June 2020

Impact of Heat-Related Illness and Natural Environments on Behavioral Health Related Emergency and Hospital Utilization in Florida

Natasha Kurji
University of South Florida

Follow this and additional works at: https://scholarcommons.usf.edu/etd

Part of the Psychiatric and Mental Health Commons

Scholar Commons Citation
Kurji, Natasha, "Impact of Heat-Related Illness and Natural Environments on Behavioral Health Related Emergency and Hospital Utilization in Florida" (2020). Graduate Theses and Dissertations. https://scholarcommons.usf.edu/etd/8238

This Dissertation is brought to you for free and open access by the Graduate School at Scholar Commons. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of Scholar Commons. For more information, please contact scholarcommons@usf.edu.
Impact of Heat-Related Illness and Natural Environments on Behavioral Health Related Emergency and Hospital Utilization in Florida

by

Natasha Kurji

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Public Health with a concentration in Health Services Research
College of Public Health
University of South Florida

Co-Major Professor: Etienne Pracht, Ph.D.
Co-Major Professor: Sandra Potthoff, Ph.D.
Barbara Orban, Ph.D.
Timothy Boaz, Ph.D.

Date of Approval:
June 3, 2020

Keywords: public health, health services research, mental health, environmental factors

Copyright © 2020, Natasha Kurji
# TABLE OF CONTENTS

List of Tables ................................................................................................................................. iii

List of Figures ................................................................................................................................. v

Abstract ........................................................................................................................................ vi

Chapter One: Introduction .............................................................................................................. 1
  Prevalence and Multidimensional Effects of Behavioral Health Disorders .............................. 1
  A Changing Mental Health Delivery System and Ongoing Challenges ................................. 2
  Natural Environment and Weather ......................................................................................... 5
  Literature Gaps and Proposed Hypotheses ............................................................................... 9
  References ................................................................................................................................. 15

Chapter Two: The Impact of Social Vulnerability Index and Availability of Behavioral Health Providers on Hospital Utilization ................................................................. 19
  Introduction ............................................................................................................................. 19
  Methods .................................................................................................................................. 22
    Data Description .................................................................................................................... 22
    Rate of Emergency Department Visits and Inpatient Admissions ....................................... 22
    Social Vulnerability Index (SVI) ......................................................................................... 23
    Physical Access to Care ....................................................................................................... 24
    Demographic Factors (Confounding Variables) ..................................................................... 25
    Statistical Analysis ............................................................................................................... 26
  Results ..................................................................................................................................... 27
  Discussion ................................................................................................................................. 37
  References ................................................................................................................................. 40

Chapter Three: Emergency Department Revisits and Inpatient Readmissions ........................... 44
  Introduction ............................................................................................................................. 44
  Emergency Department Revisits ............................................................................................. 44
  Inpatient Readmissions .......................................................................................................... 46
  Methods .................................................................................................................................. 49
    Data Description .................................................................................................................... 49
    Statistical Analysis ............................................................................................................... 49
    Hypotheses ............................................................................................................................ 51
  Results ..................................................................................................................................... 51
    Demographics ....................................................................................................................... 51
    Regression Results ................................................................................................................ 55
  Discussion ................................................................................................................................. 57
Chapter Four: Impact of Public Park and Beach Availability on Anxiety and Depression-Related Emergency Department Visits in Florida ................................................................. 68
  Introduction .................................................................................................................. 68
  Methods ....................................................................................................................... 72
    Data Description ......................................................................................................... 72
    Statistical Analysis ..................................................................................................... 73
    Hypotheses .................................................................................................................. 75
  Results ......................................................................................................................... 75
  Discussion .................................................................................................................... 84
  References ................................................................................................................... 88

Chapter Five: Discussion ............................................................................................ 92
  Part I: Co-occurring Heat-Related Illness and Behavioral Health Disorders .......... 92
    Importance of Outpatient Care Availability to Reduce Hospital Utilization....... 93
    Increased Likelihood of Hospital Reutilization for HRI Especially Among Individuals with Nicotine Dependence, Male Gender, and Uninsured Status ................................................................. 97
  Part II: Natural Environments ................................................................................. 102
    Importance of County Park Access in Reducing Anxiety and Depression ED Visits ................................................................. 102
  Limitations ................................................................................................................. 104
  Conclusions ............................................................................................................... 105
  References ................................................................................................................. 106
LIST OF TABLES

Table 1.1: Rates of Inpatient Episodes per 100,000 Population for Diagnosis Groups .................4

Table 2.1: Average Distribution of Demographic Characteristics Among Individuals with Co-Occurring BHD and HRI Emergency and Inpatient Visits from 2016-2018 ............30

Table 2.2: Descriptive Statistics of Independent Variables at the County Level in Florida from 2016-2018 .............................................................................................................31

Table 2.3: Multiple Regression Results for Emergency Department Data Models A-E ..........33

Table 2.4: Multiple Regression Results for Emergency Department Data Models F-I .........34

Table 2.5: Multiple Regression Results for Inpatient Data Models A-E ..............................35

Table 2.6: Multiple Regression Results for Inpatient Data Models F-I ...............................36

Table 3.1: Average Demographic Information and Distribution of Patients with HRI ED Visits from 2016-2018 ........................................................................................................52

Table 3.2: Average Demographic Information and Distribution of HRI Inpatient Admissions from 2016-2018 ..........................................................................................................53

Table 3.3: Emergency Department Visit Frequency Among Patients Diagnosed with Heat-Related Illness in Florida (2016-2018) ..........................................................................55

Table 3.4: Hospital Inpatient Admission Frequency Among Patients Diagnosed with Heat-Related Illness in Florida (2016-2018) .................................................................55

Table 3.5: Odd Ratios for Heat-Related ED Revisits within 30 days ..................................56

Table 3.6: Odd Ratios for Heat-Related ED Revisits within 365 days ..................................56

Table 3.7: Odd Ratios for Heat-Related IP Readmissions within 30 days .........................57

Table 3.8: Odd Ratios for Heat-Related IP Readmissions within 365 days .......................57

Table 4.1. Average Distribution of Demographic Characteristics Among Individuals with Anxiety or Depression-related ED Visits within Hillsborough, Pinellas, and Pasco Counties from 2016-2018 .................................................................76
Table 4.2: Descriptive Statistics of Dependent Variables at Zip Code level in Pasco, Pinellas, and Hillsborough County from 2016-2018 .................................................................77

Table 4.3: Zip code, Park, and Beach Distribution in Hillsborough, Pasco, and Pinellas County, FL ..................................................................................................................78

Table 4.4: Ordinary Least Squares Regression Models for Anxiety and Depression-Related Emergency Department Visits .................................................................................80
LIST OF FIGURES

Figure 1.1: Climate Change and Health Conceptual Diagram .............................................................11

Figure 1.2: Flow Chart Illustration of Hypotheses Related to Co-Occurring Heat-Related Illness and Behavioral Health Disorders ........................................................................................................13

Figure 2.1: Centers for Disease Control and Prevention’s Social Vulnerability Index ...............24

Figure 2.2: Behavioral Health Related NAICS Definitions .................................................................25

Figure 2.3: Average Rate of Co-Occurring HRI and BHD ED Visits per 100,000 ....................28

Figure 2.4: Average Rate of Co-Occurring HRI and BHD Inpatient Visits per 100,000 ..........28

Figure 3.1: Distribution of Behavioral Health Disorder Diagnoses for Patients with Co-Occurring Heat-Related Illness in Florida Hospitals 2016-2018 ...............................................54

Figure 3.2: Distribution of Substance Use Disorders for Patients with Co-Occurring Heat-Related Illness in Florida Hospitals 2016-2018 .................................................................54

Figure 4.1: Geographic Area of Interest Defined as Tampa Bay .........................................................74

Figure 4.2: Geographic Distribution of Parks in Hillsborough, Pasco, and Pinellas Counties .....78

Figure 4.3: Geographic Distribution of Beaches in Hillsborough, Pasco, and Pinellas Counties ..78

Figure 4.4: Number of Anxiety and Depression-Related Emergency Department Visits in Florida between 2016-2018 ............................................................................................................79
ABSTRACT

Behavioral health disorders are the leading cause of disability in the United States and are known to have multidimensional effect on wellbeing. Several environmental factors are known to impact behavioral health such as weather (i.e. heat) and access to natural environments (i.e. parks and beaches). The study goals were to identify contextual factors that increase the co-occurrence of heat-related illness and behavioral health disorders, illustrate the re-utilization patterns of these co-occurring cases in Florida emergency and inpatient settings, and explore the association between behavioral health disorders such as anxiety and depression, and natural environments such as parks and beaches. The study was conducted among all Florida residents for 2016-2018 and used Agency for Health Care Administration emergency and inpatient data. Regression modeling was used to predict hospital utilization. The results indicate that increases in outpatient services are associated with a significant decline in emergency and inpatient utilization for co-occurring heat-related illness and behavioral health disorders. Individuals with nicotine dependence, male gender, and uninsured status were found to be significantly more likely to revisit the ED or be readmitted to the hospital for another heat-related illness. Furthermore, availability of county parks was associated with a significant decline in anxiety and depression-related ED visits. Overall, the results presented indicate that uninsured white non-Hispanic middle-aged males are highly vulnerable and more likely to utilize hospitals in Florida for co-occurring HRI and BHDs. It is suggested that communities focus their resources on outpatient mental health care in order to improve continuity of care and reduce the costs of hospital utilization. In addition, there is a need for improved risk communication, education, and
awareness, particularly for those at increased risk of a heat event. Lastly, parks need to be valued as a vital resource for community health, the environment, and social resilience. Policy makers, city planners, and public health practitioners must work together to ensure parks are equitably distributed in easily accessible areas and have an adequate variety of amenities to benefit residents. As climate change persists and temperatures continue to rise, it is important that we as a society strategize by identifying vulnerable populations and preparing adequate public health interventions that promote health and safety when enjoying the outdoors.
CHAPTER ONE:
INTRODUCTION

Prevalence and Multidimensional Effects of Behavioral Health Disorders

Behavioral health disorders, including mental illnesses and substance use, are the leading
cause of disability worldwide and are highly prevalent in the United States. An estimated 46.6
million (one in five) American adults live with a mental illness, 24.3 million Americans ages 12
and older have a substance use disorder, and 8.4 million Americans have both a mental illness
and a substance use disorder (National Institute of Mental Health, 2019; Heslin et al., 2015). In
the United States, neuropsychiatric disorders are the leading cause of years lost due to illness,
disability, or premature death (also known as disability adjusted life years (DALYs). The
specific disorders found to be contributing the highest percentages of DALYs are major
depression, drug use, and anxiety disorders (Murray et al., 2013).

Given these circumstances, behavioral health conditions are known to contribute to high
rates of disability, as well as to increased economic and social burden. Individuals with
behavioral health conditions are known to struggle with homelessness, poverty, chronic medical
conditions, and stigma that impacts treatment seeking behavior (Brown et al., 2010; Stafford &
Wood, 2017). The U.S. national expenditure for mental health care and substance use is
estimated at $280.5 billion dollars in 2020 (Substance Abuse and Mental Health Services
Administration (SAMHSA), 2014). When combined with the projected lost earnings and public
disability insurance payments, the estimated financial cost increased to at least $467 billion (Insel, 2008; Insel, 2015).

Not only do behavioral disorders affect morbidity and quality of life, but research indicates these disorders also influence life expectancy and mortality. Adults with serious mental illnesses have shorter life expectancy by approximately 25 years compared to individuals without serious mental illnesses (Substance Abuse and Mental Health Services Administration (SAMHSA), 2016). In addition, from 1999 to 2017, the U.S. national suicide rate increased by 33%, from 10 per 100,000 to 14 per 100,000 (Hedegaard et al., 2018).

A Changing Mental Health Delivery System and Ongoing Challenges

The mental health care delivery system has changed drastically since the 1960s. This began with the Community Mental Health Act signed by President John F. Kennedy in 1963 that initiated the process of deinstitutionalization (Mental Retardation Facilities Construction Act of 1963; Fiorentini, 2015). Deinstitutionalization refers to the process of moving individuals out of state-run “mental asylums” and back into their communities. Funding was shifted from these state-run hospitals to community mental health centers (CMHC) where patients could be treated in less restrictive settings and continue working and living at home. Unfortunately, this process was not sustainable as only half of the proposed CMHC were built and none were fully funded. Communities did not have the resources to provide treatment to this population and therefore many individuals ended up in prisons/jails or homeless (Kliwer et al., 2009).

Presently, there is a clear “workforce crisis” in the behavioral health field. Fifty-five percent of U.S. counties do not have any practicing behavioral health workers. Seventy-seven
percent report having unmet behavioral health needs. The Substance Abuse and Mental Health Services Administration explains that this situation is not only due to demand, but because the behavioral health workforce experiences high turnover rates, ageing workers, and low compensation. This lack of access to behavioral health specialists can drive individuals to inappropriately utilize emergency and hospital services (SAMHSA, 2014), a topic that is closely related to this analysis.

From 2003 to 2011 mental illness related hospitalizations increased at a faster rate than all other types of hospitalizations (Heslin et al., 2015b). In 2012, an estimated 8.6 million inpatient episodes involved at least one mental illness or substance use disorder (MI/SUDs). This means 32.3%, or almost a third, of all inpatient episodes that year were affected by mental health. An astounding 1.8 million inpatient episodes were primarily for a MI/SUD, which accounts for 6.7% of all stays. A greater percentage of these individuals with MI/SUDs (13.9%) are uninsured compared to those without MI/SUDs (6.0%). However, government payers (Medicare and Medicaid) cover a majority (56.0%) of all inpatient episodes, with or without MI/SUDs, suggesting a substantial burden on taxpayers (Heslin et al., 2015a).

In Florida, the data show that inpatient episodes per 100,000 population, associated with mental health conditions either directly or indirectly, increased by 144% between 1992 and 2014. The next highest growth rate in inpatient episodes per 100,000 occurred for diseases of the blood or blood forming organs which increased by 81.2% in the same period (Table 1.1).
Table 1.1. Rates of Inpatient Episodes per 100,000 Population for Diagnosis Groups

<table>
<thead>
<tr>
<th>Diagnosis Group</th>
<th>Year</th>
<th>%Δ (1992-2014)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>92</td>
<td>95</td>
</tr>
<tr>
<td>Infectious/parasitic (001-139)</td>
<td>366</td>
<td>447</td>
</tr>
<tr>
<td>Neoplasms (140-239)</td>
<td>766</td>
<td>713</td>
</tr>
<tr>
<td>Endocrine, nutritional, metabolic (240-279)</td>
<td>383</td>
<td>388</td>
</tr>
<tr>
<td>Blood/blood forming organs (280-289)</td>
<td>115</td>
<td>112</td>
</tr>
<tr>
<td>Mental disorders (290-319)</td>
<td>426</td>
<td>465</td>
</tr>
<tr>
<td>Nervous system/sense organs (320-389)</td>
<td>178</td>
<td>150</td>
</tr>
<tr>
<td>Circulatory system (390-459)</td>
<td>2461</td>
<td>2636</td>
</tr>
<tr>
<td>Respiratory system (460-519)</td>
<td>1064</td>
<td>1218</td>
</tr>
<tr>
<td>Digestive system (520-579)</td>
<td>1169</td>
<td>1130</td>
</tr>
<tr>
<td>Genitourinary system (580-629)</td>
<td>715</td>
<td>601</td>
</tr>
<tr>
<td>Pregnancy, child birth, puerperium (630-679)</td>
<td>1548</td>
<td>1408</td>
</tr>
<tr>
<td>Skin/subcutaneous tissue (680-709)</td>
<td>172</td>
<td>170</td>
</tr>
<tr>
<td>Musculoskeletal system (710-739)</td>
<td>549</td>
<td>521</td>
</tr>
<tr>
<td>Congenital anomalies (740-759)</td>
<td>47</td>
<td>39</td>
</tr>
<tr>
<td>Originating in perinatal period (760-779)</td>
<td>39</td>
<td>37</td>
</tr>
<tr>
<td>Symptoms, signs, ill-defined (780-799)</td>
<td>543</td>
<td>541</td>
</tr>
<tr>
<td>Injury &amp; poisoning (800-999)</td>
<td>1023</td>
<td>965</td>
</tr>
</tbody>
</table>

*Values in parentheses are ICD9CM three-digit stems.

Of particular interest to this research is the observation that many individuals with MI/SUDs are prone to hospital readmissions. The two most common diagnoses associated with readmissions are mood disorders and schizophrenia. In 2012, 15% of initial inpatient episodes for mood disorders were readmitted for any cause within 30 days, whereas 22% of inpatient stays for schizophrenia involved readmission. Individuals covered by Medicare or Medicaid had 40 to 75% higher rates of 30-day readmission than individuals with private insurance or the uninsured (Heslin et al., 2015b). Such high readmission rates are known to indicate poor clinical outcomes for patients and are associated with poor-quality care and lack of coordination with community-based aftercare.

Most scientists believe mental illnesses and substance use disorders originate from issues with neurotransmission in the brain, specifically serotonin, dopamine, and norepinephrine (National Institute of Health (NIH), 2007). For example, individuals with depression have been
found to exhibit lower levels of serotonin. This led to the development of selective serotonin reuptake inhibitors, also known as SSRIs, which increase the volume of serotonin available at the synapse of neurons. Another example is the decreased levels of norepinephrine in brain of individuals with Attention Deficit Hyperactivity Disorder (ADHD). The dysfunctioning transporter system can be treated with norepinephrine reuptake inhibitors which increase the synaptic level of norepinephrine that is available.

**Natural Environment and Weather**

The development of a behavioral disorder may be influenced by an array of factors that are interrelated. This includes biological (genetics) and environmental factors (overcrowding, abuse, poverty, parent’s mental illness, poor nutrition, head injury, exposure to toxins, weather, etc.; NIH, 2007). The biological foundation of behavioral disorders has been heavily investigated using hereditary, familial, and twin studies (NIH, 2007). Specific genes have been associated with an increased risk of developing illnesses such as schizophrenia, bipolar disorder, major depressive disorder, Alzheimer’s, and obsessive-compulsive disorder (NIH, 2007; Gandal et al., 2018). In addition to this biological component, the environment, both prenatally and postnatally, has been shown to contribute to behavioral disorders (NIH, 2007).

Parks and recreational areas are an essential part of the natural environment of most communities. Multiple economic, social, and health benefits are associated with the availability and access to public parks. For example, in 2013, local and regional parks combined with national and state park systems contributed $200 billion in economic activity and generated one million jobs (Recreation and Park Administration, 2018). Green spaces, such as parks, also
improve local tax base and increase property values (Recreation and Park Administration, 2018). 
Cities with higher tree density also have an approximate $400 billion savings in storm retention 
facility costs (Recreation and Park Administration, 2018). Businesses also cite quality parks and 
recreation as one of the top three reasons for relocating (Recreation and Park Administration, 
2018). Therefore, parks and recreational areas may play a significant role in local economies.

Concerning health, access to parks and recreational areas increase residents’ physical 
activity levels and improve community health overall (Recreation and Park Administration, 
2018). Previous studies found that individuals who spend prolonged periods of time visiting 
parks have lower blood pressure, reductions in stress, and improved perceived physical health 
(Recreation and Park Administration, 2018). Parks are natural environments that provide 
vegetative buffers to urban development and allow residents to connect with nature. 
Furthermore, parks provide a place for families and social groups to gather regardless of age or 
economic status and have been linked to reductions in crime and vandalism (Recreation and Park 
Administration, 2018).

