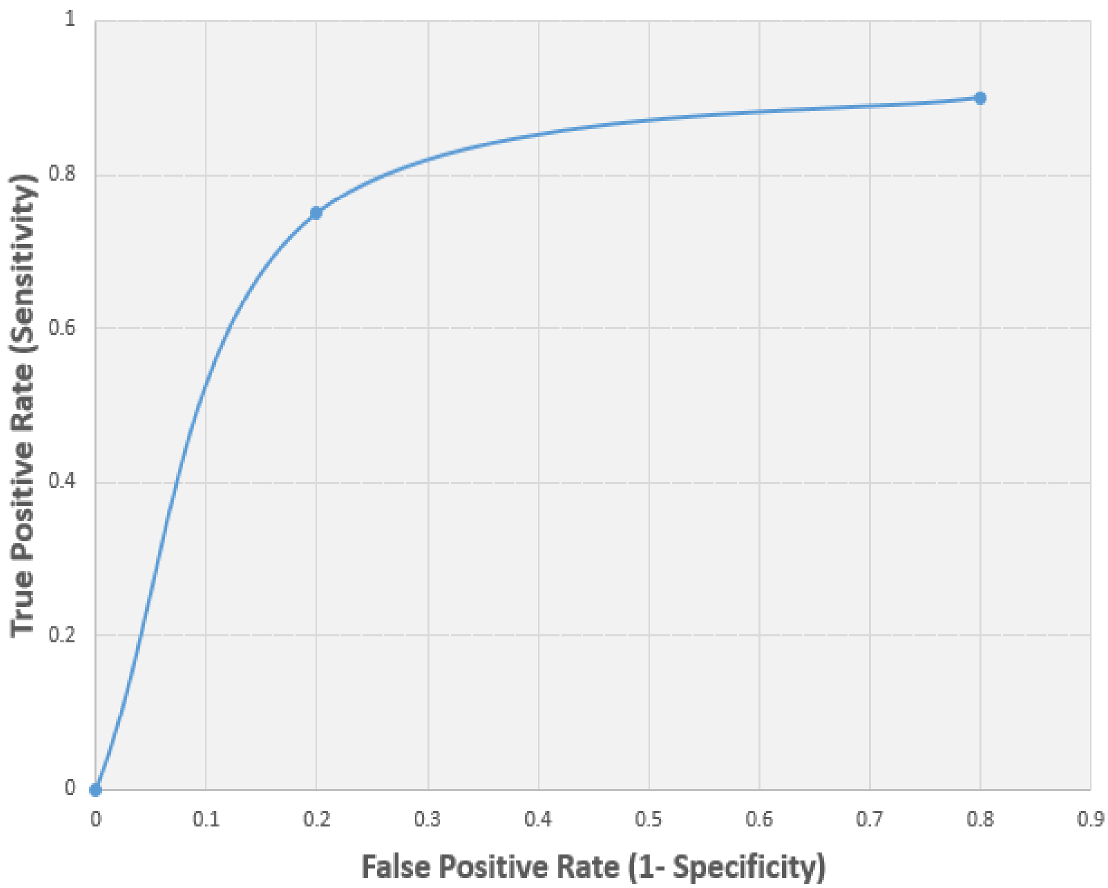

Figure 15: ROC curve for simple logistic regression model with an area under the curve of 0.755

Table 53: Results of Simple Logistic Regression analysis with AGE as independent variable

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	EMERGENCY

Model Information	
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	28584301
Number of Observations Used	28582517

Response Profile		
Ordered Value	**EMERGENCY**	**Total Frequency**
1	1	4848966
2	0	23733551

Probability modeled is EMERGENCY=1.

Note: 1784 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics		
Criterion	**Intercept Only**	**Intercept and Covariates**

AIC	26028819	22458681
SC	26028834	22458711
-2 Log L	26028817	22458677

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	3570139.82	1	<.0001
Score	3583671.45	1	<.0001
Wald	3037094.34	1	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.8274	0.00153	6251076.09	<.0001
AGECAT	1	0.6155	0.000353	3037094.34	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
AGECAT	1.851	1.849	1.852

Association of Predicted Probabilities and Observed Responses

Percent Concordant	68.9	**Somers' D**	0.510
Percent Discordant	17.9	**Gamma**	0.587
Percent Tied	13.2	**Tau-a**	0.144
Pairs	1.1508318E14	**c**	0.755

For the multiple logistic model, the logit formula can be written as:

Predicted Logit of (EMERGENCY) = -2.7501 + (-0.2163)*PAY1 + (-0.2616)*FEMALE + (0.0223)* ZIPINC_QRTL + (-0.0815)*PL_NCHS2006 + (0.5416)*AGECAT + (0.0109)*HOSP_REGION (Equation 8)

Because this is a multiple logistic model, we will test the validity of this multiple logistic model using the parameter estimates with the assumption that for unit of change from one categorical variable to another, the odds ratio that ED visits are made will equal the odds ratio of particular coefficients, considering all other variables are unchanged. In Table 54, the results of this multiple logistic model used to predict the likelihood of an emergency visit (i.e., EMERGENCY = 1) show that six different independent variables can alter such an outcome. PAY1, which stands for primary payer, is a negative predictor variable, which means that the higher the PAY1 category (with Medicare = 1, Medicaid = 2, Private Insurance including HMO = 3, and Self Pay = 4), the less likely that an emergency visit is made. By example, a patient with private health insurance is less likely to make an ED visit for an emergency condition than a patient with Medicaid by an odds ratio of 0.805. FEMALE, which stands for gender, is also a negative predictor variable. As expected, the model shows that the likelihood of an ED visit decreases with gender. Given that male = 0 and female 1, the model shows that the odds ratio of woman making an emergency visit is 0.77 time smaller than those of a man. ZIPINC_QRTL, which stands for income, is a positive predictor variable. The model shows that people in higher income categories are more likely to make emergency visits. By example, for each unit of categorical change of income the odds ratio increase by 1.023. PL_NCHS2006, which stands for patient's urban-rural location, is again a negative predictor variable in this model. Unexpectedly, the results of the model show that people in higher location categories are less likely to make emergency visits. In other words, patients who live in less urban areas are less likely to make ED visits by odds ratio of 0.922 times greater than those in more urban or metropolitan areas. Similarly as in the simple model, AGECAT positively impacts the outcome of ED visits. In this multiple model, it is shown that the older the patients the more likely they make ED visits by odds ratio of 1.719 times greater than the nearest age category. Finally, HOSP_REGION is a positive predictor variable. The model shows that patients in higher region categories are more likely to make ED visits. Otherwise stated, the odds ratio of patients in a higher region of making ED visits are 1.011 times than those of patients in the next lower region category. Consequently, those significant results from the interpretation of coefficients of this multiple logistic model validate the statistical tests of individual predictors. Next, the values of likelihood ratio, score, and Wald tests and related *p* with very small values < 0.0001 lead to conclusions that the multiple logistic model is more suitable than a null model, which validates the overall evaluation test of the model. Again, the goodness-of-fit or fitness of the model is validated by AIC, SC, and -2 Log L as they positively adjust the log-likelihood of the model depending on the number of predictors. Lastly, the value of the *c* statistic, which equals 0.769, shows that the predicted probabilities are validated for this multiple logistic model. Also, given that the *c* statistic equals to 0.769 compared to 0.755 for the simple model, the consideration can be made that this multiple model is slightly better at predicting positive outcomes of ED visits. While the simple model can correctly predicts up 75.5% of ED visits with a positive outcome, the multiple model can correctly predict 76.9% of those ED visits. Finally, results of logic regression analysis confirm our hypotheses that there are statistically significant predictive associations between certain patient's demographics and characteristics represented by independent variables of AGE, FEMALE, PL_NCHS2006, ZIPINC_QRTL, PAY1 and the outcome dependent variable EMERGENCY. For this model, the concordance statistic c of 0.769 can be used to plot a ROC curve shown in Figure 16. ROC curve analysis of this model also validates its discriminative ability for correctly predicting 76.9% outcomes of ED visits within the model.

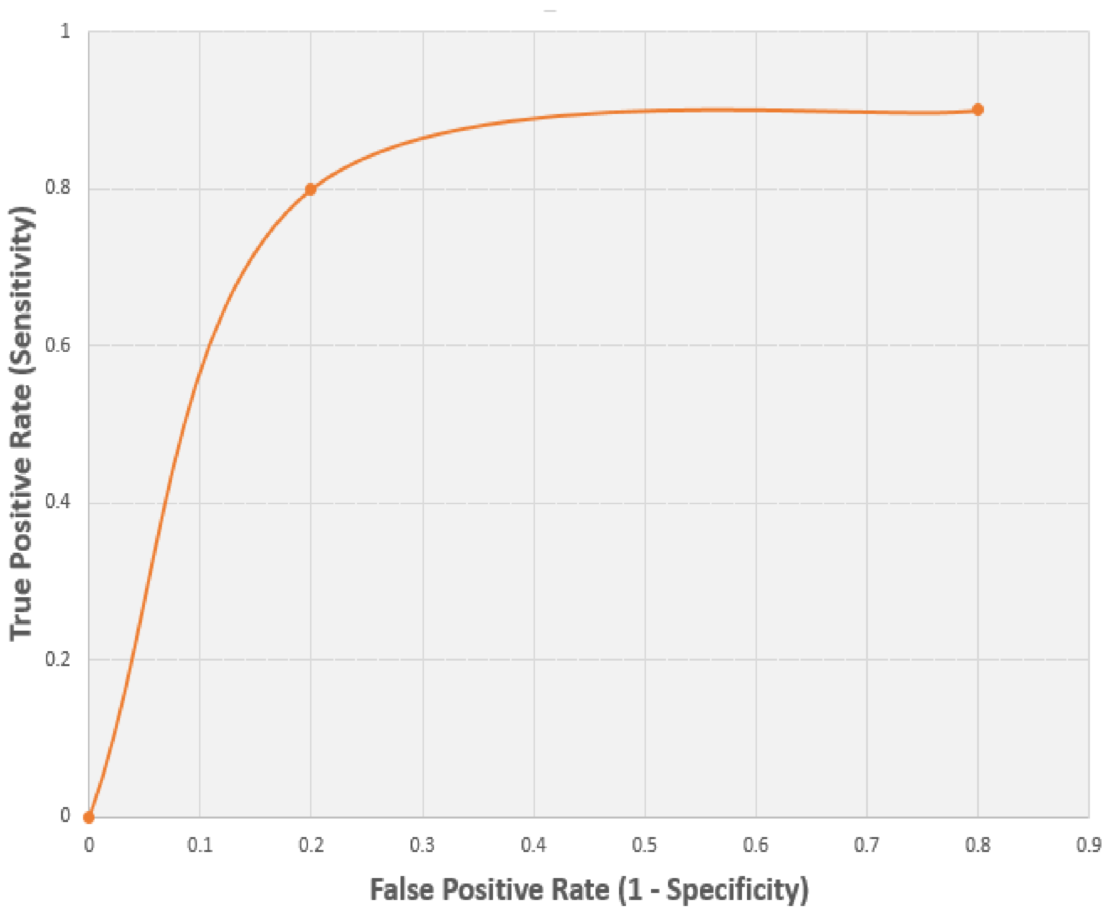

Figure 16: ROC curve for the multiple logistic regression model with an area under the curve of 0.769

Table 54: Results of Multiple Logistic Regression analysis with payer, gender, income, location of residence, age, and region as independent variables

Logistic Regression Results by PATIENTS' CHARACTERISTICS

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	EMERGENCY
Number of Response Levels	2

Model Information	
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	28584301
Number of Observations Used	27815613

Response Profile

Ordered Value	EMERGENCY	Total Frequency
1	1	4690028
2	0	23125585

Probability modeled is EMERGENCY=1.

Note: 768688 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	25238636	21425962
SC	25238652	21426068
-2 Log L	25238634	21425948

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	3812686.53	6	<.0001
Score	3958894.28	6	<.0001
Wald	3289309.98	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.7501	0.00335	673599.649	<.0001
PAY1	1	-0.2163	0.000507	181670.706	<.0001
FEMALE	1	-0.2616	0.00111	55555.3913	<.0001
ZIPINC_QRTL	1	0.0223	0.000522	1816.7518	<.0001
PL_NCHS2006	1	-0.0815	0.000373	47726.1957	<.0001
AGECAT	1	0.5416	0.000401	1821019.14	<.0001
HOSP_REGION	1	0.0109	0.000560	376.9954	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits

PAY1	0.805	0.805	0.806
FEMALE	0.770	0.768	0.772
ZIPINC_QRTL	1.023	1.021	1.024
PL_NCHS2006	0.922	0.921	0.922
AGECAT	1.719	1.717	1.720
HOSP_REGION	1.011	1.010	1.012

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	76.7	**Somers' D**	0.538
Percent Discordant	22.9	**Gamma**	0.541
Percent Tied	0.5	**Tau-a**	0.151
Pairs	1.0845964E14	**c**	0.769

Finally, a ROC curve analysis for the 2010 NEDS data set as a binary classifier, based on results of descriptive and statistical methods shown in Figure 17, again demonstrates a very relevant area under the curve with sensitivity (true-positive rate) of 0.85 and false-negative rate (1-specificity) of 0.33. This area under the curve can be generated using a case scenario in which ED visits can be described based on the four possible outcomes of (Table 55):

True Positive (TP): ED visits predicted to be caused by an emergency condition and for which the outcome is an emergency condition with admission.

False Positive (FP): ED visits predicted to be caused by an emergency condition and for which the outcome is a non-emergency condition without admission.

False Negative (FN): ED visits predicted to be caused by a non-emergency condition and for which the outcome is an emergency condition with admission.

True Negative (TN): ED visits predicted to be caused by a non-emergency condition and for which the outcome is a non-emergency condition without admission.