In addition to the traditional green spaces, blue spaces, which refers to specific water 
environments such as coastal and river front areas, have also been found to promote social 
connectedness, exercise, and relaxation (Volker et al., 2018). Investigations by Wheeler et al. 
(2012) and White at al. (2013) both found that individuals living in closer proximity to the 
seashore were more likely to be in good health and that coastal regions promoted better mental 
health than those living further away. However, blue space has not been investigated as 
thoroughly as green space (Foley and Kistemann, 2015; Volker and Kistemann, 2011). 
Exploration of neighborhood features such as green and blue space allows for a deeper
understanding of mental health promotion and therefore may assist in reducing this major source of disease burden.

Weather, on the other hand, is a key environmental factor affecting the entire globe and known to affect behavioral health. Acute weather events such as hurricanes and earthquakes have been found to increase the likelihood of developing a new behavioral disorder or significantly exacerbate symptoms of pre-existing behavioral disorders. For example, Sullivan et al. (2013) found veterans with preexisting mental illnesses (mood disorders, anxiety, PTSD, or schizophrenia) prior to Hurricane Katrina were 6.8 times more likely to develop a new disorder compared to veterans with no preexisting mental illness. Six months after the 2008 earthquake in Sichuan Province, China which killed over 15,000 people, Liu et al. (2011) surveyed 330 children effected and found 23.3% experienced anxiety, 14.5% experienced depression, and 11.2% experienced post-traumatic stress disorder (PTSD). Furthermore, six months after Hurricane Maria made landfall in Puerto Rico, Scaramutti et al. (2019) found 65.7% of displaced Puerto Ricans experienced PTSD, 25% experienced anxiety, and 46.5% experienced depression.

Chronic weather events, such as extreme heat, have been equally likely to influence an individual’s behavioral health. Heat is a significant environmental factor because heat-related deaths are the leading cause of weather-related mortality in the United States (EPA) and patients with mental illnesses have twice the risk of mortality during a heat wave than the general population (Bark, 1998). Globally, researchers have investigated the impact of heat on numerous types of behavioral disorders and related outcomes such as mortality. Heat and humidity have been linked to increase incidence of mental stress, depression, violence, and aggression (Hansen et al., 2008). A study conducted by Basagana et al. in Catalonia, Spain found a statistically significant 19% increase in suicide rates on extremely hot days (81.1 °F to 100.4 °F). Shiloh et
al. (2007) experimentally increased psychiatric ward temperatures in Israel and found that the delusions and hallucinations experienced by patients with schizophrenia were temperature sensitive. In terms of substance use, Page et al. (2012) found individuals in England with primary diagnoses of alcohol abuse or substance misuse had an increased risk of mortality as temperatures increased.

Researchers proposed three key explanations for why individuals with behavioral health disorders are highly vulnerable to heat-related morbidity and mortality.

1) **Underlying physical pathology:** In a literature review, Chong and Castle (2003) found that individuals with schizophrenia had higher baseline temperatures, abnormal daily range of temperature and diurnal variation, and an impaired ability to lose heat compared to controls without schizophrenia. Therefore, it is hypothesized that individuals with behavioral disorders which change anatomical pathology could make them innately more susceptible to temperature related illnesses.

2) **Effects of psychiatric medications:** Medications known to act on the monoamine neurotransmitters such as serotonin, dopamine, and noradrenaline have been found to suppress the function of the thermoregulatory center within the anterior hypothalamus (Cusack et al, 2010). This can lead to anhidrosis, the inability to sweat, and serotonergic syndrome, which leads to hyperthermia (Cusack et al, 2010). Particularly neuroleptic (antipsychotics) and anticholinergic (antiparkinsonian) medications have been associated with heat intolerance and heat stroke and specific serotonin reuptake inhibitors (SSRI’s) and serotonin and noradrenaline reuptake inhibitors (SNRI’s), used for treatment of anxiety and depression, have been found to play a role in hyperthermia which is exacerbated by heat waves (Cusack et al, 2010; Martin-Latry et al., 2007). On the other
hand, substances such as alcohol and opioids have been found to increase cutaneous
vasodilation and perspiration which lowers body temperature but increases the risk for
dehydration (Cusack et al, 2010).

3) *Physical and mental impairment interfering with one's ability to cope and adapt to
temperature changes:* Individuals with behavioral health disorders are found to have
decreased cognition of their environment and higher risk of overlooking preventative
measures for heat-related illness such as removing excess clothing and drinking
additional fluids (Wang, 2013; Bark, 1998; Hansen et al., 2008). Furthermore, those with
severe activity limitations and high dependency on others, such as senility, can contribute
to this susceptibility (Hansen et al., 2008).

However, these factors are only part of the context in which an individual operates.
Figure 1.1 illustrates the conceptual framework of the relationship between climate change and
health provided by the researchers working on the U.S. Global Change Research Program
(Balbus et al., 2016). Climate drivers essentially represent all the identified threats of climate
change that are said to occur as time persists. This includes more frequent elevated temperature,
prolonged heat waves, and seasonal timing of events. Humans are exposed to climate change
effects through different exposure pathways which can ultimately lead to health effects. These
exposure pathways differ for each individual and community.

**Literature Gaps and Proposed Hypotheses**

Although researchers tend to investigate climate change threats individually (i.e. one
hurricane, one heat wave, one forest fire, etc.), climate change threats can occur simultaneously,
and effects can accumulate leading to long-term changes in resilience and health. Whether or not
an individual will be affected by exposure depends on a complex set of vulnerability factors.
Vulnerability factors are described as the “predisposition to be adversely affected by climate-
related health effects.” This includes individual level factors that originate from the social and
behavioral context such as poverty, homelessness, access and use of air conditioning, chronic
illness, commuting, medication use, etc. These social determinants of health shape the conditions
in which people are born, grow, live, work, and age and are known to influence health outcomes.
Vulnerability also stems from the community/societal level factors which originate from the
environmental and institutional context. This includes the infrastructure of the natural and built
environment and the adaptability of governance, management, and institutions.

In terms of individuals living with behavioral health disorders, previous literature has
focused on solidifying the link between exposure pathways (elevated temperatures) and health
outcomes (behavioral health related death, ED visit, or inpatient visit). Numerous studies have
established the relationship between high temperature and death rates, ED utilization, and
hospital admissions, however an in depth review of the literature revealed a gap in knowledge in
terms of key factors from the social and behavioral context such as socioeconomic status,
household composition and disability, minority status and language, housing and transportation,
and the availability of behavioral health care services such as mental health specialist, mental
health practitioners, outpatient centers, and residential facilities.
Social vulnerability factors such as the ones mentioned above play an important role in health outcomes. For example, poverty is associated with higher rates of illness and nutritional deficits. This can limit individual’s adaptive capacity and therefore make them more vulnerable to climate and weather threats (Balbus et al., 2016). Furthermore, individuals who are uninsured, living in lower income zip codes, and racial/ethnic minorities may also be increasingly vulnerable to heat morbidity due to inequities in access to care, discrimination, and lack of education (Schmeltz et al., 2016).

Figure 1.1. Climate change and health conceptual diagram. Adapted from “The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment,” by Sarofim et al., 2016, Figure 2.1: Climate Change and Health-Extreme Heat. Used with Permission.
Furthermore, availability of health care services affects mental health status and quality of life. As of December 2018, Florida is considered a mental health care health professional shortage area (HPSA; Kaiser Family Foundation, 2018). Therefore, it is imperative to understand whether access to certain types of behavioral health providers in certain counties is associated with lower rates of ED and hospital utilization.

Accordingly, hypotheses 1a and 1b (Figure 1.2) are as follows:

**H1a. Counties with higher social vulnerability indexes have a significantly higher rate of heat-related ED visits by individuals with behavioral health disorders.**

**H1b. Counties with less behavioral health providers have a significantly higher rate of heat-related ED visits by individuals with behavioral health disorders.**

Furthermore, research has primarily focused on the rates of hospital utilization as temperatures rise but they have not assessed hospital utilization patterns among individuals exposed to heat and living with a behavioral health disorder. This is due to the fact that most researchers are utilizing deidentified publicly available datasets which inhibits tracking of patients. ED revisits and hospital readmissions are important quality indicators. Individuals with prior heat-related illnesses are found to be more susceptible to another heat-related event (revisit or readmission) due to neurological and organ damage, in addition to increased heat intolerance (Morano, 2016; Epstein, 1990; Shapiro et al., 1979; O’Conner et al., 2010).

Therefore, hypotheses 2 and 3 (Figure 1.2) are:
**H2.** Of all patients who visited a Florida ED for a heat-related illness, those who had a co-occurring behavioral health disorder (BHD) will be more likely to revisit the ED within 30 days and 365 days for a heat-related illness compared to those with no BHD.

**H3.** Of all patients who had an inpatient admission to a Florida hospital for a heat-related illness, those who had a co-occurring behavioral health disorder (BHD) will be more likely to be re-admitted as an inpatient within 30 days and 365 days for a heat-related illness compared to those with no BHD.

**Figure 1.2.** Flow Chart Illustration of Hypotheses Related to Co-Occurring Heat-Related Illness and Behavioral Health Disorders
Overall, previous literature clearly indicates that individuals with behavioral health disorders are more susceptible to heat-related morbidity and mortality than the general population however, not much is known about the social determinants and hospital utilization patterns of these individuals. Investigation of this topic will assist health care providers, public health practitioners, city planners, and policy makers in identifying interventions, such as patient/provider education, changes to the built environment (i.e. addition of shade and fans at bus stops, easily accessible hydration stations), home visits for elderly or disabled living alone etc., to prevent avoidable heat-related morbidity and mortality.

From the environmental and institutional context, incorporation and preservation of natural environments within urban settings would fall under city planning. Most literature investigating nature and its impact on mental health has focused on self reported information from surveys and questionnaires, in combination with geographic information such as tree density and proximity to parks (Volker et al., 2018; Karden et al., 2015). This proposed investigation substitutes self-reported perceived mental health with an objective health outcome: ED utilization.

Further investigation of how public park and beach availability influence health outcomes, such as anxiety and depression related ED visits, is needed to understand whether natural environments can be used to decrease preventable hospital utilization.

Therefore, hypothesis 4 is:

\[ H4. \text{Zip codes with a greater availability of public parks and beaches will have a significantly lower rate of anxiety and depression related ED visits.} \]
Abbreviations:

BHD- Behavioral Health Disorder

HRI- Heat-Related Illness

ED- Emergency Department

IP- Inpatient Setting

References


Kaiser Family Foundation. (2019). Mental Health Care Health Professional Shortage Areas. Available online at https://www.kff.org/other/state-indicator/mental-health-care-health-professional-shortage-areas-hpsas/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort %22:%22asc%22%7D.


CHAPTER TWO:

THE IMPACT OF SOCIAL VULNERABILITY INDEX AND AVAILABILITY OF BEHAVIORAL HEALTH PROVIDERS ON HOSPITAL UTILIZATION

Introduction

When examining health care outcomes, most theoretical models consider not only direct individual-level risk factors, but also the community-level contextual characteristics that influence health outcomes and disparities. For example, the Anderson Health Care Utilization Model defines contextual characteristics as “the circumstances and environment of health care access (Anderson, 2001).” This includes community characteristics such as distribution of health organizations, provider-related factors, demographic characteristics, social characteristics, health policy, physical environment, etc. all measured at the aggregate rather than individual level (Anderson, 2001; Anderson & Newman, 1973). Factors such as these have been found to impact the health outcomes of individuals with behavioral health disorders.

The Substance Abuse and Mental Health Services Administration (SAMHSA, 2016) found that adults aged 26 or older living below the poverty line were more likely to experience severe mental illness than those living at or above the poverty line (7.5% vs. 4.1% and 3.1% respectively; SAMHSA, 2016). Furthermore, adults with behavioral disorders who are living in poverty are more likely to have higher health care costs, decreased productivity, and poor general
health (SAMHSA, 2016). In addition, unemployment and lack of affordable housing are identified as risk factors that exacerbate mental health and substance use disorders (SAMHSA, 2019). Individuals without adequate transportation have been shown to delay health care which increases unmet health care needs and worsens health outcomes (Syed et al., 2013). Racial and ethnic minorities tend to be disproportionately affected by these factors (i.e. poverty, lack of insurance, homelessness) and they have higher rates of unmet health care needs, less participation in treatment, and overrepresentation in inpatient and emergency departments (Chow et al., 2003).

Although heat-related illness and behavioral health disorder have been investigated in emergency departments and inpatient hospital settings, contextual characteristics such as social vulnerability factors as predictors of these events have yet to be explored. Social vulnerability is defined by the Centers of Disease Control and Prevention (CDC) as the resilience of a community when confronted with external stresses such as natural disasters (CDC, 2018b). It is believed that by reducing social vulnerability, human suffering and economic loss can be decreased (CDC, 2018b). The social vulnerability index (SVI), developed by the CDC, isolates 15 variables from the U.S. census and categorizes them into four themes: socioeconomic status, household composition and disability, minority status and language, and housing and transportation (CDC, 2018b).

Lack of practitioners and availability of services is another key factor known to impact health outcomes. Fifty five percent of U.S. counties do not have any practicing behavioral health workers (SAMHSA, 2014). Seventy-seven percent report having unmet behavioral health care needs (SAMHSA, 2014). This lack of behavioral health specialist availability (such as outpatient centers, residential centers, mental health physicians, and mental health practitioners)
can drive individuals to inappropriately utilize emergency and hospital services (SAMHSA, 2014), a topic which is closely related to this analysis.

These social, economic, and environmental factors can predict 50% of a community’s health outcomes and have a significant impact on residents’ longevity and quality of life (County Health Rankings, 2019). Individuals who live in poverty, have disabilities, are from a minority group, are unable to speak English, do not have a vehicle, or live in crowded areas are disproportionately vulnerable to poor health outcomes and environmental stressors such as heat (County Health Rankings, 2019). Understanding the community in which a person resides can enhance insight into external factors that might be impacting their health care utilization and outcomes.

The purpose of this study is to investigate the effect of contextual characteristics on the rate of emergency department and inpatient visits for individuals with comorbid diagnoses of heat-related illnesses and behavioral health disorder in Florida counties. It is hypothesized that 1) counties with higher social vulnerability indexes will have a significantly higher rate of ED and inpatient visits for individuals with comorbid heat-related illness and behavioral health disorder than those counties with lower social vulnerability indexes and 2) counties with fewer behavioral health providers will have a significantly higher rate of ED and inpatient visits for individuals with comorbid heat-related illness and behavioral health disorder compared to those counties with more behavioral health providers.
Methods

Data Description

This study utilized de-identified Florida emergency department and inpatient data from the 2016-2018 Agency for Health Care Administration (AHCA). The data contain demographic information (patient sex, age, race, and ethnicity), patient zip code and county, length of service, arrival and discharge time, principal payer, principal and up to nine other diagnoses that are classified by the International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10-CM) and total gross charges. The Centers for Disease Control Social Vulnerability Index dataset contains 15 U.S. census variables including poverty, lack of vehicle access, and crowded housing, and groups them into four related themes. The four theme rankings are then combined to create an overall ranking that measures overall resiliency of communities. The United States Census Bureau County Business Patterns data provides subnational economic data by industry and provides information such as the number of establishments, employment, first quarter payroll, and annual payroll. An in-depth description of the dependent and independent variables can be found below.

Rate of Emergency Department Visits and Inpatient Admissions

The rate of ED visits and inpatient hospital admissions for persons with co-occurring primary and/or secondary diagnoses of heat-related illness (HRI) and behavioral health disorder (BHD) per 100,000 of population in each Florida county (n=67) were the outcomes of interest (dependent variable). This rate was calculated using individuals who were specifically designated as Florida residents. Foreign patients, homeless patients, and individuals from states
other than Florida were omitted (n=1,417). Visits involving cases with heat-related illness diagnoses (ICD-10 T67 and X30) and concurrent behavioral health disorder diagnoses (ICD-10 F00-F99) were identified and the total number of such visits was divided by the county population (obtained from U.S. Census). Population data were available through 2017. The 2018 population data were extrapolated using the average population growth rate for each county for the previous past 6 years (2012-2017).

**Social Vulnerability Index (SVI)**

The Centers of Disease Control and Prevention created publicly accessible files which contain social vulnerability indexes at either the county level or census tract level for each state (CDC, 2018b). Since the AHCA data includes county (but not census tract) of residence for each patient, the SVI data set were merged with the AHCA data by county. There are four social vulnerability variables of interest for each county: 1) socioeconomic status, 2) household composition and disability, 3) minority status and language, and 4) housing and transportation (Figure 2.1). The possible values for each social vulnerability variable ranges from zero to one. The higher the value, the more vulnerable the population. The SVI data set also includes an overall vulnerability rating for each county that takes into account all four themes. More information regarding the social vulnerability index can be found at [https://svi.cdc.gov/factsheet.html](https://svi.cdc.gov/factsheet.html).
Physical Access to Care

Using the United States Census Bureau County Business Patterns data, the North American Industry Classification System (NAICS) for behavioral health related businesses were identified. This included physician offices with mental health specialists (NAICS category 621112), offices of mental health practitioners (except physicians; NAICS category 621330), outpatient mental health and substance abuse centers (NAICS category 621420), and residential mental health and substance abuse facilities (NAICS category 623220). Detailed definition for

Figure 2.1. has been previously published in Spatial Analysis of Social Vulnerability and Heat-Related Health Outcomes in Georgia, 2018, Copyright 2018 by Public Domain. Reprinted with permission.
each of these business can be found in Figure 2.2 or online at https://www.census.gov/cgi-bin/sssd/naics/naicsrch?chart=2017. The most recent iteration of this dataset was from 2016.

Therefore, 2017 and 2018 county mental health business data was extrapolated using the average growth rate for each county over the previous five years (2012-2016).

### Figure 2.2. Behavioral Health Related North American Industry Classification System (NAICS) Definitions

#### Demographic Factors (Confounding Variables)

Using county level census data, specific demographic factors (not included in the social vulnerability index) were used as control variables. In order to avoid issues of multicollinearity, one unique variable, gender, was included. Therefore, for each county, the population percentage

<table>
<thead>
<tr>
<th>NAICS Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>621112</td>
<td>Number of physician offices with mental health specialists&lt;br&gt;• Comprises of establishments of health practitioners having the degree of M.D. (Doctor of Medicine) or D.O. (Doctor of Osteopathy) primarily engaged in the independent practice of psychiatry or psychoanalysis.</td>
</tr>
<tr>
<td>621330</td>
<td>Offices of Mental Health Practitioners (except Physicians)&lt;br&gt;• Comprises of establishments of independent mental health practitioners (except physicians) primarily engaged in (1) the diagnosis and treatment of mental, emotional, and behavioral disorders and/or (2) the diagnosis and treatment of individual or group social dysfunction brought about by such causes as mental illness, alcohol and substance abuse, physical and emotional trauma, or stress.</td>
</tr>
<tr>
<td>621420</td>
<td>Outpatient Mental Health and Substance Abuse Centers&lt;br&gt;• Comprises of establishments with medical staff primarily engaged in providing outpatient services related to the diagnosis and treatment of mental health disorders and alcohol and other substance abuse.&lt;br&gt;• These establishments generally treat patients who do not require inpatient treatment. They may provide a counseling staff and information regarding a wide range of mental health and substance abuse issues and/or refer patients to more extensive treatment programs, if necessary.</td>
</tr>
<tr>
<td>623220</td>
<td>Residential Mental Health and Substance Abuse Facilities&lt;br&gt;• Comprises of establishments primarily engaged in providing residential care and treatment for patients with mental health and substance abuse illnesses. These establishments provide room, board, supervision, and counseling services. Although medical services may be available at these establishments, they are incidental to the counseling, mental rehabilitation, and support services offered. These establishments generally provide a wide range of social services in addition to counseling.</td>
</tr>
</tbody>
</table>
of males was included in the regression model. Furthermore, in order to account for intercounty variability in population density, the most recent county level rural-urban continuum codes were used to identify metropolitan and non-metropolitan. Each county is assigned one of nine codes ranging from counties in metropolitan areas of 1 million population or more (1) to non-metropolitan counties in completely rural areas/areas less than 2,500 urban population (9; United States Department of Agriculture, 2013). Florida counties identified as non-metropolitan were added to the model and metropolitan counties were used as a reference.