Table 55: Prediction of Results from ED visits of the 2010 NEDS

TP = 3,768,077	**FP = 15,564,191**
FN = 664,955	**TN = 8,096,786**

True-Positive Rate = Sensitivity = TP/(TP + FN) = 3768077/4433032 = 0.85

False-Positive Rate = 1 - Specificity = 1- FP/(FP + TN) = 1 - 15564191/23660977 = 0.34

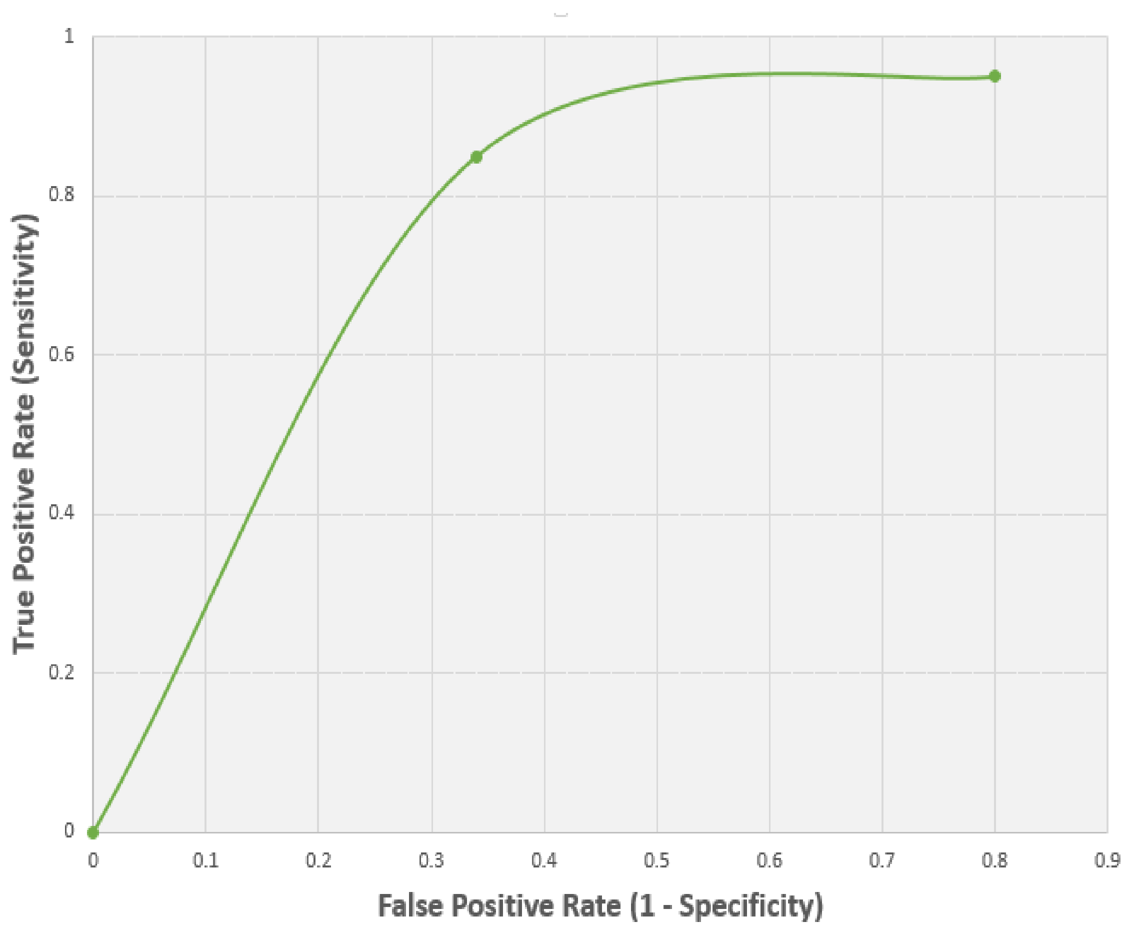

Figure 17: ROC curve for the 2010 NEDS data set with a sensitivity of 0.85 and 1-specificity of 0.34

In summary, results of those various statistical analyses of the 2010 NEDS data set lead to conclusions identical to our main hypotheses made earlier in this dissertation. Findings from descriptive statistical analysis suggest that, in the 2010 NEDS data set, around 83% of ED visits were routine, 77% lacked the presence of injury, 83% were for conditions that were not chronic, and 98.63% were for injuries of low severity. Moreover, results of ED CPT severity level analysis demonstrate that 54.02% of ED visits were classified as of non-emergency while only 45.98% were of emergency. Furthermore, results of the NYU ED classification algorithm analysis indicate that 65.78% of ED visits were for non-emergency events in 2010 compared to 34.22% were for emergency events, given that ED visits for conditions deemed unclassifiable or associated with injury, mental health, and substance abuse were excluded for the classification. Additionally, results of analysis of variance confirm the underlying hypothesis that ED visits for which patients were not admitted, conditions were not chronic, injury diagnosis was either not present, of low severity, and less than or equal to zero, are more likely to have been caused by non-emergency conditions. Finally, results of logistic regression analysis confirmed by ROC curves' analyses, whether simple or multiple, imply that predictor variables such as age, gender, income, payer, location of residence, and hospital region can predict the odds ratio that ED visits were made for an emergency condition. Results of our analyses were consistent with our hypotheses that: there are statistically significant numerical observations within the 2010 NEDS indicative of non-emergency medical use, there exist statistically effective diagnostic and procedural methods that can be used to differentiate non-emergency visits from emergency visits, emergency visits within the 2010 NEDS are statistically significantly different from non- emergency visits, and there are statistically significant relations between patient’s demographic characteristics and non-emergency visits.

CHAPTER V

DISCUSSIONS AND LIMITATIONS

So far, study results of the 2010 NEDS's analyses have revealed that non-emergency medical use is an enormous healthcare issue that derived from the misuse of emergency care services by patients whose conditions are neither emergent nor critically harmful. Consequently, the four hypotheses at the roots of our analyses provided consistent insights that have allowed us first to depict statistical observations indicative of non-emergency medical use, second to discover diagnostic and procedural characteristics of non-emergency visits, third to understand variations among non-emergency and emergency visits, and fourth to assess predictive associations between non-emergency visits and different types of patients. Clearly, over the last three decades, non-emergency medical use has grown at an alarming rate, which has also impacted the healthcare system in the United States in ways that will be discussed in this section of the dissertation. Earlier in this dissertation, we suggested that non-emergency medical use can have a negative impact on the delivery of emergency care services and the healthcare practice in general. Accordingly, our focus here will be to discuss how non-emergency medical use can impact patient outcomes of ED waiting time primarily, total ED charges secondarily, and inpatient mortality tertiarily.

5.1 Impact of Non-Emergency Medical Use on ED Waiting Time

Generally, ED waiting time is defined as the time interval from when a patient first arrives at the emergency room to when the patient is seen by a healthcare provider such as medical doctor, physician assistant, and advanced registered nurse practitioner. Undoubtedly, ED waiting time is accepted as a critical indicator of access to care through hospital's emergency rooms. ED waiting time is not to be confused with neither ED boarding time, the time it takes for admitted ED patients to receive inpatient beds, nor ED length of stay, the total time from a patient's arrival to the ED to the time from a patient's departure from the ED. Some hospitals have inaccurately refer to ED waiting time as the time from a patient's arrival until being assessed by a triage nurse, which can ultimately be erroneous given that it can sometimes take up to 30 additional minutes from triage until the first contact with a clinician. Over the last decade, an ongoing increase in ED waiting time nationwide has spawned both a concern and a mandate among private and public players to measure and report ED waiting time as an operational and benchmarking metric that gauges ED performance. As a response, hospitals have gone to great lengths to widely promote and broadcast up-to-date ED waiting times using billboards, radio and television ads, newspapers, magazines, and websites. In addition to be used as a tool for measuring ED performance, ED waiting time is an important patient outcome that can be critical to patient's health and the likelihood that a serious injury will result in a fatal event. As per the legal definition of EMTALA, an emergency medical condition requires immediate medical attention in order to prevent serious injuries, impairments, and even deaths. Thus, extended ED waiting times can be extremely harmful to ED patients in need of urgent medical attention. As explained in a 2013 report, "waiting at an ED due to overcrowding tends to generate a negative outcome for all patients...as has been the conclusion of these authors."[39] Also, findings from their cross-sectional study revealed that, "on average, waiting an extra hour at the ED increases the likelihood of a negative outcome by 1.9%."[39(5)] Moreover, similar suggestions were made that, "many negative aspects of over-using EDs, such as the incomplete assessment of patients' needs because examinations are rushed, staff burnout and patient dissatisfaction with the long waiting times, affect patient outcomes...as has been the conclusion of this author."[40] Although the 2010 NEDS data set does not include a data variable that represents ED waiting time, in this section of the dissertation we tend to discuss the relationship between non-emergency medical use and prolonged ED waiting time. Our study results from CPT ED severity level and NYU ED algorithm analyses have shown that around 54.02% to 65.78% of all ED visits are made for non- emergency conditions. Non-emergency medical use can play a significantly negative role in the increase of the primary patient outcome of ED waiting time. Like so, non-emergency medical use is commonly associated with lengthy ED waiting time by increasing the workloads of ED staff and putting additional strains on other resources. While hospital's EDs usually prioritize ED patients based on acuity, which allows the treatment of critically injured and trauma patient first, time and resources must still be invested in the triage and emergency medical screening of all people present at the ED as legally mandated by EMTALA. In general, most hospitals lack resources and enough employees to handle all patients who come to their EDs with urgent and emergency conditions. Nevertheless, hospitals struggle to medically screen patients with conditions deemed of non-emergency. Similarly, the Institute of

Medicine's (IOM) Committee on the Future of Emergency Care wrote, "when the ED is at full capacity, treating additional patients who could be cared for in a different environment means fewer resources—physicians, nurses, ancillary personnel, equipment, and time and space—available to respond to emergency cases…as has been the conclusion of this author."[41] If we compare the graphs of the number of non-emergency visits between 2000 and 2009 (Figure 18) to ED waiting times between 2000 and 2009 (Figure 19), they both show a somehow similar upward trend. Between 2000 and 2009, the number of non-emergency visits increased from 61.76 to 76.19 millions, an increase of 23%, whilst ED waiting times increased from 45 to 58.1 minutes, an increase of 29%. Factually, the difference in percentages of increase can be explained by the fact that other factors, independent of non-emergency medical use, such as hospital's characteristics and patient's flow processes can also influence ED waiting times. In *Health, United States, 2012*, a yearly report of the health status of America by Centers for Disease Control and Prevention's (CDC) National Center for Health Statistics (NCHS), the authors agreed and declared "Wait times can be influenced by a variety of factors, such as hospital location, available emergency department staff, and other resources, as well as the number and nature of the patients waiting to be seen…as has been the conclusion of these authors."[42]

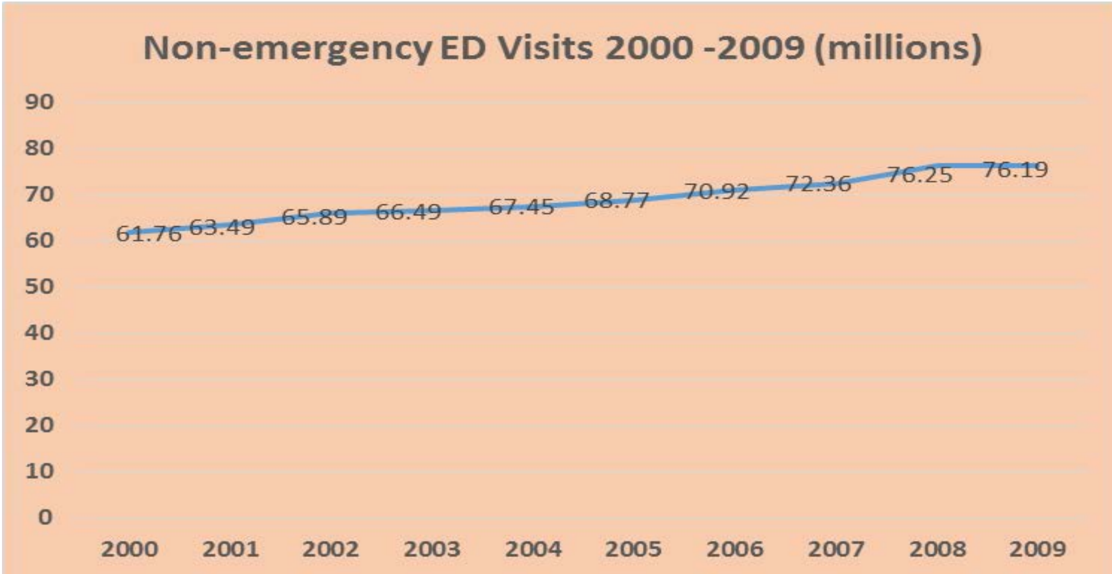

Figure 18: Non-emergency visits (2000 – 2009)

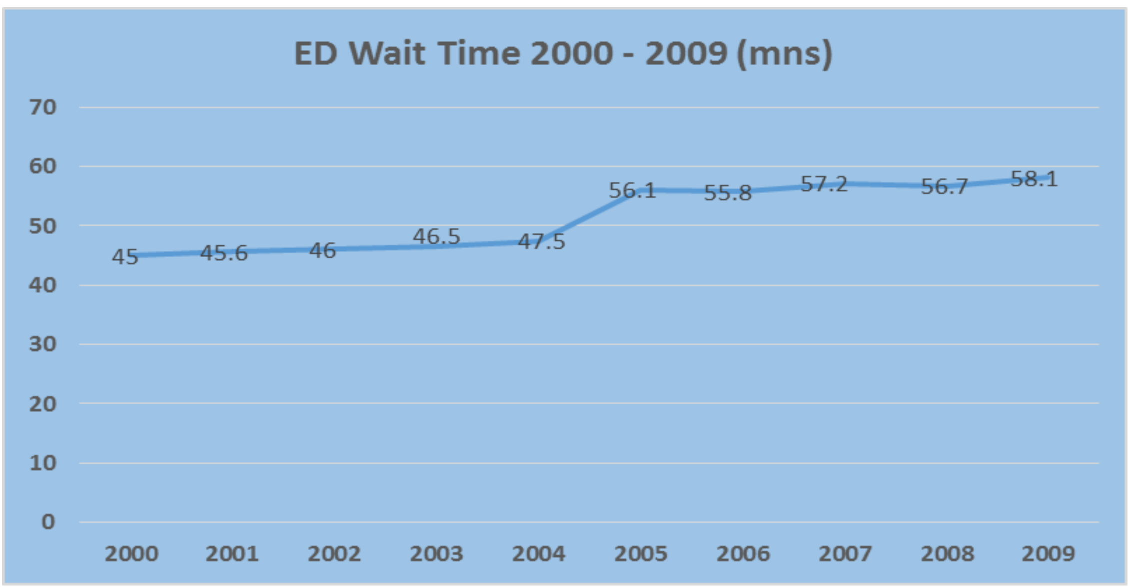

Figure 19: ED waiting times (2000 – 2009) (Source: National Center for Health Statistics)

Subsequently, various studies have investigated the various causes of increasing ED waiting times in emergency rooms across the nation and some of those studies have shown that ED waiting time can be negatively affected by overcrowding and boarding, which in turn can highly be associated with non-emergency medical use of emergency medical care services. It has been advanced in a 2008 related study that “the ED healthcare delivery model is problem- focused and episodic; it is not well suited to providing ongoing primary care. Non-urgent use of the ED can result in overcrowding...as has been the conclusion of this author.”[40(73)] Another such study by the Centers for Disease Control and Prevention's (CDC) National Center for Health Statistics (NCHS) in 2009 has indicated that the overall volume of ED visits can unfavorably affect ED waiting time. Additionally, a key finding from that study proclaimed, “mean wait time increased as the volume of annual ED visits increased; from 33.8 minutes in EDs with less than 20,000 annual visits, to 69.8 minutes in EDs with 50,000 or more annual visits…as has been the conclusion of this author.”[43] As follows, a finding from that same study revealed, “longer wait times were associated with EDs in urban areas (62.4 minutes), compared with nonurban areas (40.0 minutes)…as has been the conclusion of this author.”[43(5)] Thusly, another finding from that study indicated, “Mean wait times were longer in EDs that went on ambulance diversion or boarded admitted patients in hallways and in other spaces…as has been the conclusion of this author.”[43(6)] Moreover, it has been known that the causes, effects, and solutions to ED crowding can be linked to delays in treatments. Authors of a related 2008 study explained, “Patients who arrived at one ED during crowded periods waited 30 minutes longer for an ED bed. Crowding was associated with increased door-to-needle time for patients with suspected myocardial infarction…as has been the conclusion of these authors.”[44]

5.2 Impact of Non-Emergency Medical Use on ED Cost per Visit

In addition to negatively impact ED waiting time, non-emergency medical use frequently manifested through ED overcrowding has been known to be a factor in the surge of the secondary patient outcome of ED charges in recent years. Indeed, it is important to recall that EMTALA's mandate requires hospital's EDs to conduct an emergency medical screening on all ED patients regardless of their ability to pay for care services rendered. Because hospitals do not receive federal incentives to counterbalance for those financial losses, EMTALA's legal and regulatory requirement has been blamed for causing hospitals tremendous financial losses and forcing them to continuously raise ED charges to offset for uncompensated care. Unquestionably, some studies have designated non-emergency medical use and/or related inappropriate use of ED care as major causes of mounting ED charges. Accordingly, IOM Committee on the Future of Emergency Care declared, "But uncompensated care can be an extreme burden at hospitals that have large numbers of uninsured patients. Many hospital ED and trauma center closures are attributed to financial losses associated with emergency and trauma care…as has been the conclusion of this author."[41(34)] In the same light, in a report published in 2006 it was suggested, "primary care received in the ED is sometimes viewed as source of excess cost, since hospital charges include mark-ups to cover a variety of overhead expenses...as has been the conclusion of this author."[12(42)] Furthermore, a 2008 study detected the negative impact of non-emergency medical use on costs of ED care and decried, "that the marginal costs of care provided in an ED outpatient visit compared to other settings were higher than commonly believed; it concluded that directing non-urgent care to the ED instead of an outpatient clinic increases operational costs...as has been the conclusion of this author."[40(74)] In a study on ED crowding, the authors concurred, "emergency department (ED) overcrowding has become a significant problem throughout the United States, leading to possible increased health care costs…as has been the conclusion of these authors."[45] Also, a similar report published in 2012 acknowledged that patients can pay up higher ED charges because of ED overcrowding.[46] Understandably, numerous other factors such as lack of health insurance coverage, aging population, medication costs, severity of diseases among the general public, decline in population health due to cancer and obesity, and malpractice insurance for clinicians have also contributed to the escalation of ED charges. Thus, determining the average cost of an ED visit can be a very complex and challenging endeavor because ED cost utilization analysis is known to be a multifaceted process associated with factors not directly related to ED care. Despite our estimations that non-emergency medical use is highly responsible for the increase of ED charges, there is a significant disparity between the rate of increase of non-emergency medical use and average ED cost per visit between 2000 and 2010. Non-emergency medical use has only increased 27% between 2000 and 2010 (Figure 20), however, during the same period of time the average ED cost per visit has increased 77%. Again, in *Health, United States, 2012*, the authors conveyed that, "between 2000 and 2010, the mean expense for emergency department visits that did not result in a hospital admission visibly increased 77%, from $546 (in 2010 dollars) to $969…as has been the conclusion of these authors."[42(51)] (Figure 21)

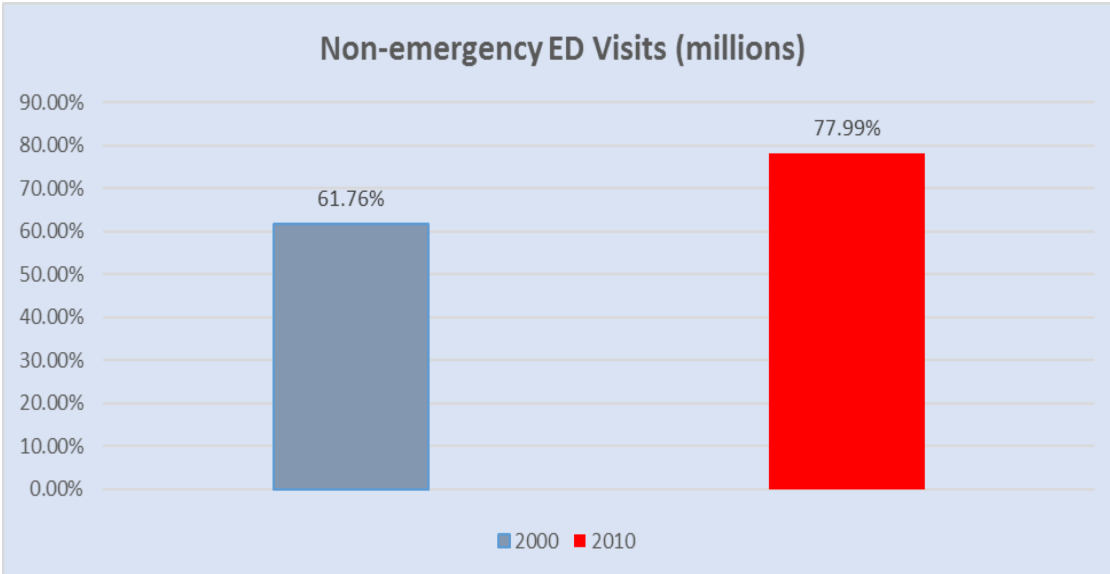

Figure 20: Non-emergency visits (2000 – 2009)

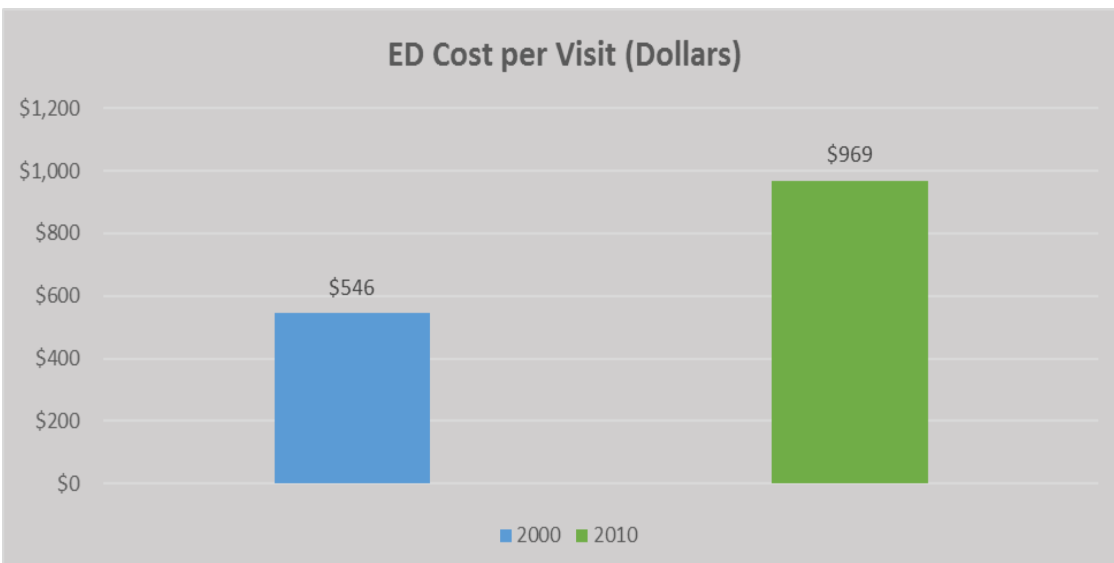

Figure 21: ED Cost per Visit (2000 – 2010)

Hence, they also stated, "Estimates of emergency department visit expenses presented here include both hospital facility and physician charges and are limited to visits that did not result in a hospital admission…as has been the conclusion of these authors."[42(51)] This phenomenon has been regarded as a crisis by most experts and led others to insinuate that the average ED cost per visit is greater than the average month's rent in America. Recent estimations have shown that both non-emergency visits and ED charges are continuing to increase at an alarming pace. Some unconfirmed data claimed that around 82 million non-emergency visits took place in 2013, an increase of 8% from 2009 (Figure 22). Some researchers have shown that the average ED cost per visit was $1,233 in 2013, an increase of 30% from 2009 (Figure 23). So far, various initiatives aimed at reducing the cost of ED charges have not been successful because appropriate measures were not concurrently taken to lessen the impact of non- emergency medical use.

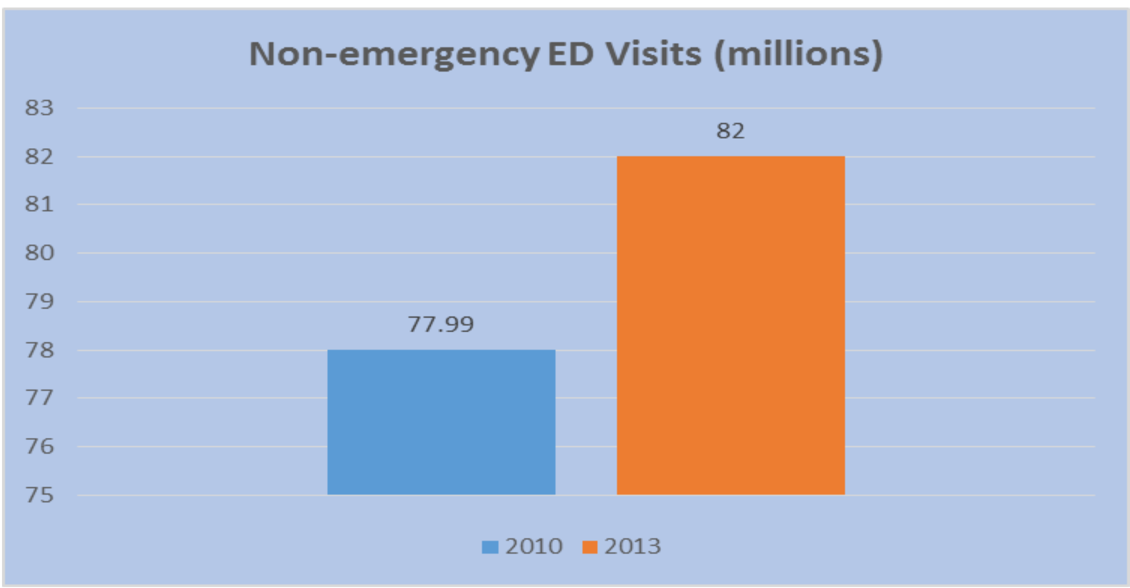

Figure 22: Non-emergency visits (2010 – 2013)