**Statistical Analyses**

Descriptive analyses were conducted for the dependent variable and independent variables. A linear regression model was used to assess the association between the rate of ED and inpatient visits for co-occurring HRIs and BHDs per county, controlling for covariates. The research question associated with this model is: What contextual factors influence the rate of ED and inpatient visits for individuals with co-occurring HRI and BHD?

The proposed model is as follows:

$$\text{Rate}_c = \alpha + \beta_c X_c + \gamma_c V_c + \lambda_c P_c + \epsilon$$

$C =$ county level aggregate

$X =$ vector of county level demographics and inpatient care access

$V =$ vector of county level vulnerability factors

$P =$ vector of county level behavioral health providers
\[ Rate_c \] is defined as the rate of HRI and BHD ED or inpatient visits per 100,000 in each county (67 total). \[ X_c \] is defined as gender distribution. \[ V_c \] is defined as the social vulnerability factors which include socioeconomic status, household composition and disability, minority status and language, housing and transportation and \[ P_c \] is defined as the number of behavioral health care services such as mental health specialists, mental health practitioners, outpatient centers, residential facilities. In addition to behavioral health providers, the model includes bed days used per population for each county in the previous year. This variable reflects the capacity of the county’s inpatient facilities and acts as a proxy for availability, or access, to inpatient services. Data for each county was analyzed by quarters for each year of analysis. Therefore, the potential for correlation among repeated observations exists. To account for this correlation in the data, a generalized estimation equations (GEE) model with logit distribution was used to produce robust standard errors and examine the influence of the treatment variable (Ziegler and Liang, 1986).

**Results**

Descriptive analyses were conducted and used in conjunction with ArcMap to illustrate which counties had the highest rates of HRI and BHD related ED and inpatient visits (Figure 2.3 and 2.4). The top five counties with the highest average rate of HRI and BHD related ED visits per 100,000 population were Okeechobee (10.50), Bradford (9.26), Gulf (8.94), Franklin (8.45), and Jackson (8.10) counties. The counties with the highest average rate of HRI and BHD related inpatient visits per 100,000 population were Jefferson (7.11), Gilchrist (5.67), Holmes (5.13), Bradford (4.93), and Hardee (4.38).
Figure 2.3. Average Rate of Co-Occurring HRI and BHD ED Visits per 100,000

Figure 2.4. Average Rate of Co-Occurring HRI and BHD Inpatient Visits per 100,000
For average social vulnerability index over the three-year period (2016-2018), Hamilton (SVI=1.00), Hardee (SVI=0.98), Hendry (SVI=0.97), DeSoto (SVI=0.95), and Gadsden (SVI=0.94) were found to be the most vulnerable counties. On the other hand, Sarasota (SVI=0.00), St. Lucie (SVI=0.02), Sumter (SVI=0.03), Santa Rosa (SVI=0.05), and Nassau (SVI=0.06), were found to be the least vulnerable counties.

Table 2.1 summarizes key demographic characteristics for the dependent variable: individuals with co-occurring BHD and HRI. A majority of the population from 2016 through 2018 is male (ED=78.56%; Inpatient=83.33%), white race (ED=75.49%; Inpatient=72.84%), and non-Hispanic ethnicity (ED=89.62%; Inpatient=86.45%). In the ED, approximately 88.47% of the population were between the age of 18 and 65 with an average age of 41.67 years. In the inpatient setting, the majority of the population were between the age of 18 to 65 (77.37%), however 21.68% of the inpatient population were 65 and older which is more than double compared to the ED (9.39%). The inpatient average age was 50.30 years. In terms of insurance status, a high percentage of individuals with HRI and BHD in the emergency room were uninsured (37.95%). In the inpatient setting, a majority of patients have either Medicaid (31.28%) or are uninsured (29.80%). Over half of the ED and inpatient visits for co-occurring HRI and BHDs (ED=59.81%; inpatient=64.14%) occur during the third quarter of the year (July-September) which tends to be the warmest time period.
Table 2.1. Average Distribution of Demographic Characteristics Among Individuals with Co-Occurring BHD and HRI Emergency and Inpatient Visits from 2016-2018

<table>
<thead>
<tr>
<th></th>
<th>Emergency Department</th>
<th>Inpatient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N = 4,954</td>
<td>N= 1,896</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>3,892 (78.56%)</td>
<td>1,580 (83.33%)</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;18</td>
<td>105 (2.12%)</td>
<td>17 (0.90%)</td>
</tr>
<tr>
<td>18-64</td>
<td>4,383 (88.47%)</td>
<td>1,467 (77.37%)</td>
</tr>
<tr>
<td>65+</td>
<td>465 (9.39%)</td>
<td>411 (21.68%)</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>3,740 (75.49%)</td>
<td>1,381 (72.84%)</td>
</tr>
<tr>
<td>Black</td>
<td>928 (18.73%)</td>
<td>372 (19.62%)</td>
</tr>
<tr>
<td>Other</td>
<td>286 (5.77%)</td>
<td>143 (7.54%)</td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>514 (10.38%)</td>
<td>257 (13.55%)</td>
</tr>
<tr>
<td>Insurance Status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>1,880 (37.95%)</td>
<td>565 (29.80%)</td>
</tr>
<tr>
<td>Private</td>
<td>974 (19.66%)</td>
<td>274 (14.45%)</td>
</tr>
<tr>
<td>Medicaid</td>
<td>745 (15.04%)</td>
<td>232 (12.24%)</td>
</tr>
<tr>
<td>Medicare</td>
<td>774 (15.62%)</td>
<td>593 (31.28%)</td>
</tr>
<tr>
<td>Other</td>
<td>581 (11.73%)</td>
<td>232 (12.24%)</td>
</tr>
<tr>
<td>Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quarter 1 (Winter)</td>
<td>163 (3.29%)</td>
<td>45 (2.37%)</td>
</tr>
<tr>
<td>Quarter 2 (Spring)</td>
<td>1,473 (29.73%)</td>
<td>504 (26.58%)</td>
</tr>
<tr>
<td>Quarter 3 (Summer)</td>
<td>2,963 (59.81%)</td>
<td>1,216 (64.14%)</td>
</tr>
<tr>
<td>Quarter 4 (Fall)</td>
<td>355 (7.17%)</td>
<td>131 (6.91%)</td>
</tr>
</tbody>
</table>

Table 2.2 summarizes key descriptive statistics for the independent variables including the measures of central tendency (mean, median, mode) and measures of dispersion (standard deviation (SD)). Of the four type of behavioral health providers, on average there were more behavioral health practitioners (non-MD and non-DO’s; 5.69 per 100,000 population +/- SD 4.42) than any other behavioral health provider type. Bed days used per population refers to the utilization rate of the county’s inpatient services. The average number of bed days utilized in Florida between 2016-2018 is 477.13 (+/- SD 328.96) per 1,000 population. One county with a large teaching hospital had as many as 1,706 bed days used whereas others had as little as 4 bed days used per 1,000 population.
Table 2.2. Descriptive Statistics of Independent Variables at the County Level in Florida from 2016-2018

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>BH MD/DO’s per 100,000</td>
<td>2.96</td>
<td>2.92</td>
<td>0</td>
<td>8.89</td>
<td>2.51</td>
</tr>
<tr>
<td>BH non-MD/non-DO per 100,000</td>
<td>5.69</td>
<td>4.78</td>
<td>0</td>
<td>17.38</td>
<td>4.42</td>
</tr>
<tr>
<td>BH Residential Centers Per 100,000</td>
<td>1.47</td>
<td>1.13</td>
<td>0</td>
<td>12.19</td>
<td>1.96</td>
</tr>
<tr>
<td>BH Outpatient Centers Per 100,000</td>
<td>4.14</td>
<td>2.42</td>
<td>0</td>
<td>108.10</td>
<td>9.29</td>
</tr>
<tr>
<td>SVI Overall</td>
<td>0.47</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
<td>0.29</td>
</tr>
<tr>
<td>Theme 1- Socioeconomic Vulnerability</td>
<td>0.47</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
<td>0.29</td>
</tr>
<tr>
<td>Theme 2- Household Composition</td>
<td>0.48</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
<td>0.29</td>
</tr>
<tr>
<td>Theme 3- Minority Status</td>
<td>0.51</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
<td>0.29</td>
</tr>
<tr>
<td>Theme 4- Housing and Transportation</td>
<td>0.47</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
<td>0.29</td>
</tr>
<tr>
<td>Percent Male</td>
<td>50.61</td>
<td>49.17</td>
<td>47.08</td>
<td>65.65</td>
<td>3.19</td>
</tr>
<tr>
<td>Percent White</td>
<td>80.70</td>
<td>82.95</td>
<td>41.40</td>
<td>93.29</td>
<td>9.51</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>30.08</td>
<td>19.86</td>
<td>4.90</td>
<td>138.29</td>
<td>26.55</td>
</tr>
<tr>
<td>Bed Days Used per 1,000</td>
<td>477.13</td>
<td>522.04</td>
<td>3.70</td>
<td>1,705.55</td>
<td>328.96</td>
</tr>
</tbody>
</table>

Multiple regressions models were created for both the emergency and inpatient settings utilizing different confounding variables (Table 2.3-2.6). The objective of creating several models was to understand the association between the composite SVI and the four separated themes. Furthermore, other isolated census variables were explored, but ultimately it was determined that due to multicollinearity issues gender was the only added variable that could be included. Therefore, model H was determined to be the most parsimonious model. The remaining models are included for comparative purposes.

In regard to availability of behavioral health providers in each county, the hypothesis that increased behavioral health provider availability would be significantly associated with decreased rates of hospital utilization was supported for outpatient centers only. Outpatient centers were found to have a statistically significant impact on the rate of ED and inpatient visits for co-occurring HRI and BHDs. As the number of outpatient centers devoted to behavioral health increases, the rate of co-occurring HRI and BHD related ED visits decrease (p<.0001; Table 2.4). In the IP setting, the beta estimate was slightly positive (p=0.004; Table 2.6). In terms of gender, counties with a higher percentage of males were found to have
significantly higher rates of co-occurring HRI and BHD ED visits (p<.0001). The hypothesis that higher SVI would be associated with lower rates of hospital utilization was not supported. The SVI overall, which is a composite of the four SVI themes and a key variable of interest, was not statistically significant for both the ED and IP models.

**Discussion**

In this study, we explored how social vulnerability factors and availability of behavioral health providers impact the rate of ED and inpatient utilization for co-occurring HRI and BHDs in Florida from 2016-2018. It was hypothesized that counties with higher social vulnerability and less behavioral health providers would be associated with significantly higher rates of hospital utilization. In terms of behavioral health care providers, the hypothesis was partially supported as outpatient centers were found to significantly influence the rate of co-occurring BHD and HRI ED and inpatient visits. However, the SVI variable did not significantly predict hospital utilization in this context and therefore the hypothesis was unsupported. Male gender and bed availability were both found to be associated with ED visits and the summer months were found to have a significantly higher rates of co-occurring cases compared to other times of the year.

Historically, after deinstitutionalization of mental asylums in the 1960s, outpatient centers such as community mental health centers were assumed to take on the role as the main health care providers for individuals with mental health and substance use disorders. Unfortunately, to this day, many communities do not have the resources to provide treatment to this population and therefore, when in need of care, these individuals end up in high cost, acute care settings such as hospitals. Keeping this in mind, the results of this study suggests that
<table>
<thead>
<tr>
<th>Model:</th>
<th>Parameter Estimate</th>
<th>p-value</th>
<th>Parameter Estimate</th>
<th>p-value</th>
<th>Parameter Estimate</th>
<th>p-value</th>
<th>Parameter Estimate</th>
<th>p-value</th>
<th>Parameter Estimate</th>
<th>p-value</th>
<th>Parameter Estimate</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-29.3441</td>
<td>0.0012*</td>
<td>-31.7668</td>
<td>0.0012*</td>
<td>-30.3975</td>
<td>0.0020*</td>
<td>-28.8436</td>
<td>0.0027*</td>
<td>-27.6987</td>
<td>0.0009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH MD/DO’s per 100,000</td>
<td>-0.091</td>
<td>0.6626</td>
<td>-0.0418</td>
<td>0.8483</td>
<td>-0.1368</td>
<td>0.4871</td>
<td>-0.1904</td>
<td>0.3350</td>
<td>-0.0524</td>
<td>0.8046</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH non-MD/non-DO per 100,000</td>
<td>0.0246</td>
<td>0.8093</td>
<td>0.0486</td>
<td>0.6231</td>
<td>0.0798</td>
<td>0.384</td>
<td>0.0293</td>
<td>0.7638</td>
<td>0.0401</td>
<td>0.6663</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH Residential Centers Per 100,000</td>
<td>0.0342</td>
<td>0.7158</td>
<td>0.018</td>
<td>0.8510</td>
<td>0.0332</td>
<td>0.7207</td>
<td>0.0393</td>
<td>0.6694</td>
<td>0.0382</td>
<td>0.6862</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH Outpatient Centers Per 100,000</td>
<td>-0.1167</td>
<td>&lt;0.001*</td>
<td>-0.113</td>
<td>&lt;0.001*</td>
<td>-0.1123</td>
<td>&lt;0.001*</td>
<td>-0.1159</td>
<td>&lt;0.001*</td>
<td>-0.1167</td>
<td>&lt;0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVI Overall</td>
<td>2.139</td>
<td>0.0406*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.3985</td>
<td>0.6990</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Theme 1- Socioeconomic Vulnerability</td>
<td>-</td>
<td>-</td>
<td>1.3493</td>
<td>0.1981</td>
<td>0.812</td>
<td>0.4080</td>
<td>-</td>
<td>-</td>
<td>1.9837</td>
<td>0.0337*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Theme 2- Household Composition</td>
<td>-</td>
<td>-</td>
<td>1.0054</td>
<td>0.1700</td>
<td>1.1923</td>
<td>0.1153</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Theme 3- Minority Status</td>
<td>-</td>
<td>-</td>
<td>1.5257</td>
<td>0.2737</td>
<td>-1.1107</td>
<td>0.9179</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Theme 4- Housing and Transportation</td>
<td>-</td>
<td>-</td>
<td>-1.5271</td>
<td>0.2237</td>
<td>-1.948</td>
<td>0.1671</td>
<td>-</td>
<td>-</td>
<td>-1.3045</td>
<td>0.3103</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Male</td>
<td>0.5857</td>
<td>&lt;0.001*</td>
<td>0.6348</td>
<td>&lt;0.001*</td>
<td>0.6469</td>
<td>&lt;0.001*</td>
<td>0.6046</td>
<td>0.0002*</td>
<td>0.59</td>
<td>&lt;0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent White</td>
<td>0.0713</td>
<td>0.0358*</td>
<td>0.0623</td>
<td>0.094</td>
<td>0.0417</td>
<td>0.1720</td>
<td>0.0541</td>
<td>0.0641</td>
<td>0.0506</td>
<td>0.1188</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>-0.0224</td>
<td>0.0071*</td>
<td>-0.0234</td>
<td>0.0429*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0135</td>
<td>0.1033</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Age65+</td>
<td>-0.0054</td>
<td>0.8443</td>
<td>-0.0006</td>
<td>0.9828</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0076</td>
<td>0.7649</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bed Days Used per 1,000</td>
<td>0.0026</td>
<td>0.0578</td>
<td>0.0025</td>
<td>0.0421*</td>
<td>0.0028</td>
<td>0.0214*</td>
<td>0.0027</td>
<td>0.0357*</td>
<td>0.0023</td>
<td>0.0818</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QTR1 (Winter)</td>
<td>-6.2627</td>
<td>&lt;0.001*</td>
<td>-6.3055</td>
<td>&lt;0.001*</td>
<td>-6.3099</td>
<td>&lt;0.001*</td>
<td>-6.2699</td>
<td>&lt;0.001*</td>
<td>-6.2769</td>
<td>&lt;0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QTR2 (Spring)</td>
<td>-3.6902</td>
<td>&lt;0.001*</td>
<td>-3.6927</td>
<td>&lt;0.001*</td>
<td>-3.6936</td>
<td>&lt;0.001*</td>
<td>-3.6936</td>
<td>&lt;0.001*</td>
<td>-3.6936</td>
<td>&lt;0.0018*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QTR4 (Fall)</td>
<td>-5.8145</td>
<td>&lt;0.001*</td>
<td>-5.8523</td>
<td>&lt;0.001*</td>
<td>-5.8585</td>
<td>&lt;0.001*</td>
<td>-5.8376</td>
<td>&lt;0.001*</td>
<td>-5.8409</td>
<td>&lt;0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Metro County</td>
<td>0.3274</td>
<td>0.7144</td>
<td>0.9921</td>
<td>0.3198</td>
<td>1.2803</td>
<td>0.2328</td>
<td>0.7886</td>
<td>0.3990</td>
<td>0.9742</td>
<td>0.3680</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*significance at alpha level 0.05
<table>
<thead>
<tr>
<th>Model:</th>
<th>Model:</th>
<th>Model:</th>
<th>Model:</th>
<th>Model:</th>
<th>Model:</th>
<th>Model:</th>
<th>Model:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>G</td>
<td>H</td>
<td>I</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Parameter</td>
<td>Estimate</td>
<td>p-value</td>
<td>Parameter</td>
<td>Estimate</td>
<td>p-value</td>
<td>Parameter</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-29.9389</td>
<td>0.0008*</td>
<td>-24.5156</td>
<td>0.0006*</td>
<td>-21.3414</td>
<td>0.0038*</td>
<td>-29.3312</td>
</tr>
<tr>
<td>BH MD/DO’s per 100,000</td>
<td>-0.0759</td>
<td>0.7169</td>
<td>-0.0698</td>
<td>0.7314</td>
<td>-0.1126</td>
<td>0.6007</td>
<td>-0.0832</td>
</tr>
<tr>
<td>BH non-MD/non-DO per 100,000</td>
<td>0.0646</td>
<td>0.4923</td>
<td>0.0313</td>
<td>0.7356</td>
<td>-0.0386</td>
<td>0.7186</td>
<td>0.0233</td>
</tr>
<tr>
<td>BH Residential Centers Per 100,000</td>
<td>0.0344</td>
<td>0.7204</td>
<td>0.0302</td>
<td>0.7467</td>
<td>0.0373</td>
<td>0.6967</td>
<td>0.0325</td>
</tr>
<tr>
<td>BH Outpatient Centers Per 100,000</td>
<td>-0.1141</td>
<td>&lt;.0001*</td>
<td>-0.1121</td>
<td>&lt;.0001*</td>
<td>-0.1157</td>
<td>&lt;.0001*</td>
<td>-0.1168</td>
</tr>
<tr>
<td>SVI Overall</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-1.278</td>
<td>0.8920</td>
<td>2.1511</td>
</tr>
<tr>
<td>Theme 1- Socioeconomic Vulnerability</td>
<td>1.2572</td>
<td>0.2120</td>
<td>0.8441</td>
<td>0.4003</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 2- Household Composition</td>
<td>1.0234</td>
<td>0.1452</td>
<td>1.0503</td>
<td>0.1499</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 3- Minority Status</td>
<td>-</td>
<td>-</td>
<td>-0.2471</td>
<td>0.8117</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 4- Housing and Transportation</td>
<td>-1.2864</td>
<td>0.3048</td>
<td>-2.3256</td>
<td>0.1218</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Percent Male</td>
<td>0.6267</td>
<td>&lt;.0001*</td>
<td>0.609</td>
<td>&lt;.0001*</td>
<td>0.5570</td>
<td>0.0002*</td>
<td>0.5882</td>
</tr>
<tr>
<td>Percent White</td>
<td>0.0486</td>
<td>0.0702</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.068</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>-0.0119</td>
<td>0.1493</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0222</td>
</tr>
<tr>
<td>Percent Age65+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Bed Days Used per 1,000</td>
<td>0.0025</td>
<td>0.0430*</td>
<td>0.0023</td>
<td>0.0219*</td>
<td>0.0021</td>
<td>0.0591</td>
<td>0.0025</td>
</tr>
<tr>
<td>QTR1 (Winter)</td>
<td>-6.2823</td>
<td>&lt;.0001*</td>
<td>-6.2937</td>
<td>&lt;.0001*</td>
<td>-6.2731</td>
<td>&lt;.0001*</td>
<td>-6.2629</td>
</tr>
<tr>
<td>QTR2 (Spring)</td>
<td>-3.692</td>
<td>&lt;.0001*</td>
<td>-3.6919</td>
<td>&lt;.0001*</td>
<td>-3.691</td>
<td>&lt;.0001*</td>
<td>-3.6901</td>
</tr>
<tr>
<td>QTR4 (Fall)</td>
<td>-5.8404</td>
<td>&lt;.0001*</td>
<td>-5.8533</td>
<td>&lt;.0001*</td>
<td>-5.8268</td>
<td>&lt;.0001*</td>
<td>-5.8144</td>
</tr>
<tr>
<td>Non-Metro County</td>
<td>0.9538</td>
<td>0.3665</td>
<td>1.4053</td>
<td>0.2088</td>
<td>0.8576</td>
<td>0.3701</td>
<td>0.3313</td>
</tr>
</tbody>
</table>