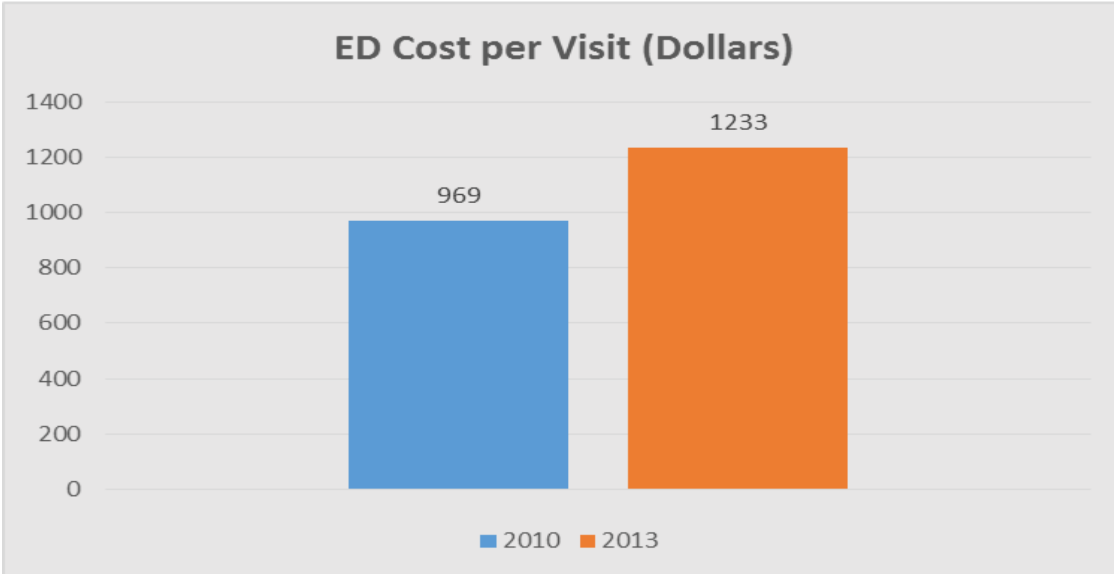

Figure 23: ED Cost per Visit (2010 – 2013)

5.3 Impact of Non-Emergency Medical Use on Inpatient Mortality

Lastly, non-emergency medical use, confirmed as a dire consequence of ED overcrowding through the results of this dissertation, has been shown to be connected to the tertiary patient outcome of inpatient mortality. Granting the 2010 NEDS data set does not contain a data element for inpatient mortality, our interpretations and findings from various studies will suffice to demonstrate how non-emergency medical use can impact mortality of patients following their admission as inpatients. Within the healthcare spectrum, increases in inpatient mortality has generally been linked to common diseases and health risks of cancer, congestive heart failure, epidemic outbreaks, medication errors, medical negligence, obesity, diabetes, smoking, excessive alcohol drinking, substance abuse, and other injuries that derived from cuts, drownings, falls, fires, firearms, machineries, motor vehicles, natural disasters, poisons, struck, and suffocations. Mostly, general assumptions only consider simplistic factors, those easily understood and identified, as causes of inpatient mortality. Nevertheless, recent studies have found consequential relations between ED overcrowding and the increase of inpatient mortality. Thereby, a 2012 study of 995,379 ED across 187 hospitals, found that ED overcrowding can increase inpatient mortality by odds of 5%.[46] Subsequently, the authors wrote "patients who were admitted on days with high ED crowding experienced 5% greater odds of inpatient death...as has been the conclusion of these authors."[46(4)] In that same observational study, it was shown that odds of inpatient mortality can go as high as 9% when models were adjusted to simulate ED overcrowding over a period of 3 days.[46(4)] Moreover, a 2011 literature review study of 276 articles examining the impact of ED overcrowding on inpatient mortality, stated, "eight studies examined the association between ED crowding and mortality. Although ED crowding was measured differently in each study, the majority of these studies found that correlations exist between ED crowding and increased mortality...as has been the conclusion of these authors."[47] In the same perspective, a 2013 study found a positive relationship between ED crowding and inpatient mortality and admitted, "Notably, studies found that ED crowding is associated with higher rates of inpatient mortality among those admitted to the hospital from the ED and discharged from the ED to home...as has been the conclusion of these authors."[48] Lastly, in a report on the solutions to ED crowding, the American College of Emergency Physicians (ACEP) provided a critical insight describing the association between ED crowding and inpatient mortality. The 2008 ACEP report suggested:

> The emergency medicine community has long been aware of the dangers of crowding and delays in care. Several recent studies, looking at large

> databases that compare mortality rates in patients seeking emergency care during times of crowding versus times of no crowding, conclude that the rate of death is higher during times of crowding. This effect (hazard ratio for death of approximately 1.3) offers a target larger than those of other initiatives given great importance, such as the administration of antibiotics for pneumonia patients within 4 hours, which now is a performance measure by which hospitals are paid. Compliance with this initiative is estimated to reduce the number per 100 who would have died to 93. Crowding studies estimate that deaths would be reduced from 100 to between 75 and 83. These are substantial numbers and apply to a very large population. As such, crowding appears to be a far more important issue to resolve.[49]

As shown earlier, there is increasing evidence confirmed by the results of this dissertation and findings from various other studies to assert the negative impact of non-emergency medical use on primary outcome of ED waiting time, secondary outcome of ED cost per visit, and tertiary outcome of inpatient mortality. In this discussion section, we have explored the associations between non-emergency medical use, often observed through ED crowding, and adverse patient outcomes to demonstrate the significance of the results of this dissertation.

First, our study results on the evidence of highly increasing number of non-emergency visits will be useful in reducing non-emergency medical use through critical modifications and revisions of EMTALA combined with new initiatives. Second, our study results on the procedural and diagnostic differences among ED visits will permit to design new triage systems that can effectively identify and deter non-emergency visits. Third, our study results on the predictive relations between patient's demographic characteristics and non-emergency visits can be used to craft highly effective ED management programs that take in consideration patient's demographics and related ED visit's characteristics. Fourth, our study results on the impact of non-emergency medical use of on adverse patient outcomes of ED waiting time, ED cost per visit, and inpatient mortality can encourage policymakers, private and public healthcare organizations to take critical measures that address and lessen the growing crisis of non- emergency medical use in the United States.

5.4 Study Limitations

While this study generated important results, there are some limitations that need to be highlighted and discussed. In all, this study contains three main limitations. First, this study only uses the NEDS data set as data source. The use of multiple data sets as data sources would have provided a more valid insight to our analyses and help strengthen our findings and assumptions. Second, this study only uses ED visits records for the calendar year 2010. Results generated from analyses of a multi-year data set can infuse a deeper perspective in terms of reliability. Third, some statistical analyses were based on the categorization of routine ED visits as non-emergency and admission ED visits as emergency. In one hand, although routine ED visits are more likely to be made for non-emergency conditions, it is not absolutely evident that all routine ED visits lead to non-emergency medical use. There are instances when routine ED visits, for which patients are not admitted to the hospitals, are derived from emergency events. In the other hand, even though there is a higher likelihood that routine ED visits are made for a non-emergency medical use, there can be some rare circumstances when patients are admitted to hospitals for events that are deemed of non-emergency.

CHAPTER VI

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This final chapter of the dissertation will contain a complete summary of the previous sections including the goals of this study and how those goals were attained. Additionally, viable recommendations will made that can be useful as to finding durable solutions to the non- emergency medical use crisis. Lastly, a section will consist of various undertakings, if correctly performed through future work, can quell the limitations of this dissertation discussed earlier.

6.1 Summary and Conclusions

In conclusion, using the 2010 NEDS data set, this dissertation is intended to thoroughly investigate non-emergency medical use and its impact on the healthcare sector, and make solid recommendations for possible solutions. In order to accomplish such purpose, we devised four main hypotheses that were later analyzed using five statistical research methods. Our first hypothesis examined whether numerical observations within the 2010 NEDS data set were statistically significant to indicate non-emergency medical use. Using descriptive statistical analysis as a method, we were able to positively prove this hypothesis by finding that 82.78% of all ED visits were routine whilst 16.91% resulted in admission, 76.72% of all ED visits were not injury related whilst 23.28% had an injury diagnosis, 83.06% of all ED visits were for non- chronic conditions whilst 16.91% were for chronic conditions, and 98.63% of ED visits were for non-critical injuries whilst 1.04% was for critical injuries. Our second hypothesis tested whether diagnostic and procedural methods were statistically effective to help differentiate non- emergency visits from emergency visits. To achieve our goals, we used the NYU ED Algorithm, a statistical algorithm, designed to analyze ICD-9 diagnostic codes within data sets and the ED CPT Severity analysis, a procedural-based method, developed to analyze the severity of ED visits. Consequently, our findings showed that the utilization of those two methods provided satisfactory results that were statistically relevant to distinguish non-emergency visits from emergency visits. Using diagnostic and procedural codes, the results of analysis methods of NYU ED Algorithm and ED CPT Severity revealed that between 54.02 to 65.78% of ED visits were caused by non-emergency events whilst between 34.22 to 45.95% of those visits derived from emergency events. Moreover, our third hypothesis investigated whether emergency visits within the 2010 NEDS were statistically significantly different from non-emergency visits. Accordingly, ANOVA was performed to explore differences between emergency visits and non- emergency visits. The results of analysis of variance validated our third hypothesis by unveiling statistically significantly differences in the means of ED visits made for non-emergency events and those made for emergency events. At last, our fourth hypothesis probed for predictive relationships between patient's demographic characteristics and emergency visits through the utilization of logistic regression analysis. Thereupon, findings from logistic regression analysis suggested that there were statistically significant predictive associations between certain patient's demographics and characteristics such as age, gender, income, location of residence, and method of payment and the outcomes of

ED visits in 76.9% of occasions. The performance and fitness of the logistic regression models were validated by the ROC curve and goodness-of-fit test, both of which confirmed that our logistic regression models were a good fit for the 2010 NEDS data set and that predictive associations were not randomly generated.

6.2 Recommendations

As established earlier, the purpose of this dissertation is to study non-emergency medical use and its impact on healthcare and find viable solutions. As such, we have suggested and demonstrated that many factors tend to influence non-emergency medical use, which in turn can negatively affect patient outcomes. In this section, we will make some critical recommendations that can be regarded as potential solutions and deterrents to non-emergency medical use.

First, public and private healthcare organizations need to promote new patient education initiatives on emergency medical conditions and the danger of abusing emergency medical services. It is critical that the general population and especially all frequent users of ED services are continuously educated on the difference between emergency and non-emergency events and negative consequences of non-emergency medical use.

Second, insurance reimbursement claims must be either reduced or totally discarded for ED visits in which the patient's conditions were determined not be urgent, emergent, and acute. Given that a patient makes an ED visit for a condition such as Open Wound of Fingers without Complication, the insurance reimbursement claim for such visit must be denied on the basis that such condition is neither urgent nor life-threating and that the condition could have easily been treated at an urgent care center setting.

Third, modifications must be made to EMTALA's mandate that will preliminarily except certain ICD-9 diagnostics as emergency medical conditions (Table 55 and Table 56) and allow hospitals to redirect patients with related conditions to urgent care centers and/or primary care facilities. The data in Table 56 and Table 57 graphed in Figure 24 and Figure 25 show ICD-9 diagnostic codes for the 20 most common non-emergent conditions and emergent primary care treatable as per the NYU ED Algorithm software tool. Indeed, the data show those 20 most common non-emergent conditions and emergent primary care treatable accounted for 8,154.655.00 million of ED visits, a percentage of 28.53% within the 2010 NEDS data set. Measures to refrain patients from making ED visits for some of those conditions will significantly reduce non-emergency medical use, help private and public hospitals save billions of dollars annually, and play a positive role in improving related patient's outcomes.

Fourth, enact and develop highly effective ED disease management programs. Disease management programs focused especially on those conditions commonly and frequently for non- emergency visits will allow hospitals to efficiently utilize care resources, improve workflow processes, and ultimately contain non-emergency medical use.

Fifth, provide financial incentives to patients who use urgent care centers or primary care physicians for non-emergency care services. In order to help hospitals lessen non-emergency medical use, state and federal health authorities need to allocate funds to be used by hospitals as special vouchers for patients willing to bypass hospital's EDs and seek care services from urgent care centers or other primary care facilities for conditions deemed non-emergent. Such initiatives would alleviate financial losses for hospitals, which has been shown by various studies to be associated with ED closing.

Sixth, expand and enhance access to primary care nationwide. Earlier in this dissertation, we blamed the lack of access to primary care as one of the causes of non-emergency medical use. A greater movement by private and public health agencies to significantly boost access to primary care services will create more options within the healthcare spectrum and discourage patients from making non-emergency visits for conditions that can be treated at primary care institutions.

Table 56: List of the 20 most common diagnoses used for non-emergent conditions

ICD-9	Code Description	Frequency
7248	OTHER SYMPTOMS REFERABLE TO BACK	376,889
462	ACUTE PHARYNGITIS	359,979
5990	URINARY TRACT INFECTION SITE NOT SPECIFIED	268,957
7870	NAUSEA WITH VOMITING	240,900
6918	OTHER ATOPIC DERMATITIS AND RELATED CONDITIONS	180,068
71946	PAIN IN JOINT INVOLVING LOWER LEG	175,352
64893	OTHER CURRENT CONDITIONS CLASSIFIABLE ELSEWHERE OF MOTHER ANTEPARTUM	172,499
5259	UNSPECIFIED DISORDER OF THE TEETH AND SUPPORTING	165,204
7295	PAIN IN LIMB	153,716
7804	DIZZINESS AND GIDDINESS	144,097
3829	UNSPECIFIED OTITIS MEDIA	141,084
5589	OTHER AND UNSPECIFIED NONINFECTIOUS GASTROENTERITIS	131,463
4019	UNSPECIFIED ESSENTIAL HYPERTENSION	109,601
7235	TORTICOLLIS UNSPECIFIED	103,272
4619	ACUTE SINUSITIS UNSPECIFIED	88,534
75	OTHER OBSTETRIC OPERATIONS	87,477
779	CONVULSIONS IN NEWBORN	79,780
38110	CHRONIC SEROUS OTITIS MEDIA SIMPLE OR UNSPECIFIED	77,292
4739	UNSPECIFIED SINUSITIS (CHRONIC)	71,241
6259	UNSPECIFIED SYMPTOM ASSOCIATED WITH FEMALE GENITAL	65,094
	TOTAL	**3,192,499**