*significance at alpha level 0.05
**Table 2.5. Multiple Regression Results for Inpatient Data Models A-E**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4.7447</td>
<td>0.1844</td>
<td>-3.334</td>
<td>0.2935</td>
<td>-3.4942</td>
<td>0.3061</td>
<td>-4.2576</td>
<td>0.2946</td>
<td>-4.6668</td>
<td>0.1772</td>
</tr>
<tr>
<td>BH MD/DO’s per 100,000</td>
<td>-0.0994</td>
<td>0.2920</td>
<td>-0.1213</td>
<td>0.2582</td>
<td>-0.0471</td>
<td>0.6233</td>
<td>-0.0991</td>
<td>0.3317</td>
<td>-0.0673</td>
<td>0.5129</td>
</tr>
<tr>
<td>BH non-MD/non-DO per 100,000</td>
<td>-0.0345</td>
<td>0.4680</td>
<td>-0.0031</td>
<td>0.9521</td>
<td>-0.018</td>
<td>0.7250</td>
<td>-0.0325</td>
<td>0.5557</td>
<td>-0.0297</td>
<td>0.5385</td>
</tr>
<tr>
<td>BH Residential Centers Per 100,000</td>
<td>0.0105</td>
<td>0.8294</td>
<td>0.0383</td>
<td>0.4131</td>
<td>0.0097</td>
<td>0.8397</td>
<td>-0.0158</td>
<td>0.7686</td>
<td>0.0195</td>
<td>0.7021</td>
</tr>
<tr>
<td>BH Outpatient Centers Per 100,000</td>
<td>0.0383</td>
<td>0.0031*</td>
<td>0.035</td>
<td>0.0042*</td>
<td>0.0366</td>
<td>0.0073*</td>
<td>0.0398</td>
<td>0.0043*</td>
<td>0.0367</td>
<td>0.0032*</td>
</tr>
<tr>
<td>SVI Overall</td>
<td>1.0434</td>
<td>0.0287*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.3954</td>
<td>0.3780</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 1- Socioeconomic Vulnerability</td>
<td>-</td>
<td>-</td>
<td>1.1758</td>
<td>0.0355*</td>
<td>1.1425</td>
<td>0.0645</td>
<td>-</td>
<td>-</td>
<td>1.2277</td>
<td>0.0040*</td>
</tr>
<tr>
<td>Theme 2- Household Composition</td>
<td>-</td>
<td>-</td>
<td>-0.0113</td>
<td>0.9811</td>
<td>0.2262</td>
<td>0.6516</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 3- Minority Status</td>
<td>-</td>
<td>-</td>
<td>-1.4069</td>
<td>0.0120*</td>
<td>-1.097</td>
<td>0.0168*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 4- Housing and Transportation</td>
<td>-</td>
<td>-</td>
<td>-0.0799</td>
<td>0.8752</td>
<td>0.0013</td>
<td>0.9981</td>
<td>-</td>
<td>-</td>
<td>-0.319</td>
<td>0.4980</td>
</tr>
<tr>
<td>Percent Male</td>
<td>0.0573</td>
<td>0.4087</td>
<td>0.0593</td>
<td>0.3311</td>
<td>0.0803</td>
<td>0.2207</td>
<td>0.0812</td>
<td>0.2909</td>
<td>0.0625</td>
<td>0.3453</td>
</tr>
<tr>
<td>Percent White</td>
<td>0.0577</td>
<td>0.0012*</td>
<td>0.0433</td>
<td>0.0194*</td>
<td>0.0169</td>
<td>0.2506</td>
<td>0.025</td>
<td>0.0736</td>
<td>0.0526</td>
<td>0.0042*</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>-0.0111</td>
<td>0.0032*</td>
<td>0.0009</td>
<td>0.8272</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0088</td>
<td>0.0071*</td>
</tr>
<tr>
<td>Percent Age65+</td>
<td>-0.0438</td>
<td>0.0008*</td>
<td>-0.0463</td>
<td>0.0018*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0437</td>
<td>0.0024*</td>
</tr>
<tr>
<td>Bed Days Used per 1,000</td>
<td>0.0011</td>
<td>0.0088*</td>
<td>0.001</td>
<td>0.0371*</td>
<td>0.0006</td>
<td>0.1124</td>
<td>0.0009</td>
<td>0.0273*</td>
<td>0.001</td>
<td>0.0280*</td>
</tr>
<tr>
<td>QTR1 (Winter)</td>
<td>-1.3994</td>
<td>&lt;.0001*</td>
<td>-1.3035</td>
<td>&lt;.0001*</td>
<td>-1.3485</td>
<td>&lt;.0001*</td>
<td>-1.5186</td>
<td>&lt;.0001*</td>
<td>-1.3709</td>
<td>&lt;.0001*</td>
</tr>
<tr>
<td>QTR2 (Spring)</td>
<td>-0.9562</td>
<td>0.0001*</td>
<td>-0.9329</td>
<td>0.0001*</td>
<td>-0.923</td>
<td>0.0002*</td>
<td>-0.9645</td>
<td>0.0001*</td>
<td>-0.9307</td>
<td>0.0001*</td>
</tr>
<tr>
<td>QTR4 (Fall)</td>
<td>-1.5655</td>
<td>&lt;.0001*</td>
<td>-1.5135</td>
<td>&lt;.0001*</td>
<td>-1.5307</td>
<td>&lt;.0001*</td>
<td>-1.6102</td>
<td>&lt;.0001*</td>
<td>-1.5519</td>
<td>&lt;.0001*</td>
</tr>
<tr>
<td>Non-Metro County</td>
<td>0.3891</td>
<td>0.3426</td>
<td>0.4007</td>
<td>0.2846</td>
<td>0.385</td>
<td>0.3096</td>
<td>0.6388</td>
<td>0.1662</td>
<td>0.4709</td>
<td>0.2220</td>
</tr>
</tbody>
</table>

*significance at alpha level 0.05
**Table 2.6. Multiple Regression Results for Inpatient Data Models F-I**

<table>
<thead>
<tr>
<th>Model</th>
<th>Parameter Estimate</th>
<th>Parameter p-value</th>
<th>Parameter Estimate</th>
<th>Parameter p-value</th>
<th>Parameter Estimate</th>
<th>Parameter p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4.5971</td>
<td>0.2183</td>
<td>-1.1572</td>
<td>0.7336</td>
<td>-0.7904</td>
<td>0.8366</td>
</tr>
<tr>
<td>BH MD/DO’s per 100,000</td>
<td>-0.016</td>
<td>0.8807</td>
<td>-0.0145</td>
<td>0.8788</td>
<td>-0.0542</td>
<td>0.595</td>
</tr>
<tr>
<td>BH non-MD/non-DO per 100,000</td>
<td>-0.0359</td>
<td>0.5047</td>
<td>-0.0413</td>
<td>0.4379</td>
<td>-0.0696</td>
<td>0.2104</td>
</tr>
<tr>
<td>BH Residential Centers Per 100,000</td>
<td>-0.0045</td>
<td>0.9318</td>
<td>0.0096</td>
<td>0.8346</td>
<td>-0.0159</td>
<td>0.7683</td>
</tr>
<tr>
<td>BH Outpatient Centers Per 100,000</td>
<td>0.0382</td>
<td>0.0065*</td>
<td>0.0362</td>
<td>0.0071*</td>
<td>0.0394</td>
<td>0.0044*</td>
</tr>
<tr>
<td>SVI Overall</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.1461</td>
<td>0.7000</td>
</tr>
<tr>
<td>Theme 1- Socioeconomic Vulnerability</td>
<td>1.1291</td>
<td>0.0944</td>
<td>1.1391</td>
<td>0.0662</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 2- Household Composition</td>
<td>0.2401</td>
<td>0.6399</td>
<td>0.1742</td>
<td>0.7272</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 3- Minority Status</td>
<td>-</td>
<td>-</td>
<td>-1.1629</td>
<td>0.0080*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Theme 4- Housing and Transportation</td>
<td>-0.2536</td>
<td>0.6517</td>
<td>-0.1443</td>
<td>0.7775</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Percent Male</td>
<td>0.0837</td>
<td>0.2330</td>
<td>0.0659</td>
<td>0.3364</td>
<td>0.0592</td>
<td>0.4419</td>
</tr>
<tr>
<td>Percent White</td>
<td>0.025</td>
<td>0.0702</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>-0.0064</td>
<td>0.0760</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Percent Age65+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Bed Days Used per 1,000</td>
<td>0.0007</td>
<td>0.0760</td>
<td>0.0005</td>
<td>0.2199</td>
<td>0.0006</td>
<td>0.0891</td>
</tr>
<tr>
<td>QTR1 (Winter)</td>
<td>-1.4123</td>
<td>&lt;.0001*</td>
<td>-1.3453</td>
<td>&lt;.0001*</td>
<td>-1.5209</td>
<td>&lt;.0001*</td>
</tr>
<tr>
<td>QTR2 (Spring)</td>
<td>-0.9246</td>
<td>0.0002*</td>
<td>-0.9213</td>
<td>0.0002*</td>
<td>-0.9657</td>
<td>0.0001*</td>
</tr>
<tr>
<td>QTR4 (Fall)</td>
<td>-1.5675</td>
<td>&lt;.0001*</td>
<td>-1.5089</td>
<td>&lt;.0001*</td>
<td>-1.5809</td>
<td>&lt;.0001*</td>
</tr>
<tr>
<td>Non-Metro County</td>
<td>0.4797</td>
<td>0.2705</td>
<td>0.4348</td>
<td>0.2277</td>
<td>0.6664</td>
<td>0.1441</td>
</tr>
</tbody>
</table>

*significance at alpha level 0.05
increased availability of mental health outpatient centers is associated with decreases ED utilization for HRI and BHD. Therefore, in the context of this study population, these outpatient centers can serve as a substitution for ED utilization. One plausible explanation for this relationship is that the services provided in outpatient clinics (i.e. counseling, group therapy, medical consultations and psychiatry) can aid in the prevention of more serious health outcomes that would warrant an ED visit. Consequently, lower severity cases can be addressed outside the hospital care setting. On the other hand, the opposite effect was found in the inpatient setting suggesting that outpatient centers complement inpatient care for co-occurring HRI and BHDs. Once an individual is ill enough to warrant inpatient hospital care, outpatient care may not be sufficient to prevent further medical intervention.

Previous literature highlights the importance of continuity of care post-hospital discharge for BHDs and receipt of outpatient follow-up care within 7 days (Fontanella et al., 2016; Orlosky et al., 2007; Croake et al., 2017; Gerson et al., 2012; Stein et al., 2017). Busch et al. (2015) found that counties with lower rate of seven-day post discharge follow-up had a higher risk of hospital readmission. Furthermore, Beadles et al. (2014) found that follow-up within seven days was associated with increased medication adherence and outpatient utilization. Lastly, Olfson et al. (2010) analyzed the 2003 national Medicaid claims data and found patients residing in counties with a higher number of psychiatrists per capita were more likely to receive follow-up care. Therefore, moving forward, it is important for health care providers to actively engage patients with previous HRI and BHDs in outpatient follow-up care to reduce the risk of readmissions and improve patient outcomes.

The current workforce crisis in the behavioral health field clearly plays a role in the availability and access to outpatient care for this patient population. Nationally, over 123 million Americans live in a Mental Health Professional Shortage Areas. Projections by the Health Resources and Services Administration (2016) indicate that by 2025 the national demand for full time employed psychiatrists will exceed the supply by approximately 6,080-15,400. Some suggestions to tackle this issue include training other health care providers (i.e. develop capacity
for other health care providers other than behavioral health specialists to address behavioral health needs), utilizing consumers as providers (i.e. train and utilize people in recovery), and incentivizing the pursuit of behavioral health careers (i.e. providing compensation that matches the required education, levels of responsibility, and work demands; Hoge et al. 2013). Politically, it is recommended that federal legislation be used to create greater parity between medical and behavioral health care (Hoge et al., 2013). This will challenge the societal stigma surrounding mental illness and also set the foundation for integration of care and workforce growth (Hoge et al., 2013).

Gender has been found to significantly influence rates of both HRI and BHDs. Results from the present study indicate that as the percentage of males in a county increased, the rate of co-occurring HRI and BHD ED visits also increased. These results build on existing evidence that males in the U.S. are more vulnerable to HRI than women (Lippmann et al., 2015; Li et al., 2015; Morano et al., 2016). When investigating the association between environmental temperatures and the occurrence of ED visits for HRI in North Carolina, Lippman et al. found temperature effects were greater for males; three times that of females (Lippmann et al., 2015). Morano et al.’s retrospective study of HRI during the Florida warm season found similar results indicating the rate of HRI ED visits was higher among men (RR=2.77) than women. Researchers hypothesize this may be due to different exposures, working characteristics, and personal behaviors between genders (Lippmann et al., 2015; Li et al., 2015; Morano et al., 2016).

When investigating specific behavioral disorders, previous research indicates that women tend to experience higher rates of anxiety and depression, whereas men experience more externalizing and substance use disorders (Seedat et al., 2009). In this study, the majority of males with HRI suffered from substance use disorders. Biologically, alcohol use is known to cause cutaneous vasodilation, increase perspiration, and result in dehydration. Furthermore, alcohol acts as a diuretic and can directly contribute to hyperthermia. Therefore, those in contact with individuals with substance use disorders, such as healthcare workers and pharmacists, must educate patients and families regarding safety measures during extreme heat events (i.e. increase
water intake, wear appropriate clothing, stay in well-shaded area) and signs and symptoms of heat stroke.

Unsurprisingly, a majority of co-occurring HRI and BHD ED and inpatient visits occurred during the third quarter of the year (July, August, September), which tends to be the warmest period in Florida. Recently (July-September of 2019), The Florida Climate Center found mean temperatures to be above normal, with the greatest anomalies occurring in the western panhandle (Florida Climate Center, 2019). Several maximum and minimum temperature records were either tied or broken across the state (Florida Climate Center, 2019). As global warming persists, future scenarios indicate that the majority of Florida may be at high heat risk with temperature between 95-100° F (Florida Department of Health, 2015). Therefore, there is an apparent need to mitigate this increased risk and adapt to future conditions.

Limitations of this study include the possible underreporting of HRI and BHDs which can restrict the sample size used in the analysis. Hospital settings are designed to provide acute care, HRI and BHDs may not present themselves as critical conditions if other comorbidities are clinically more severe and apparent. Furthermore, there can be unobserved confounding variables not included within the chosen model that directly or indirectly influence the dependent variables. Although we accounted for inter-county variability using RUCA codes and attempted to measure county resilience using SVI, county level data does not account for intra-county variability. Therefore, by aggregating at the county level, some significant factors that may influence hospital utilization might be masked.

This present study identified Florida counties with higher rates of hospital utilization for co-occurring HRI and BHD, however, further research is needed to establish where specific clusters of vulnerable populations might reside within these counties. For example, Harlen et al. (2006) conducted vulnerability mapping in eight specific neighborhoods in Phoenix-Mesa Metropolitan Statistical Area and determined areas with the most heat-stress had inferior resources to cope with extreme heat. They then were able to influence policy by suggesting specific neighborhoods to target heat reduction resources and heat warnings. Future research
similar to Harlen et al.’s study, will allow for prioritization of vulnerable areas, appropriate use of resources, and creation of targeted and tailored interventions in communities with the greatest needs.

References


CHAPTER THREE

EMERGENCY DEPARTMENT REVISITS AND INPATIENT READMISSIONS

Introduction

Emergency Department Revisits

Heat-related illnesses can range from mild heat edema, heat syncope, heat cramps, and heat exhaustion, to the most severe case of heat stroke. A study conducted in California found that heat-related illness was more likely to result in emergency department (ED) visits than hospitalizations (Knowlton et al., 2009). However, even though ED visits are considered less severe than inpatient (IP) hospitalizations, each visit is an indicator of a potential serious health outcome and a burden on the health care system (Davis et al., 2002). Therefore, it is important to understand how HRIs impact ED utilization in the humid subtropical climate of Florida.

Previous literature indicates that as temperatures rise, individuals with behavioral health disorders are more likely to utilize the ED. For example, Vida et al. (2012) investigated the impact of both temperature and humidity on ED visits for a major group of diagnoses called “mental and psychosocial problems” in Quebec, Canada. They found that as temperature and humidity increased so did the use of emergency services for mental and psychosocial problems. Mayner et al. (2010) also found an increase in ED utilization for mental health conditions during heat waves in Adelaide, Australia. Instead of grouping all mental conditions into one category, Wang et al. (2013) assessed how temperature impacts ED utilization for individuals with
schizophrenia, mood disorders, neurotic disorders, and substance use. They too found that ED utilization for these conditions significantly increased during periods of higher temperatures (schizophrenia RR=1.10 95% CI 1.03-1.17; mood disorders RR=1.68 95% CI 1.17-2.40; neurotic disorders RR=1.12 95% CI 1.00-1.27; substance use 1.05 95% CI 0.99-1.11), particularly among individuals age 60 and older.32

In Berlin, Germany Brandl et al. (2018) investigated the influence of meteorological parameters on number of behavioral health related emergency department visits between 2008 and 2014. Using a principle component analysis, higher temperature was found to be the main component associated with number of behavioral health patients visiting the ED. Admissions for mania and psychotic disorders were found to increase and peak during the spring and summer months indicating seasonality.

In Florida, The Florida Health Department explored the associations between daily maximum temperature or daily maximum heat index and rates of emergency department (ED) visits for particular health conditions (i.e. cardiovascular diseases, behavioral disorders, and respiratory disorders). In terms of mental health and behavioral disorders, they focused on two categories: organic psychotic conditions and substance-related disorders. Organic psychotic conditions were defined as dementia, alcohol and drug induced mental disorders, delirium, and amnestic disorders. Substance related disorders were defined as alcohol and drug-induced mental disorders, alcohol and drug dependence, and nondependent abuse of drugs. For both organic psychotic conditions and substance related disorders ED visits were found to decrease as temperatures increased. This finding is surprising and contradicts previous research however, because the Florida Health Department only looked at organic psychotic conditions and disregarded all other types of conditions associated with high ambient temperature, we do not
have a clear picture of ED utilization for heat-related illnesses by individuals with behavioral health disorders living in Florida.

In addition to an increased risk of an ED visit among individuals with a behavioral health disorder, research indicates that individuals with prior heat-related illnesses are more susceptible to another heat-related event due to neurological and organ damage and increased heat intolerance (Morano, 2016; Epstein, 1990; Shapiro et al., 1979; O’Conner et al., 2010). Therefore, part one of this proposed study is to determine the effect of previous heat-related emergency visits on the number of subsequent heat-related ED visits among individuals with a behavioral health disorder in Florida. This will give greater insight into the ED utilization patterns of this subpopulation.

**Inpatient Readmissions**

Repeated hospitalizations among patients with psychiatric disorders can be categorized as a characteristic of mental illness, but also may indicate the underlying inefficiencies in post-discharge treatment and community resources. The 2015 National Survey on Drug Use and Health found that overall 17.9% of U.S. adults experienced a mental illness in the past twelve months (Substance Abuse and Mental Health Services Administration (SAMHSA), 2016). Data gathered from the Healthcare Cost and Utilization Project and 2012 State Inpatient Database indicates that individuals diagnosed with psychiatric disorders are more likely to be readmitted to a hospital within 30 days of initial discharge than those without mental illness-related diagnoses (Heslin and Weiss, 2015). Overall, it was found that 13% of mental health discharges are readmitted within 30 days (Agency for Health Care Research and Quality (AHRQ), 2014). The lack of proper intervention among this population has led to an increase in healthcare costs (Bureau of Economic Analysis, 2013; Boccuti & Casillas, 2017), decrease in quality of life
Hospital readmissions are detrimental for everyone involved: providers, payers, and patients. Readmission rates are considered indicators for quality of hospital care. When a patient is readmitted, it is seen as though the hospital’s initial care was not sufficient. This can lead to penalties and withholding of funds by subsidiaries like Medicare (Boccuti & Casillas, 2017). Nationally there were 531,650 mood disorder readmissions to the same hospital with an average charge of $19,686 per patient in 2014 (AHRQ, 2014). Overall, spending on mental illness treatment accounts for $89 billion (Bureau of Economic Analysis, 2013). This economic burden is clear. However, even more disturbing is that adults with serious mental illnesses were found to have shorter life expectancies by an average of 25 years compared to those without mental illnesses (SAMHSA, 2016). This shorter life expectancy is accompanied by the fact that the national suicide rate has increased an astonishing 33% between 1999 and 2017 (CDC, 2018).

Individuals with behavioral health disorders are at an increased risk of having a heat-related illness compared to persons without a behavioral health disorder due to underlying differences in pathophysiology, effects of psychiatric medications, and physical and mental impairments that interfere with coping. Heat-related illnesses can range from mild heat edema, heat syncope, heat cramps, and heat exhaustion, to the most severe case of heat stroke. Choudhary and Vaidyanathan (2014) from the National Center for Environmental Health conducted a study assessing heat-related hospitalizations in 20 states from 2001 through 2010. They found approximately 28,000 total HRI hospitalizations occurred in this ten-year period. There was a 2%-5% increase in the rate of hospitalizations compared with 2001 and the highest
rates were seen in midwestern and southern states. Florida had one of the highest crude and age-adjusted rate of HRI per 100,000 population per year for all 20 study years.

In Florida, intense heat is a regular occurrence as temperatures reach 90-degrees Fahrenheit frequently throughout the year, but especially during summer months (May through October; Wan, 2004). In addition to high temperatures, Florida is known as the most humid state in the nation because it is surrounded by warm water (Florida Climate Center (FCC), 2014). In order for the human body to regulate its temperature and cool down it must secrete sweat which then evaporates, but this process is disrupted by high humidity (FCC, 2014). With increased humidity, there is less evaporation of sweat and therefore less cooling of the body which leads to an increase chance of a heat-related illness (HRI; FCC, 2014).

Furthermore, previous research indicates that individuals with prior heat-related illnesses are more susceptible to another heat-related event due to neurological and organ damage, in addition to increased heat intolerance (Morano, 2016; Epstein, 1990; Shapiro et al., 1979; O’Conner et al., 2010). For example, a case-control study conducted by Shapiro et al. (1979) assessed how nine men with previous history of heat strokes and ten volunteers with no previous history of heat stroke would respond physiologically to exercise in hot environments. All the control subjects were able to complete the exercise under severe heat load, however none of the heat-intolerant subjects completed the exercise due to high body temperature and high heart rates. It was concluded that the subjects with previous heat strokes suffered from inefficient thermoregulation which makes them more susceptible to a subsequent HRI.

Therefore, part two of this proposed study is to determine the effect of previous heat-related hospital admissions on the number of heat-related rehospitalizations among individuals with a behavioral health disorder in Florida. This will give greater insight into the hospital
utilization patterns of this subpopulation. Considering the previous literature, it is hypothesized that among individuals who have had a previous ED visit or IP admission for an HRI, those with a co-occurring BHD will be more likely to revisit the ED or IP setting for another HRI within both 30 days and 365 days compared to individuals without BHDs.

Methods

Data Description

This study utilized pooled 2016-2018 Florida ED and IP data from the Agency for Health Care Administration (AHCA). Scrambled social security numbers (SSNs) were utilized to track patients over time. All ED visits and IP admissions in the data set for patients diagnosed with heat-related illness (ICD-10 T67 and X30) and specified behavioral health disorders (dementia, substance use, schizophrenia, bipolar, major depressive disorder, and anxiety) were identified. Then, all ED visits and IP admissions were identified that occurred within 30 days or 365 days of a prior ED visit or IP hospitalization. Individuals who were not identified as Florida residents were excluded from the analysis, this includes out of state, foreign, and homeless individuals.

Statistical Analyses

Four logistic regression models were used to assess the association between ED revisit/IP readmissions for HRI among individuals with BHDs compared to those without BHDs, after controlling for covariates. The research question associated with this model is: Does having a BHD impact the probability of having a subsequent heat-related emergency visits or inpatient admission? Odds ratios were used to estimate and compare the risk of a subsequent HRI
visit/admission between individuals with a BHD and those without BHDs. All analyses were conducted in SAS 9.4 Software.

The proposed models are as follows:

\[
\text{ReVisit30}_i = \alpha + \beta_i X_i + \gamma_i B_i + \epsilon \\
\text{ReVisit365}_i = \alpha + \beta_i X_i + \gamma_i B_i + \epsilon \\
\text{ReAdmission30}_i = \alpha + \beta_i X_i + \gamma_i B_i + \epsilon \\
\text{ReAdmission365}_i = \alpha + \beta_i X_i + \gamma_i B_i + \epsilon
\]

I= individual level

X= vector of individual level demographics

V= vector of individual level behavioral health disorders

ReVisit30\_i is defined as 0 for individuals with no heat-related ED visits in 30 days and 1 for individuals with a heat-related ED visit in 30 days, ReVisit365\_i is defined as 0 for individuals with no heat-related ED visits in 365 days and 1 for individuals with a heat-related ED visit in 365 days, ReAdmission30\_i is defined as 0 for individuals with no heat-related readmission in 30 days and 1 for individuals with a heat-related readmission in 30 days, ReAdmission365\_i is defined as 0 for individuals with no heat-related readmission in 365 days and 1 for individuals with a heat-related readmission in 365 days, X\_i is defined as the gender (male), age (65+), race (white), ethnicity (Hispanic), payer (Uninsured), and Bi is defined as behavioral health disorders which include: ICD-10 F01-03 (dementia), F10-19 (substance use), F20-29 (schizophrenia), F30-39 (bipolar, manic, depression), and F40-48 (anxiety).
**Hypotheses**

The research and null hypotheses for part one of this study are as follows:

**H1**: Of all patients who were admitted to a Florida hospital for a heat-related illness, those who had a co-occurring behavioral health disorder (BHD) will be more likely to re-visit the ED within 30 days and 365 days for a heat-related illness compared to those with no BHD.

**H0**: There will be no significant difference in the number of subsequent heat-related ED visits within 30 days and 365 days between individuals with behavioral health disorders and a previous heat-related ED visit and individuals without a BHD.

The research and null hypotheses for part 2 of this study are as follows:

**H1**: Of all patients who had an inpatient admission to a Florida hospital for a heat-related illness, those who had a co-occurring behavioral health disorder (BHD) will be more likely to be re-admitted as an inpatient within 30 days and 365 days for a heat-related illness compared to those with no BHD.

**H0**: There will be no significant difference in the number of subsequent heat-related hospital admissions within 30 days and 365 days between individuals with BHDs and a previous heat-related hospital admission and individuals without BHDs.

**Results**

**Demographics**

Demographic data for the patients in the ED and IP samples are presented in Table 3.1 and Table 3.2, respectively. Among all the patients with an ED visit with an HRI diagnosis in the ED, almost 30% had a co-occurring BHD. In the ED, a majority of individuals with both HRI
and BHDs were found to be male (78%), white race (77%), non-Hispanic (91%), and they had an average age of 42 years. Among patients with HRI and no BHDs, the majority were similarly found to be male (71%), white race (70%), non-Hispanic (87%), with an average age of 44. Overall, 96% of ED patients were discharged to home. In terms of insurance status, approximately 17% more patients were uninsured in the HRI and BHD group compared to the HRI only group.

Table 3.1. Average Demographic Information and Distribution of Patients with HRI ED Visits from 2016-2018

<table>
<thead>
<tr>
<th>Variable</th>
<th>ALL HRI</th>
<th>HRI + BHD</th>
<th>HRI ONLY</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N=16,804</td>
<td>N=4,562</td>
<td>N=12,242</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (mean, sd years)</td>
<td>44, 19</td>
<td>42, 16</td>
<td>44, 20</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>73%</td>
<td>78%</td>
<td>71%</td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>72%</td>
<td>77%</td>
<td>70%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>22%</td>
<td>19%</td>
<td>23%</td>
<td></td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>12%</td>
<td>9%</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td>Behavioral Health Related</td>
<td>27%</td>
<td>98%</td>
<td>0%</td>
<td></td>
</tr>
<tr>
<td>Insurance Status</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>25%</td>
<td>38%</td>
<td>21%</td>
<td></td>
</tr>
<tr>
<td>Discharge to Home</td>
<td>96%</td>
<td>95%</td>
<td>97%</td>
<td></td>
</tr>
</tbody>
</table>

In contrast to the sample with ED visits, over half (55%) of the sample with IP admissions for HRI had a co-occurring BHD. The demographic distribution for patients with IP admissions indicates a majority of this population are males, white race, and non-Hispanic ethnicity. The average age of IP admissions was 53 years, which is higher than the average age of ED patients (44 years). Fewer patients in the IP setting were discharged to home, especially those with a BHD (72%) compared to those with only a HRI diagnosis (80%). On average, the length of stay for all HRI admissions was approximately 3.5 days.
Table 3.2. Average Demographic Information and Distribution of HRI Inpatient Admissions from 2016-2018

<table>
<thead>
<tr>
<th>Variable</th>
<th>ALL HRI</th>
<th>HRI + BHD</th>
<th>HRI ONLY</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=3309</td>
<td>N=1,837</td>
<td>N=1,472</td>
<td></td>
</tr>
<tr>
<td>Age (mean, sd years)</td>
<td>53, 20</td>
<td>51, 18</td>
<td>55, 21</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Length of Stay (days)</td>
<td>3.43</td>
<td>3.69</td>
<td>3.09</td>
<td>0.080</td>
</tr>
<tr>
<td>Gender Male</td>
<td>84%</td>
<td>83%</td>
<td>84%</td>
<td>0.480</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>72%</td>
<td>74%</td>
<td>69%</td>
<td>0.003</td>
</tr>
<tr>
<td>Black</td>
<td>21%</td>
<td>20%</td>
<td>23%</td>
<td>0.010</td>
</tr>
<tr>
<td>Ethnicity Hispanic</td>
<td>13%</td>
<td>11%</td>
<td>15%</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Behavioral Health Related</td>
<td>55%</td>
<td>98%</td>
<td>0%</td>
<td></td>
</tr>
<tr>
<td>Insurance Status Uninsured</td>
<td>23%</td>
<td>29%</td>
<td>17%</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Discharge to Home</td>
<td>75%</td>
<td>72%</td>
<td>80%</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

When breaking down the behavioral health disorders into separate categories we find that the highest percentage of diagnoses are substance use disorders (ED 76%, IP 55%), followed by anxiety disorders (ED 13%, IP 16%), and depression (ED 5%, IP 14%; Figure 3.1). Within the substance use disorder category, nicotine dependence (ICD F17) is the most diagnosed condition in both the ED (80%) and IP setting (53%; Figure 3.2). This is followed by alcohol related disorders (ED 8%, IP 17%) and cannabis related disorders (ED 5%, IP 14%; Figure 3.2).
In terms of visit frequency, 40% of ED revisits occurred within 30 days of the initial HRI visit (Table 3.3). Although individuals with HRI and BHD had a smaller sample size (n=4,562), this group had more 30 day and 365-day ED revisits when compared to the HRI only group.
Although less readmissions for HRI occurred in the IP setting compared to ED re-visits, 58% of these readmissions occurred within 30 days of the initial visit (Table 3.4). In addition, individuals with HRI and BHD IP admissions outnumbered those with only HRI IP admissions and had three times the number of readmissions.

Table 3.3. Emergency Department Visit Frequency Among Patients Diagnosed with Heat-Related Illness in Florida (2016-2018)

<table>
<thead>
<tr>
<th>ED Visit Frequency</th>
<th>HRI + BHD</th>
<th>HRI Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>N= 4,562</td>
<td>N= 12,242</td>
</tr>
<tr>
<td>Once</td>
<td>97%</td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>(n=4,422)</td>
<td>(n=12,120)</td>
</tr>
<tr>
<td>More than Once</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 days</td>
<td>n=59</td>
<td>n=50</td>
</tr>
<tr>
<td>Within 365 days</td>
<td>n=140</td>
<td>n=122</td>
</tr>
</tbody>
</table>

Table 3.4. Hospital Inpatient Admission Frequency Among Patients Diagnosed with Heat-Related Illness in Florida (2016-2018)

<table>
<thead>
<tr>
<th>Inpatient Admission Frequency</th>
<th>HRI + BHD</th>
<th>HRI Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Totals</td>
<td>N= 1,837</td>
<td>N= 1,472</td>
</tr>
<tr>
<td>Once</td>
<td>98%</td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>(n=1,801)</td>
<td>(n=1,460)</td>
</tr>
<tr>
<td>More than Once</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 days</td>
<td>n= 21</td>
<td>n= 7</td>
</tr>
<tr>
<td>Within 365 days</td>
<td>n=36</td>
<td>n= 12</td>
</tr>
</tbody>
</table>

Regression Results

Regression results indicate that patients with BHDs were 2.79 times more likely to revisit the ED within 30 days (95% CI 1.889-4.116, p <.0001) and 2.74 times more likely to revisit the ED within 365 days (95% CI 2.126-3.526, p <.0001; Table 3.5). Males were three times more likely to revisit the ED within 30 days compared to females (OR 3.114, 95% CI 1.614 - 6.010, p value=0.0007; Table 3.5). Furthermore, uninsured patients were 34% more likely than insured
patients to revisit the ED within 365 days (OR 1.337, 95% CI= 1.027-1.741, p=0.0306; Table 3.6).

Table 3.5. Odd Ratios for Heat-Related ED Revisits within 30 days

<table>
<thead>
<tr>
<th>Behavioral Health Related</th>
<th>Odds Ratio Point Estimate</th>
<th>95% Wald Confidence Limits</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Behavioral Health Related</td>
<td>2.788</td>
<td>1.889</td>
<td>4.116</td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.100</td>
<td>0.732</td>
<td>1.654</td>
</tr>
<tr>
<td>Age 65+</td>
<td>0.462</td>
<td>0.211</td>
<td>1.014</td>
</tr>
<tr>
<td>Male</td>
<td>3.114</td>
<td>1.614</td>
<td>6.010</td>
</tr>
<tr>
<td>Hispanic</td>
<td>1.462</td>
<td>0.865</td>
<td>2.470</td>
</tr>
<tr>
<td>White</td>
<td>1.155</td>
<td>0.748</td>
<td>1.785</td>
</tr>
</tbody>
</table>

*indicates significance at alpha level .05

Table 3.6. Odd Ratios for Heat-Related ED Revisits within 365 days

<table>
<thead>
<tr>
<th>Behavioral Health Related</th>
<th>Odds Ratio Point Estimate</th>
<th>95% Wald Confidence Limits</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Behavioral Health Related</td>
<td>2.738</td>
<td>2.126</td>
<td>3.526</td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.337</td>
<td>1.027</td>
<td>1.741</td>
</tr>
<tr>
<td>Age 65+</td>
<td>0.645</td>
<td>0.409</td>
<td>1.017</td>
</tr>
<tr>
<td>Male</td>
<td>2.329</td>
<td>1.519</td>
<td>3.412</td>
</tr>
<tr>
<td>Hispanic</td>
<td>1.133</td>
<td>0.781</td>
<td>1.643</td>
</tr>
<tr>
<td>White</td>
<td>0.994</td>
<td>0.755</td>
<td>1.308</td>
</tr>
</tbody>
</table>

*indicates significance at alpha level .05

In the IP setting the only significant factor indicating a readmission within either 30 days or 365 days was the BHD (Table 7 and Table 8). Patients with BHDs were found to be 2.3 times more likely to be readmitted within 30 days (95% CI 1.0002-5.343, p=0.0494; Table 3.7) and 2.4 times more likely to be readmitted within 365 days (95% CI 1.263-4.662, p=0.0078; Table 3.8).
Table 3.7. Odd Ratios for Heat-Related IP Readmissions within 30 days

<table>
<thead>
<tr>
<th>Behavioral Health Related</th>
<th>Odds Ratio</th>
<th>95% Wald Confidence Limits</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Point Estimate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioral Health Related</td>
<td>2.314</td>
<td>1.002</td>
<td>5.343</td>
</tr>
<tr>
<td>Uninsured</td>
<td>0.371</td>
<td>0.106</td>
<td>1.294</td>
</tr>
<tr>
<td>Age 65+</td>
<td>1.242</td>
<td>0.538</td>
<td>2.867</td>
</tr>
<tr>
<td>Male</td>
<td>1.186</td>
<td>0.433</td>
<td>3.252</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.596</td>
<td>0.140</td>
<td>2.535</td>
</tr>
<tr>
<td>White</td>
<td>1.215</td>
<td>0.485</td>
<td>3.039</td>
</tr>
</tbody>
</table>

*indicates significance at alpha level .05

Table 3.8. Odd Ratios for Heat-Related IP Readmissions within 365 days

<table>
<thead>
<tr>
<th>Behavioral Health Related</th>
<th>Odds Ratio</th>
<th>95% Wald Confidence Limits</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Point Estimate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioral Health Related</td>
<td>2.427</td>
<td>1.263</td>
<td>4.662</td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.000</td>
<td>0.488</td>
<td>2.052</td>
</tr>
<tr>
<td>Age 65+</td>
<td>1.489</td>
<td>0.750</td>
<td>2.958</td>
</tr>
<tr>
<td>Male</td>
<td>1.961</td>
<td>0.749</td>
<td>5.131</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.049</td>
<td>0.441</td>
<td>2.501</td>
</tr>
<tr>
<td>White</td>
<td>0.892</td>
<td>0.471</td>
<td>1.689</td>
</tr>
</tbody>
</table>

*indicates significance at alpha level .05

Discussion

In this study, we explored the hospital utilization patterns (both ED visits and IP admissions) among individuals with HRI, specifically comparing those with and without BHDs. Results indicate that 27% of patients with HRI ED visits had a co-occurring BHD, whereas 55% of patients with HRI IP admissions had a co-occurring BHD. Of all the BHDs, substance use disorders, particularly nicotine dependence, was found to be most prevalent. The majority of ED revisits and IP readmissions occurred within the first 30 days of the initial visit. Furthermore,
logistic regression models indicate that the addition of a BHD significantly increases the risk of both ED revisits and IP readmissions. Males and those who were uninsured were found to be particularly vulnerable to ED revisits.