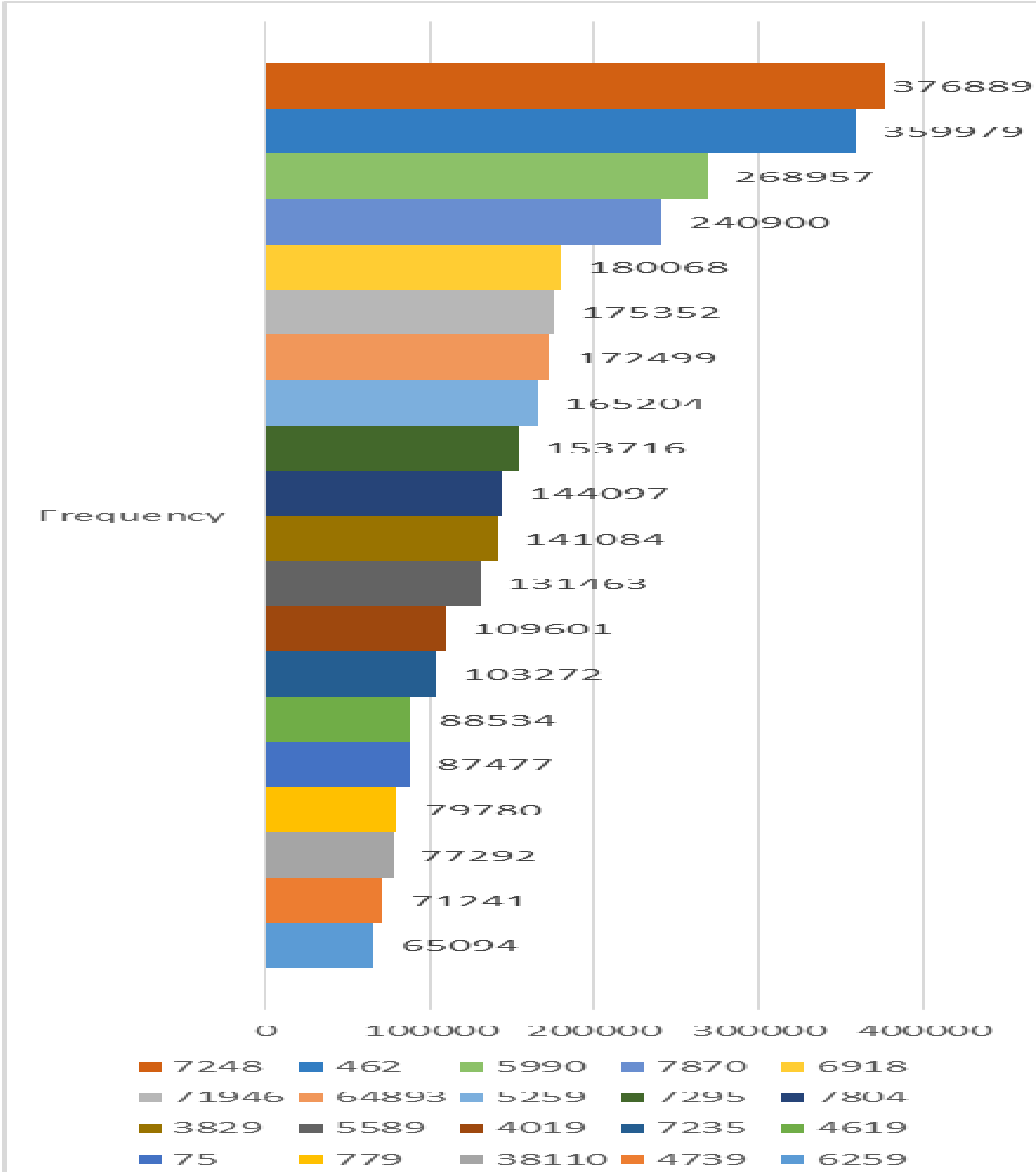

Figure 24: The 20 Most common diagnoses used for non-emergent conditions

Table 57: List of the 20 most common diagnoses used for emergent primary care treatable conditions

ICD-9	Code Description	Frequency
4660	ACUTE BRONCHITIS	809,156
7890	ABDOMINAL PAIN	802,205
682	OTHER CELLULITIS AND ABSCESS	435,594
78659	OTHER CHEST PAIN	285,872
95901	OTHER AND UNSPECIFIED INJURY TO HEAD	226,505
3829	UNSPECIFIED OTITIS MEDIA	224,454
8472	LUMBAR SPRAIN	223,081
84500	UNSPECIFIED SITE OF ANKLE SPRAIN	208,098
5990	URINARY TRACT INFECTION SITE NOT SPECIFIED	173,050
49121	OBSTRUCTIVE CHRONIC BRONCHITIS WITH (ACUTE) EXACERBATION	163,518
462	ACUTE PHARYNGITIS	155,485
8470	NECK SPRAIN	155,248
78650	UNSPECIFIED CHEST PAIN	153,498
92400	CONTUSION OF THIGH	153,246
92300	CONTUSION OFSHOULDER REGION	149,771
920	CONTUSION OF FACE SCALP AND NECK EXCEPT EYE(S)	145,357
3000	ANXIETY STATE UNSPECIFIED	138,020
8830	OPEN WOUND OF FINGERS WITHOUT COMPLICATION	131,158
78652	PAINFUL RESPIRATION	122,428
5589	OTHER AND UNSPECIFIED NONINFECTIOUS GASTROENTERITIS AND	106,401
	TOTAL	**4,962,14**

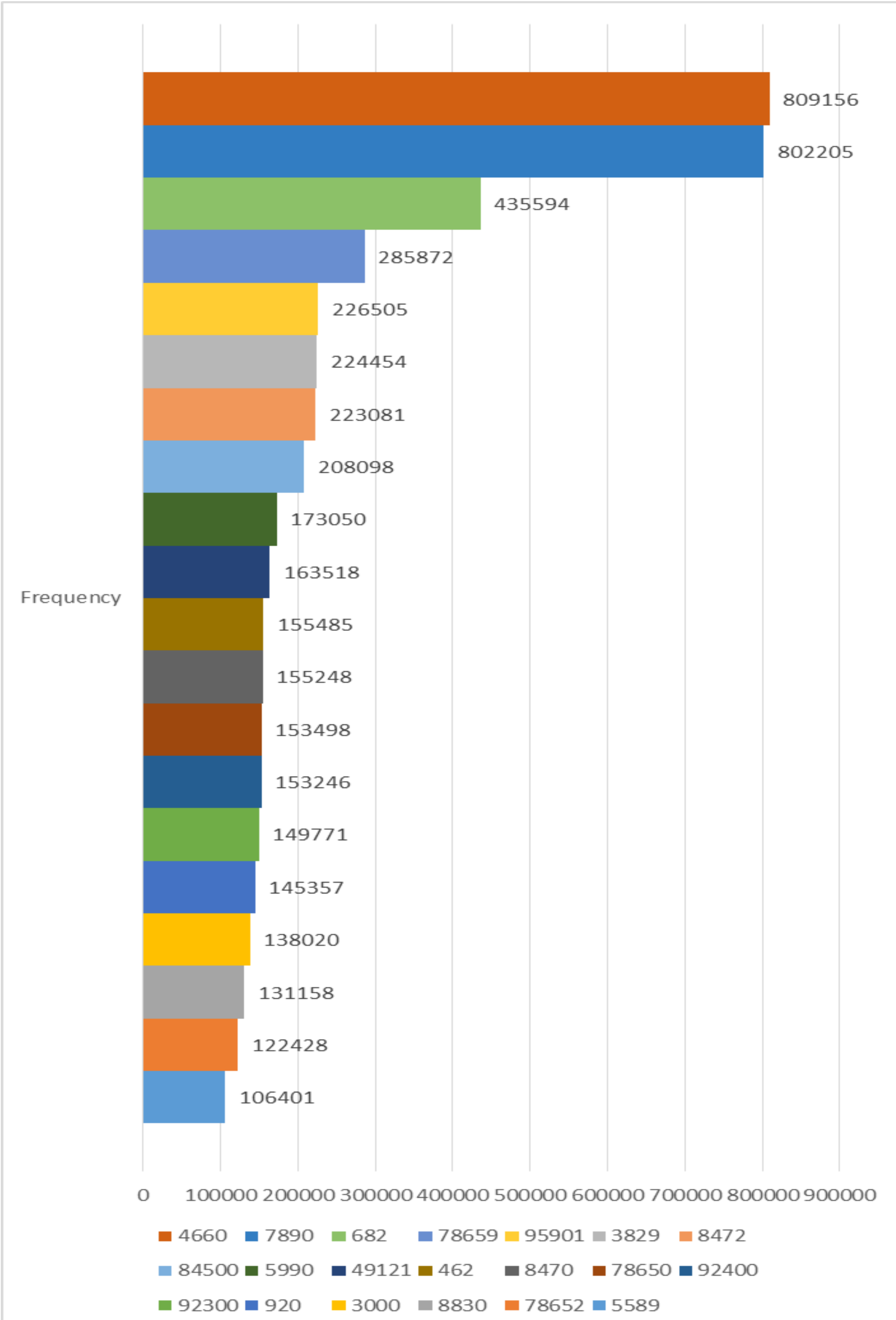

Figure 25: The 20 most common diagnoses used for emergent primary care treatable conditions

6.3 Future Work

Earlier in Section 5.4, we reviewed and discussed three main limitations of this dissertation. Hence, there are multiple propositions to be undertaken through future studies in order to overcome those limitations and improve this dissertation. First, we suggest that further analyses of NEDS data sets for calendar years prior to and after 2010 will be conducted and results of those analyses to be compared with those of this dissertation for consistency and relevancy. Second, more advanced descriptive and inferential analyses of the 2010 NEDS must be performed to uncover new patterns and numerical observations and investigate more complex predictive associations among data variables within the 2010 NEDS. Third, standardized criteria must be used in the definition, identification, classification, and assessment of non-emergency visits, which will allow researchers, hospitals, and health authorities to better investigate and assess non-emergency medical use in the future.

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APPENDICES

APPENDIX A – HCUP Data Use Agreement

H·CUP
HEALTHCARE COST AND UTILIZATION PROJECT

DATA USE AGREEMENT for the Nationwide Databases from the Healthcare Cost and Utilization Project Agency for Healthcare Research and Quality

This Data Use Agreement ("Agreement") governs the disclosure and use of data in the HCUP Nationwide Databases from the Healthcare Cost and Utilization Project (HCUP) which are maintained by the Center for Delivery, Organization, and Markets (CDOM) within the Agency for Healthcare Research and Quality (AHRQ). The HCUP Nationwide databases include the Nationwide Inpatient Sample (NIS), Nationwide Emergency Department Sample (NEDS), and Kids' Inpatient Database (KID). Any person ("the data recipient") seeking permission from AHRQ to access HCUP Nationwide Databases data must sign and submit this Agreement to AHRQ or its agent, and complete the online Data Use Agreement Training Course at http://www.hcup-us.ahrq.gov, as a precondition to the granting of such permission.

Section 944(c) of the Public Health Service Act (42 U.S.C. 299c-3(c)) ("the AHRQ Confidentiality Statute"), requires that data collected by AHRQ that identify individuals or establishments be used only for the purpose for which they were supplied. Pursuant to this Agreement, data released to AHRQ for the HCUP Databases are subject to the data standards and protections established by the Health Insurance Portability and Accountability Act of 1996 (HIPAA) (P.L. 104-191) and implementing regulations ("the Privacy Rule"). Accordingly, HCUP Databases data may only be released in "limited data set" form, as that term is defined by the Privacy Rule, 45 C.F.R. § 164.514(e). HCUP data may only be used by the data recipient for research which may include analysis and aggregate statistical reporting. AHRQ classifies HCUP data as protected health information under the HIPAA Privacy Rule, 45 C.F.R. § 160.103. By executing this Agreement, the data recipient understands and affirms that HCUP data may only be used for the prescribed purposes, and consistent with the following standards:

No Identification of Persons–The AHRQ Confidentiality Statute prohibits the use of HCUP data to identify any person (including but not limited to patients, physicians, and other health care providers). The use of HCUP Databases data to identify any person constitutes a violation of this Agreement and may constitute a violation of the AHRQ Confidentiality Statute and the HIPAA Privacy Rule. This Agreement prohibits data recipients from releasing, disclosing, publishing, or presenting any individually identifying information obtained under its terms. AHRQ omits from the data set all direct identifiers that are required to be excluded from limited data sets as consistent with the HIPAA Privacy Rule. AHRQ and the data recipient(s) acknowledge that it may be possible for a data recipient, through deliberate technical analysis of the data sets and with outside information, to attempt to ascertain the identity of particular persons. Risk of individual identification of persons is increased when observations (i.e., individual discharge records) in any given cell of tabulated data is less than or equal to 10. This Agreement expressly prohibits any attempt to identify individuals, and information that could be used to identify individuals directly or indirectly shall not be disclosed, released, or published. Data recipients shall not attempt to contact individuals for any purpose whatsoever, including verifying information supplied in the data set. Any questions about the data must be referred exclusively to AHRQ. By executing this Agreement, the data recipient understands and agrees that actual and considerable harm will ensue if he or she attempts to identify individuals. The data recipient also understands and agrees that actual and considerable harm will ensue if he or she intentionally or negligently discloses, releases, or publishes information that identifies individuals or can be used to identify individuals.

Use of Establishment Identifiers–The AHRQ Confidentiality Statute prohibits the use of HCUP data to identify establishments unless the individual establishment has consented. Permission is obtained from the HCUP data sources (i.e., state data organizations, hospital associations, and data consortia) to use the identification of hospital establishments (when such identification appears in the data sets) for research, analysis, and aggregate statistical reporting. This may include linking institutional information from outside data

sets for these purposes. Such purpose does *not* include the use of information in the data sets concerning individual establishments for commercial or competitive purposes involving those individual establishments, or to determine the rights, benefits, or privileges of establishments. Data recipients are prohibited from identifying establishments directly or by inference in disseminated material. In addition, users of the data are prohibited from contacting establishments for the purpose of verifying information supplied in the data set. Any questions about the data must be referred exclusively to AHRQ. Misuse of identifiable HCUP data about hospitals or any other establishment constitutes a violation of this Agreement and may constitute a violation of the AHRQ Confidentiality Statute.