HRIs are highly preventable conditions that can be avoided through conscious behavioral changes at the individual and community level. Although thermoregulation is a natural and automatic process of the body, individuals with BHDs have been found to have problems with this process. Reasons include physiology, prescription medications, and cognitive impairment (Chong and Castle, 2003; Cusack et al, 2010; Martin-Latry et al., 2007; Wang, 2013; Bark, 1998; Hansen et al., 2008). In this study, we found that one third of patients with ED visits and over half of patients with inpatient admissions for HRI had at least one co-occurring BHD. This finding is supported by previous research which indicates that during heat waves there is an increase in the number of ED visits and IP admissions for patients with pre-existing BHDs (Hansen et al., 2008; Mayner et al., 2010; Vida et al., 2012; Brandl et al., 2018). Of all the BHDs, substance use was found to be the most prevalent in both hospital settings (ED 76%; IP 55%).

Substances, such as alcohol and opioids have previously been linked to increased morbidity and mortality during hot weather. Biologically, both alcohol and opioids have been found to increase cutaneous vasodilation and increase perspiration, while alcohol use specifically acts as a diuretic, further contributing to dehydration (Cusack et al., 2011). Other substances, such as amphetamines (i.e. cocaine and MDMA) lead to vasoconstriction and activation of the HPA axis which increases body heat (Fernandez et al., 2002; Eyer & Zilker, 2007; Cusack et al., 2011). Nicotine use (smoking and ingestion) similarly causes vasoconstriction, increased heart rate, reduced blood flow to extremities, and increased core temperature (Druyan et al., 2016;
Department of Health & Human Services, 2019). Interestingly, nicotine use is not discussed as a possible risk factor in temperature and behavioral health studies, literature reviews, or federal, state, local public health websites.

Within this study, nicotine dependence was the most used diagnosis code among individuals with co-occurring HRI and BHD. Only one clinical trial was located related to this topic. Druyan et al. investigated the effect of smoking on thermoregulation. The physiological performance and heat tolerance of eight nicotine users and eight non-users were compared. Both smoking and ingesting nicotine increased body temperature and were associated with higher sweat rates during the heat tolerance test. This increase in body temperature and sweating in a hot and humid climate like Florida, can increase risk of HRI among individuals with nicotine dependence. In addition, smokers are further exposed to environmental/external heat due to the societal shift of banning indoor smoking. Although the nicotine used in e-cigarettes is not burned, but vaporized, the heated vapor ingested acts similarly to traditional cigarettes (Papaefstathiou et al., 2019). Therefore, there is an increased need for smoking prevention and cessation initiatives to avoid the numerous detrimental health effects associated with this habit/addiction.

In terms of gender, HRI morbidity is higher among men than women residing in Florida. This has been observed and discussed in previous literature (CDC, 2006; Morano et al., 2016; Trang et al., 2016; Zhao et al., 2016; CDC, 2019). One explanation proposed by researchers is the difference in activities each gender engages in. Physical activity levels are higher among men than women which can contribute to exertional heat illness (Azevedo et al., 2007; Morano et al., 2016). Furthermore, male high school athletes were found to account for the majority of exertional health illness, particularly football players (Kerr et al., 2013; Morano et al., 2016).
Another proposed explanation includes the occupational differences among genders. Men are more likely to work in jobs with increased HRI risk, such as agriculture, transportation, forestry and fishing, fire protection, and construction (Morano et al., 2016; Morano et al., 2015a). Occupations and activities (i.e. sports) with high physical labor demands and regular outdoor exposure need proper regulation and guidelines to limit heat exposure. In addition, men with co-occurring HRI and BHD were found to be over three times more likely to revisit the ED within 30 days of their initial visit. Therefore, on a patient-provider level, patient education during the initial visit and post-visit follow up is imperative to reduce this risk. On a community level, prevention-focused collaborative efforts should be pursued to understand the social factors contributing to the vulnerability of males.

Uninsured individuals were also found to be at an increased risk of HRI re-visits. In the ED approximately 40% of patients with co-occurring HRI and BHDs were uninsured and 30% in the IP setting. Previous studies have estimated 30% of HRI ED visits were uninsured (Hess et al. 2014) and 20.6% of BHD related ED visits (Owens et al., 2010). However, of all BHDs, substance use disorders were found to have a higher percentage of uninsured visits (35.6%; Owens et al., 2010). Schmeltz et al. (2015) similarly found being uninsured significantly predicted HRI (RR 2.51, 95% CI: 2.31-2.72, p<.0001). This lack of health insurance can lead to the inability to utilize preventative care and neglect of chronic health conditions, which has been found to increase emergency care utilization and worsen health outcomes (Bovbjerg and Hadley, 2007). Individuals with behavioral health disorders are found to have a high prevalence of comorbid health conditions such as hypertension (20%), asthma (15%), and diabetes (10%) further emphasizing the need for not only preventative care but continuity of care (Kaiser Family Foundation, 2015). Behavioral health services are known to be higher cost which is an access to
care barrier for low income individuals with behavioral health disorders (57%; Kaiser Family Foundation, 2015). Compared to individuals without insurance or with private insurance, individuals with Medicaid were more likely to receive mental health treatment. Medicaid covers many inpatient and outpatient mental health services making it more comprehensive than many private insurances and emphasizing the importance of policies supporting its expansion.

Even though the body’s biological reaction to substances increases the risk of heat-related illnesses, previous research on hospital utilization related to behavioral disorders has led to conflicting results. In Australia, Hansen et al. (2008) estimated the effect of heat waves on behavioral health related hospital admissions from 1993-2006 and found a positive association (7.3% increase compared to non-heat wave periods). Substance use related admissions and deaths were significant among the elderly (75+; IRR 1.567 95% CI: 1.002-2.450) and females (IRR 3.098 95% CI: 1.342-7.155). Furthermore, Wang et al. (2013) found substance abuse related ED visits were significantly associated with high temperatures in Toronto, Canada. However, individuals ages 0–14 were found to be at higher risk of increased ER visits during high temperature compared to older individuals, which contradicts other publications indicating older individuals with BHDs are at higher risk. In contrast, the Florida Department of Health investigated the relationship between heat (daily max temp and heat index) and BHDs and found no association between substance-related ED visits, heat index statewide, and temperatures between 2005-2012 (Morano et al., 2015b).

Some of these discrepancies between these aforementioned global research studies can be associated with the different data sources used, confounding variables, and geography. There are numerous meteorological and physical factors that influence temperature such as humidity, precipitation, pollution, latitude, longitude, elevation, topography etc. (NOAA, 2015). Without a
set guideline for measuring temperature and related confounders it can be difficult to compare findings. Furthermore, temperature data is usually aggregated to the nearest weather station and therefore does not account for local variations in temperature.

Limitations of this study include data accuracy, small sample sizes, and confounding variables. In terms of AHCA data, one must be aware of the questionable clinical accuracy as with any study relying solely on ICD-10-CM codes (Morano, 2016). As Morano et al. noted, assignment of ICD-10 codes and their usage vary by facility and geography; there is no uniform guideline to inform the assignment of HRI. Also, conditions that are not a focus treatment may not be noted in the clinical record. Therefore, underreporting of HRI is likely. In addition, ED revisits and IP readmissions for the three-year period resulted in small sample sizes ranging from 7 to 59 revisits in 30 days and 12-140 revisits in 365 days. Specific confounding variables were unavailable due to the nature of the administrative data such as the income of these patients, what activity they were participating in prior to the heat event, whether they have access to air conditioning, what prescription medications they are consuming, etc. This information would be useful in understanding how these co-occurring conditions emerge. However, even with these limitations, it is important to keep in mind that the strength of this study stems from the ability to track revisits and readmissions for HRI in Florida hospitals which has not been reported previously and therefore further adds to the foundation of knowledge regarding HRI and BHDs.

Overall, this investigation of ED revisits and IP readmissions for co-occurring HRI and BHDs indicates that individuals with BHDs, compared to individuals without BHDs, are more likely to either revisit or be readmitted to Florida hospitals within 30 days of their initial visit or admission. The majority of this population is made up of non-Hispanic white males of working age (18-65). Nicotine dependence was found to be a major factor associated with the behavioral
health disorders in this population. Smoking cessation is a major on-going public health initiative and therefore, this research further emphasizes the need to prevent smoking due to its association with numerous co-morbidities.

Future research should utilize qualitative methods to further understand the context in which a heat event occurs and a HRI is diagnosed. Although this study was able to assess the administrative data available, obtaining not only the clinical perspective, but also the patient perspective, would allow for additional identification of susceptibility factors. In addition, larger sample sizes are needed to ensure that this utilization pattern holds true on a larger population level. Conducting a similar analysis at the national level would be beneficial. Further analysis is needed to understand what social factors can be targeted by hospitals, social workers, and policy makers, to reduce these preventable hospitalizations, especially as climate change persists and mental health prevalence increases.

References


axis and sympathetic activity on neurochemical consequences of 3,4-methylenedioxyamphetamine (MDMA) administration in Fischer 344 rats. European Journal of Neuroscience 16(4), 607–618.


Morano, L. H., Bunn, T., Lackovic, M., Lavender, A., Dang, G., Chalmers, J., . . . Flammia, D.


Vida, S., Durocher, M., Ouarda, T. B., & Gosselin, P. (2012). Relationship Between Ambient Temperature and Humidity and Visits to Mental Health Emergency Departments in Québec. *Psychiatric Services, 63*(11), 1150-1153. doi:10.1176/appi.ps.201100485


CHAPTER FOUR

IMPACT OF PUBLIC PARK AND BEACH AVAILABILITY ON ANXIETY AND
DEPRESSION-RELATED EMERGENCY DEPARTMENT VISITS IN FLORIDA

Introduction

There is ample evidence showing the natural environment to be associated with quality of life and overall wellbeing. As nations continue to urbanize, systematic changes occur in how residents live, eat, play, work, and travel (WHO, 2010). Some distinct challenges emerge from urbanization such as increases in non-communicable diseases (diabetes, heart disease, obesity, etc.), violence, injuries, unhealthy diets, and physical inactivity (WHO, 2010). In terms of mental health, urbanization has specifically been linked to increased rates of anxiety and depression (Bratman et al., 2015). Furthermore, the economic pressure to continuously develop land leads to a distinct reduction in natural green environments (Pretty et al, 2005). As availability of and access to natural environments decreases, individuals find themselves surrounded by man-made structures that limit the opportunities to recover from mental stress (Pretty et al., 2005).

Numerous emotional benefits have been linked with exposure to natural environments. The U.S. Environmental Protection Agency (EPA) highlights key literature dating back to the 1980s which indicates how engagement with nature improves attention and cognitive function, decreases cortisol and blood pressure, increases social cohesion, and improves overall mood and
mental health (EPA, 2014; Pasanen et al., 2014). A longitudinal study by White et al. (2013) tracked more than 10,000 people for two decades and found a significant positive effect of proximity to greenspace on well-being. It is hypothesized that nature experiences decrease rumination, a maladaptive pattern of self-referential thought which activates the subgenual prefrontal cortex (sgPFC) of the brain and acts as a risk factor for mental illnesses such as anxiety and depression (Bratman et al., 2015). Specifically, Bratman et al. found that 90-minute nature walks significantly reduced self-reported rumination and activity in the sgPFC compared to urban walks. In other words, natural environments act as a positive or neutral distraction that shifts attention to distracting stimuli.

Although positive effects of nature are evident, inequalities in park availability, access, and quality have been noted. Previous research indicates mixed results in terms of potential disparities in park proximity. For example, Jones et al. (2015) investigated parks and recreational facility distribution in six US regions and found lower availability in predominantly minority census tracts compared to non-Hispanic white census tracts. However, Wen et al. (2013) conducted a nationwide ecological study of spatial access to parks and green spaces and found individuals who reside in low-income or minority neighborhoods were actually closer to parks. Therefore, it seems different urban communities may have distinct social and political qualities that dictate whether or not inequalities in natural environment availability exist.

Considering the plethora of information indicating the positive health effects of natural environments and the risks of urbanizing areas at the expense of nature, special attention must be brought to this issue. Other countries, such as Bhutan, focus their efforts on preserving the natural environment in order to promote happiness. Bhutan has created a national measure called the Gross National Happiness Index which includes nine domains: psychological wellbeing,
health, education, time use, cultural diversity and resilience, good governance, community vitality, ecological diversity and resilience, and living standards (Oxford Poverty & Human Development Initiative (OPHI), 2015). The use of extrinsic and intrinsic measures allows policy makers to consider how certain interventions will impact society multidimensionally (OPHI, 2015). Bhutan’s approach to modernization is hailed by the United Nations as “a holistic approach to development” and considered a new economic paradigm based on sustainability and wellbeing (OPHI, 2015). As anxiety and depression rates continue to rise in the United States, it is evident that changes are needed to ensure psychological well-being for all residents.

Current literature on this topic of natural environments and health have focused on self-reports and perceptions gathered from surveys and questionnaires. For example, in an attempt to understand how green and blue space visibility impacts mental health, Nutsford et al. (2016) measured psychological distress using the Kessler Psychological Distress Scale (K10) in the New Zealand Health Survey. Volker et al. (2018) used the Medical Outcomes Study Short Form (SF-12v2) to measure health-related quality of life in association with walking distance to freshwater urban blue space. Astell-Burt et al. (2014) conducted a longitudinal study assessing the association between green space and mental health across the life course and used the 12-item General Health Questionnaire (GHQ) to measure minor psychiatric morbidity.

Therefore, the purpose of this proposed study is to determine and quantify the effect of natural environments, specifically public parks and beaches, on the rate of anxiety and depression related ED visits in zip codes within the Tampa Bay Area (Hillsborough, Pinellas, and Pasco county). Analyzing the rate of ED diagnoses allows for an objective and clinically based measure for study. Rates of anxiety and depression diagnoses were chosen as the key dependent variable because these two mental conditions show the strongest association with
natural environments (Maas et al., 2009). Furthermore, a needs assessment will be conducted to
determine if inequities in park distribution exist based on demographic and socioeconomic
factors such as race, income, education, etc. Theoretically, this study will investigate the
relationship between nature, mental illness, and health care utilization and determine (a) if an
association exists and (b) how strong it is. It is hypothesized that zip codes with access to public
parks and beaches will have lower rates of anxiety and depression related ED visits.

In urbanized areas, such as the ones of focus in this study, parks and green open spaces
are the most available forms of natural environments created for the public benefit. The
association between these natural environments and mental wellbeing has been investigated on
multiple occasions. For example, Wood et al. (2017) found that as the number of parks increased
within a neighborhood, residents measure of positive mental health also increased. Dempsey et
al. (2018) examined the link between coastal blue space and depression among older adults.
They found that exposure to blue space is associated with positive mental health effects.
Specifically, individuals living closer to the coastline had lower depression scores than those
living more than 10km (6.21 miles) from the coastline.

In addition, public parks and beaches, to some extent, meet the definition of a quasi-
public good (Jordan, 1995). Unless overcrowding occurs, the “good” in question, enjoying a
park or beach, is non-rival in consumption, meaning enjoyment of the facilities by one person
does not subtract from the enjoyment by another. Furthermore, up to the point of overcrowding,
the marginal cost of providing the good in question to an additional consumer is zero. On the
other hand, public parks and beaches are excludable. In Hillsborough County, for example, state
and conservation parks are gated and a fee is required for entry (Hillsborough County Florida,
2019; Florida State Parks, 2019). Practically, this study will provide greater insight into the park
and recreational needs of these three counties and clear guidance for policy makers and city planners working in this area.

Methods

Data Description

This study utilizes pooled Florida emergency department (ED) data from the 2016 through 2018 Agency for Health Care Administration (AHCA). The data is all-inclusive containing a record for each ED visit occurring at a Florida hospital, describing patient characteristics, outcomes, and up to 10 diagnoses. ED visits for Florida residents diagnosed with either anxiety or depression were identified using the International Classification of Diseases, 10th Revision, Clinical Modification (ICD10-CM) codes, specifically F41 and F32-F33.

Geographic information of public parks and beaches was obtained from the USA Parks layer and USA Recreational Areas layer provided by Esri. The USA Parks shape file includes parks, gardens, and forests within the United States at a national, state, county, regional, and local level (https://www.arcgis.com/home/item.html?id=578968f975774d3fab79fe56c8c90941). Parks within the three counties of interest (Hillsborough, Pasco, and Pinellas) were isolated using the ‘select by location’ tool in ArcMap. Beach locations were gathered from the USA Recreational Areas layer which includes points for parks, beaches, amusement parks, and golf courses. Similar to the park isolation method, beaches within the three counties of interest were isolated using the ‘select by location’ tool in ArcMap.

Other zip code level demographic variables (gender, race, ethnicity, age, education, income, poverty, employment, insurance status) were gathered from American Community
Survey (ACS). These variables were chosen based on the Anderson Health Care Utilization Model. Community level demographics have been shown to correlate to differences in healthcare utilization (Anderson and Newman, 1973). Therefore, predisposing (existing conditions that influence people to use or not use services) and enabling (conditions that facilitate or impede use of service) contextual characteristics at the zip code aggregate were isolated from census data. Predisposing factors include gender, race, ethnicity and age, whereas enabling factors refer to income, poverty, employment, insurance status, and educational attainment. The ACS survey does not report information regarding disease status, disability levels, or the perceived and actual health needs at the zip code level; Consequently, these factors could not be included.

The 2012-2016 and 2013-2017 ACS 5-year estimates were used due to the necessity of zip code level data to join with the AHCA ED data sets. According to the census bureau, the 5-year estimates have increased reliability and precision compared to 1-year estimates (U.S. Census Bureau, 2019). Currently, the 2018 ACS 5-year estimates have not been released, therefore, the independent variables for this year were extrapolated using the average growth rate from the previous two years (2016-2017).

**Statistical Analyses**

The statistical analysis consists of two phases. In the first phase, the analysis will examine anxiety and depression related ED visits from 2016 through 2018 to establish the scope of the problem.

The second phase utilizes a linear regression model to assess the association between natural environments (public parks and beaches) and the rate of anxiety and depression related ED visits, after controlling for covariates. The dependent variable in the model is the rate per
10,000 population of anxiety and depression related ED visits at the zip code level. The geographic area for the analysis is defined as the Tampa Bay area (Figure 4.1). The research question of interest examines how does the availability of public parks and beaches influence the number of anxiety and depression related ED visits per 10,000 population? The model results will inform city/county planners about the differences in the probability of an anxiety or depression related ED visit in zip codes with diverse availability of public parks and beaches. Analyses will be conducted in SAS 9.4 Software and ArcMap 10.3. The primary variables of interest focus on the natural environment, defined as the presence of public parks and beaches.

Stated more formally, the proposed model is as follows:

\[
Rate_z = \beta_0 + \beta_1 N_z + \sum \beta_z X_z + \varepsilon_z
\]

where \( Rate_z \) is the rate per 10,000 population of anxiety and depression-related ED visits; \( N \) is the presence of parks and beaches; and \( X \) is a vector of confounding characteristics, defined below. The subscript \( z \) represents the zip-codes included in the geographic area targeted by the analysis. The variables contained in the vector \( X_z \) may be categorized as demographic characteristics (gender, race, ethnicity, and age), economic factors (income, poverty, and employment), insurance status, and educational attainment.
The research and null hypotheses for this study are as follows:

- **H$_1$**: Rate of anxiety and depression related ED visits per 10,000 population declines with the presence of natural environments (public parks and beaches).
- **H$_0$**: Rate of anxiety and depression related ED visits per 10,000 population does not differ by the presence of natural environments (public parks and beaches).