The undersigned data recipients provide the following affirmations concerning HCUP data:

Protection of Individuals

- I will not release or disclose, and will take all necessary and reasonable precautions to prohibit others from releasing or disclosing, any information that directly or indirectly identifies persons. I acknowledge that the release or disclosure of information where the number of observations (i.e., individual discharge records) in any given cell of tabulated data is less than or equal to 10 can increase the risk for identification of persons. I will consider this risk and avoid publication of cell sizes less than or equal to 10.

- I will not attempt to link, and will prohibit others from attempting to link, the discharge records of persons in the data set with individually identifiable records from any other source.

- I will not attempt to use and will take all necessary and reasonable precautions to prohibit others from using the data set to contact any persons in the data for any purpose.

Protection of Establishments

- I will not publish or report, through any medium, data that could identify individual establishments directly or by inference.

- When the identities of establishments are not provided in the data sets, I will not attempt to use and will take all necessary and reasonable precautions to prohibit others from using the data set to learn the identity of any establishment.

- I will not contact and will take all necessary and reasonable precautions to prohibit others from contacting establishments identified in the data set to question, verify, or discuss data in the HCUP databases.

- I acknowledge that the HCUP NIS and KID may contain data elements from proprietary restricted computer software (3M APR-DRGs, OptumInsight APS-DRGs, and Medstat Disease Staging) supplied by private vendors to AHRQ for the sole purpose of supporting research and analysis with the HCUP NIS and KID. While I may freely use these data elements in my research work using the HCUP NIS and KID, I agree that I will not use and will prohibit others from using these proprietary data elements for any commercial purpose. In addition, I will enter into a separate agreement with the appropriate organization or firm for the right to use such proprietary data elements for commercial purposes. In particular, I agree not to disassemble, decompile, or otherwise reverse-engineer the proprietary software, and I will prohibit others from doing so.

Limitations on the Disclosure of Data and Safeguards

- I, the undersigned data recipient, acknowledge and affirm that I am personally responsible for compliance with the terms of this Agreement, to the exclusion of any other party, regardless of such party's role in sponsoring or funding the research that is the subject of this Agreement.

- I will not release or disclose, and will prohibit others from releasing or disclosing, the data set or any part to any person who is not an employee, member, or contractor of the organization (specified below), except with the express written approval of AHRQ. I acknowledge that when releasing or disclosing the data set or any part to others in my organization, I retain full responsibility for the privacy and security of the data and will prohibit others from further release or disclosure of the data.

- I will require others employed in my organization who will use or will have access to HCUP data to become authorized users of the data set by signing a copy of this data use agreement and completing the online Data Use Agreement Training Course at http://www.hcup-us.ahrq.gov. Before granting any individual access to the data set, I will submit the signed data use agreements to the address at the end of this Agreement.

- I will ensure that the data are kept in a secured environment and that only authorized users will have access to the data.

- I will not use or disclose and I will prohibit others from using or disclosing the data set, or any part thereof, except for research, analysis, and aggregate statistical reporting, and only as permitted by this Agreement.

- I acknowledge and affirm that interpretations, conclusions, and/or opinions that I reach as a result of my analyses of the data sets are my interpretations, conclusions, and/or opinions, and do not constitute the findings, policies, or recommendations of the U.S. Government, the U.S. Department of Health and Human Services, or AHRQ.

- I will indemnify, defend, and hold harmless AHRQ and the data organizations that provide data to AHRQ for HCUP from any or all claims and losses accruing to any person, organizations, or other legal entity as a result of violation of this agreement. This provision applies only to the extent permitted by Federal and State law.

- I agree to acknowledge in all reports based on these data that the source of the data is the "Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality." Substitute Nationwide Emergency Department Sample (NEDS) or Kids' Inpatient Database (KID), as appropriate.

- I agree to report the violation or apparent violation of any term of this Agreement to AHRQ without unreasonable delay and in no case later than 30 calendar days of becoming aware of the violation or apparent violation.

Terms, Breach, and Compliance

Any violation of the terms of this Agreement shall be grounds for immediate termination of this Agreement. AHRQ shall determine whether a data recipient has violated any term of the Agreement. AHRQ shall determine what actions, if any, are necessary to remedy a violation of this Agreement, and the data recipient(s) shall comply with pertinent instructions from AHRQ. Actions taken by AHRQ may include but not be limited to providing notice of the termination or violation to affected parties and prohibiting data recipient(s) from accessing HCUP data in the future.

In the event AHRQ terminates this Agreement due to a violation, or finds the data recipient(s) to be in violation of this Agreement, AHRQ may direct that the undersigned data recipient(s) immediately return all copies of the HCUP Nationwide Databases to AHRQ or its designee without refund of purchase fees.

Acknowledgment

I understand that this Agreement is requested by the United States Agency for Healthcare Research and Quality to ensure compliance with the AHRQ Confidentiality Statute. My signature indicates that I understand the terms of this Agreement and that I agree to comply with its terms. I understand that a violation of the AHRQ Confidentiality Statute may be subject to a civil penalty of up to $10,000 under 42 U.S.C. 299c-3(d), and that deliberately making a false statement about this or any matter within the jurisdiction of any department or agency of the Federal Government violates 18 U.S.C. § 1001 and is punishable by a fine of up to $10,000 or up to five years in prison. Violators of this Agreement may also be subject to penalties under state confidentiality statutes that apply to these data for particular states.

Signed: ______________________________ Date: ________________

Print or Type Name: ____

Title: ____

Organization: ____

Address: ____

Address: ____

City: _______________________ State: _______ ZIP Code: __________

Phone: _____________________ Fax: _________________________

E-mail: ____

The information above is maintained by AHRQ only for the purpose of enforcement of this Agreement.

Note to Purchaser: Shipment of the requested data product will only be made to the person who signs this Agreement, unless special arrangements that safeguard the data are made with AHRQ or its agent.

Submission Information

Please send signed HCUP Data Use Agreements and proof of online training to:

HCUP Central Distributor
Social & Scientific Systems, Inc.
8757 Georgia Avenue, 12th Floor
Silver Spring, MD 20910
E-mail: HCUPDistributor@AHRQ.gov
Fax: (866) 792-5313

APPENDIX B – 2010 NEDS STATE-SPECIFIC RESTRICTIONS

Confidentiality of Hospitals

Limitations on sampling are required to ensure hospital confidentiality:

- All States:
  - Prior to collapsing stratum: if there is a "unique" hospital in the State, it is excluded from sampling. "Unique" is defined as the only hospital in the state universe for a stratum. For example, if there is only one rural, non-teaching, trauma level III hospital in a State, then it is excluded from the sampling frame.
  - After sampling: stratifier data elements are set to missing if the stratum had fewer than two hospitals in the universe of the State's hospitals.
- CT: Connecticut Hospital Association (CHA)
  - CHA is to be notified if more than 50% of their hospitals appear in the NEDS. The 2010 NEDS includes 38 percent of CT hospitals.

Confidentiality of Records

Limitations on selected data elements are required by the following data sources to ensure patient confidentiality:

- CT: Connecticut Hospital Association (CHA)
  - Admission month (AMONTH) is set to missing on all records.
- FL: Florida Agency for Health Care Administration
  - Admission month (AMONTH) is set to missing on all records.
- GA: Florida Agency for Health Care Administration
  - Patient age (AGE) is set to 99 if the patient is 100 years or older.

Limited Reporting of External Cause of Injury Codes

The following data sources have limitations on the reporting of external cause of injury codes (E codes):

- CA: Office of Statewide Health Planning and Development
  - California does not require the reporting of E codes in the range E870-E879 (medical misadventures and abnormal reactions).
- GA: Georgia Hospital Association (GHA)
  - GHA removes E codes in the range E870-E879 (medical misadventures) and E930-E949 (adverse effects) from the data files supplied to HCUP.
- SC: South Carolina State Budget & Control Board
  - South Carolina removes E codes in the range E870-E876 (medical misadventures) from the data files supplied to HCUP.

Missing Discharges for Specific Populations of Patients

The following data sources may be missing discharge records for specific populations of patients:
 	
• IA: Iowa Hospital Association
    ○ The Iowa Hospital Association prohibits the release of two types of discharges: HIV infections (defined by MDC of 25) and behavioral health including chemical dependency care or psychiatric care (defined by a service code of BHV). These discharges were not included in the source file provided to HCUP and were therefore not included in the NEDS.
 	
• NE: Nebraska Hospital Association
    ○ The Nebraska Hospital Association prohibits the release of discharge records for patients with HIV diagnoses. These discharges were not included in the source file provided to HCUP and were therefore not included in the NEDS.
 	
• NY: New York State Department of Health
    ○ The New York State Department of Health masks the hospital identifiers on abortion records. As a result, these records were not included in the NEDS.

APPENDIX C - INSTRUCTIONS FOR USING THE NYU ED CLASSIFICATION ALGORITHM

NEW YORK UNIVERSITY
A private university in the public service
ROBERT F. WAGNER SCHOOL OF PUBLIC SERVICE

Instructions for Use of the ED Classification Algorithm

Background/Introduction

With support from the Commonwealth Fund, the Robert Wood Johnson Foundation, and the United Hospital Fund of New York, the NYU Center for Health and Public Service Research has developed an algorithm to help classify ED utilization. The algorithm was developed with the advice of a panel of ED and primary care physicians, and it is based on an examination of a sample of almost 6,000 full ED records. Data abstracted from these records included the initial complaint, presenting symptoms, vital signs, medical history, age, gender, diagnoses, procedures performed, and resources used in the ED. Based on this information, each case was classified into one of the following categories:

- Non-emergent - The patient's initial complaint, presenting symptoms, vital signs, medical history, and age indicated that immediate medical care was not required within 12 hours;
- Emergent/Primary Care Treatable - Based on information in the record, treatment was required within 12 hours, but care could have been provided effectively and safely in a primary care setting. The complaint did not require continuous observation, and no procedures were performed or resources used that are not available in a primary care setting (e.g., CAT scan or certain lab tests);
- Emergent - ED Care Needed - Preventable/Avoidable - Emergency department care was required based on the complaint or procedures performed/resources used, but the emergent nature of the condition was potentially preventable/avoidable if timely and effective ambulatory care had been received during the episode of illness (e.g., the flare-ups of asthma, diabetes, congestive heart failure, etc.); and
- Emergent - ED Care Needed - Not Preventable/Avoidable - Emergency department care was required and ambulatory care treatment could not have prevented the condition (e.g., trauma, appendicitis, myocardial infarction, etc.).

This information that was used to develop the algorithm required analysis of the full medical record. Since such detailed information is not generally available on computerized ED or claims records, these classifications were then "mapped" to the discharge diagnosis of each case in our sample to determine for each diagnosis the percentage of sample cases that fell into these four categories. For example, patients discharged with a final diagnosis of "abdominal pain" may include both patients who arrived at the ED complaining of stomach pain, as well as those who reported chest pain (and a possible heart attack). Accordingly, for abdominal pain, the algorithm assigns a specific percentage of the visit into the categories of "non-emergent", "emergent/primary care treatable", and "emergent/ED care needed-not preventable/avoidable" summary records aggregated by zip code, insurance status, age and gender groupings, and other classification variables if available.

Using the SAS or SPSS Version of the ED Algorithm

The computer programming that applies the ED algorithm to your ED data is contained in the following files.

For the **SPSS** version, the files are:

- "DX GROUPS.SAV" - This file is merged onto your ED data in order to recode and group diagnoses;
- 'EDDXS.SAV" - This file lists diagnoses and the proportion of cases that are to be assigned to the classification categories; and
- "ED Algorithm.sps" - This is the SPSS program that is used to run the algorithm.

For the **SAS** version (which will run in either SAS 7 or SAS 8), the files are:

- "ED Macros.sas" - This file contains SAS macros that group or recode diagnoses and classify them into the categories described above;
- 'FINDXACS.SD7" - This file lists diagnoses and the proportion of cases that are to be assigned to the classification categories; and
- "ED Algorithm Sample Program.sas" - This is the SAS program that is used to run the algorithm.

All files are contained in the compressed (zipped) file. Applying the algorithm involves three simple steps:

STEP 1: Put the unzipped files in a directory along with the ED encounter data set you want to classify (containing one record for each ED visit). The ED data set should be in the appropriate format (SAS 7 or 8, or SPSS) and contain a variable with the principal discharge diagnosis for the ED visit. The principal diagnosis variable should be in character or string format, left-justified, with leading zeroes (where appropriate), and WITHOUT an embedded decimal.

STEP 2: Set the appropriate names in the LET statements at the top of the program.

For the **SPSS** version, specify the following: 1) IN SINGLE QUOTES, the full path name (including a final backslash) of the directory on your computer that contains the files, 2) IN SINGLE QUOTES, the name of the SPSS data set (including the .SAV extension) containing ED records to be classified, 3) the name of the variable in your data set that contains the principal diagnosis, and 4) IN SINGLE QUOTES, the name you want the program to use to write the output data set (including the .SAV extension).

For the **SAS** version, specify the following: 1) the full path name of the directory on your computer that contains the files (which will be used as the LIBNAME for the run), 2) the name of the data set to be classified (without its libname prefix), and 3) the name of the variable in your data set that contains the principal diagnosis

STEP 3: Run the program and analyze the output data set, which will be written to the same directory the other files are in.