**Results**

Descriptive analyses were conducted to understand the demographic characteristics of the target population (individuals with anxiety or depression related ED visits; Table 4.1). The majority of ED utilization for anxiety and depression was by women of non-Hispanic white race, ages 18-64. Across the three counties, the majority of visits are paid for by Medicare (anxiety= 31%; depression= 34%), Medicaid (anxiety= 23%; depression= 21%), and private insurance (anxiety= 28%; depression 23%). From 2016 to 2018, there was a steady rise in both anxiety and
depression ED visits across all three counties. Anxiety visits are the most predominant visit (average of 18,004 visits per year) compared to depression-related ED visits (average of 9,157 visits per year). Pasco County was also found to have the highest mean rate of both anxiety- and depression-related ED visits per 10,000 population, 242 and 123 respectively (Table 4.2).

In terms of the quantity of parks and beaches, Hillsborough County had the highest number of zip codes (n=53) and parks (n=271) overall (Table 4.3; Figure 4.2 and Figure 4.3). Pinellas County was found to have the second highest number of zip codes (n=48) and parks (n=168), but the highest number of beaches (n=40) due to its location in the Gulf of Mexico. Pasco County had the least number of both parks (n=26) and beaches (n=4). Throughout the target area, the geographic distribution of parks illustrates that state parks are larger in size and reside mostly on the outskirts of the county, whereas county parks are located in more populated areas and are smaller in size. Local and regional parks were omitted from the analysis due to the extremely small sizes of local parks (< .01 square mile) and the lack of regional park availability (only one among the three counties).

The analysis revealed an increase in both anxiety and depression-related ED visits. Between 2016 and 2018 there was a 25.36% rate change in the number of anxiety-related ED visits and a 31.42% rate change in the number of depression-related ED visits (Figure 4.4).

The ordinary least squares regression models for the combined rate of anxiety- and depression-related ED visits revealed that county park availability was associated with a decrease in ED utilization ($\beta = -55.63; p=0.0195; Table 4.4$). Since some beaches are located near or associated with other public parks, two models were created to determine if omitting beaches changes the relationship between parks and the dependent variable. It was found that omission of beaches did not significantly change the association between parks and ED utilization.
**Table 4.1.** Average Distribution of Demographic Characteristics Among Individuals with Anxiety or Depression-related ED Visits within Hillsborough, Pinellas, and Pasco Counties from 2016-2018

<table>
<thead>
<tr>
<th>Gender</th>
<th>Anxiety</th>
<th>Depression</th>
<th>Anxiety</th>
<th>Depression</th>
<th>Anxiety</th>
<th>Depression</th>
<th>Anxiety</th>
<th>Depression</th>
<th>Anxiety</th>
<th>Depression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>17,863  (69%)</td>
<td>8,255 (68%)</td>
<td>14,815  (67%)</td>
<td>6,835 (65%)</td>
<td>6,841 (69%)</td>
<td>3,225 (68%)</td>
<td>13,173 (73%)</td>
<td>6,105 (67%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;18</td>
<td>1,058 (4%)</td>
<td>687 (6%)</td>
<td>633 (3%)</td>
<td>524 (5%)</td>
<td>412 (4%)</td>
<td>285 (6%)</td>
<td>701 (4%)</td>
<td>499 (5%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-64</td>
<td>20,910 (81%)</td>
<td>9,436 (77%)</td>
<td>17,195 (78%)</td>
<td>7,695 (73%)</td>
<td>7,780 (78%)</td>
<td>3,436 (72%)</td>
<td>15,295 (85%)</td>
<td>6,856 (75%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>65+</td>
<td>3,812 (15%)</td>
<td>2,083 (17%)</td>
<td>4,273 (19%)</td>
<td>2,288 (22%)</td>
<td>1,768 (18%)</td>
<td>1,036 (22%)</td>
<td>3,284 (18%)</td>
<td>1,802 (20%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>19,025 (74%)</td>
<td>8,957 (73%)</td>
<td>18,247 (83%)</td>
<td>8,838 (84%)</td>
<td>9,045 (91%)</td>
<td>4,357 (92%)</td>
<td>15,439 (86%)</td>
<td>7,384 (81%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>4,436 (17%)</td>
<td>2,266 (19%)</td>
<td>3,050 (14%)</td>
<td>1,369 (13%)</td>
<td>430 (4%)</td>
<td>190 (4%)</td>
<td>2,639 (15%)</td>
<td>1,275 (14%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>2,318 (9%)</td>
<td>982 (8%)</td>
<td>804 (4%)</td>
<td>301 (3%)</td>
<td>485 (5%)</td>
<td>210 (4%)</td>
<td>1,202 (7%)</td>
<td>498 (5%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>6,163 (24%)</td>
<td>2,606 (21%)</td>
<td>1,288 (6%)</td>
<td>548 (5%)</td>
<td>945 (9%)</td>
<td>401 (8%)</td>
<td>2,799 (16%)</td>
<td>1,185 (13%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insurance Status</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>3,772 (15%)</td>
<td>1,547 (13%)</td>
<td>3,607 (16%)</td>
<td>1,520 (14%)</td>
<td>1,488 (15%)</td>
<td>659 (14%)</td>
<td>2,956 (16%)</td>
<td>1,242 (14%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Private</td>
<td>7,133 (28%)</td>
<td>2,917 (24%)</td>
<td>5,526 (25%)</td>
<td>2,314 (22%)</td>
<td>2,516 (25%)</td>
<td>1,039 (22%)</td>
<td>5,058 (28%)</td>
<td>2,090 (23%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicaid</td>
<td>5,897 (23%)</td>
<td>2,741 (22%)</td>
<td>4,307 (19%)</td>
<td>2,052 (20%)</td>
<td>2,418 (24%)</td>
<td>1,070 (22%)</td>
<td>4,207 (23%)</td>
<td>1,954 (21%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicare</td>
<td>6,526 (25%)</td>
<td>3,692 (30%)</td>
<td>7,034 (32%)</td>
<td>3,801 (36%)</td>
<td>3,075 (31%)</td>
<td>1,747 (37%)</td>
<td>5,545 (31%)</td>
<td>3,080 (34%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>2,451 (10%)</td>
<td>1,308 (11%)</td>
<td>1,627 (7%)</td>
<td>821 (8%)</td>
<td>463 (5%)</td>
<td>243 (5%)</td>
<td>1,514 (8%)</td>
<td>791 (9%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2016</td>
<td>23,153</td>
<td>10,992</td>
<td>17,235</td>
<td>7,513</td>
<td>8,412</td>
<td>3,831</td>
<td>12,437</td>
<td>7,445</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2017</td>
<td>26,759</td>
<td>12,971</td>
<td>19,954</td>
<td>8,833</td>
<td>9,411</td>
<td>4,534</td>
<td>18,708</td>
<td>8,779</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2018</td>
<td>27,427</td>
<td>12,652</td>
<td>29,114</td>
<td>15,178</td>
<td>12,058</td>
<td>5,905</td>
<td>22,866</td>
<td>11,245</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**Table 4.2.** Descriptive Statistics of Dependent Variables at Zip Code level in Pasco, Pinellas, and Hillsborough County from 2016-2018

<table>
<thead>
<tr>
<th>Rate of Anxiety-Related ED Visits per 10,000 population</th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pasco</td>
<td>242.43</td>
<td>186.99</td>
<td>82.03</td>
<td>1406.25</td>
<td>216.93</td>
</tr>
<tr>
<td>Pinellas</td>
<td>223.27</td>
<td>204.11</td>
<td>78.88</td>
<td>788.81</td>
<td>104.39</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>190.40</td>
<td>180.28</td>
<td>60.30</td>
<td>384.25</td>
<td>66.91</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rate of Depression-Related ED Visits per 10,000 population</th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pasco</td>
<td>123.40</td>
<td>87.56</td>
<td>32.19</td>
<td>1250.00</td>
<td>163.85</td>
</tr>
<tr>
<td>Pinellas</td>
<td>106.06</td>
<td>91.06</td>
<td>11.97</td>
<td>431.59</td>
<td>60.67</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>90.73</td>
<td>84.59</td>
<td>20.97</td>
<td>258.97</td>
<td>37.76</td>
</tr>
</tbody>
</table>

**Average Rate of Anxiety and Depression-Related Visits per 10,000 population in Florida**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>315.95</td>
<td>272.40</td>
<td>98.05</td>
<td>2,656.25</td>
<td>204.18</td>
</tr>
</tbody>
</table>
Table 4.3. Zip code, Park, and Beach Distribution in Hillsborough, Pasco, and Pinellas County, FL.

<table>
<thead>
<tr>
<th>County</th>
<th>Zip Codes</th>
<th>Local</th>
<th>Regional</th>
<th>County</th>
<th>State</th>
<th>Beaches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pasco</td>
<td>23</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Pinellas</td>
<td>48</td>
<td>162</td>
<td>0</td>
<td>4</td>
<td>2</td>
<td>40</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>53</td>
<td>248</td>
<td>1</td>
<td>18</td>
<td>4</td>
<td>8</td>
</tr>
</tbody>
</table>
Zip codes with a higher percentage of females had a significantly higher rate of anxiety- and depression-related ED visits (p<.0001). Furthermore, zip codes with higher percentages of poverty, uninsured, and education high school or greater had significantly higher rates of anxiety- and depression-related visits. Interestingly, zip codes with higher percentages of unemployment resulted in a statistically lower rate of anxiety- and depression-related ED-visits (p <.0001).
<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-1716.69 (&lt;.0001)*</td>
<td>-1703.58 (&lt;.0001)*</td>
</tr>
<tr>
<td>Percent Female</td>
<td>22.91 (&lt;.0001)*</td>
<td>23.03 (&lt;.0001)*</td>
</tr>
<tr>
<td>Percent White</td>
<td>0.32 (0.4571)</td>
<td>0.31 (0.4553)</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>-0.21 (0.7657)</td>
<td>-0.23 (0.7515)</td>
</tr>
<tr>
<td>Percent Age 17 and Younger</td>
<td>0.66 (0.7442)</td>
<td>0.77 (0.6973)</td>
</tr>
<tr>
<td>Percent Age 65 and Older</td>
<td>-0.50 (0.6793)</td>
<td>-0.49 (0.6820)</td>
</tr>
<tr>
<td>Average Income in Thousands</td>
<td>0.69 (0.2347)</td>
<td>0.66 (0.2502)</td>
</tr>
<tr>
<td>Percent Below Poverty</td>
<td>15.86 (&lt;.0001)*</td>
<td>15.55 (&lt;.0001)*</td>
</tr>
<tr>
<td>Percent Unemployed</td>
<td>-37.78 (&lt;.0001)*</td>
<td>-37.55 (&lt;.0001)*</td>
</tr>
<tr>
<td>Percent Uninsured</td>
<td>13.01 (&lt;.0001)*</td>
<td>13.08 (&lt;.0001)*</td>
</tr>
<tr>
<td>Percent with High School Degree or More</td>
<td>6.19 (0.0191)*</td>
<td>5.97 (0.0207)*</td>
</tr>
<tr>
<td>Population Density</td>
<td>-0.01 (0.0979)</td>
<td>-0.01 (0.1080)</td>
</tr>
<tr>
<td>Park</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Local Park</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Regional Park</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>County Park</td>
<td>-55.63 (0.0195)*</td>
<td>-55.67 (0.0193)*</td>
</tr>
<tr>
<td>State Park</td>
<td>-14.20 (0.6050)</td>
<td>-14.76 (0.5899)</td>
</tr>
<tr>
<td>Beach Available</td>
<td>-8.43 (0.6854)</td>
<td>-</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Significance at alpha level 0.05
**Discussion**

In this study, we explored how the availability of parks and beaches impact the rate of ED utilization for anxiety and depression in Hillsborough, Pasco, and Pinellas counties in Florida from 2016-2018. Increased availability of county parks was associated with significantly lower anxiety and depression related ED visits after controlling for confounding variables. However, the county with the least number of parks and beaches had the highest rate of anxiety and depression ED visits (Pasco) and vice versa for the county with the most parks and beaches (Hillsborough). Furthermore, zip codes with higher percentages of females, poverty, and educated persons were found to have higher rates of anxiety and depression ED visits. However, there was a significantly lower rates of anxiety- and depression-related ED visits for zip-codes with higher percentages of unemployment.

Results of this study indicate county parks are significantly associated with lower rates of anxiety and depression-related ED visits. County parks differ from other park types (regional, local, and state) as they usually contain sport amenities and recreational facilities for residents. For example, Wang et al. (2005) conducted a cost-benefit analysis of physical activity in Lincoln, Nebraska and found that every dollar spent on creating and maintaining park trails saves approximately $3 in healthcare expenses. Furthermore, Cohen et al. (2016) assessed 174 neighborhood parks in the United States and found amenities such as walking loops, gymnasias, and programmed activities led to increased park utilization and physical activity levels. Therefore, when policy makers and urban planners evaluate the location and components of existing and future parks, this distinction in available amenities and programs must be taken into
consideration as factors such as these can impact the utilization of community parks and therefore the mental health status of residents.

When measuring blue space availability there are different perspectives researchers have taken into consideration such as coastal proximity, self-reported usage, proportion of land occupied, distance from home, and visibility from home (Pearson et al., 2017). In this present study, due to the zip code aggregate of anxiety and depression-related ED visits, we utilized an objective measurement of blue space based on the presence of at least one beach (Yes/No) within each designated zip code. However, beach presence was not significantly associated with the rate of anxiety and depression ED visits. More detailed data sets are needed to understand the intricacy of exposure and utilization of these spaces.

Consistent with past research studies, the results of this present study indicate that zip codes with higher proportion of females had higher rates of anxiety and depression-related ED visits. This can be attributed to numerous factors. For example, it has been established by the National Institute of Mental Health that women are twice as likely as men to experience anxiety and depression (NIMH, 2005). This can be associated with the several hormone related life changes that occur in a woman’s lifetime (i.e. puberty, premenstrual, perinatal, perimenopause etc.). In addition to the biological reasons for higher prevalence rates, women are more likely to be diagnosed by physicians and seek help for their mental illnesses compared to men. Numerous risk factors also make women increasingly susceptible to certain mental conditions such as higher poverty rates, violence victimization, and caregiver status. Therefore, increased exposure to natural environments such as parks and beaches should be considered in treatment plans for women suffering from anxiety and depression as a means to decrease rumination and stress levels.
Adults living below the poverty line are more likely to experience a serious mental illness than those living at or above the poverty line (SAMHSA, 2015). The toxic consequences of chronic stress related to poverty include physiological and neurobiological changes in the body and brain. Increased levels of cortisol are found to disrupt synapse regulation and reduce the size of the prefrontal cortex which can lead to memory and learning issues (Kooij et al., 2014; Kang et al., 2012). Moreover, chronically high levels of cortisol can increase the size of the amygdala, making these individuals more susceptible to future stress. When enduring poverty, the daily struggles such as food insecurity, unstable housing, inability to pay bills, etc. leaves little brain capacity left for productive activities (i.e. education, identifying social services, helping children, and providing for the family; The Urban Institute, 2013). Furthermore, children growing up in poverty have been found to be particularly affected by mental health problems such as anxiety and depression and therefore may require tailored interventions to prevent these negative health effects (The Urban Institute, 2013).

Although higher educational levels have been found to act as a protective factor against anxiety and depression (Herzog et al., 1998), there are several factors that might increase rates among individuals with higher education. The immense workload associated with higher level jobs, the remaining loans from pursuing higher degrees, and the pressure to maintain a certain standard can enable feelings of immense stress. Another reason for higher rates could be associated with increased mental health literacy. Individuals with higher educational attainment are able to recognize the signs and symptoms of mental illness and seek help or treatment.

Surprisingly, the present model indicates higher rates of unemployment was associated with statistically lower rates of anxiety and depression-related ED visits. There are two plausible explanations. Individuals who are unemployed are more likely to also be uninsured, and
therefore, they may use more discretion in their health care utilization since costs will be out of pocket. Another possibility is individuals who are unemployed might be ill in actuality but are putting off primary care until in crisis and in need of emergency services. Unfortunately, due to the nature of this variable, we do not know which of these two forces are stronger and therefore we are forced to examine unemployment empirically.

This study has some limitations. Although we were able to assess designated parks and beaches, the data sets utilized in the methodology do not take into consideration small patches of green space such as street trees and median grass or blue space such as fountains and ponds or lakes. Some previous studies note that these sporadic green and blue spaces play a role in quality of life (Barton & Rogerson, 2017; NASA, 2019; Engemann et al., 2019; Wolf & Flora, 2010). Furthermore, we were unable to measure park or beach utilization since many smaller parks (such as county parks), do not track utilization. Although our measure of availability is important, future research should focus on identifying more sophisticated data collection methods that would allow for measures of utilization and exposure time. It is important to note that severity of illness and other health needs could not be measured at the zip code level due to limitations in data availability.

At a systematic level, the results of this study support the idea that urban planning, public health, and public policy are interdependent in both research and intervention activities (Kochtitzky et al., 2006; Mehdipanah et al., 2017). Although exposure to natural environments has been associated with positive health outcomes, such as the results of this present study, this type of information has not greatly affected urban planning as a public health priority (Pretty et al., 2005). A disconnect between the disciplines has been noted ever since infectious disease prevalence has decreased. City planning moved toward economic development and public health
focused on education and social determinants of illness (Mehdipanah et al., 2017). However, the association between chronic illnesses and the built environment is evident and therefore collaboration is essential now more than ever.

It is recommended that park access is recognized as a necessity and not a luxury. Policy makers and city planners should focus efforts on placing parks in more populated areas to improve access and utilization. One example of how to accomplish this is by assessing the state of New Jersey. New Jersey is the most heavily urbanized states in America with approximately 94.7% of its population residing in urban areas. In 1986, state governmental officials realized the critical role they play in coordinating land-use planning among state agencies and different levels of government. They adopted the State Planning Act and mandated the creation of the State Development and Redevelopment Plan to assist in the vision for strong communities and preserved open lands. According to the U.S. Census, Florida has the third largest urban population in the United States. Therefore, state and local officials must come together to also create a vision of what we foresee our communities to look like in the future and how we plan on achieving a balance between urbanization and the natural environment.

References


CHAPTER FIVE
DISCUSSION

Part I: Co-occurring Heat-Related Illness and Behavioral Health Disorders

BHDs impact an estimated one in five U.S. adults with many individuals suffering from multiple mental illnesses or co-occurring substance use disorders. Thermoregulation among individuals with BHDs is disrupted by underlying physical pathology, prescribed psychiatric medications, and physical and/or mental impairments (Chong & Castle, 2004; Wang et al., 2013; Hansen et al., 2008; Cusack et al., 2011). This can increase the population's vulnerability to high ambient heat. As climate change persists, it is imperative that we understand how extreme heat events will impact these individuals and our society as a whole.

In Florida, 17.54% of adults are estimated to have a BHD, however only 36.1% report having received mental health services compared to the national annual average percentage of 42.9% (Substance Abuse and Mental Health Services Administration (SAMHSA), 2017a; National Institute of Mental Illness, 2019). Of those individuals who received treatment in the Florida public mental health system, 84% of children and adolescents and 86% of adults reported improved functioning post-treatment, indicating that this may not be a quality of care issue (SAMHSA, 2017b). However, it has been found that among the United States, Florida ranks 44th for mental health care access and is a designated mental health care health professional shortage area (HPSA; Mental Health America, 2018; Kaiser Family Foundation, 2019). This lack of
access to behavioral health care specialist leads to inappropriate use of emergency and hospital services (SAMHSA, 2014).

Therefore, the first two objectives addressed in this dissertation include: 1) identifying the contextual factors that influence the rate of co-occurring BHDs and HRI in Florida counties and 2) understanding the hospital utilization patterns of individuals with co-occurring BHDs and HRI. The first objective examined how differing availability of mental health providers and variation of social vulnerability factors such as socioeconomic status, household composition, minority status, and housing and transportation between counties impacts the rate of hospital utilization for these co-occurring conditions. The second objective utilized scrambled social security numbers to track patient hospital utilization and determine the likelihood of ED revisits and hospital readmissions among this population. Both of these studies resulted in unique information with implications pertaining to research and practice discussed below.

**Importance of Outpatient Care Availability to Reduce Hospital Utilization**

Of all the mental health care providers investigated in this analysis, increased availability of outpatient mental health and substance use centers was found to have the most significant impact on decreasing hospital utilization. These establishments provide services such as counseling, group therapy, medical consultations, and psychiatry which aid in with treatment of mental illness and substance use outside of the acute care, inpatient setting. Availability and access to such services outside the hospital setting allows individuals with mental and substance use disorders to manage their symptoms and needs in a more timely and cost-effective manner. However, even though mental health awareness is growing in the United States, the capacity and resources to serve this population are lacking.
One cost effective and efficient way to address the access to mental health care issue we are experiencing in Florida is telehealth. Telehealth is a form of video conferencing that allows health practitioners such as psychiatrists and therapists to provide services to patients outside of the office and in less severe cases, substitute for emergency department care (Florida Behavioral Health, 2019). This virtual treatment model has been heavily utilized by the Department of Veterans Affairs as a means to improve access to timely care. Turvey et al. (2017) conducted a randomized clinical trial comparing a telemedicine outreach for PTSD program and those who receive usual care. During both the 6-month (p=.0002) and 12-month (p=.04) follow-up period, individuals who were assigned to the telemedicine program had significantly larger decreases in Posttraumatic Diagnostic Scale scores (6 month: 35.0 to 29.1, 12 month: 35.0 to 30.1) compared to those in the usual care (6 month: 33.5 to 32.1, 12 month: 33.5 to 31.7). This indicates that tele- mental health care can successfully reach and engage patients in evidence-based treatments while also improving long-term health outcomes.

The use of tele-mental health dates back to the 1950s, however there are numerous policy and privacy barriers that have inhibited national adoption. Each state addresses telehealth differently as they do other laws, regulations, and Medicaid program policies. Reimbursement policies are one the most important aspects of tele-health adoption. In 2012, only 18 states (not including Florida) established private payer laws that require the reimbursement amount for a telehealth-delivered service be equal to the amount that would have been reimbursed had the same service been delivered in person (Center for Connected Health policy, 2019). However, by 2019, 40 states (including Florida) adopted a private payer law requiring some form of reimbursement (Center for Connected Health policy, 2019). In Florida, the legislation indicates that contracts between health insurers or health maintenance organizations and telehealth...
providers must establish mutually acceptable payment rates for services provided (Section 456.67, 2019). In terms of Medicaid reimbursement, real time interactive telehealth is reimbursed only for Community Behavioral Health Services (Center for Connected Health policy, 2019; Section 456.67, 2019). Although Florida state legislature has yet to recognize telehealth appointments as equal to in-person appointments, expanding reimbursement is a step in the right direction.

Another aspect of the health care system in the United States that adds to the morbidity and mortality is the separation of mental and physical health. Although the word “patient-centered” is motioned regularly in the health care field, a true patient centered approach requires integration of care that allows for a holistic perspective. Currently, the United States healthcare system follows a disease-oriented approach where primary care physicians and patients mainly discuss and address how to subside certain side effects and outcomes related to deeper underlying issues. Individuals with behavioral health disorders are found to have a shorter life span, mostly due to “untreated and preventable chronic illnesses like hypertension, diabetes, obesity, and cardiovascular disease that are aggravated by poor health habits such as inadequate physical activity, poor nutrition, smoking, and substance abuse. Barriers to primary care — coupled with challenges in navigating complex healthcare systems” create further obstacles to care (SAMHSA, 2019). An integrative care model would allow for systemic coordination between mental health, substance abuse, and primary care services and therefore lead to effective treatment and continuity of care for individuals with multiple health care needs. This team-based approach has proven effective for individuals with mental illnesses as previous research indicates an increase in screening rates, improved hypertension management, decreased probability of
hospitalization (18%; p<.001), and an estimated savings due to decreased hospitalizations of $1,000 per patient (Wells et al., 2018).

All facets of health and wellness as we know it cannot be addressed within the doctor’s office as many health issues stem from the social determinants of health such as inadequate housing, food insecurity, and insufficient access to transportation services just to name a few. One way to address the complex myriad of factors that impact behavioral health is utilization of the Assertive Community Treatment (ACT). ACT dates back to the 1970s and was developed to serve individuals with severe mental illnesses who were high users of inpatient and emergency services (Woesner et al., 2014). The ACT model embodies all the key components a health system should strive for such as 24/7 holistic care, continuity of care, multidisciplinary teams, individualized services, low client-to-staff ratio, integration of services (i.e. psychopharmacologic, substance use, and rehabilitative treatment), medical monitoring, collaboration with primary care treatment team, and social services (Woesner et al., 2014). This approach to health care has shown reduce hospital usage, reduce costs, improvement substance use outcomes, and improve functional and consumers’ quality of life (Phillips et al., 2001; Bond and Drake, 2015).

One of the major issues individuals with severe mental illnesses have been found to struggle with outside their health issues is obtaining and maintaining adequate housing. Residential services are extremely important in the recovery process as they help combat barriers such as cost, availability of units, and resistance in many neighborhoods (Cunningham et al, 2006). Investments in these types of social services are not only to serve individual need, but to lift a community up as a whole. Decreasing homelessness and incarceration requires investment from each level of the socio-ecological model and emphasizes the reciprocal relationship
between individuals and the community they live in. In essence, the health of the individual depends on the community and the health of the community depends on its individuals.

**Increased Likelihood of Hospital Reutilization for HRI Especially Among Individuals with Nicotine Dependence, Male Gender, and Uninsured Status**

The hypothesis that individuals with BHDs would be significantly more likely to endure a repeated ED or IP visit for HRI compared to those without BHDs was supported. As a result of this dissertation, individuals with substance use disorders, particularly nicotine dependence, were found to be at a higher risk of suffering from multiple HRIs. One key issue when addressing HRI is risk perception and heat-health awareness. Madrigano et al. (2018) conducted a random telephone survey about extreme heat in New York City (n=801 adults) and found many individuals, particularly males and low-income households, have lower awareness of heat warnings and risk perception. Therefore, there is a clear need for risk communication, education, and awareness.

Physicians also have the ability to initiate behavior change (i.e. smoking or alcohol cessation) by referring the patient to a health coach or psychologist (Alaszewski and Horlick-Jones et al., 2003). Pharmacists are another key medical personal that are able to communicate risks and precautions with patients or caregivers that pick up their prescriptions. Specifically, well-informed pharmacists can communicate heat-related risks and precautions to individuals who are prescribed anti-depressants and anti-psychotics.

Due to the increased risk of hospital reutilization among individuals with BHDs and previous HRIs, special attention needs to be given to the timeliness of post-discharge follow-up care. Previous literature indicates that follow-up care within seven days of hospital admission is
the most effective in preventing 30-day readmissions, especially among individuals with BHDs (Fontanella et al., 2016; Sorbero et al., Orlosky et al., 2007; Croake et al., 2017; Gerson et al., 2012; Stein et al., 2017). Hospitalization takes a toll on the individual and their family as their entire lifestyle is disrupted by the event, however, follow-up care can assist with keeping a patient on track with their health goals and requirements (i.e. medication management and adherence). Most follow-up care studies focus on in-person appointments and found that males, African Americans, and those living in rural areas were less likely to receive this type of care. Therefore, this is another sector of health care that can utilize video conferencing as a means to meet with individuals that would be unable to receive care otherwise. Simon et al. (2011) assessed an online depression care management program at nine primary care clinics in Washington state and found patients who participated in the program had higher rates of anti-depressant adherence, lower depression scores, and greater satisfaction with depression treatment. This indicates that organized follow-up care can be delivered efficiently and effectively through tele-health tools such as video conferencing and online messaging.

Analysis of hospital re-utilization patterns revealed that males are particularly vulnerable to experiencing heat-related ED re-visits and IP readmissions. As noted previously in Chapter 3, this increased likelihood is associated with the outdoor-related recreational and occupational activities males tend to engage in. OSHA, the Occupational Safety and Health Administration, identifies numerous outdoor and indoor occupations with increased risk of HRI such as agriculture, construction, landscaping, mail delivery, laundries, manufacturing, and fire service. Surprisingly, only three states have been found to have adopted specific heat illness prevention standards not addressed by federal OSHA standards- California, Minnesota, and Washington (Occupational Safety and Health Administration, 2019; Department of Industrial Relations,
Furthermore, employers’ responsibilities outlined by the General Duty Clause are “to provide their employees with a place of employment that ‘is free from recognized hazards that are causing or likely to cause death or serious harm to employees’” (Occupational Safety and Health Administration, 2019). This broad obligation can be interpreted in several ways and does not require any specific actions be taken in terms of water breaks, exposure time, training and acclimation programs, or emergency plans and first aid education.

One example to consider is landscaping, a predominantly male dominated occupation that is extremely popular and successful in the state of Florida. This billion-dollar industry is made up of approximately 63% family-owned and 32% privately held businesses. Without clear industry standards or regulations, there is an obvious variety in safety compliance by businesses and employees. Compared to other industries, the landscaping industry has a higher fatality rate per 100,000 workers (3.8 versus 25.1, respectively; Centers for Disease Control and Prevention, 2017). California Department of Health created the Californian Fatality Assessment and Control Evaluation (CA-FACE) program to investigate these worker deaths and produce written educational materials and short safety videos that highlight best practices for worker safety and health (Centers for Disease Control and Prevention, 2017). FACE collaborates with numerous stakeholders (employers, workers, and trade associations) and provides them with materials for use in safety trainings and improvements of worker practices (Centers for Disease Control and Prevention, 2017). This information is easily disseminated to small businesses and has been found to reach a wide audience.

Furthermore, in 2015, California created new requirements for employers and employees regarding heat illness prevention. This includes legislation that requires provision of water, access to shade, high heat procedures, emergency response procedures, acclimatization, training,
and health illness prevention plans (Title 8 Section 3395; Department of Industrial Relations, 2015). These precautions are important to health and also economic stability of both the employer and employee. OSHA estimates the cost of one HRI on the job is $53,589 ($25,519 direct costs + $28,070 indirect costs; OSHA, 2020). Therefore, following in California’s footsteps would be particularly beneficial for Florida residents due to the increased risks such as year-round humidity and heat.

Another key factor that contributed to increased likelihood of 30-day ED revisits was a lack of health insurance. Due to this decreased access to care, uninsured individuals tend to go without medical care for prolonged period of time and are less likely to receive preventative care and services for chronic diseases (Kaiser Family Foundation, 2019). Even after the implementation of the Affordable Care Act, the most cited reason for being uninsured is cost. Most uninsured individuals are in low-income families and therefore when they do seek care they are faced with unaffordable medical bills. Among individuals with severe mental illness, decreased access to mental health care due to high cost and/or lack of insurance is a particularly prevalent issue. Furthermore, low income households are associated with higher risk for anxiety, substance use, mood disorders, and suicide attempts (Sareen et al., 2011). This complex reciprocal relationship between health and income is exacerbated by behavioral and environmental factors such as smoking, obesity, decreased physical activity, higher levels of violence, discrimination, and material deprivation (i.e. lack of housing, cooling, heating, water, and electricity; Khullar and Chokshi, 2018).

One particular environmental factor that increases the risk of HRI among this population of low income, uninsured individuals with mental illness is the inadequacy or lack of air conditioning. The CDC notes that air conditioning (AC) is the strongest protective factor against
HRI (CDC, 2012). Previous literature indicates that individuals in low-income households have lower rates of air-conditioning use and the highest risk of being hospitalized for HRI (Schmeltz et al., 2015). Furthermore, heat-related mortality has been shown to decrease with increased prevalence of central AC units (O’Neill et al., 2005). Therefore, increased support and awareness of programs that provide grants for improving low income homes, such as The Florida Weatherization Assistance Program and The Low-Income Home Energy Assistance Program (LIHEAP), is necessary to reach target populations (Benefits.gov, 2020; U.S. Department of Health and Human Services, 2020). In addition, public health agencies can work with AC providers to improve the availability and affordability of air conditioning.

The complex social issues discussed above indicate a need for building community capacity to address systemic issues in communities. Even though social needs are clearly linked with health outcomes, the present medical model in the U.S. does not address this connection. Despite how much the U.S. spends on medical care, health outcomes are not improving proportionally. Therefore, instead of increasing spending without tangible returns, attention should be placed on nonmedical determinants of health such as early childhood development, economic opportunities, and education as a means to establish better health at not only the individual level, but also the community level. This responsibility to improve community capacity and resilience does not lie on one organization or group. It will require a multisectoral approach made up of strong leadership from various stakeholder groups, a growth mindset, and shared responsibility. In order to improve outcomes, such as poor mental health, we cannot wait until individuals end up in the emergency department or inpatient setting seeking care. Initiative must be taken outside the doctor's office.
Part II: Natural Environments

Natural environments are found to have a positive impact on both mental and physical health. Access and utilization of natural environments has shown to decrease cortisol levels, lower blood pressure, increase physical activity levels, and improve perceived health (Recreation and Park Administration, 2018). Although the positive effects on individual health have been heavily explored and made evident, there is a gap in understanding how these factors impact community health and hospitalization utilization specifically.

Therefore, the third objective of this dissertation explored the relationship between the natural environment and ED utilization rates. Public parks, public beaches, and anxiety and depression-related ED visits were isolated at the zip code level in Hillsborough, Pasco, and Pinellas Counties. Beaches did not have a significant effect on the rate of anxiety and depression-related ED utilization, however increased access to county parks was found to significantly decrease the ED utilization rate.

Importance of County Park Access in Reducing Anxiety and Depression ED Visits

Looking at the Tampa Bay Area (Hillsborough, Pasco, and Pinellas Counties), an apparent negative correlation exists between park availability and the rate of anxiety and depression ED visits. Pasco County had the least number of parks and beaches and the highest rate of anxiety and depression ED visits, whereas Hillsborough County had the highest number of parks and beaches among the three counties, the lowest rate of anxiety and depression related ED visits. When assessing the size and distribution of parks in Tampa Bay, it is evident that Pasco County has several larger parks concentrated at the east and west end of the county. In comparison, Hillsborough and Pinellas counties have many smaller parks sporadically spread
across the county. One can deduce that more evenly distributed parks across inhabited areas of the county allows residents easier access compared to concentrated distribution of larger parks.

County parks in particular were significantly associated with ED utilization rate. County parks differ from other park types (i.e. local and state) as they usually contain a variety of sport amenities and recreational facilities for residents. Previous research indicates that availability and quality of amenities leads to increased utilization and therefore decreased healthcare spending (Wang et al., 2005; Cohen et al., 2016). As policy makers and urban planners evaluate the location and components of existing and future parks, this distinction in available amenities and programs must be taken into consideration as factors such as these can impact the utilization of community parks and therefore the mental health status of residents.

Taking into consideration the risks associated with extreme heat, it can be difficult for individuals with BHDs to safely enjoy the outdoors without proper precautions. Therefore, from a community standpoint, it is imperative that parks and beaches have adequate availability of shaded areas, either pavilions or tree canopies, and well-maintained hydration stations that provide clean, cool water throughout the area. Individuals can take extra precautions such as using a hat to block the sun from the head and face, wearing loose, light weight clothing, having a buddy when going outside for a prolong period of time, and keeping water on hand for easy hydration.

Ensuring equitable access of parks is essential to public health. Instead of viewing parks as something that is “nice to have,” they need to be valued as a vital resource for community health, the environment, and social resilience (Moore, 2019). As funding to local governments decreases, parks and recreation programs have struggled to obtain and maintain financial resources (Fulton, 2012). However, by quantifying and demonstrating the benefits of parks, cities
can use this information to inform policy and build advocate coalitions (Eldridge et al., 2019). As emphasized by this dissertation, increased access to public parks is associated with decreased rates of anxiety and depression related ED visits. Therefore, by investing in the preservation of the natural environment and ensuring residents have equitable access, communities can reduce preventable hospital utilization and achieve better health care outcomes.

**Limitations**

Study limitations stem from the fact that the data sets utilized were not designed specifically for this research. For example, AHCA ED and IP data is an administrative hospital data set that allows for exploration of epidemiological trends, however hospital records are not primarily designed for research as they are often incomplete and unstandardized. There is also a risk of diagnostic variability between hospitals as different clinicians may capture different aspects of disease during each visit. The use of ICD-10 codes relies heavily on clinical judgement; therefore, accuracy can be questionable. Furthermore, there is no uniform guideline to inform the assignment of HRI leading to under-reporting and many BHDs have overlapping symptomology which can lead to misdiagnosis.

Another key limitation is the aggregation of data at the county and zip code levels. Although steps were taken to account for inter-county variability, aggregation can mask significant factors that influence the relationship being investigated. Furthermore, specific confounding variables were unavailable due to the nature of the administrative data such as the income of these patients, what activity they were participating in prior to the heat event, whether they have access to air conditioning, what prescription medications they are consuming, etc. This information would be useful in understanding how these co-occurring conditions emerge.
Although park and beach availability were easily measurable, utilization rates and exposure time was not available for many smaller parks (such as county parks). The re-visit and re-admission analysis was also limited by the small sample sizes, particularly in the inpatient setting. Lastly, due to the cross-sectional nature of this analysis, the conclusions made are based on associations that emerged at one point in time and do not indicate causality.

Despite these limitations, this in-depth analysis of hospital utilization adds to the foundation of knowledge regarding co-occurring HRI and BHDs and the health benefits of the natural environment.

**Conclusions**

Overall, the results presented here indicate that uninsured white non-Hispanic middle-aged males are highly vulnerable and likely to utilize hospitals in Florida for co-occurring HRI and BHDs. The importance of outpatient mental health care access was emphasized as a means to reduce utilization of high cost hospital care. The majority of co-occurring cases were among individuals with substance use disorders, particularly, nicotine dependence. Therefore, public health messaging and communication regarding the health risks associated with substance use and temperature is needed. Individuals with co-occurring disorders were also found to have higher rates of ED revisits and IP readmissions compared to individuals with HRI only. Future research includes assessing reutilization rates at a national level with a larger sample size and obtaining qualitative data to understand what transpired prior to the hospital utilization and contributed to the heat event. Lastly, the availability of county parks was associated with a decrease in anxiety and depression-related ED visits. This emphasized the importance of promoting mental health through preservation of natural environments. As climate change
persists and temperatures continue to rise, it is important that we as a society strategize by identifying vulnerable populations and preparing adequate public health interventions that promote health and safety when enjoying the outdoors.

References


Follow-Up Care After Emergency Department Visits for Mental and Substance Use Disorders Among Medicaid Beneficiaries. *Psychiatric Services*, 68(6), 566-572. doi:10.1176/appi.ps.201500529


Kaiser Family Foundation. (2019a). Mental Health Care Health Professional Shortage Areas. Available online at https://www.kff.org/other/state-indicator/mental-health-care-health-professional-shortage-areas/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D.


Occupational Safety and Health Administration. (2019). Safety and Health Topics: Heat