Analyzing ~~Microdata~~ (Record-Level) Output of all Three Versions of the ED Algorithm

All three versions of the ED algorithm programming – the Access, SAS, and SPSS versions – will produce a microdata (record-level) file, with one record for each encounter record in your ED database. (The Access version additionally produces spreadsheets with summary records aggregated by zip code, insurance status, age and gender groupings, and other classification variables if available.) The output microdata file will simply have a new set of variables in addition to your original data set variables. The names of the new variables are:

- ne = "Non-emergent"
- epct = "Emergent/Primary Care Treatable"
- edcnpa = "Emergent - ED Care Needed - Preventable/Avoidable"
- edcnnpa = "Emergent - ED Care Needed - Not Preventable/Avoidable"
- injury = "Injury principal diagnoses"
- psych = "Mental health principal diagnoses"
- alcohol = "Alcohol-related health principal diagnoses"
- drug = "Drug-related health principal diagnoses (excluding alcohol)"
- unclassified = "Not classified - not in one of the above categories"

For each ED encounter, the numbers in the new fields represent the relative percentage of cases for that diagnosis falling into the various classification categories. For example, in the case of urinary tract infections (ICD-9-CM code 599.0), each case is assigned 66% "non-emergent", 17% "emergent/primary care treatable", and 17% "emergent - ED care needed -

preventable/avoidable". The sum of the values in the new data fields will always total 1, and the injury, psych, alcohol, drug, and unclassified fields are always binary (equal to 1 or 0). To profile a hospital, payor group, zip code area, patient type, etc., simply aggregate these values to find the total percentage of cases falling into each of the categories.

For more information on how these categories were constructed, please consult the articles on our website, at http://www.nyu.edu/wagner/chpsr/index.html?p=62.

Questions or Problems?

To resolve any questions or problems you have in running the algorithm or analyzing the output, please contact Tod Mijanovich at tm11@nyu.edu.

APPENDIX D – FULL LIST OF DIAGNOSES AND PROPORTIONS IN THE NYU ED ALGORITHM

	prindx	nonemerg	emergpc	emedpa	emednpa
1	0030	0	1	0	0
2	0059	0.3714285714	0.4571428571	0	0.1714285714
3	0090	1	0	0	0
4	01190	0	0	1	0
5	03400	0	1	0	0
6	0341	0.3333333333	0.6666666667	0	0
7	035	0	1	0	0
8	0381	0	0.2307692308	0	0.7692307692
9	03810	0	1	0	0
10	042	0.0666666667	0	0	0.9333333333
11	0529	0.4666666667	0.4666666667	0	0.0666666667
12	0539	0.75	0.25	0	0
13	05410	0	0.5	0	0.5
14	0549	0.75	0	0	0.25
15	0569	1	0	0	0
16	05700	0.2857142857	0.7142857143	0	0
17	0709	1	0	0	0
18	0743	0.5	0.5	0	0
19	075	0.4621848739	0.4369747899	0	0.1008403361
20	0779	0.6744186047	0.2325581395	0	0.0930232558
21	07799	1	0	0	0
22	0781	1	0	0	0
23	07889	0	0	0	1
24	0829	1	0	0	0
25	0846	0	0	0	1
26	0971	0.6666666667	0.3333333333	0	0
27	0979	0.75	0	0	0.25
28	0980	0.6923076923	0.1538461538	0	0.1538461538
29	0990	0	1	0	0
30	0999	0.9166666667	0.0833333333	0	0
31	1100	0.6923076923	0.2307692308	0	0.0769230769
32	1103	1	0	0	0
33	1105	1	0	0	0
34	1120	0.3636363636	0.6363636364	0	0
35	1121	0.7272727273	0.2727272727	0	0
36	1129	0.6666666667	0.3333333333	0	0

37	1179	1	0	0	0
38	1274	1	0	0	0
39	13101	0.25	0.75	0	0
40	1322	1	0	0	0
41	1329	1	0	0	0
42	1330	0.8181818182	0.1818181818	0	0
43	1349	1	0	0	0
44	1363	0	0	0	1
45	1369	0	1	0	0
46	1539	0	0	0	1
47	1830	0	0	0	1
48	1838	0	0	0	1
49	185	1	0	0	0
50	20280	0	0	0	1
51	2189	0.6666666667	0	0	0.3333333333
52	23770	1	0	0	0
53	2390	0	0	0	1
54	24290	0	1	0	0
55	2449	1	0	0	0
56	25000	0.6	0.0571428571	0.3428571429	0
57	25002	0	0	1	0
58	25003	0	0	1	0
59	2501	0	0	1	0
60	25080	0	0.3333333333	0.6666666667	0
61	25090	0.6666666667	0	0.3333333333	0
62	2512	0	0.2222222222	0.7777777778	0
63	2529	1	0	0	0
64	2554	0	0	0	1
65	2720	1	0	0	0
66	2725	1	0	0	0
67	2749	0	0.6666666667	0	0.3333333333
68	2760	0	0	0	1
69	2765	0	0.1052631579	0.8947368421	0
70	2767	0	0	0	1
71	27700	1	0	0	0
72	2780	0	1	0	0

73	28181	0	0	0	1
74	28260	0	0.3333333333	0	0.6666666667
75	2859	0.5	0.1666666667	0	0.3333333333
76	2875	0	0	0	1
77	2893	0.5	0	0	0.5
78	29181	0	0	0	1
79	2920	0	0	0	1
80	2939	0	0	0	1
81	29530	0.3157894737	0.0526315789	0	0.6315789474
82	29580	0	0	0	1
83	29620	0	1	0	0
84	29624	0	1	0	0
85	2967	1	0	0	0
86	30000	0	0.7804878049	0	0.2195121951
87	30272	0	1	0	0
88	30301	0.5	0	0	0.5
89	30390	0	0.3461538462	0	0.6538461538
90	30391	0	0	0	1
91	30401	1	0	0	0
92	30501	0.2857142857	0	0	0.7142857143
93	30561	0	1	0	0
94	30746	0	1	0	0
95	3089	1	0	0	0
96	3099	0.3333333333	0.3333333333	0	0.3333333333
97	3101	1	0	0	0
98	3102	0.25	0.5	0	0.25
99	311	0.2	0	0	0.8
100	31230	1	0	0	0
101	3129	0.5	0.5	0	0
102	31400	0	1	0	0
103	31401	1	0	0	0
104	3229	0	0	0	1
105	3310	0.5	0	0	0.5
106	3314	0	0	0	1
107	3320	0	1	0	0
108	3332	0	1	0	0

109	34620	0	0	0	1
110	3510	0	0.6666666667	0	0.3333333333
111	3529	0	0	0	1
112	3540	1	0	0	0
113	3549	0.3333333333	0.3333333333	0	0.3333333333
114	3580	0	1	0	0
115	36000	0	0	0	1
116	36043	1	0	0	0
117	36210	0	1	0	0
118	3643	0	1	0	0
119	3669	0	1	0	0
120	3670	0	1	0	0
121	3688	0	0.5	0	0.5
122	3699	0	1	0	0
123	37034	1	0	0	0
124	37182	1	0	0	0
125	37240	0.5	0.5	0	0
126	37272	0	0.5	0	0.5
127	37311	1	0	0	0
128	37312	0	1	0	0
129	37313	1	0	0	0
130	3732	0	1	0	0
131	37515	1	0	0	0
132	37601	0	0	0	1
133	37800	1	0	0	0
134	37991	0	1	0	0
135	37992	0.5	0.25	0	0.25
136	37993	1	0	0	0
137	37999	1	0	0	0
138	38010	0.8	0.2	0	0
139	3804	0.8333333333	0.1666666667	0	0
140	38110	1	0	0	0
141	3814	0	1	0	0
142	3829	0.3713080169	0.5907172996	0.0379746835	0
143	38420	0.3333333333	0.6666666667	0	0
144	3849	1	0	0	0

145	38630	0.5	0.5	0	0
146	38810	0	1	0	0
147	38830	1	0	0	0
148	38860	1	0	0	0
149	38869	0.6666666667	0.3333333333	0	0
150	38870	0.8	0.1	0	0.1
151	3888	0	1	0	0
152	3899	1	0	0	0
153	4019	0.6129032258	0.1774193548	0.2096774194	0
154	41091	0	0	0	1
155	4111	0	0	1	0
156	4139	0	0	1	0
157	4149	0	1	0	0
158	42613	0	0	0	1
159	4270	0	0	0	1
160	42731	0	0	0	1
161	4275	0	0	0	1
162	42789	0	0.125	0	0.875
163	4280	0	0.04	0.96	0
164	430	0	0	0	1
165	431	0	0	0	1
166	4359	0	0	0	1
167	4476	1	0	0	0
168	4519	0	1	0	0
169	4538	0	0	0	1
170	4540	0	1	0	0
171	4550	0.6	0.4	0	0
172	4552	0	0.75	0	0.25
173	4590	0	1	0	0
174	45981	0.5	0	0	0.5
175	4599	0	0.6666666667	0	0.3333333333
176	4619	1	0	0	0
177	462	0.6578947368	0.2842105263	0.0578947368	0
178	4640	0.5	0.5	0	0
179	46410	0	1	0	0
180	4644	0.2380952381	0.1904761905	0	0.5714285714

181	46509	0	1	0	0
182	4660	0	0.8225806452	0.1774193548	0
183	46619	0.5	0	0	0.5
184	4720	1	0	0	0
185	4739	0.75	0.15	0	0.1
186	475	0.5	0	0	0.5
187	47803	0	1	0	0
188	4781	0.3333333333	0.6666666667	0	0
189	47829	1	0	0	0
190	485	0.0925925926	0.2407407407	0.6666666667	0
191	4871	0.5	0.25	0	0.25
192	49120	0	1	0	0
193	49121	0	0.5	0.5	0
194	4919	1	0	0	0
195	4928	1	0	0	0
196	493	0	0.0188679245	0.9811320755	0
197	496	0	0.5	0.5	0
198	514	0	0	0	1
199	515	0	0	0	1
200	5183	1	0	0	0
201	5184	0	0	1	0
202	51881	0	0	0	1
203	51882	0	0	0	1
204	51909	0	0	0	1
205	5191	0.3636363636	0.4545454545	0	0.1818181818
206	5198	0.037037037	0.4074074074	0	0.5555555556
207	5199	0.1428571429	0.6428571429	0	0.2142857143
208	5220	0	0.7586206897	0.2413793103	0
209	5224	1	0	0	0
210	5231	0.8333333333	0.1666666667	0	0
211	5244	0	1	0	0
212	5251	1	0	0	0
213	5258	1	0	0	0
214	5259	0.8974358974	0.1025641026	0	0
215	5269	1	0	0	0
216	5280	0.4615384615	0.5384615385	0	0

217	5283	0	1	0	0
218	5285	0.5	0.5	0	0
219	5289	0.8	0.2	0	0
220	5296	1	0	0	0
221	5301	0.25	0.75	0	0
222	5305	0	0	0	1
223	53190	0	1	0	0
224	5339	0.2727272727	0.1818181818	0	0.5454545455
225	53500	0	0.5344827586	0	0.4655172414
226	53510	0	1	0	0
227	53530	1	0	0	0
228	53540	0.25	0.25	0	0.5
229	5368	0	0.9411764706	0	0.0588235294
230	5370	1	0	0	0
231	541	0	0	0	1
232	55090	0.5714285714	0.2857142857	0	0.1428571429
233	55220	0	0	0	1
234	5531	0.5	0	0	0.5
235	5539	0.5	0.5	0	0
236	5559	0.5	0	0	0.5
237	5589	0.4615384615	0.3736263736	0.1648351648	0
238	5601	0	1	0	0
239	56039	0	0	0	1
240	5609	0	0	0	1
241	56210	0	0	0	1
242	56211	0	0	0	1
243	5640	0.25	0.3571428571	0	0.3928571429
244	5641	0.25	0.5	0	0.25
245	5650	0.5	0.5	0	0
246	5651	1	0	0	0
247	566	0	0	0	1
248	5691	0	0	0	1
249	5693	0	1	0	0
250	56942	0	0	0	1
251	56949	0	0	0	1
252	56989	0	1	0	0

253	5733	0.5	0	0	0.5
254	57420	0.2	0.2	0	0.6
255	5751	0	0.2	0	0.8
256	5772	0	0	0	1
257	5780	0	0	0	1
258	5781	0.6	0	0	0.4
259	5789	0	0	0	1
260	5798	0.6666666667	0.3333333333	0	0
261	586	0	0.3333333333	0	0.6666666667
262	59010	0	0	1	0
263	59080	0.3333333333	0	0.6666666667	0
264	5920	0	0.0588235294	0	0.9411764706
265	5939	0	1	0	0
266	5942	0	1	0	0
267	59509	0	1	0	0
268	59789	1	0	0	0
269	5990	0.4615384615	0.2967032967	0.2417582418	0
270	5997	0	0.4	0	0.6
271	600	0	1	0	0
272	6030	1	0	0	0
273	60490	0.6666666667	0.3333333333	0	0
274	605	0	1	0	0
275	6071	0.8	0.2	0	0
276	60789	0.5	0.5	0	0
277	6082	0.6666666667	0	0	0.3333333333
278	6084	1	0	0	0
279	6108	1	0	0	0
280	6110	1	0	0	0
281	6111	1	0	0	0
282	61171	0	1	0	0
283	61172	1	0	0	0
284	6118	1	0	0	0
285	6149	0	0.5	0.5	0
286	6160	0.6153846154	0.3846153846	0	0
287	6162	0	1	0	0
288	6202	0.25	0.5	0	0.25

289	6235	1	0	0	0
290	6238	0.8666666667	0.1333333333	0	0
291	6252	0	0.6666666667	0	0.3333333333
292	6253	0.5555555556	0.1111111111	0	0.3333333333
293	6254	0.5	0.5	0	0
294	6258	1	0	0	0
295	6259	1	0	0	0
296	6261	0	1	0	0
297	6262	1	0	0	0
298	6264	0.8	0	0	0.2
299	6268	0.6153846154	0.3076923077	0	0.0769230769
300	6271	1	0	0	0
301	6288	1	0	0	0
302	632	0	0.6666666667	0	0.3333333333
303	6339	0	0.5	0	0.5
304	63490	0	0.3333333333	0	0.6666666667
305	6359	1	0	0	0
306	63790	0	0	0	1
307	63791	0	0	0	1
308	6390	0	0	0	1
309	64000	0	0.6666666667	0	0.3333333333
310	64303	0.7272727273	0.0909090909	0	0.1818181818
311	64403	0	0	0	1
312	64410	0	0.3333333333	0	0.6666666667
313	64893	1	0	0	0
314	65813	0	0	0	1
315	6622	1	0	0	0
316	6806	0	0.6666666667	0	0.3333333333
317	6808	1	0	0	0
318	68100	0	0.6428571429	0.3571428571	0
319	682	0	0.661971831	0.338028169	0
320	6851	0	1	0	0
321	6860	1	0	0	0
322	69000	1	0	0	0
323	69010	1	0	0	0
324	6910	0.3333333333	0.6666666667	0	0

325	6918	0.7543859649	0.2105263158	0	0.0350877193
326	69271	1	0	0	0
327	6930	1	0	0	0
328	6931	1	0	0	0
329	6961	1	0	0	0
330	6963	0	1	0	0
331	6981	1	0	0	0
332	6988	1	0	0	0
333	6989	1	0	0	0
334	7030	0.8333333333	0.1666666667	0	0
335	70401	0	1	0	0
336	7048	0	1	0	0
337	7051	1	0	0	0
338	70589	1	0	0	0
339	7061	0	1	0	0
340	7062	0.8181818182	0.1818181818	0	0
341	7063	1	0	0	0
342	7069	0	1	0	0
343	7070	0	1	0	0
344	7071	0.5	0.3333333333	0.1666666667	0
345	7080	0	0.5	0	0.5
346	7083	1	0	0	0
347	7088	1	0	0	0
348	7089	0.875	0.125	0	0
349	7092	1	0	0	0
350	7094	1	0	0	0
351	7098	0	1	0	0
352	7099	0.8333333333	0.1666666667	0	0
353	71598	1	0	0	0
354	71695	0	1	0	0
355	7179	0.5	0.5	0	0
356	71840	1	0	0	0
357	71906	0.6666666667	0.1666666667	0	0.1666666667
358	71907	1	0	0	0
359	71942	0.5	0.5	0	0
360	71944	1	0	0	0

361	71945	1	0	0	0
362	71946	0.75	0.15625	0	0.09375
363	71947	0.6666666667	0.3333333333	0	0
364	71996	1	0	0	0
365	7234	1	0	0	0
366	7235	0.9375	0	0	0.0625
367	7243	0	0.3333333333	0	0.6666666667
368	7244	1	0	0	0
369	7248	0.7361111111	0.1527777778	0	0.1111111111
370	7265	0	1	0	0
371	72664	0	1	0	0
372	72679	1	0	0	0
373	72690	1	0	0	0
374	72691	1	0	0	0
375	72705	1	0	0	0
376	72743	0.5	0.5	0	0
377	72885	0.6666666667	0	0	0.3333333333
378	7291	0.6282051282	0.2564102564	0	0.1153846154
379	7293	1	0	0	0
380	7295	0.7083333333	0.1666666667	0	0.125
381	7296	1	0	0	0
382	72981	0.6	0.2	0	0.2
383	73026	0	0	0	1
384	7324	1	0	0	0
385	7329	0.2222222222	0.6666666667	0	0.1111111111
386	7336	0.2	0.4	0	0.4
387	73730	1	0	0	0
388	7714	1	0	0	0
389	7729	0	1	0	0
390	77439	1	0	0	0
391	7746	0	0	0	1
392	78009	0	0	0	1
393	7801	0	0	0	1
394	7802	0	0.3333333333	0	0.6666666667
395	78039	0	0.25	0.75	0
396	7804	0.72	0.2	0	0.08

397	78050	0.5	0.25	0	0.25
398	7806	0.431372549	0.3725490196	0	0.1960784314
399	7807	0.6363636364	0.1818181818	0	0.1818181818
400	7809	0.2926829268	0.0487804878	0	0.6585365854
401	7810	0	0.3333333333	0	0.6666666667
402	7811	0	0	0	1
403	7820	1	0	0	0
404	7822	0.6666666667	0.3333333333	0	0
405	7824	0.5	0	0	0.5
406	7827	1	0	0	0
407	7828	0	1	0	0
408	7830	0.5	0	0	0.5
409	7836	0.6666666667	0.3333333333	0	0
410	7840	0.7792207792	0.0909090909	0	0.1298701299
411	7842	0	0.75	0	0.25
412	78441	0	1	0	0
413	7847	0	0.7857142857	0	0.2142857143
414	7849	0	0.5	0	0.5
415	7850	0	0	0	1
416	7851	0	0.4444444444	0	0.5555555556
417	7852	0	1	0	0
418	7856	0.5	0.5	0	0
419	78605	0	0.4	0	0.6
420	78609	0	0.6129032258	0	0.3870967742
421	7862	0.6470588235	0.2352941176	0	0.1176470588
422	7863	0	0	0	1
423	78650	0	0.323943662	0	0.676056338
424	78651	0	1	0	0
425	78652	0	0.8235294118	0	0.1764705882
426	78659	0	0.6111111111	0	0.3888888889
427	7870	0.5882352941	0.2352941176	0	0.1764705882
428	7871	0	1	0	0
429	7872	0	1	0	0
430	7873	0.6666666667	0.3333333333	0	0
431	7877	0	0	0	1
432	78791	0.5	0.5	0	0

433	78799	1	0	0	0
434	7881	0.6666666667	0.3333333333	0	0
435	7884	0.6666666667	0.3333333333	0	0
436	7890	0	0.6697247706	0	0.3302752294
437	7891	1	0	0	0
438	7893	0	1	0	0
439	78930	0	1	0	0
440	7906	0	0	0	1
441	7951	1	0	0	0
442	7953	1	0	0	0
443	7955	1	0	0	0
444	7964	0	1	0	0
445	7992	1	0	0	0
446	7999	0	0.5	0	0.5
447	8020	0	0.7142857143	0	0.2857142857
448	80220	0	0	0	1
449	8028	0	1	0	0
450	80311	0	0	0	1
451	8040	0	1	0	0
452	80700	0	0.3333333333	0	0.6666666667
453	80701	0	0.5	0	0.5
454	81000	0	0.2	0	0.8
455	81200	0	0.125	0	0.875
456	81341	0	0.4285714286	0	0.5714285714
457	81383	0	0.3333333333	0	0.6666666667
458	81401	0	0	0	1
459	81500	0	0.6	0	0.4
460	81610	0	0	0	1
461	81612	0	1	0	0
462	8199	0	0.5	0	0.5
463	8208	0	0.4	0	0.6
464	82100	0	1	0	0
465	82121	0	0	0	1
466	8220	0	1	0	0
467	82382	0	0	0	1
468	82390	0	0	0	1

469	82408	0	0	0	1
470	8242	0	0.25	0	0.75
471	82520	0	0.6428571429	0	0.3571428571
472	8270	0	0.5	0	0.5
473	83100	0	0.6666666667	0	0.3333333333
474	83200	0	1	0	0
475	83300	0	1	0	0
476	83400	0	0	0	1
477	8362	0	1	0	0
478	8363	0	1	0	0
479	8398	0	0	0	1
480	8409	0	0.3333333333	0	0.6666666667
481	8418	0	0.5	0	0.5
482	84200	0	0.7	0	0.3
483	84209	0	1	0	0
484	8438	0	1	0	0
485	8439	0	0.5555555556	0	0.4444444444
486	8448	0	0.7777777778	0	0.2222222222
487	84500	0	0.6909090909	0	0.3090909091
488	84519	0	1	0	0
489	8460	0	0.9	0	0.1
490	8470	0	0.5833333333	0	0.4166666667
491	8472	0	1	0	0
492	8485	0	1	0	0
493	8488	0	1	0	0
494	8489	0	0.5	0	0.5
495	850	0	0	0	1
496	85181	0	0	0	1
497	854	0	0.3333333333	0	0.6666666667
498	8700	0	1	0	0
499	8708	0	0.6666666667	0	0.3333333333
500	87201	0	0	0	1
501	8730	0	0.1904761905	0	0.8095238095
502	8730E	0	0	0	1
503	87320	0	0.3012048193	0	0.6987951807
504	87349	0	0.2	0	0.8

505	87351		0	0	0	1
506	87363		0	0.7777777778	0	0.2222222222
507	8744		0	0.5	0	0.5
508	8750		0	0	0	1
509	8782		0	1	0	0
510	8784		0	0	0	1
511	87908		0	1	0	0
512	8792		0	0	0	1
513	8798		0	0.3684210526	0	0.6315789474
514	88000		0	0.35	0	0.65
515	88101		0	1	0	0
516	88102		0	0.425	0	0.575
517	88120		0	0	0	1
518	8822		0	0	0	1
519	88220		0	0	0	1
520	8830		0	0.5	0	0.5
521	8850		0	1	0	0
522	8860		0	0	0	1
523	8900		0	0.4545454545	0	0.5454545455
524	8901		0	0	0	1
525	8920		0	0.7333333333	0	0.2666666667
526	8940		0	1	0	0
527	9052		0	0	0	1
528	9060		0	0.6	0	0.4
529	9061		0	1	0	0
530	9100		0	0.72	0	0.28
531	9101		0	1	0	0
532	9105		0	1	0	0
533	9111		0	0.5	0	0.5
534	9135		0	1	0	0
535	9141		0	1	0	0
536	9145		0	1	0	0
537	9155		0	1	0	0
538	9156		0	0.5	0	0.5
539	9161		0	0	0	1
540	9162		0	1	0	0

541	9175	0	1	0	0
542	9181	0	0.2857142857	0	0.7142857143
543	9191	0	0	0	1
544	9194	0	0.9444444444	0	0.0555555556
545	920	0	0.5729166667	0	0.4270833333
546	9211	0	1	0	0
547	9221	0	0.6428571429	0	0.3571428571
548	92231	0	0.3333333333	0	0.6666666667
549	9224	0	0	0	1
550	92300	0	0.6842105263	0	0.3157894737
551	92303	0	1	0	0
552	92321	0	1	0	0
553	92400	0	0.6857142857	0	0.3142857143
554	92410	0	1	0	0
555	9248	0	0.5882352941	0	0.4117647059
556	9249	0	0.5769230769	0	0.4230769231
557	9273	0	0.8	0	0.2
558	9300	0	0	0	1
559	9301	0	0	0	1
560	9308	0	1	0	0
561	9309	0	0.75	0	0.25
562	931	0	0.4444444444	0	0.5555555556
563	932	0	0.6666666667	0	0.3333333333
564	933	0	0.5	0	0.5
565	9350	0	1	0	0
566	936	0	0.25	0	0.75
567	9409	0	0	0	1
568	94100	0	0	0	1
569	94118	0	0	0	1
570	94120	0	0.6	0	0.4
571	94401	0	1	0	0
572	94410	0	1	0	0
573	94420	0	0.5	0	0.5
574	94423	0	0	0	1
575	94504	0	0	0	1
576	9493	0	1	0	0

577	9523	0	0	0	1
578	9579	0	0	0	1
579	9583	0	0.5	0	0.5
580	95901	0	1	0	0
581	95909	0	1	0	0
582	9591	0	0.8	0	0.2
583	9593	0	1	0	0
584	9594	0	1	0	0
585	9595	0	0	0	1
586	9596	0	0.5	0	0.5
587	9597	0	0.8	0	0.2
588	9599	0	0.8	0	0.2
589	9620	0	1	0	0
590	9654	0	0	0	1
591	9661	0	0	0	1
592	9688E	0	1	0	0
593	9689	0	1	0	0
594	9691	0	0.5	0	0.5
595	9734	0	0	0	1
596	9760	0	1	0	0
597	9778	0	0	0	1
598	9779	0	0.4444444444	0	0.5555555556
599	9809	0	0	0	1
600	9839	0	1	0	0
601	9849	0	1	0	0
602	986	0	0	0	1
603	9879	0	0.3333333333	0	0.6666666667
604	9882	0	1	0	0
605	9894	0	1	0	0
606	9895	0	1	0	0
607	9898	0	1	0	0
608	9919	0	1	0	0
609	9925	0	0.5	0	0.5
610	9947	0	1	0	0
611	9950	0	0	0	1
612	9951	0	0	0	1

613	9952	0	0.6363636364	0	0.3636363636
614	9953	0	0.875	0	0.125
615	9955	0	0.4	0	0.6
616	99581	0	1	0	0
617	99659	0	0	0	1
618	99670	0	1	0	0
619	99673	0	1	0	0
620	99676	0	0	0	1
621	9970	0	0	0	1
622	9973	0	0	0	1
623	9974	0	1	0	0
624	99760	0	1	0	0
625	9981	0	0.75	0	0.25
626	9983	0	1	0	0
627	99883	0	1	0	0
628	99989	0	1	0	0
629	E8197	0	0	0	1
630	E8199	0	1	0	0
631	E969	0	1	0	0
632	V037	1	0	0	0
633	V045	1	0	0	0
634	V202	0.5	0.5	0	0
635	V221	0	1	0	0
636	V222	0.5789473684	0.3684210526	0	0.0526315789
637	V412	0	0	0	1
638	V4589	1	0	0	0
639	V479	1	0	0	0
640	V501	1	0	0	0
641	V548	0.6666666667	0.3333333333	0	0
642	V551	0.3333333333	0.3333333333	0	0.3333333333
643	V583	0.8947368421	0.0526315789	0	0.0526315789
644	V5889	0	1	0	0
645	V642	0.5	0.5	0	0
646	V655	0.347826087	0.6086956522	0	0.0434782609
647	V662	0	1	0	0
648	V670	0.3333333333	0.3333333333	0	0.3333333333
649	V6759	0.8	0.2	0	0
650	V679	0.8571428571	0.1428571429	0	0
651	V681	0.8235294118	0.1176470588	0	0.0588235294
652	V6881	0	1	0	0
653	V708	1	0	0	0
654	V715	0	0	0	1
655	V718	1	0	0	0
656	V719	1	0	0	0
657	V72	1	0	0	0
658	V741	1	0	0	0
659	V802	1	0	0	0